Dynamic Analysis of Agile Manufacturing Planning and Control (MPC) Systems Using Control Theory

By

Ahmed Mahmoud Deif

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To My Parents

ABSTRACT

Although the term "agility" is still controversial in the literature of manufacturing systems, a consensus can be drawn in terms of how it is related to responsive and cost effective manufacturing in response to turbulent market. This dissertation proves that dynamic (rather than static) manufacturing planning and control (MPC) systems play an important role in realizing agility in manufacturing systems through linking management level with production level.

The objective of this research is to develop a dynamic MPC system which has the ability to accomplish rapid and feasible dynamic switching between the adoption of different policies, mainly inventory based and capacity based policies, in order to adhere to management strategies.

This objective is accomplished by developing an approach that integrates control theoretic approaches with classical MPC knowledge to model and analyze the proposed MPC system. The model incorporates different controllers for capacity, WIP and inventory and the whole system is controlled by a decision logic unit (DLU). Various dynamic analyses were conducted for the developed system including transient time, stability and steady state error.

A multi-layer architecture for the DLU was developed. The first layer contained the switching protocol between different controllers (policies) based on market demand. The second layer was responsible for deciding on optimal values for the controllers' gains in each policy by manipulating a multi-objective optimization algorithm. The last layer was responsible for online production control to meet required demand.

The system proposed was demonstrated with an industrial case and its efficiency was validated using comparative cost analysis with classical MPC polices. Also numerical simulation experiments were conducted to show the ability of the proposed system to deal with turbulent environment.

Results showed that dynamic analysis gives an insight about tradeoffs between competing agility requirement and the role of MPC parameters to decide on optimal MPC policy. Furthermore, dynamic models provide a clearer picture about the behavior of manufacturing systems against turbulent demand patterns. Finally, the proposed approach closes the gap between management and operational levels and thus gears the enterprise towards agility. This research provides an innovative approach to the design and analysis of agile MPC systems.

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A final appreciation to all those who taught me that knowledge is the way for honor and helped me to create my mission to continue seeking knowledge throughout my life.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABREVIATIONS

MPC: Manufacturing planning and control

DLU: Decision logic unit

WIP*: Desired WIP level (parts)

WIP: Actual WIP level (parts)

DPR: Desired production rate (parts/h)

PR: Actual production rate (parts/h)

T_{LT*}: Expected lead time (h)

T_{LT}: Lead time (h)

G_W: WIP-based control gain (1/h)

Cap*: Desired capacity rate (parts/h)

G_C: Capacity-based control gain (parts/h)

T_D: Capacity installation delay time (h)

I*: Desired inventory level (parts)

I: Actual inventory level (parts)

OR: Expected order rate (parts/h)

SR: Shipment rate (parts/h)

T_{SR}: Shipment time (h)

G_I: Inventory-based control gain (1/h)

PCB: Printed Circuit Board

SMT: Surface Mount Technology

RAM: Random Access Memory

EOQ: Economic order quantity

m/c: machine

NOMENCLATURE

α_C: Weight of the objective function in the capacity based MPC policy

α_I: Weight of the objective function in the inventory based MPC policy

E: Accepted error in the regression analysis

Pr: Actual price of single RAM module

Ps: Selling price of single RAM module

P_B: Penalty for backlog

C_{LGW}: Cost for loss of good will

Q_H: Holding inventory quantity

C_H: Holding Cost

Q_B: Backlog quantity

C_B: Backlog quantity

K: Order setup cost

Chapter One

Agile Manufacturing Planning and Control Systems

1.1 Introduction

Manufacturing is the economic term of making goods and services available to satisfy human wants. Manufacturing implies creating value by applying useful mental or physical labour. The collection and arrangement of processes and material handling equipments defines the basic design of manufacturing systems. The manufacturing system takes inputs and produces products for the customers as its output (Black 2002).

The manufacturing system includes the actual equipment composing the processes and the arrangement of those processes and/or people. Figure 1.1 explains this definition. A Manufacturing System is a complex arrangement of physical elements characterized by measurable parameters.

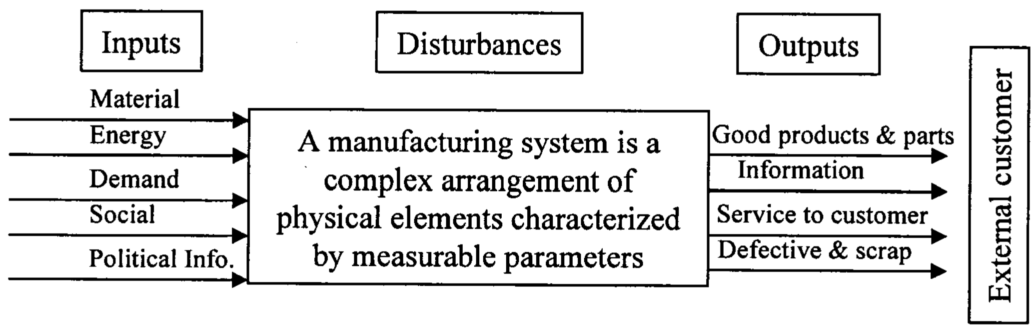


Figure 1.1: Definition of Manufacturing System (Black 1991)

Salzmann (2002) derived the following definition of manufacturing systems: "A manufacturing system is an objective oriented network of people, entities, and processes that transform inputs into desired products and other outputs; all managed under an operating policy". Where objective is defined as the ultimate objective of the manufacturing system that should be able to help satisfy corporate goals, entities as machines, tools, floor space, software, transport equipment, suppliers, etc., inputs as raw materials, energy, and information, outputs: Desired products, wasted materials, wasted energy, and knowledge and finally operating policy as a set of rules that determine how people, system entities, and the processes are interconnected, added, removed, used and controlled.

The history of manufacturing systems shows how these systems evolved over time from classical paradigms starting from mass production to the modern paradigms of agile manufacturing. This evolution over the years was in response to an increasingly dynamic and global market with greater need for globalization and competitiveness. The nature of manufacturing system and its paradigms will also evolve in response to changes in the technological, political, and economic climate. Figure 1.2 describes the evolution of manufacturing systems in terms of manufacturing goals and enabling technologies.

In this thesis agile manufacturing systems are of interest. Manufacturing planning and control (MPC) systems in this new manufacturing paradigm are the main focus of this research, and in the following sections a brief introduction about both agile manufacturing systems and their MPC systems will be offered.

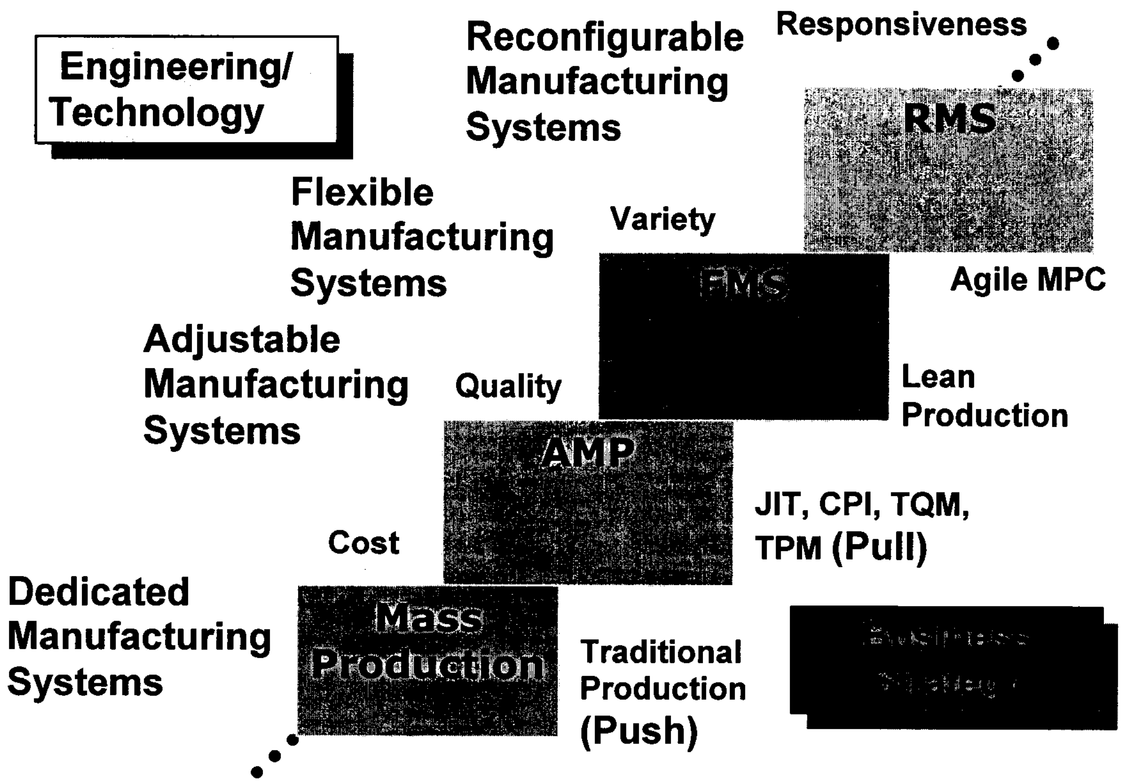


Figure 1.2: Evolution of Manufacturing System (ElMaraghy 2002)

1.2 Agile Manufacturing Systems

The first question that arises when attempting to describe an agile manufacturing system is a definition for the term agile manufacturing. There are currently many definitions of agile manufacturing. Many people seem to define agile manufacturing in terms of the ''buzzword'' programs they have implemented (Tracy 1994). This quote sums up the haphazard convention of defining agility rather well. Below are various definitions given to the term agile manufacturing.

Agility: The measure of a manufacturer's ability to react fast to sudden, unpredictable change in customer demand for its products and services and make a profit (Noaker.1994).

The National Science Foundation defines agility as "the ability to rapidly alter any aspect of the manufacturing enterprise in response to changing market demands". Thus, agility introduces a notion of speed in the pace of changes driven by the enterprise (Gottlieb 1994).

In the business world, to be `agile' is to master change and uncertainty, and to integrate the business' employees and information tools in all aspects of production (Gunaskeran 1998)

For the customer, agility translates into customer enrichment. The goal of an agile manufacturer is to present a solution to its customer's needs and not just a product. A producer does this by learning what a consumer needs now and will need in the future.

For businesses, agility translates into co-operation that enhances competitiveness. An agile partnership crosses company borders and works together. A company that can best perform a particular business function shares that knowledge with other companies in the industry.

Moreover, agility is a comprehensive, strategic response to fundamental and irreversible structural changes that are undermining the economic foundations of mass production-based competition (Goldman et al. 1995).

Agile manufacturing: This term refers to the ability to produce so called custom-engineered or custom-specific parts usually in short production runs or one-of-a-kind batches. The concept of agile manufacturing was propounded in 1991 at the end of a government-sponsored research effort at Lehigh University (Gunaskeran 1998).

Terrence Schmoyer, executive director of the Agile Manufacturing Enterprise Forum, wrote: Agile manufacturing provides the ability to thrive and prosper in a competitive environment of continuous and unanticipated change and to respond rapidly to changing markets (O'Connor 1994).

In addition to economic justification, customer satisfaction can also be a driving factor. Automotive Engineering uses the following definition for agile manufacturing: The agile manufacturer is the fastest to market, with the lowest total cost and the greatest ability to meet varied customer requirements. The final measure is the ability to ''delight'' the customer (Tracy 1994).

Agile Manufacturing System: a system that can fabricate different objects simultaneously, without having to be shutdown for retooling (Kaplan 1993). Agile manufacturing assimilates the full range of flexible production technologies, along with the lessons learned from total quality management, ''just-in-time'' production and ''lean'' production (Goldman and Nagel 1993).

Agile manufacturing systems are new systems of commercial competition, a successor to the still dominant systems that were developed around mass production based competition once they were coupled to the modern industrial corporation. Like the latter, agile manufacturing systems were made possible by the synthesis of innovations in manufacturing like reconfigurable manufacturing systems (RMS), information, and communication technologies with radical organizational redesign and new marketing strategies.

Agile Manufacturing Enterprise: They can be defined along four dimensions: (i) value-based pricing strategies that enrich customers; (ii) co-operation that enhances competitiveness; (iii) organizational mastery of change and uncertainty; and (iv) investments that leverage the impact of people and information (Gunaskeran 1998). That is, agility has four underlying principles: delivering value to the customers; being ready for change; valuing human knowledge and skills; and forming virtual partnerships.

Agility in action represents a paradox to enterprises, because firms compete and co-operate simultaneously. Agility, as the conventional meaning, denotes a fast-moving, agile actor. As described by the proponents of the agility concept, agile corporations are able to rapidly re-organize and even reconfigure themselves in order to capitalize on immediate, and perhaps only temporary, market opportunities. It is readily acknowledged, however, that no one firm will have all the necessary resources to meet every such opportunity. Core competencies of organizations can be pooled to reduce the time to market. Virtual corporations, enterprise re-engineering and adaptive/agile manufacturing are all new concepts based on the accomplishments of integrated manufacturing of the past decade. The new manufacturing enterprises are characterized by ability to effect flexible reconfiguration of resources, shorter cycle times and quick responses to customer demands. Information is a key factor in transcending physical barriers and imparting the enterprise-oriented agility and adaptiveness to organizations (Pant et al. 1994).

For many, "Lean manufacturing" and "Agile manufacturing" sound similar, but they are different. Table 1.1 compares both systems in some selected aspects.

Aspect	Lean Manufacturing	Agile Manufacturing
Definition	describe efficient, un-wasteful, less costly manufacturing	said of a manufacturing system's speed in reconfiguring itself to meet changing demands
Market Driver	Response to competitive pressure	Complexity brought by constant change
Strategy	Collection of operational techniques focused on productive use of resources	Overall strategy focused on thriving in an unpredictable environment
Manufacturing Enablers	JIT, TQM…etc.	RMS
MPC	Pull systems	Agile MPC systems

Table 1.1 Comparing Lean and Agile Manufacturing

In a similar sense, some researchers contrast flexible manufacturing systems (FMS) and agile manufacturing systems (AMS). Although agile manufacturing is more comprehensive in the sense of including the technical aspect and the business aspect while FMS is more a technical paradigm rather than a business one, however they both share the dedication to cope with variety of products with short life cycle within a minimum changeover time and cost. A significant difference among both systems can be viewed according to the type of adaptation: FMS provides generalized flexibility designed for the anticipated variations and built-in a priori (ElMaraghy, H. 2006) while AMS provides customized flexibility. Other differences can be also realized through comparing the cost of both systems where AMS are designed to be more feasible than FMS. Finally, from a volume perspective, FMS can deal with part families with limited volumes while AMS can be extended to more products with higher volumes. Based on the last perspective it can be said that reconfigurable manufacturing systems (RMS) are the best candidate systems to suite agile manufacturing paradigm together with other enterprise-level enablers.

1.3 Agile Manufacturing Planning and Control (MPC) Systems

Amongst a number of sub-systems of manufacturing, the manufacturing planning and control (MPC) system is recognized as one of the pivotal infrastructures that firmly supports the organization's manufacturing to align with its higher level market strategy (Wacker and Hanson 1997). It is well established that manufacturing planning and control (MPC) systems are fundamental to the successful operations of a manufacturing organization. MPC systems are designed to ensure that production meets the demand specified by marketing (Berry and Klompmaker 1999). The MPC systems are diverse and extensive, however, from an operational standpoint they can be defined as the functioning or operating policies of the manufacturing system that ensure meeting the changing market demand.

Agile manufacturing system is not simply concerned with being flexible and responsive to current demands, though that is an obvious requirement. It also requires an adaptive capability to be able to respond to future changes. This has two elements: (i) development of internal capability. For example, a lead-time reduction target may be achieved through product redesign or the improvement of an MRP system, leading to capabilities in design, factory-floor organization; (ii) ability to configure the company's assets (human and capital) to take advantage of future short-lived opportunities. This may depend on the use of technology, flexible organization, or the reliance on shifting alliances, created and dissolved according to market needs (Gunaskeran 1998). Based on the previous analysis, Agile MPC systems should be dynamically designed so that they are able to internally adapt to different market trends and strategies and at the same time their parameters and components can be reconfigured to implement any required manufacturing strategy adopted by the higher level management. The proposed agile MPC system in this dissertation fulfills both requirements.

Traditionally, MPC systems were categorized into two main categories, push and pull systems (sometimes referred to as level scheduling and chase strategies) where each has its various enabling tools (Venkatesh et al. 1996). The development of new technology such as modular design and open control architecture and the evolution of modern reconfigurable manufacturing systems (where exact capacity and functionality can be supplied to the system when needed) gave the previous two general MPC systems new dimensions. One can perceive the push and pull MPC systems in today's modern manufacturing context as inventory based MPC system and capacity based MPC system respectively.

As stated before, Agile MPC should be adaptable and reconfigurable. In other words, an agile MPC system is supposed to operate in capacity based modes to be responsive and cost effective when mass customization is the marketing competitive strategy and in the case of variety of products with short life cycle. It also can operate in inventory based modes in cases where market is stable for a long period or the demand forecast is of high degree of certainty or if the organization is currently focusing on cost as the only market competitive strategy or finally if the customer service level is based on the availability of the products at any time. In addition, a mix between these two modes is sometimes required (hybrid mode) as in the case of seasonal products.

Chan and Burns (2002) showed that the general consensus based on various comparative studies is that the existing MPC systems are complementary rather than competitive. There is no single perfect MPC system suited for all types of manufacturing conditions and marketing trends. Thus, agile MPC system will be subject to continuous reconfiguration over time in response to changing demand environments. Agile MPC should intend to integrate conflicting objectives of the manufacturing strategy and at the same time reflect the strategic enterprise demand management strategy.

In this dissertation, agile MPC system is defined as:

The ability to accomplish rapid and feasible dynamic changeover between the adoption of different manufacturing policies, mainly inventory based and capacity based policies, (utilizing essentially a reconfigurable manufacturing system) in order to adhere to the higher level management strategies dictated by market needs or trends.

1.4 Agile MPC Systems Modeling

1.4.1 What is MPC system modeling?

A model is a description of a system and is generally regarded as a representation of reality. Details that are unnecessary are not included. MPC systems are usually modeled for the following purposes (which are the motives for the developed agile MPC system in this dissertation):

- Understanding
- Learning
- improving/optimizing
- decision making

1.4.2 Types of MPC systems models

Manufacturing planning and control (MPC) system models can be classified into several categories as explained below:

From the objective stand point they can be classified into:

- *Prescriptive*: The model determines how to set the decision variables to optimize the MPC system's performance
- *Descriptive:* Given a set of values for the decision variables, the MPC model estimates the system's performance

From the approach stand point they can be classified into:

- *Physical*: They are models which manifest themselves in physical terms (real component)
- *Mathematical*: They are a set of mathematical equations and/or logical relationships used to describe the MPC system

From the time dimension stand point they can be classified into:

- *Static*
- *Dynamic*

Since agility is highly related to fast response and quick adaptation, thus the time is a very important factor in modeling agile MPC. Below is a detailed explanation of both static and dynamic system models.

Static models

Static models attempt to provide a static representation of dynamic systems. Static models generally portray the possible flow paths of objects through a system. This information is very helpful in determining what items participate in the process and the functions performed by the system. Although static representations can indicate the allowable system behaviours, they cannot depict the range of time-variant behaviour generated as a result of resource availability or the number of items flowing through the process. To adequately predict the performance characteristics of dynamic systems, the time-variant behaviours of the system must be defined and represented (Whitman et al. 1998).

Dynamic models:

Dynamic representations of systems attempt to capture and describe the behavior of the system over time under different operating conditions. Although the static system representations are capable of providing the vast majority of the information needed to construct a dynamic systems model, they do not possess the mechanisms needed to enact the process behaviour constraints defined in their representations. Dynamic models in contrast, are capable of executing sets of system behaviour roles and tracking the system's transition through a series of states. In this manner, a dynamic model can provide information about the state of the system at a given instance in time or can generate performance measures of the system over a given period of time. This range of potential behaviours is very difficult to represent with a static system model. Dynamic models are typically used to aid analyst in a predictive manner. These models are frequently used to provide answers to "what-if" scenarios (Whitman et al. 1998). Dynamic models can be used iteratively to study MPC system behaviour under different operating conditions. Subtle changes in resource availability or system loading (example sudden change in demand) can have dramatic effects on the performance of the MPC system.

The modeling approach for the developed agile MPC system in this dissertation can be classified as a descriptive mathematical dynamic one. This can be justified since MPC systems aims towards planning and predicating the system performance under different scenarios in order to control the system so it is descriptive, also it is more feasible especially for control purposes to have a mathematical model and finally no doubt that working in an agile environment needs high sensitivity to time-variant events and quick responses and thus the model should be dynamic.

1.5 Problem Statement

In today's agile environment, decisions related to various areas become more dynamic and interrelated. Firms need to couple their manufacturing strategy to their market strategy to remain responsive and competitive. Agile manufacturing planning and control (MPC) systems play the major role in satisfying this requirement and they should be capable of quickly reconfiguring to adhere to different market strategies adopted by the enterprise.

Traditional static view of MPC systems is not a realistic way to represent agile systems. Therefore, there is a need to have a comprehensive dynamic model for today's agile MPC systems that can manage to synchronize and control the continuous reconfiguration of these systems.

1.6 Research Objectives

The objective of this research is to study how agility can be enhanced in manufacturing systems through dynamic analysis of agile manufacturing planning and control (MPC) systems. This is achieved through dynamic modeling and analysis of a reconfigurable MPC system and coupling it to the high level business strategy. Such coupling is achieved by developing an intelligent decision making unit that optimally decide the best MPC configuration (policies) and its parameters settings so that it can meets the business strategic goals.

The thesis statement can be as follows:

"Enhancing agility in modern enterprises can be achieved through linking business strategy with manufacturing strategy via an agile MPC system. An approach to achieve this goal is through developing an intelligent dynamic decision logic architecture that intakes the high-level business strategy and subsequently delivers an optimal manufacturing strategy to a reconfigurable MPC system"

1.7 Research Approach

The objective of this research work was achieved through the following approach:

- ***Developing a comprehensive agile MPC model:*** The model incorporates, for the first time, different distributed controllers to be able to adopt different MPC policies according to the market strategy. These controllers represent the system major parameters as WIP (work in progress), inventory and capacity levels as being dynamic and adaptable The modeling approach is based on control theory were the transfer function of each policy is derived to be further analyzed. The model also includes a supervisory controller referred to as the decision logic unit (DLU). The DLU intakes the high level strategic market decisions and constraints together with a feedback of the current manufacturing system state and optimally adapt the manufacturing system to the required operation policy at these conditions. This centralized control unit is also be responsible for reacting to all unpredicted internal disturbances
- ***Analysis of the developed agile MPC Model:*** The proposed MPC model is dynamically analyzed. The analysis includes different time response measures, steady state error and stability analysis for every MPC system configuration. In addition, a sensitivity analysis is conducted to examine the effect of different system time parameters on the system performance. Some control-based solutions to improve the performance (or agility) of the developed MPC system is suggested. The objective of these analyses is to better understand the dynamic behaviour of the agile MPC system and in turn design the DLU for optimal performance of the system.
- ***Design of the decision logic unit:*** A multi-layer architecture for the decision unit logic unit or the supervisory controller is designed. The architecture of the DLU is composed of three layers where the first layer is responsible for dynamically managing the selection of the different MPC policies that suits the market strategy (the switching protocol). The second layer describes an algorithm for the optimal settings of the distributed controllers in each of the MPC policies. A multi-

objective optimization technique is implemented to decide on the trade-off between the competing agility targets (responsiveness and cost) when determining the values of the different controllers' gains. A sensitivity analysis for the different controllers' gains (optimization variables) is also conducted. Finally the third layer of the architecture is responsible for the automatic on-line control of manufacturing system to maintain required production, work-in-process and inventory levels that meets the market demand.

- ***Validation of the developed agile MPC system***: The validation of the proposed approach is carried out through various attempts. A case study for an automatic PCB assembly line is used to highlight the applicability of the approach. In addition, a comparative cost analysis between the proposed agile MPC system and classical MPC systems is carried out to show the superiority of the developed approach in dealing with different demand patterns. A comparison between the classical inventory-based MPC policy and the inventory-based policy in the developed MPC system is also conducted to show the efficiency of the developed approach in dealing with imperfect demand anticipation scenario. Finally numerical simulation experiments are made to test the ability of the capacity-based policy in the developed agile MPC system to deal with external disturbances such as rush orders as well as internal ones such as machine failure. The simulation compares this policy with the classical capacity-based MPC policy to highlight the efficiency of the developed agile MPC system under these conditions.

1.8 Structure of the Dissertation

The remainder of this dissertation is composed of six chapters.

1. ***Chapter 2*** presents a review of the existing approaches to the dynamic analysis of manufacturing systems is carried out. The review will briefly address discrete event simulation, system dynamics and nonlinear analysis applied to manufacturing systems. The detailed review will be on the application of control

theoretic approaches to the dynamic analysis of different manufacturing aspects including MPC systems.

2. ***Chapter 3*** describes the proposed agile MPC system. The modeling approach is described together with the different MPC parameters and time variables. The different MPC policies or configurations are also presented with the detailed mathematical formulation of the characteristic equation for each configuration.
3. ***Chapter 4*** includes the proposed MPC model is analyzed. The analysis includes different time response measures, steady state error and stability analysis for every MPC system configuration. In addition, a sensitivity analysis is conducted for the different system time parameters in the system.
4. ***Chapter 5*** describes in detail the design of the decision unit logic unit or the supervisory controller. The algorithm for each layer of the designed DLU architecture is explained. In addition, some sensitivity analysis for different controllers' gains involved in the multi-objective optimization in the second layer is conducted.
5. ***Chapter 6*** outlines the validation of the proposed approach. The validation consists of a case study for an automatic PCB assembly line, a comparative cost analysis between the proposed agile MPC system and classical MPC, comparison between the classical inventory-based MPC policy and the inventory-based policy in the developed MPC system and finally simulation experiments are made to test the ability of the capacity-based policy in the developed agile MPC system to deal with disturbances.
6. ***Chapter 7*** summarizes the work performed and identifies future research areas and the natural extension of the work.

Chapter Two

Dynamic Analysis of Manufacturing Systems
Literature Review

2.1 Introduction

The application of dynamics theories and approaches to manufacturing systems is not quite recent; however, there are many areas in manufacturing systems research that still need to be viewed from a dynamical point of view. Dynamics theories and approaches provide different tools to understand, model and control the behaviour of manufacturing systems.

The dynamical approach consists mainly of modeling manufacturing systems by means of its functional structure and also its dynamical control via adjustment of the systems' parameters as in discreet event simulation approaches. The dynamical approach also provides analytical tools to understand the complexity of manufacturing systems such as chaos theory and non-linear dynamic analysis. This analysis should be very useful in understanding and controlling the manufacturing systems variations (which are the major source for its complexity) that occur due to various stochastic and unpredictable reasons in the system such as demand variation, process variation, machine breakdowns and other sources of systems variation.

This chapter will start by briefly exploring three of the main approaches to the dynamic analysis of manufacturing systems. The first approach is the discrete event simulation (DES) which has been extensively used to study the dynamic behaviour of manufacturing systems. The second approach is systems dynamics (SD) methods and their application to the field of manufacturing while the third approach is the application of different nonlinear dynamic analysis techniques to study manufacturing systems. Some research examples for each approach will be discussed.

This brief review will be followed by a detailed review for the fourth dynamic approach in studying manufacturing systems which is the control theoretic approach and its application to different manufacturing systems aspects. Control theoretic approaches and methods are used in this dissertation to model, analyze and control the proposed agile MPC system. Finally a summary of the review is presented outlining the research needs and which of these needs will be addressed in this dissertation. Figure 2.1 summarizes the different dynamic approaches adopted to analyze manufacturing systems.

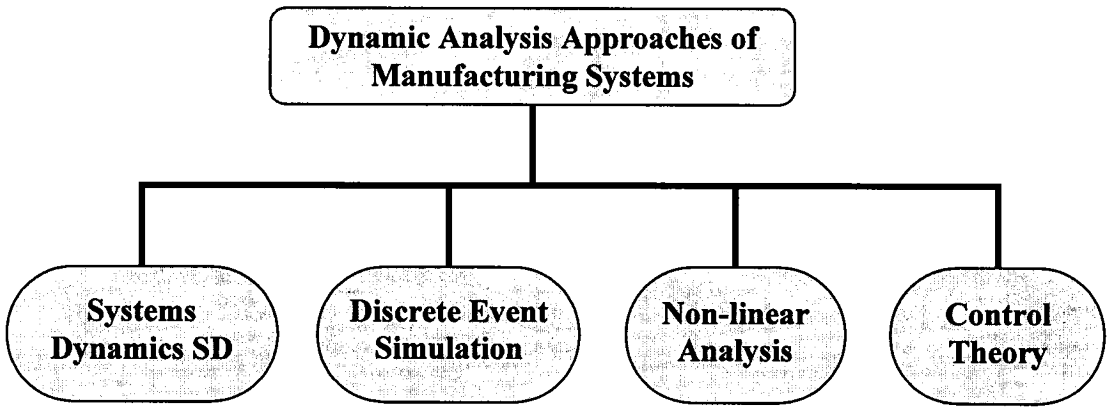


Figure 2.1: Summary of Dynamic Analysis Approaches of Manufacturing Systems

2.2 Dynamic Analysis of Manufacturing Systems Using Discreet Event Simulation

Simulation is concerned with modeling the behaviour of a system as a whole, by defining in detail how various components interact with each other. Garrido (2001) defines simulation as "...larger and more complete model built from conceptual model, for studying the behaviour of a real system". This model mimics the behaviour of the system under certain constraints. Discrete event simulation (DES) concerns the modeling of a system as it evolves over time by representation in which the stated variables change instantaneously at separate points in time (Roth 1987) when an event occurs.

Examples of dynamic analysis of manufacturing systems using DES include the approach by Hillon and Porth (1989) where they used the time event graph theory with

DES to model and analyze job-shop systems and to evaluate the steady state performance of the manufacturing system under deterministic and cyclic production process.

Cohen et al. (1989) have presented algebraic models for discrete event manufacturing systems. The systems are modeled as timed event graphs, which are special case of timed Petri nets. The discrete event manufacturing system's behaviour represented by state evolution equations using min-max algebra is shown to be linear for the deterministic case. Hence, the discrete event manufacturing system can be modeled as linear, time-invariant, finite-dimensional system. This linear algebraic formulation allows extension of certain results of manufacturing dynamic analysis from conventional linear systems theory to the discrete event case.

Queuing theory is a natural candidate for DES modeling. Baccelli and Makowski (1989) have used classical queuing theory along with stochastic ordering theory to model and analyze queuing manufacturing systems with synchronization techniques.

Mervin and Suh (2002) integrated DES and axiomatic design approach to analyze the complexity of manufacturing system design process. The advantage of using axiomatic design for a simulation model is the answer to the essential question: what to model? This is always a difficult and a major question that should be tackled before any simulation of a manufacturing process. Failing to answer that question in a good manner leads to the failure of the whole simulation experiment even if it was without any errors. They succeeded in the development of a computer-based tool that converts the problem of manufacturing system design to an axiomatic representation and then into a flow diagram that is automatically simulated based on the given design data.

Herrmann et al. (2002), presented adaptable simulation models for manufacturing systems. They developed what they called "adaptability index" to measure the ease of changing a simulation model. The types of changes include: changes to the real system that the model must incorporate, more detailed specification of the model, and changes to the questions being answered. The justification of the approach was based on the fact that new responsive manufacturing systems need a very responsive simulation tool to cope with these continues unexpected changes.

Relating DES to manufacturing planning and control systems which are the focus of this dissertation, Boughton and Love (1997) introduced an approach to the simulation of MPC systems and one which provides the necessary functionality to address control system design issues. They designed and developed an extensible class library called WBS/Control. The types of classes which populate the library are part sets, stock sets, shop calendar and suggested orders and work and purchase orders. The functionality, both current and future, offered by WBS/Control means that different planning and control systems can be modeled: standard and non-standard implementations, hybrid systems and new designs. The combination of WBS/Control and a shop-floor simulator (DES) provided an opportunity to understand how new or modified planning and control systems will perform in the context of the complete system prior to implementation. The MPC approach was geared towards lower operational level activities rather than higher level managerial decision making activities.

2.3 Dynamic Analysis of Manufacturing Systems Using System Dynamics (SD) Approaches

System Dynamics SD is a method for studying the world around us. It deals with understanding how complex systems change over time. Internal feedback loops within the structure of the system influence the entire system behaviour; it began in the 1960s by Jay Forrester at MIT in his book *Industrial Dynamics*. It has since grown to include practitioners in many fields including the physical and social sciences, mathematics, law, medicine, and education. It is a well formulated methodology for analyzing the components of a system including cause-effect relationships and their underlying mathematics and logic, time delays, and feedback loops. It began in the business and industry world, but is now affecting education and many other disciplines. More and more people are beginning to appreciate the ability of the system dynamics methodology to bring order to complex systems and to help people learn and understand such systems.

System dynamics has been defined as "a method of analyzing problems in which time is an important factor, and which involve study of how the system can be defended against, or made benefit from, the shocks which fall upon it from outside world" (Coyle 1996).

System dynamics can be considered to be a method of system enquiry, and as such occupies a position between the sciences of operations research (OR) and 'systems thinking' (a philosophical approach) (Wolstenholme 1990). In considering how SD could be related to these 'hard' and 'soft' sciences, Keys (1988) concluded that the exact position of SD remained unresolved, but maintained that it is possible for scientists in both fields to relate to it. SD may also be considered in the sense of servomechanisms (the control systems view) and cybernetics (organizational/human systems structuring for problem solving) (Pidd 1992). Two examples of the application of systems dynamics to the modeling and analysis of manufacturing systems are presented here.

Sterman (1989) proposed that the operation systems (including manufacturing systems) in the operation management field are subject to natural laws of dynamics and under certain circumstances may therefore be capable of complex and even counterintuitive behaviour. Hence for controllability, the number of control processes available should match the number of existing system variables. Such is the challenge which confronts the operations management dynamicist who wishes to understand the full systemic implications of this constellation of resources, processes and deliverables, with a mission to control. He applied this to manufacturing supply chain management using causal loops and stock flow diagrams.

Sterman (2000) derived various reasons why supply chains exhibit oscillations, amplifications and phase lag. The summary of the conclusions derived was that the main reason for this undesirable phenomenon was that every actor in the supply chain is working in isolation from the other actors. Even if each actor manages his decision rules to generate stable and smooth responses to unanticipated shocks due to market dynamics, the overall performance is not satisfactory.

Fowler (1999) proposed a design of production control systems as an example of how system dynamics approaches may be applied to improve fundamental understanding and evaluate "high-level" designs. The design integrated the core concepts of feedback and feedforward system dynamics to improve the responsiveness of the production system within the whole supply chain while maintaining a good level of system's stability. The proposed system is shown in figure 2.2. Simulation results of the dynamic behaviour of the system to a step disturbance of the sales emphasized the point that in systems which inherently possess large inertial lags and time delays, simultaneous achievement of sensitivity and stability, although problematic, is nonetheless potentially attainable, through judicious design informed by systemic understanding.

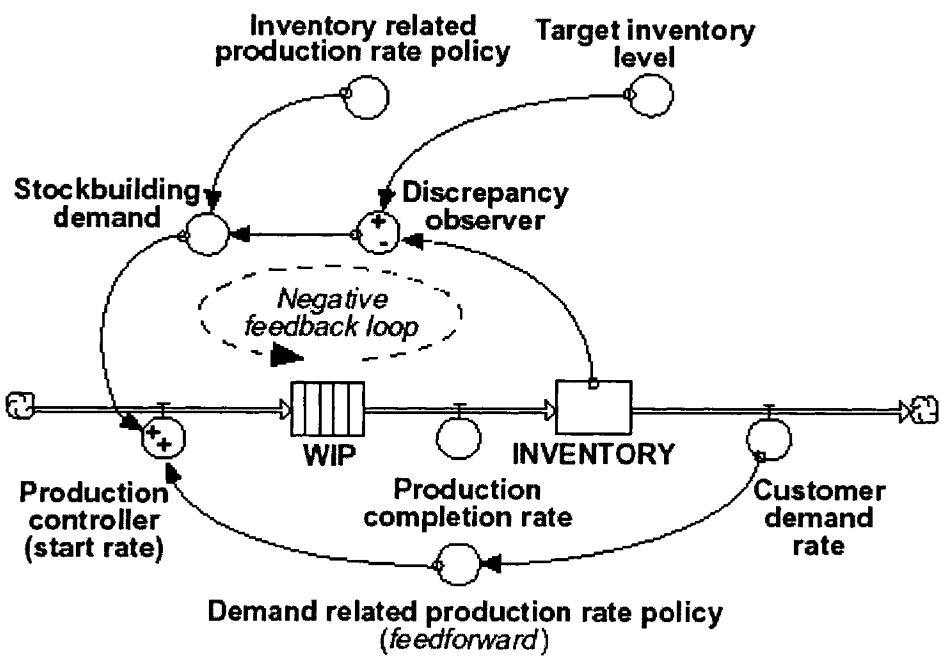


Figure 2.2: Combined feedback and feedforward control model (Fowler 1999)

Semere (2005) argued that on the aggregate level of manufacturing system modeling, system dynamics has the advantage over the analytical models in capturing its complexity. He applied system dynamics to model different manufacturing aspects; namely quality, capacity, reliability, cost and flexibility shown in figure 2.3. These models where used together with AHP and ANP approaches to develop a multi objective optimization approach to asses and select different configurations for any system. The approach was referred to as House of Assessment.

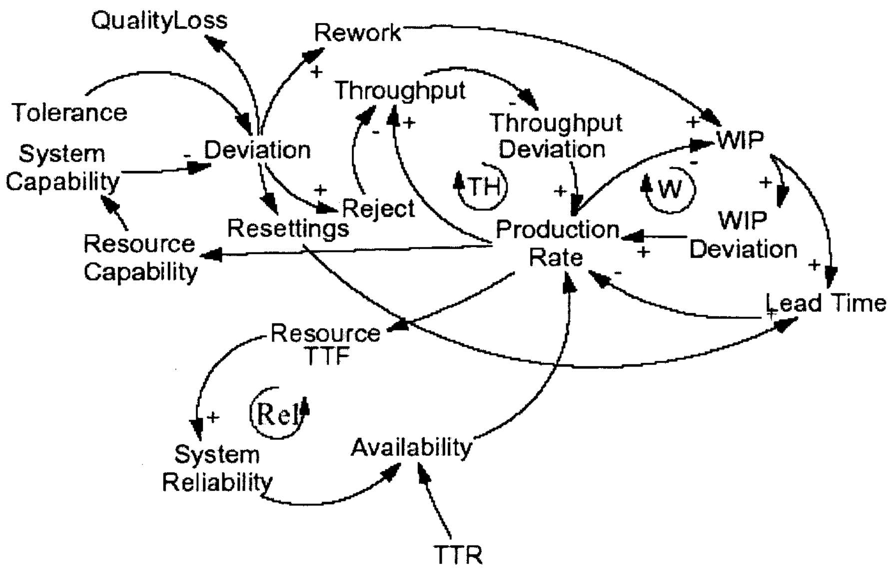


Figure 2.3: A Causal Loop Diagram for a Manufacturing Flow Dynamics, (Semere 2005)

2.4 Dynamic Analysis of Manufacturing Systems Using Non-Linear Approaches

2.4.1 Application of chaos theory to manufacturing systems

The application of chaos theory to manufacturing systems can be considered relatively recent. Chaotic phenomena in a customary sense can be found in different aspects of manufacturing systems.

Wiendahl, H and Scheffczyk, H., (1999) introduced an approach for simulation based analysis to understand the complexity of manufacturing systems using nonlinear dynamic theory. The approach started by using simulation modeling techniques to gather different data of the system and different operating conditions in order to analyze the system behaviour. The simulation data of the behaviour of some of the manufacturing system parameters after some statistical evaluation could seem chaotic and thus traditional linear analytical methods fail to give good understanding and prediction of the manufacturing system performance.

They presented a phase-space diagram as one of the nonlinear dynamic analytical tools to interpret these data and give a better understanding of the system behaviour. The long term behaviour of dynamic systems is described by geometrical structure in the phase space. System behaviour with determined or determined-chaotic components will always present an attractor during any period of observation whereas in long-term observation period random behaviour fills the phase space evenly with points. These attractors can be reconstructed from a single measured signal. The original manufacturing system behaviour is thus reconstructed by time delayed data. The new state space is diffeomorphically equivalent to the generally unknown original state space of the simulated manufacturing system. Such analysis gives a higher dimensional understanding of manufacturing systems and their dynamic behaviour.

Related to the research focus of this dissertation, Scholz-Reiter et al. (2001) applied nonlinear dynamic analysis to better understand the manufacturing planning and control (MPC) problem in modern flexible systems that show chaotic behaviour. They stated that it is possible to influence and control the state and the evolution of a production system by manipulation of the system trajectory. A dynamical system can be controlled either by forcing the system variables on defined trajectories or by variation of the system parameters. The usual method in MPC was the control of variables such as inventory levels or work-in-process. But the idea behind their approach was to control of the intrinsic dynamics of a production system. This can be done by control of the system parameters which are considered to be flexible and capable of being influenced.

They also combined the different parameters of a production system into functional groups that enable the system to work. These functional groups generate the dynamics of a production system and enable and influence the product flow through the system. They are at first a framework for modeling the production system and provide finally possibilities to control the production process by a controller or by the system itself. The latter case is a step towards self-control, which is a fundamental idea in the dynamical approach. The idea of control is the adjustment of these functional groups to meet the current requirements on the production system. They showed that the manufacturing system shows chaotic behaviour due to the coupling that exists between its different parameters and thus the nonlinear analysis of this chaotic behaviour could lead to better control over the influential parameters.

Schmitz et al (2002) conducted a good survey on the application of chaos theory to manufacturing systems and they stated that the complexity of manufacturing systems is basically due to variability in the system. In their research they proposed chaos theory to prove the complexity of manufacturing systems and used chaos theory tools to understand it. Their work focused on discrete production systems and mainly the simplest discrete system (BMMS) formed of a buffer (B), 2 parallel machines (MM) and a switch (S) to maintain recycling in the system. Their modeling approach was based on simulation. Nonlinear methods and sensitivity analysis were applied to analyze the simulation results. They claimed that sensitivity analysis is much better tool to examine and express the chaotic behaviour of the discrete manufacturing system than nonlinear analysis. The reason for that is that time-series analysis (using simulation) produces no meaningful results with nonlinear methods like phase space reconstruction due to the fact that the elements of the time series take a limited number of recurring values. As for sensitivity analysis they managed to adjust the work content machine (in terms of time) as a number that can take a value slightly less (or more) than one, although the system is discrete, and showed the effect of the perturbation of this variable. By this they proved that discrete manufacturing systems are sensitive to initial values and thus they exhibit chaotic behaviour which leads to system complexity.

Chryssolouris et al (2004) presented a chaos theory approach to study the dynamicity of scheduling problem in manufacturing systems based on the analysis of the phase space representation of the system. They presented a new dispatching rule in manufacturing systems based on the study of phase portrait (space) diagrams of already existing dispatching rules. The new rule was called phase portrait rule PPR.

Massotte (1996) considered a chaotic map to be a model of production cell. He defined X_n as the quantity of parts present in the cell which is also referred as the WIP (work in process). After some intermediate formulas the behaviour of the system was derived to be: $X_{n+1} = X_n + X_n (R - X_n /X)$ where X is the desired WIP level and R is a control constant. The previous equation is a logistic map which exhibits a chaotic behaviour with some parameters setting. He showed that the understanding of such settings will help managing the performance of the production cells.

2.4.2 Application of traffic dynamics to manufacturing systems

Concepts of traffic dynamics that are based on statistical physics and nonlinear dynamics have been applied to manufacturing systems. Helbing (2005) used these concepts to model and optimize the production processes. The manufacturing system was modeled as a one dimensional traffic flow with consumption and delivery rates that vary at each production station. The effect of demand changes over the stability of the manufacturing system was examined and simulated and he arrived to the following suggested strategies to stabilize the production:

1) Reduction of the adaptation time to demand variation
2) Anticipation of the temporal evolution of the inventories
3) Taking into account the WIP
4) Modification and adjustment of the management strategy.

Lefeber (2005) applied the traffic flow theory, namely the nonlinear versions of the LWR model, to use the analytical relation describing the flow of cars form one point to another to describe the flow of products in production lines and the homogenous highway to resemble the production line. The analogy continues where he described the manufacturing line using the same traffic model parameters; flow measured in unit lots per unit time, density measured in unit lots per unit machine and speed measured in unit machines per unit time. The three equations in the LWR model that relate these parameters were manipulated to arrive to his developed partial differential equations that describe the dynamics of manufacturing flow. A major advantage of the developed model over similar queuing theory models is the ability to incorporate the stochasticity and nonlinearity as experienced in manufacturing lines. Similar approach was also adopted to model the re-entrant manufacturing lines with different nonlinearities involved by Armbruster et al (2005).

2.4.3 Application of the notion of "Periodicity" in manufacturing systems

Nam Suh (2003) introduced the concept of periodicity (which is the other side of the chaotic approach) as an approach to decrease time-dependent combinatorial complexity in manufacturing systems. The time-dependent combinatorial complexity occurs when the system range changes as a function of time. This phenomenon will lead to having the design range outside this system range and thus increase the information content of the system leading to the increase of the complexity. To deal with such complexity Suh proposed to have functional periodicity that can be built into the manufacturing system during the design stage to make the system more stable and reliable. To convert the system from combinatorial complexity to periodic complexity the following steps should be done:

1) Determine a set of functions that repeat on a periodic basis
2) Identify the design parameters (DP) of a system that may make the system range of the functional requirements (FR) undergo a combinatorial process.
3) Transform the combinatorial complexity to a periodic complexity by introducing functional periods.
4) Set the beginning of the cycle of the set of the FRs as $t=0$.
5) Stop the process momentarily.
6) Reinitialize the system by establishing the state of each function at the instant of re-initialization.
7) Allow the initiation of the next cycle

An application of this theory to decrease the manufacturing system's complexity was presented through a case study that involved an integrated system of two subsystems one of them involves a robot and multiple machines and there is a need to have an optimal scheduling plan. Different scenarios were explored and the introduction of periodicity to each scenario lead to decreasing the complexity of the scheduling task and thus to better productivity of the system.

2.5 Dynamic Analysis of Manufacturing Systems Using Control System Theoretic Approaches:

The application of control theory in manufacturing has been extensively researched. However, its application on the system-level is not as much as on the machine and component's level. The control theory gives a powerful insight to understand the dynamics of manufacturing systems and thus the ability to manage its complexity. In this section different publications were reviewed to illustrate the application of control theory to understand the dynamicity of different manufacturing systems aspects on the system-level. these include production, quality, inventory, supply chain, aggregate planning, scheduling and capacity.

The first approach to apply control theory to manufacturing systems was by Simon in 1952 where he applied the servomechanism theory to control production rate based on an optimum inventory level. The aim of the control system developed was to minimize the cost by minimizing inventory. Customer orders per unit time where the loads of the system and the variables were the actual production rate and the planned production rate. The model was then expanded to account for production lag as shown in figure 2.4. Finally cost analysis was carried out based on a constant and an oscillating function to reflect the fluctuation of production and inventory of the manufacturing system.

The controllers design (inventory controller K_2 and production lag controller K_3) was proposed based on the objective of minimizing the cost. The approach and its analysis were quite appropriate for that time, however a lot of the assumptions which the model was based on need to be relaxed. These assumptions include having single product and continuous production.

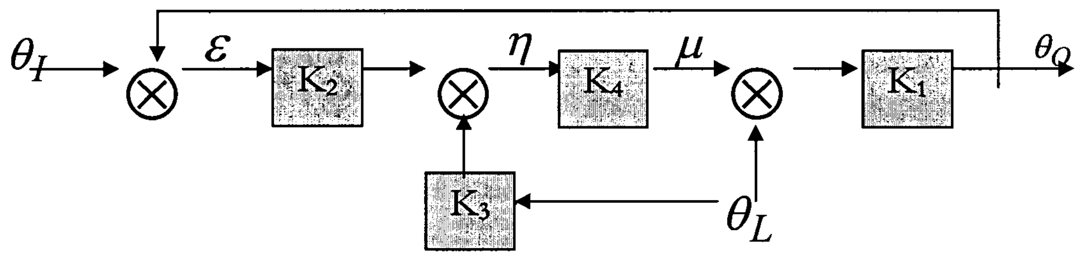


Figure 2.4: Inventory Control Systems with Production Lag (Simon 1952)

Where: θ_I is the reference inventory level

Θ_L is the system load (customer orders)

Θ_o is the finished inventory level

ε is the inventory error

η is the planned production rate

μ is the actual production rate

K_1 is an integrator

K_2 and K_3 are controllers

K_4 is production lag operator

John et al. (1994) presented a generic model of an automatic pipeline feedback compensated and order based production control systems (APIOBPCS) shown in figure 2.5. The model is a natural extension of the work of Towill (1982) where he examined the application of control theory to model a production control system (ordering system) based on inventory level requirement. They showed that when information about the production lead time, which was based on modeling the manufacturing system as a pipeline, is added into the production decision rule the dynamic behaviour of the manufacturing system is improved. This addition was achieved through adopting work in process (WIP) compensation based on comparing the current WIP to the desired WIP level based on the estimated production lead time times the demand. The work presented was based on the assumption that the pipeline lead time is fixed and known. Results showed that the response of the manufacturing system to the change in demand when compensating for WIP based on a WIP target that varies with demand is much better than when the target WIP is fixed. They also suggested some optimal parameters setting for the developed design. The settings are having the *Tw* (inverse of WIP based production control law gain) equals *Ta* (consumption averaging time) and both values equal double *Tp* (estimate of the production lead-time) and finally *Ti* (inverse of inventory based production control law gain) should equal *Tp*.

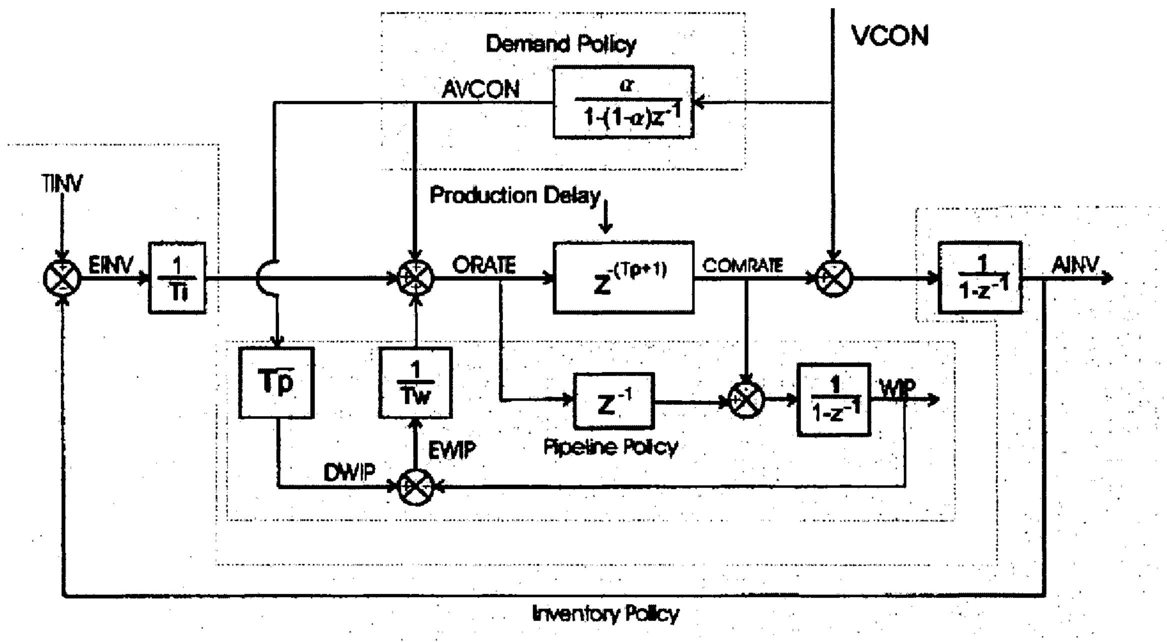


Figure 2.5: The Structure of APIOBPCS (John et al. 1994)

Where: AINV Actual INVentory,

$\alpha = 1 / (T+a)$,

AVCON: average virtual consumption,

COMRATE: completion rate,

CONS: consumption or market demand,

DINV: distributors inventory holding,

DWIP: desired Work In Progress,

EINV: error in Inventory Holding,

EWIP: error in Work In Progress,

FINV: factory inventory,

ORATE: production order rate,

Ta: consumption averaging time constant,

Tp: estimate of the production lead-time,

Ti: inverse of inventory based production control law gain,

TINV: target system inventory holding,

Tp: the production lead-time in units of sampling intervals,

Tw: inverse of WIP based production control law gain,

VCON: virtual consumption

Towill et al. (1997) developed a master production scheduling decision support system (MPS DSS) within a multi product medical supplies market. The model was based on the same APIOPBCS model where the previous assumption of known and fixed lead time was relaxed and assuming the lead time to be adaptive. The total system input is based on the inventory and production levels required. The system contained multiple feedback control loops to adjust the inventory (based on customer service level) and production level together with an adaptation of the current lead time of the system. The structure of the system is shown in figure 2.6.

As for the dynamic analysis of the system, the lead time T_P was estimated once by exponential lag and another time with a cubic lag. In addition, different system parameters settings were investigated in terms of their effect on the system performance and customer service level. Different simulation results of various settings combinations showed the importance of lead time adaptation (achieved through feedback loop) and the use of integral controller for controlling the inventory level in achieving the required customer service level of this market

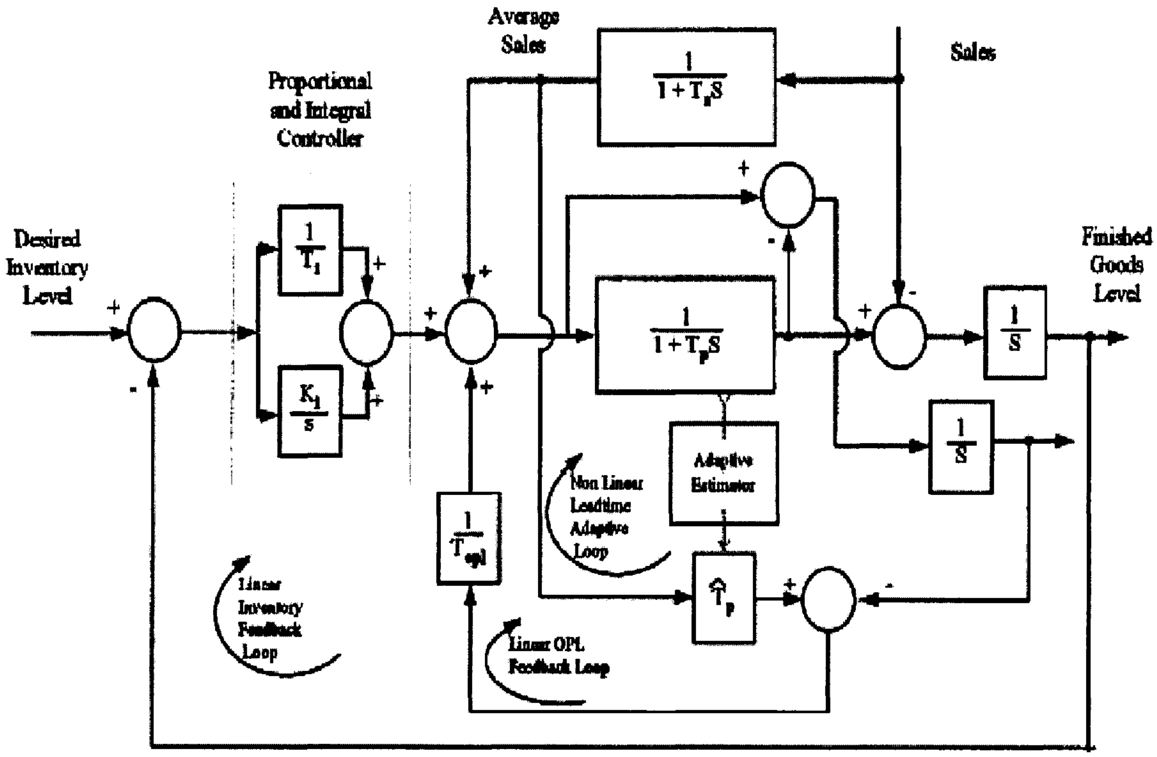


Figure 2.6: The Structure of MPS DSS with Adaptive Pipeline Feedback Loop Structure (Towill et al. 1997)

The same APIOPBCS model was used by Disney and Towill (2002) in the analysis of supply chain management. Their focus was on a vendor managed inventory (VMI) systems where they integrated it with the production and inventory algorithm APIOBPCS as shown in figure 2.7. They described this system using z-transforms technique. The transform functions developed for the system were used to study its behavior in the time domain. The focus of the analysis was mainly on the stability conditions of the VMI-APIOBPCS system against the variation of different parameters and a procedure for determining general stability conditions for the investigated system.

The results showed different parameters settings of the controllers that will stabilize the system and showed the effect of different system parameters on each other. The most important result was that when the WIP controller T_W value is equal to the inventory controller T_I value, the system will always be stable (much more robust) whatever the other settings are and with different production delays calculations. Also if both values cannot be practically equal, limiting conditions were presented to guarantee stability of the whole supply chain system.

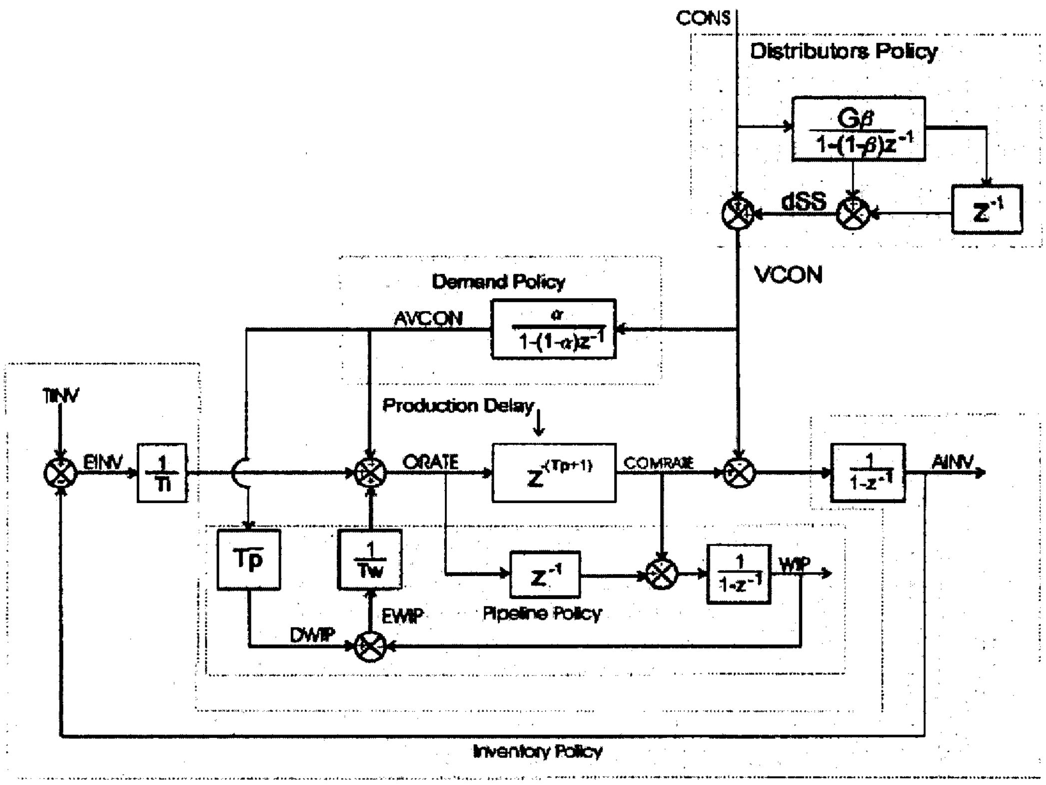


Figure 2.7: The VMI- APIOBPCS System's Structure (Disney and Towill 2002)

Where: $\beta = 1 / (T+q)$,

COMRATE completion rate,

CONS consumption or market demand,

DES dispatches,

DINV distributors inventory holding,

dSS incremental change in the re-order point, *R*,

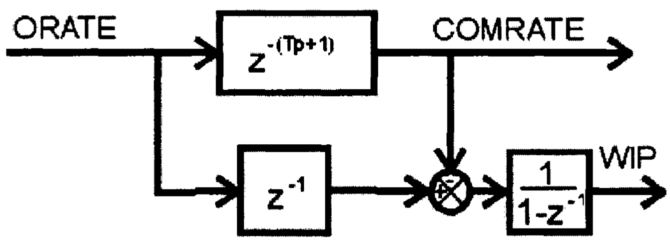
G gain (distributors re-order point/average consumption),

R re-order point,

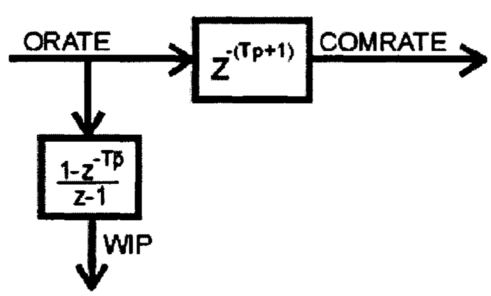
T transport quantity,

Tq exponential smoothing constant used at the distributor to set *R*, The APIOPBCS model was further modified by Disney and Towill (2005) to study the effect of the variation of lead time on the inventory drift. They explained the reason why the Final Value of the inventory levels of APIOPBCS experience an offset is because the desired WIP level is based on the ''perception'' of the production lead-time Tp and the actual WIP is based on the ''actual'' production lead-time. They also verified this observation by the Final Value Theorem. To over come this problem, the structure of the system was modified. The modification, shown in figure 2.8, aimed at avoiding this effect by replacing the ''actual'' WIP signal with a WIP signal that would have been generated if the previous T p' (rather than Tp) is added to the ORATE signals.

Results showed that the production offset was solved even if the estimated lead time was different than the actual lead time. However, the stability of the system to various parameters settings was questionable and they declared that further research should be carried to investigate the stability boundaries of the modified model.



(a)



(b)

Figure 2.8: (a) Original APIOBPCS WIP Estimation,
(b) Modified APVIOBPCS WIP Estimation (Disney and Towill 2005)

Wikner (2003) explored the problem of variable lead time in models like the APIOBPCS using continuous time dynamic modeling. Based on the correspondence between the n^{th} order delay and the Erlang-k distribution, he proved that the interpretation of the deterministic delays can be extended also to involve probabilistic properties. The analysis suggested that the point of departure for modeling a lead time using linear control theory could be to estimate which Erlang-k distribution best fits the historical data and then set the order of the delay and the time-constant according to the analysis. A model of the expected dynamic behaviour was obtained.

Modeling manufacturing systems using the pipeline approach developed by john et al. (1994) gave the dynamic analysis of manufacturing systems in the previous researches a significant thrust. Although most of the applications were geared towards supply chain management, there is still a great potential for the application of this model to represent agile manufacturing systems. One of the enhancement opportunities for the APIOBPCS model in the agile paradigm is to include a capacity scalability component that can be also controlled and related to the demand inputs. This is justified because in real practice production disturbances are expected and WIP adjustment can not accommodate large disturbance. Thus capacity increase via a capacity controller can handle this in a more efficient manner. Also other modern control design approaches can be implemented not only to increase the responsiveness and robustness of this model but to synchronize the work of the different controllers involved in the systems. Examples of this can be switching and supervisory controllers.

Pritschow and Wiendahl (1995) presented an approach to apply control theory for production logistics. They tried to propose the idea of having a planning controller as well as a process controller as shown in figure 2.9. However, in the work presented the planning controller just used the logistic curve to indicate the operating points of the system. As for the process controller, a proportional controller was used to control WIP level. WIP as the control variable was corrected by adding more capacity to the system as shown in figure 2.10. A dead band in the controller was suggested to allow for some WIP deviation from the planned level so that the capacity is added in a more realistic manner. Loading curves were presented to quantify the influence of several parameters known from practice to the system's performance. The dynamic response of the system through quantized capacity was tested.

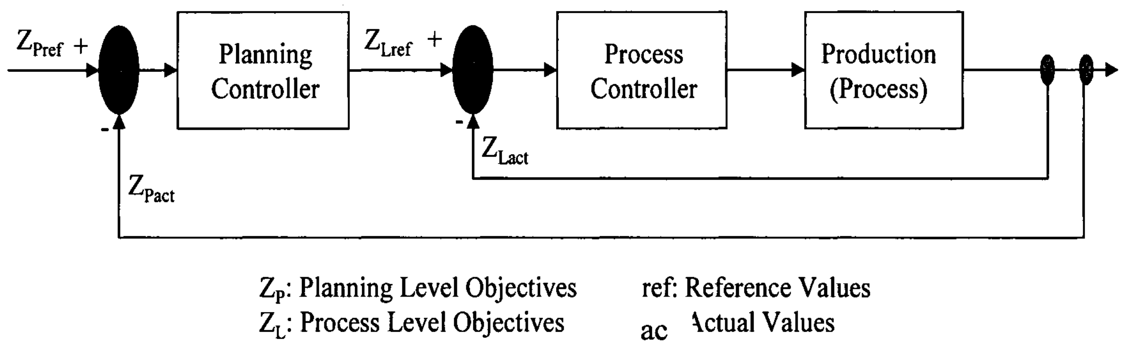


Figure 2.9: Structure of Closed Loop Production Control (Pritschow and Wiendahl 1995)

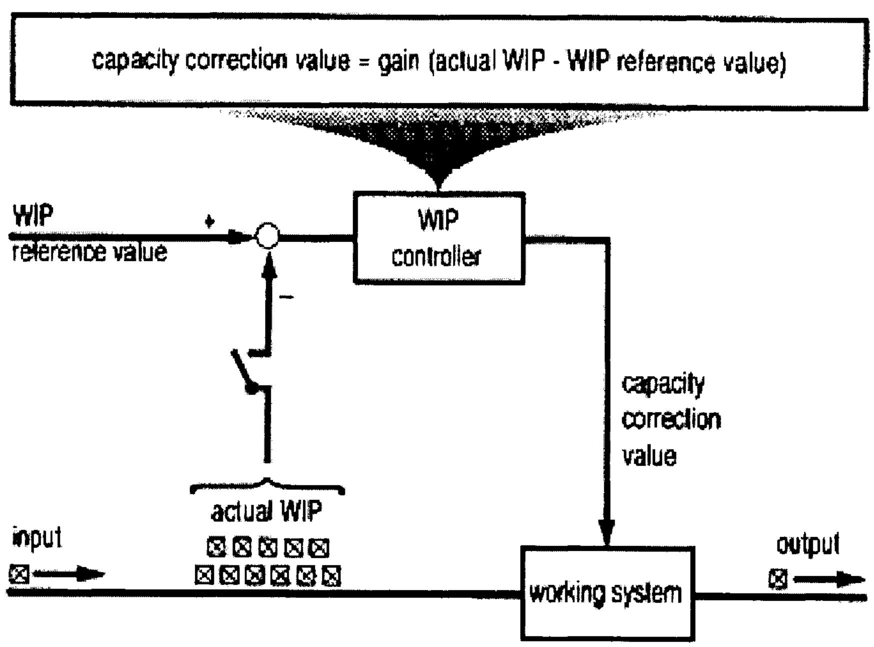


Figure 2.10: Closed Loop WIP Controller (Pritschow and Wiendahl 1995)

The approach can be considered a tentative approach to use control theory in a WIP based controlled systems. The model does not include other important system parameters such as backlog and inventory

Wiendahl and Breithaupt (1999) studied the dynamics of manufacturing systems based on the discrete funnel model shown in figure 2.11 developed by Kettner and Bechte (1981) and the logistic operating curves developed by Nyhuis (1991) shown in figure 2.12. They developed what they called the automatic production control system APC. The model describes the dynamical reaction of production systems based on structural data (mean values, estimations, etc.) and not on discrete data (single orders). The goal of this method was to reach a self-controlled process achieved by a closed-loop control with appropriate reference and correcting variables. To achieve that goal the discrete model was modified to a continuous model shown in figure 2.13 to reflect the dynamics of the system over long time horizon for the purpose of planning.

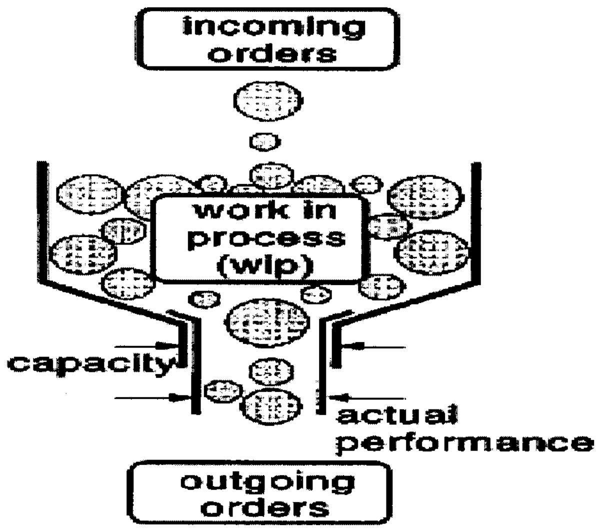


Figure 2.11: Discrete Funnel Model (Kettner and Bechte 1981)

The logistic curves were used to determine the input parameters of the system (mean WIP, mean Lead time and mean performance) based on the system's capacity and the order structure. Based on previous assumption, only two controllers can be proposed; one for the capacity (backlog) and the other for the WIP. The backlog controller uses capacity as a correcting variable based on the backlog determined by the amount of deviation between the planned performance and the actual performance of the production.

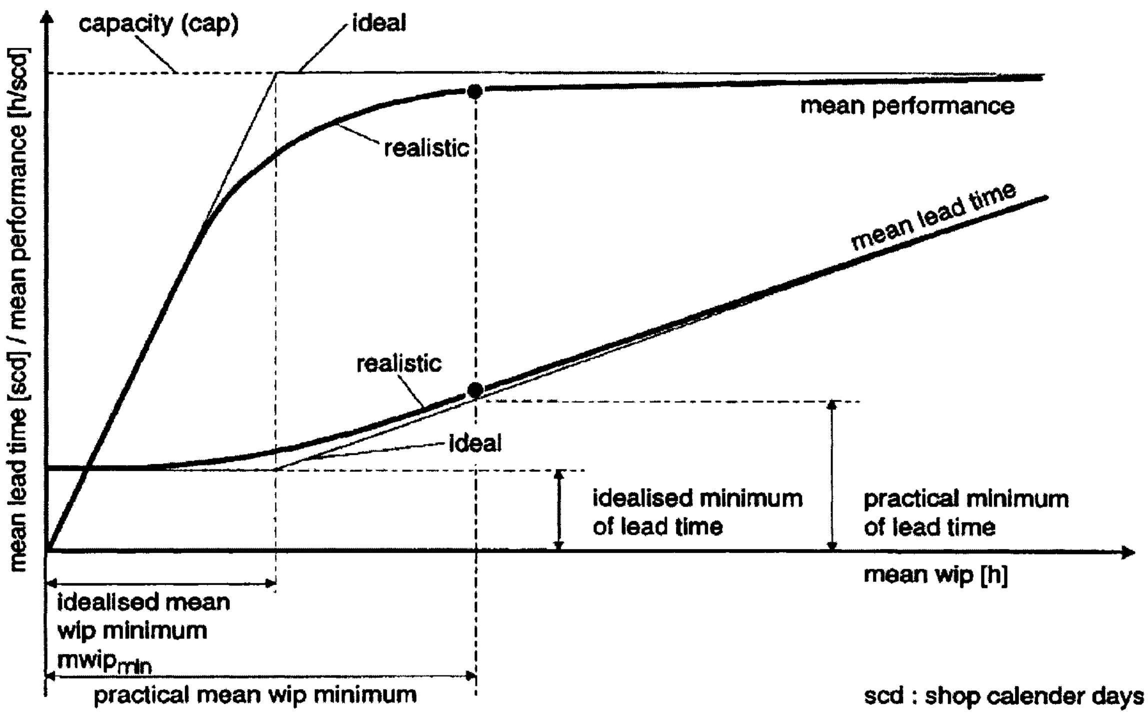


Figure 2.12: Interdependency between Output, Lead Time and Work-in-Process [WIP] (Nyhuis 1991).

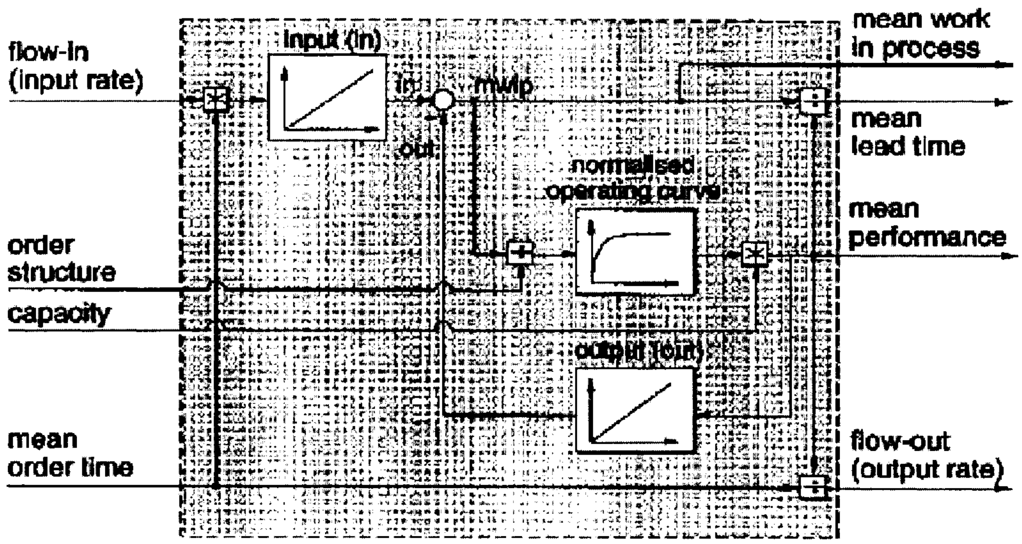


Figure 2.13: Continuous Model of a Work System (Wiendahl and Breithaupt 1999)

The capacity required is found using flexibility curves shown in figure 2.14 which indicates the time delay of each capacity scaling step. The controller is to choose the best capacity scaling decision based on the backlog value and delay acceptable. As for the

WIP controller, the mean WIP is the control variable and based on the difference between the planned and the actual WIP the WIP controller adjust the input rate. The integrated capacity and WIP controllers are shown in figure 2.15. Simulation of rush order scenario showed how both controllers can be synchronized automatically to react to the disturbance and decrease any surplus in the capacity by adjusting the input rate.

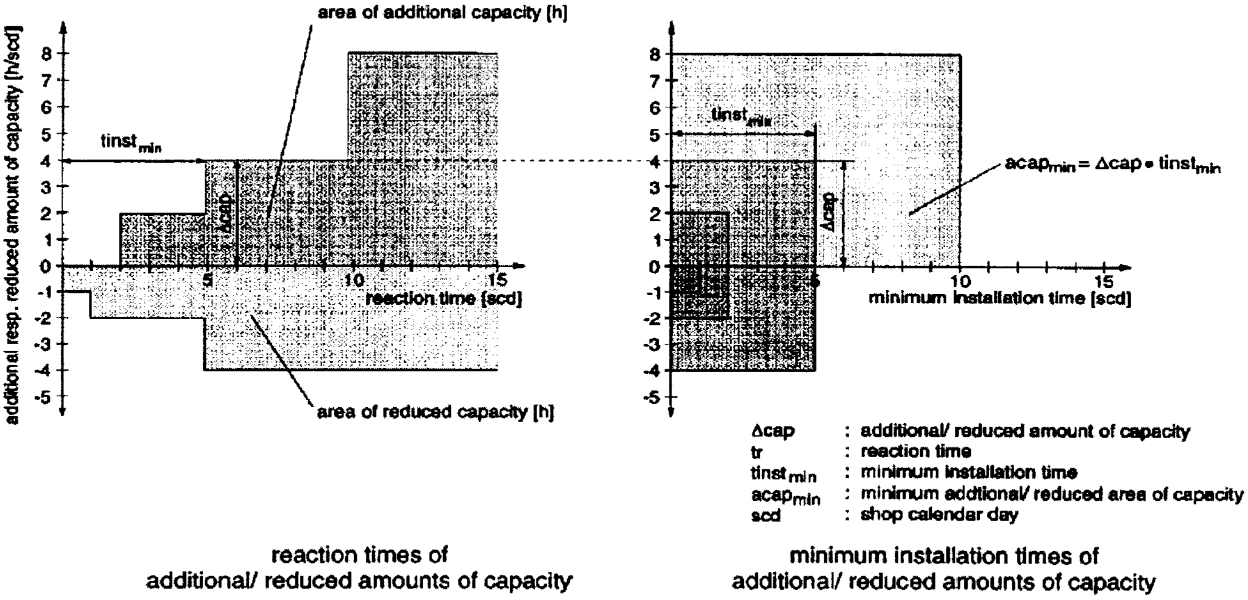


Figure 2.14: Capacity Flexibility Curves (Wiendahl and Breithaupt 1999)

A more detailed manipulation of the logistic curves to determine the relation between the capacity and the performance within the APC model was presented by Wiendahl and Breithaupt (2000).

Wiendahl and Breithaupt (2001) showed that the developed automatic production control system APC decreased the backlog for a special drilling machine factory by 80% and the WIP by 56.9% in case of varying demand. They also showed that, for another factory, automotive components' supplier, APC had the potential to decrease the backlog by 90.9%.

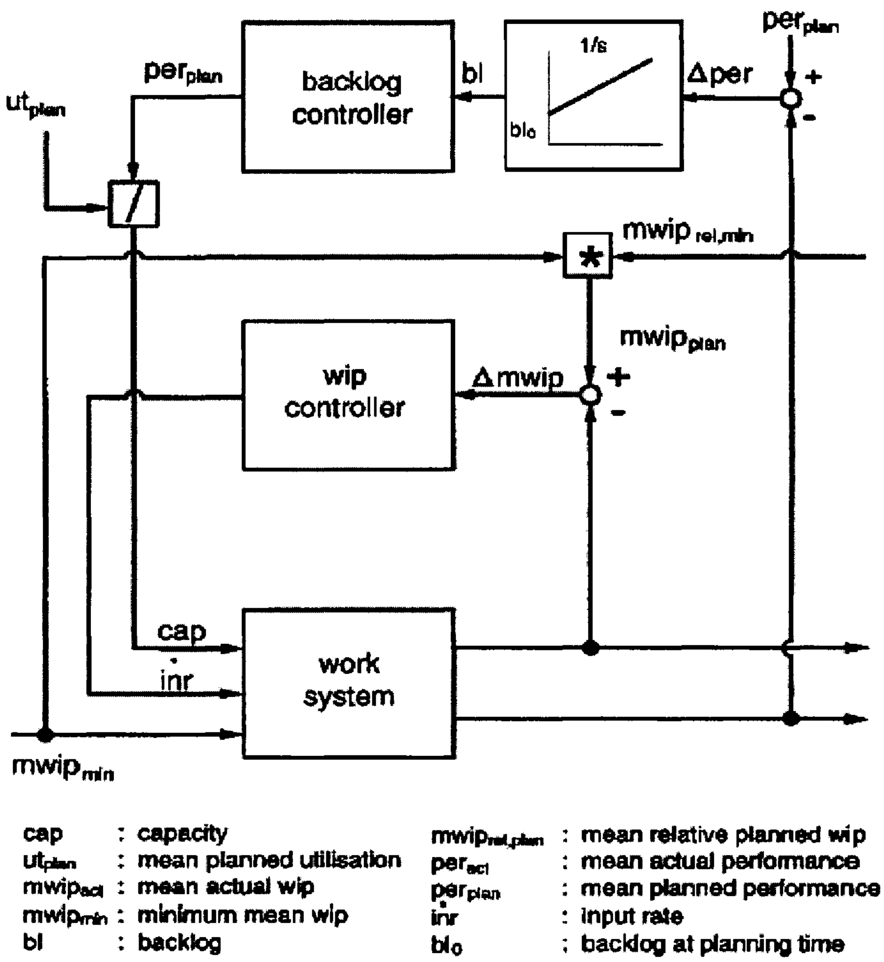


Figure 2.15: Integrated Capacity and WIP Controllers (Wiendahl and Breithaupt 1999)

The previous of works Wiendahl and Breithaupt are considered good approaches to MPC systems that are based on capacity utilization and WIP level as the main planning parameters. An extension of this work would be to include the system inventory level as another MPC parameter. The inclusion of the inventory level will give the system more alternative MPC policies to be adopted. Also the MPC model depended on the logistic curves (which are basically experimental) to indicate the reference points and the different parameters settings. However, a deeper dynamic analysis of the system performance would help more in the optimal selection of theses settings. In addition managing the work of the different controllers involved and relating the operational actions to the desired management strategy can be improved by adopting a supervisory controller to perform that task.

Duffie and Falu (2002) developed a closed loop production planning and control PPC system shown in fig 2.16. The developed model is used to control the backlog and work in process WIP under normal conditions and under uncertainties in capacity and work input that result from equipment failure, rush orders and other sources. The dynamic analysis based on the developed transfer functions, examined the relationships between system inputs which are the planned capacity, planned WIP level, capacity disturbance and WIP disturbance and the system variables such as backlog and actual WIP. In their work they assumed that the operating point of the system is the area of the logistic function where increasing the level of inventory in the system does not appreciably increase the system's performance. The developed system was a multi-rate discrete control system as to sample the WIP level with higher rate than the capacity level. The work presented was focused on the case of high WIP and suitable gain values for the capacity and WIP controllers. Also a dynamic illustration of the system's parameters response was shown for the case of no delay while adjusting the capacity and in the case of capacity adjusting delay.

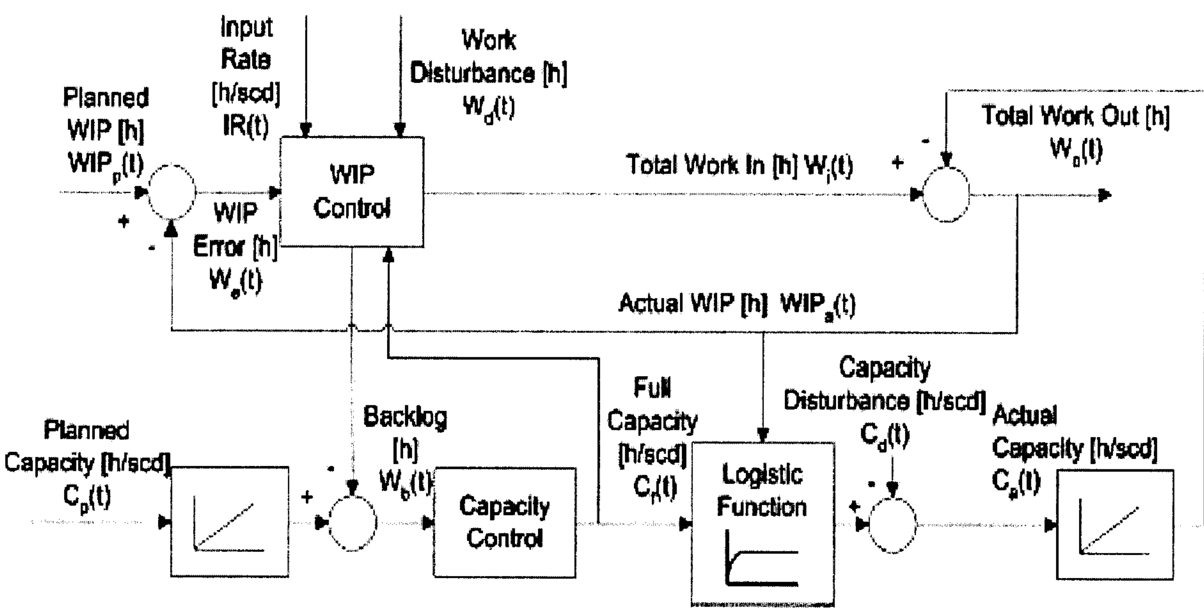


Figure 2.16: Closed Loop Production Planning and Control System (Duffie and Falu 2002)

Ratering and Duffie (2003) extended the previous single station system dynamic analysis to account for both high and low WIP cases. The characteristic equation for each case was developed. In the case of high WIP, they found that the dynamics of the systems depend on the backlog controller gain and its delay and thus the best design value for that gain was found. In case of low WIP, they showed the dynamics of the system was dependent on the WIP control gain and they also found its best range of design. The performance of the system was basically evaluated based on it being non-oscillatory. The same analysis as the previous work for the system's parameters response to disturbances was also carried out but for both WIP cases.

Kim and Duffie (2004) found that the slow response of the system for the elimination of the backlog in the previous work was due to the limitation of the control algorithm used. Thus, they proposed different control designs, proportional P and proportional plus derivative PD controllers, together with a different system structure shown in figure 2.17. The actual WIP was assumed to be almost equal to the planned WIP and thus the work output was dependent on capacity and capacity disturbances. The new characteristic dynamic equations of the system were derived together with the different control designs. The analysis showed that for capacity disturbances due to rush orders; the PD controllers showed faster response in eliminating the backlog in the system than the P controller.

However, the effect of the delay of capacity adjustment on the responsiveness of the system and the effect of periodic capacity disturbances were only examined using P controllers. For the first case of the capacity adjustment delay; results indicated the best value for the capacity backlog gain control after which the system starts to oscillate and also the maximum capacity adjustment time delay the system can have. As for the case of periodic capacity disturbances; they showed that without having certain values for the backlog controllers and time delay, the system will oscillate leading to undesirable performance of the system.

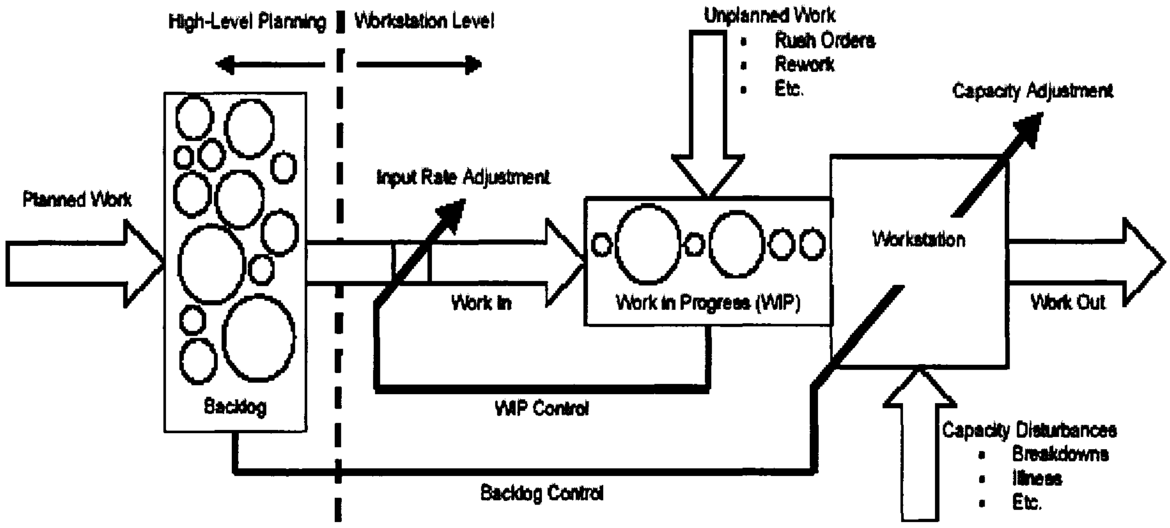


Figure 2.17: Single Workstation PPC with Closed Loop WIP and Backlog Control (Kim and Duffie 2004)

Kim and Duffie (2005) also applied the same approach to multi workstations instead of single workstation (shown in figure 2.19). Results showed again that properly chosen control gains produce a robust system even when there are delays in making capacity adjustments. However, considerable time can be required to completely eliminate backlog. They suggested based on their analysis that system performance can be improved through reduction of delay in capacity adjustment. There is also potential for improvement by feeding information forward from upstream workstations to downstream workstations to anticipate capacity adjustments that will be required, and generally by applying more complex control policies

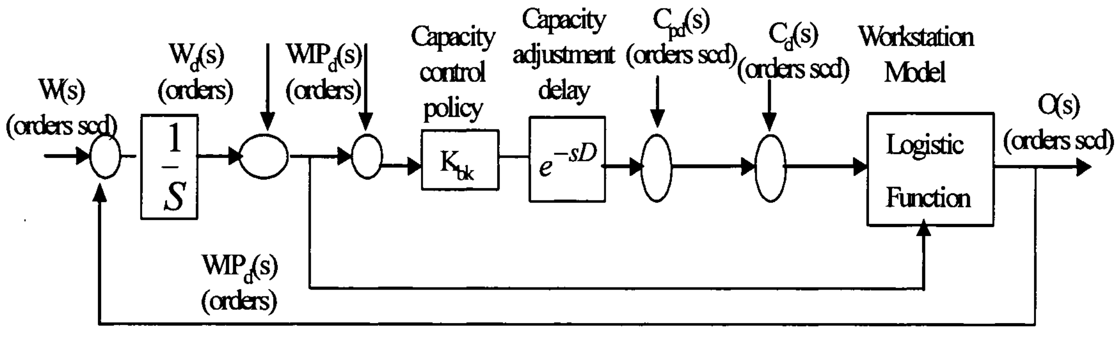


Figure 2.18: Multiple Workstations PPC with Closed Loop Backlog Control (Kim and Duffie 2005)

The multi-workstation production systems was further developed in Kim and Duffie (2006) in which capacity controls for regulating WIP in individual workstations were coupled by adding predictive control, making capacity adjustments a combination of compensation for local disturbances and anticipation of downstream effects of capacity adjustments made upstream in the system. The added coupling at the control level combined with intrinsic coupling at the order-flow level effectively integrates planning and control as shown in figure 2.19. Control-theoretic methods were used to make dynamic analysis tractable and improve decrease system complexity. The approach was illustrated using data from an industrial production system with two different delay times.

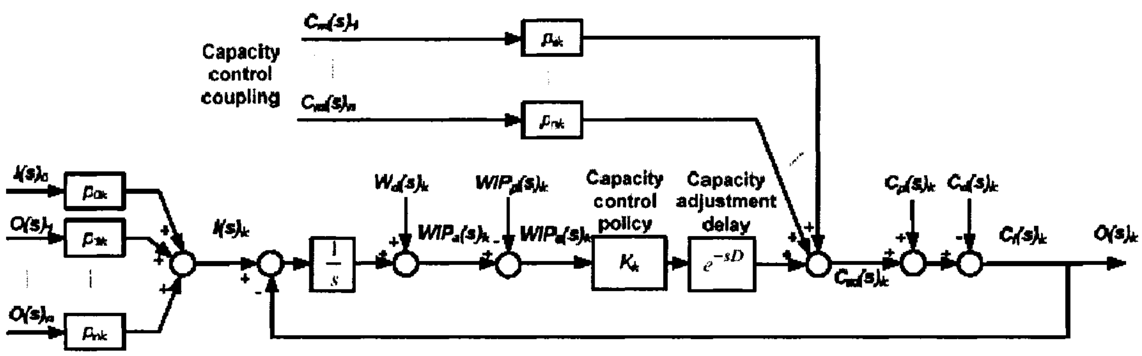


Figure 2.19 Closed-loop and Coupled Capacity Control of the Kth Workstation (Kim and Duffie 2006).

In general the PPC structure developed in the previous research work is of a good representation to the relation between the capacity and the WIP of the system as well as it is reflective to the dynamics incurred in such systems. However the existence of a relation for the system finished inventory with these two basic parameters would give the system a more comprehensive PPC approach. Their work is considered the most detailed from a dynamic standpoint but more system characteristics can be extracted other than system response to disturbances which will give a better picture of system dynamics. Such characteristics include the natural frequency and the damping ratio of the system which affect all the system transient time parameters. More quantified or physical description for the meanings of the WIP and capacity controllers' gains is also required.

In another research direction that dealt with the dynamics in the scheduling problem in manufacturing systems, Duffie et al. (2002) used the control theory to tackle the problem of distributed controls in a heterarchical manufacturing systems based on the model developed by Prablu and Duffie (1999). The complexity of the problem stems from the combinatorial explosion in the number of states the discrete system can have. To solve that, a continuous model made of linear and nonlinear differential equations for control of arrival times of the product entities was presented and used for dynamic analysis of the system. The control algorithm used feedback to expect completion time of the entity and based on the difference between the expected completion time and the due date of the product a decision is made to decide for the scheduling of the products in the system. The control approach is shown in figure 2.20.

In their work they presented a system where the dynamics of autonomous controllers (embedded in entities distributed throughout a heterarchical manufacturing systems) and the physical interactions between entities in the system combine to create system behaviour that is seemingly chaotic, but favourable. Their results of the physical implementation, simulation and control-theoretic analysis showed that the system is deterministic and converges to decisions in real time with known performance. The developed control system showed to be responsive to real-time disturbances.

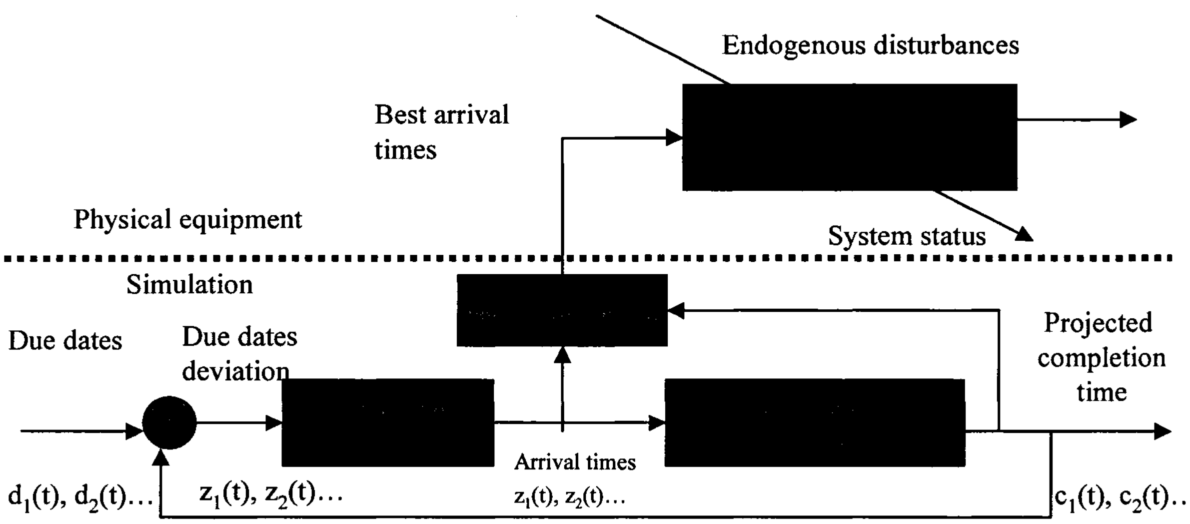


Figure 2.20: Closed Loop Approach for Real Time Manufacturing Control (Duffie et al. 2002)

The approach can be considered efficient for controlling the input rate of the system and the analysis of the dynamic characteristics of such nonlinear system. However; other system parameters, like WIP, should be considered in tackling the scheduling problem in manufacturing systems.

Fong et al. (2004) gave an insight about some of the manufacturing system dynamics characteristics. The systems investigated in their research included a single stage system that is based on inventory control and a double stage system that is based on both inventory and WIP control. Both systems were represented using causal loops and block diagrams and then transfer functions were generated for system analysis. Figure 2.21 shows the two stage production control system Where FI is finished Inventory, PSR is production start rate, PCR is production completion rate, LT is production lead-time, SR is shipment rate, ST is shipment time, WIP* is the desired work-in-process WAT is work-in-process adjustment time, AWIP is the adjustment for work-in-process, AFI is adjustment for finished inventory, DI* is the desired inventory, FAT is finished inventory adjustment time, ESR is expected shipment rate, DPR is desired production rate, DPCR is the desired production completion rate and ELT is the expected lead time.

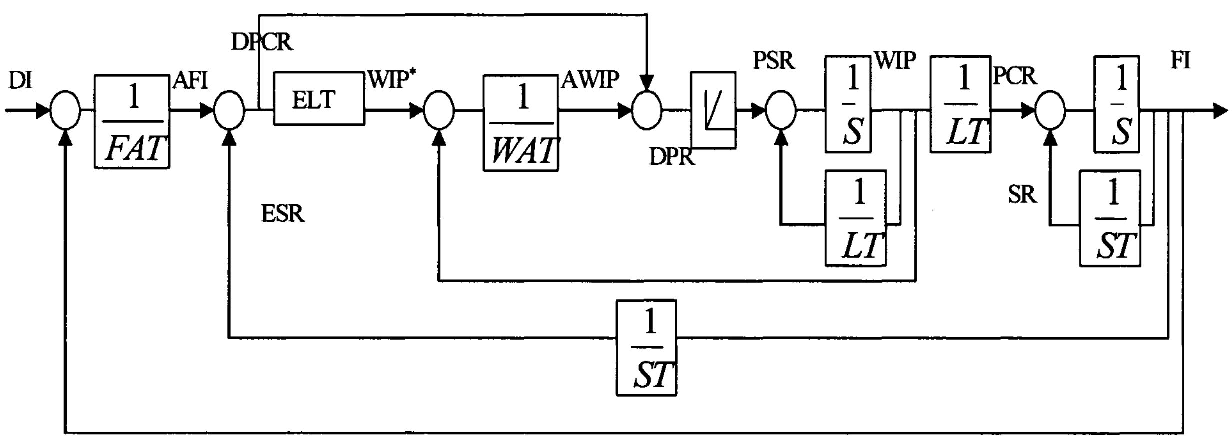


Figure 2.21: Block Diagram of Two Stage Production Control System (Fong et al. 2004).

Analysis of the system was focused on system response and how this relates to real manufacturing system responsiveness. The effect of the different parameters of the system on the dynamic characteristics as the damping ratio, undamped natural frequency, time constant rise time and settling time was also investigated. System parameters included inventory adjustment time, WIP adjustment time, lead time and shipment time. The approach presented an understanding of basic dynamical characteristics of single and double stage systems however; further work in terms of stability analysis and control design is required. In addition, other MPC system components besides WIP and inventory, such as capacity, should also be considered.

Asl and Ulsoy (2002) presented an approach to capacity scalability in reconfigurable manufacturing systems based on the use of feedback control theory to manage the capacity scalability problem. The approach is shown in figure 2.22. They showed that feedback provides suboptimal solutions for the capacity management problem which are more robust under system uncertainties and disturbances in the forecasts of market demand relative to the existing capacity management methods. Their approach proposed a formula for the capacity management via a control design without any quantified design or analysis values for that controller. Further research is required to relate the control design together with the capacity scalability requirements qualitatively and quantitatively.

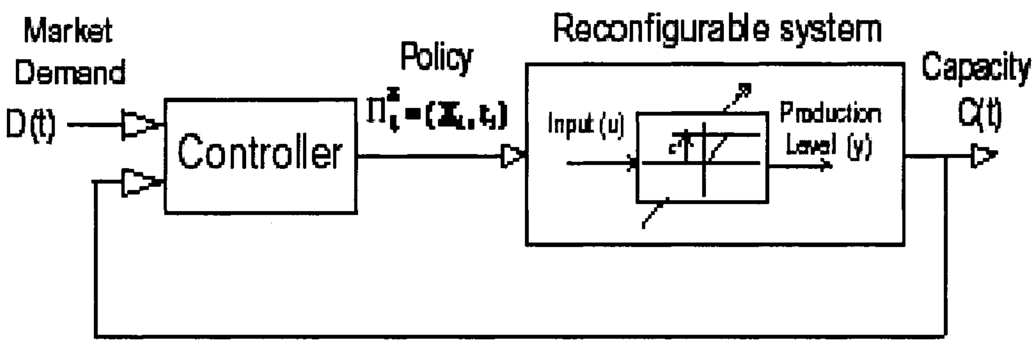


Figure 2.22: Capacity Scalability in Reconfigurable Manufacturing Systems Based on the Use of Feedback Control (Asl and Ulsoy 2002)

Ma and Koren (2004), proposed a control policy for manufacturing system operation based on modeling an *m*-machine line as an *m*-order state-space system and applying optimal control theory to adjust the WIP while keeping the production demand. For a serial line with random machine failures, the policy divides the stochastic system into multiple deterministic sub-lines, each operating optimally for the duration in which the machine state combination does not change. Their simulation results demonstrated that the proposed policy successfully generates low WIP while the demand is still fulfilled. The policy shown is capable of being easily applied to large manufacturing systems. The control policy is shown in figure 2.23.

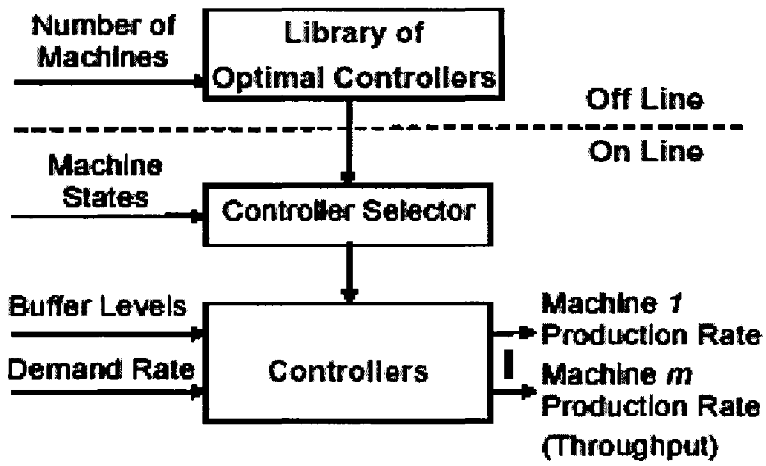


Figure 2.23: Schematic of the Control Policy for WIP and Production (Ma and Koren 2004)

Ding et al. (2000), modeled multi stage manufacturing processes using control theory. The modeling was based on the analogy between the station index (in the production line) and the time index. Such analogy enabled them to have a state space model which was used to analyze and diagnose the variation in an assembly process. The diagnoses lead to the proposal of a methodology to control the system variation propagation and hence improve the quality of manufacturing systems' production. The approach is limited to quality and cannot be extended to PPC models.

Fuzzy controllers have been used for manufacturing systems scheduling dynamic analysis by Tsourveloudis et al. (2003). A set of fuzzy controllers has been derived to reduce the WIP and synchronize the production system's operation. Their work considered multiple-part-type production networks, and it views the overall production-control system as a surplus-based system. Also as an extension to their previous work, they developed a two-level control architecture with a supervisory controller at the higher level of production used to tune the operation of the lower level distributed fuzzy controllers in Ioannidis et al. (2004). The overall control objective was to keep the WIP and cycle time as low as possible and, at the same time, maintain quality of service by keeping backlog at acceptable levels. The production rate in each production stage was controlled in a way that demand was satisfied, overloading of the production system was avoided, and the production system operation was synchronized to eliminate machine starvation or blocking.

Simulation results for a series of production systems with stochastic demand have shown noticeable improvement of performance and production-related costs, in most cases. However the above work didn't study the dynamics of the system when disturbances occur to test for its stability. Also the manufacturing system structure assumed needs enhancement to include other parameters like inventory. Finally the whole work is focused on the operational level where the link with the higher strategic planning level is not recognized in the control mechanism.

Dynamic analysis using transfer functions and the filter theory was applied by Dejonckheere et al. (2003) to aggregate planning in manufacturing systems. Their aim was to achieve a self-adaptive production level scheme triggered by appropriate sales function. The approach was based on using the filters and the frequency domain analysis to represent the volatility of the market into demand and noise. Analysis is then carried out to study the response of the aggregate plan components such as inventory, production orders and workforce level. A comparison of different aggregate planning was carried out. Results showed that practical good design of filters with the right settings of the system parameters by the designer, will lead to more practical and robust aggregate planning than classical operation research optimization techniques.

2.6 Summery of the Literature Review

Based on the previous literature review one can draw the following conclusions:

- Dynamic analysis of manufacturing systems can be classified into four main approaches; discrete event simulation, system dynamics, nonlinear analysis approaches and the control theoretic approaches.
- Dynamic modeling and understanding of manufacturing systems have been a huge research area for a long period. However, the dynamic analysis of manufacturing production and control (MPC) system is generally a new trend in the field of manufacturing systems dynamics research (started to develop at the early 90's). Therefore, there is a great potential for enhancements and research in that area and there are a lot of gaps to be filled.
- In the dynamic analysis of manufacturing production and control systems, most analysis was based on control theory. Control theory has a great potential of application in manufacturing systems as it can fill the gap between the system design level and the operation level through the feedback mechanism.
- More detailed dynamic analysis is required to give a complete understanding of manufacturing planning and control systems dynamics in today's agile manufacturing. All presented analysis focused on investigating the best parameters settings of the manufacturing planning and control systems. Examples of the required analysis include; deeper analysis in the frequency domain and sensitivity analysis to observe the effect of different system's parameters on the performance to better design the system.
- Work in process (WIP), backlog (or capacity level) and inventory control are the major manufacturing process and control parameters that have been subjected to dynamic analysis. However, there is no existing dynamic model that includes these three parameters together. A comprehensive model of the three parameter, WIP, capacity and inventory will give a more realistic and applicable understanding of the dynamics of manufacturing planning and control systems in an agile environment.

- In agile environment, there should be smooth and complete integration between the higher management level and the operational or manufacturing level. Maintaining this link will lead to an agile manufacturing system. In the previous research work there was no explicit realization of such link.

The previous analysis shows that there is a need to develop a comprehensive manufacturing planning and control model. The model should include work in process (WIP), capacity and inventory and how they are related together so that the MPC can adopt different policies based on the market strategies and trends.

There is another need also to conduct various dynamic analyses for the developed model to study the responsiveness, the stability and the steady state level performance of the manufacturing planning and control system. In addition, optimal parametric settings of the system need to be based on some sensitivity analysis for the different parameters of the system and how they affect the performance of the manufacturing system.

Finally, there should be an approach to develop an agile decision making unit that link the higher strategic market level of the enterprise with its manufacturing operational level to decide for the best MPC parameters setting and policy (or configuration) for the current market trend. The development of such a unit will gear the enterprise towards realization of agility.

The outlined needs are the objectives of this research work as will be discussed in the coming chapters of the dissertation.

Chapter Three

Dynamic Modeling of Agile MPC System

3.1 Introduction

The dynamical approach is appropriate when a system is known to include, and be greatly influenced by, core variables that are known to adjust over time and when dynamic feedback is known to occur (van Ackere et al. 1997). Agile manufacturing production planning and control systems have variables that are continuously changing over time due to the nature of today's global market. In addition, the continuous need of responsive and stable manufacturing systems dictated having feedback loops in the structure of manufacturing production and control systems. Thus it is obvious that a dynamic modeling approach is an appropriate one for modeling the agile MPC system of interest in this dissertation.

Classical manufacturing systems modeling approaches are based on concepts that do not consider the manufacturing system as a dynamical system. Usually, heuristic approaches are preferred in order to simulate the production process and its scheduling and control. But optimization methods do not provide the controller with good results if there are some changes during the optimization period.

Dynamic complexity is not related to number of nodes or actors concerned, but the behaviour they create when acting together (Davis and O'Donnell 1997). Similarly, the complexity of the dynamic modeling the MPC systems is a function of the interaction between different MPC system's parameter. The modeling approach in this chapter aims at understanding the dynamicity of agile MPC systems and at the same time decreasing the complexity of the system.

3.2 Model Description

3.2.1 Definitions of System's Parameters and Variables:

Work-In-Process (WIP): The inventory between the start and end points of a product routing. Since routings begin and end at stock points, WIP is all products in between, but not including, the ending stock point (Hopp and Spearman 2002). Thus WIP is the product in various stages of completion throughout the plant, from raw material to completed product.

Production Lead Time: The lead time of a given routing or line is the time allotted for production of a part on that routing or line (Hopp and Spearman 2002). In other words span of time required to perform a process (or series of operations). The production lead time is composed of four different time elements for each step in a part routing: Queue time Setup time Run time Move time. With this detailed information, one can generate an accurate total manufacturing lead time.

Production Rate: Sometimes called throughput: is the average output of a production process (machine, workstation...etc.) or system (line, plant...etc.). It can also be defined as the average quantity of good (non-defective) parts produced per unit time (Hopp and Spearman 2002).

Capacity: An upper limit on the throughput or production rate (Hopp and Spearman 2002). It can be defined as the maximum rate of production and the ability to yield production (Farshid et al., 2002). Releasing work into the system at or above the capacity causes the WIP to build without bound.

Finished Good Inventory: It is the stock point at the end of the production routing (Hopp and Spearman 2002). In some manufacturing systems, it can also be defined as the accumulation between the production rate and the shipment rate.

Shipment Rate: The shipment rate is calculated from dividing the inventory level by the average shipment time (Fong et al. 2004). In supply chain literature the shipment rate is calculated through different consideration of the consumption rate of the different echelons of the supply chain.

3.2.2 Agile MPC System Notations:

WIP*: Desired WIP level (parts)

WIP: Actual WIP level (parts)

DPR: Desired production rate (parts/h)

PR: Actual production rate (parts/h)

T_{LT*}: Expected lead time (h)

T_{LT}: Lead time (h)

G_W: WIP-based control gain (1/h)

Cap*: Desired capacity rate (parts/h)

G_C: Capacity-based control gain (parts/h)

T_D: Capacity installation delay time (h)

I*: Desired inventory level (parts)

I: Actual inventory level (parts)

OR: Expected order rate (parts/h)

SR: Shipment rate (parts/h)

T_{SR}: Shipment time (h)

G_I: Inventory-based control gain (1/h)

3.2.3 Agile MPC System:

The agile MPC modeling aims at constructing a model in which different planning and control strategies (configurations) can be realized as the system's dynamic variables are continuously changing with respect to time. The changes expected in an agile MPC system' variables are due to the normal production rate together with internal and external disturbances. Examples of internal disturbances are sudden breakdowns, resources unavailability, stochastic processes…etc. As for the external disturbances they are usually related to demand disturbances and rush orders. Internal disturbances are reflected in the *Lead Time* system parameter and external disturbances are reflected in the *Shipment Time* parameter as will be discussed. Agile MPC model should also be able to reconfigure based on the current market strategy which in agile competitive environment is always subjected to changes.

The system is composed of the three main parameters of manufacturing systems that work individually or two of them can work simultaneously together (based on the decision of the decision logic unit) to determine the desired production rate DPR. The parameters are the work in process WIP, the capacity rate of the system and the finished inventory. Logically in any system with three parameters, only two parameters can be controlled simultaneously. This is why all previous attempts for the planning and control of manufacturing systems were concerned only with two of these three main parameters. The selection of the parameters to be controlled was usually based on the application or the market strategy of interest. However, in today's agile environment were multiple products are required and different strategies can be adopted based on the market dynamics, agile MPC systems should be able to adopt different policies through the ability to control all parameters based on the current market need. This problem is addressed in the developed model.

The novelty of the developed agile MPC system's model can be summarized in two main aspects. First the model structure which encompasses the three main parameters of the manufacturing system and thus it has the ability to adopt different planning and control strategies (or modes). This will happen by reconfiguring its MPC system's structure through the decision logic unit. Second, maintaining real agility of manufacturing systems via linking the operational level with the high market level through the decision logic unit.

The decision logic unit, in general, is responsible for collecting external and internal data and the different disturbances and then deciding on the optimal MPC system configuration. The details of the decision logic unit design and the switching (reconfiguration) protocol are explained in chapter five. Also the algorithms for using different types of controllers are discussed in chapter five. However, the description of each of the agile MPC system configuration is presented in the following sections.

The modeling approach and its analysis are based on the application of the control theory and feedback analysis where continuous time domain is implemented to model the system states. Although discrete time domain gives a better image of the manufacturing systems, the continuous Laplace models are favoured in this research since the interesting parameters (production rate, WIP level, lead time...etc.) show a more continuous character from a planning standpoint (Wiendahl and Breithaupt 1999, Wiendahl and Breithaupt 2000). Also similar results can be obtained using discrete models (John et al. 1994). Block diagrams for each system configuration are developed and then the dynamic transfer functions for each configuration are derived.

The main time parameters of the system are the production lead time, capacity installation/un-installation delay time and the shipment time. An insight about each one of them is presented in the following paragraphs.

The determination of the production lead time depends on the production system itself. The production system or process here is modeled as a pipeline where the outflow is simply lagged by the average delay time (Sterman 2000). Thus the lead time is found by analogy with a pipeline of a known length into which material is fed and from which it flows once the material has passed through the pipe. Determining the exact value of pipeline lead time is a complex task (Hoyt 1980) and beyond the scope of this research. However exponential lag model is used in the developed model which can be considered representative of different manufacture systems (Towill et al. 1997). Simulation results of such assumption showed exponential pipeline lag to be appropriate compromise between complexity and accuracy (Winker 1994).

The capacity installation/un-installation (or scalability) delay time is important to consider when capacity controllers are involved. For simplicity it can be assumed to be zero, however, in reality it is impossible to adjust the capacity immediately (Peterman 1996). Therefore, a reaction time between the request for capacity and the following allocation was introduced in the model. The capacity scalability delay time is usually functional in the capacity size and thus it varies based on the required capacity correction. This delay can be used to measure the flexibility of the manufacturing system (Wiendahl and Breithaupt 2001)

As for the shipment time (which is used to express the shipment rate), it is indicated based on the market strategy adopted by high level of the corporation and sales. It is subject to changes based on the market dynamics and sudden disturbances in demand such as rush orders. The function or the relation that can express these changes is normally used to relate the shipment rate to the order rate.

The general structure of the agile MPC system proposed, shown in figure 3.1, can be expressed in words as being composed of two main operational layers plus a decision logic unit that links these two layers with the higher corporation management layer. The first operation layer is the default (or servo control layer) where the control is only based on the WIP level. The other layer (intelligent control layer) involves two controllers, an inventory controller and a capacity controller. The engagement of either controller to the servo control layer or to work by itself, creating different MPC configuration, is the responsibility of the decision logic unit as discussed previously. Also the decision logic unit provides the system with the reference control points and the updates of the order rate OR and shipment time and at the same time collects all the data of the current system to help in deciding for the next optimal MPC configuration.

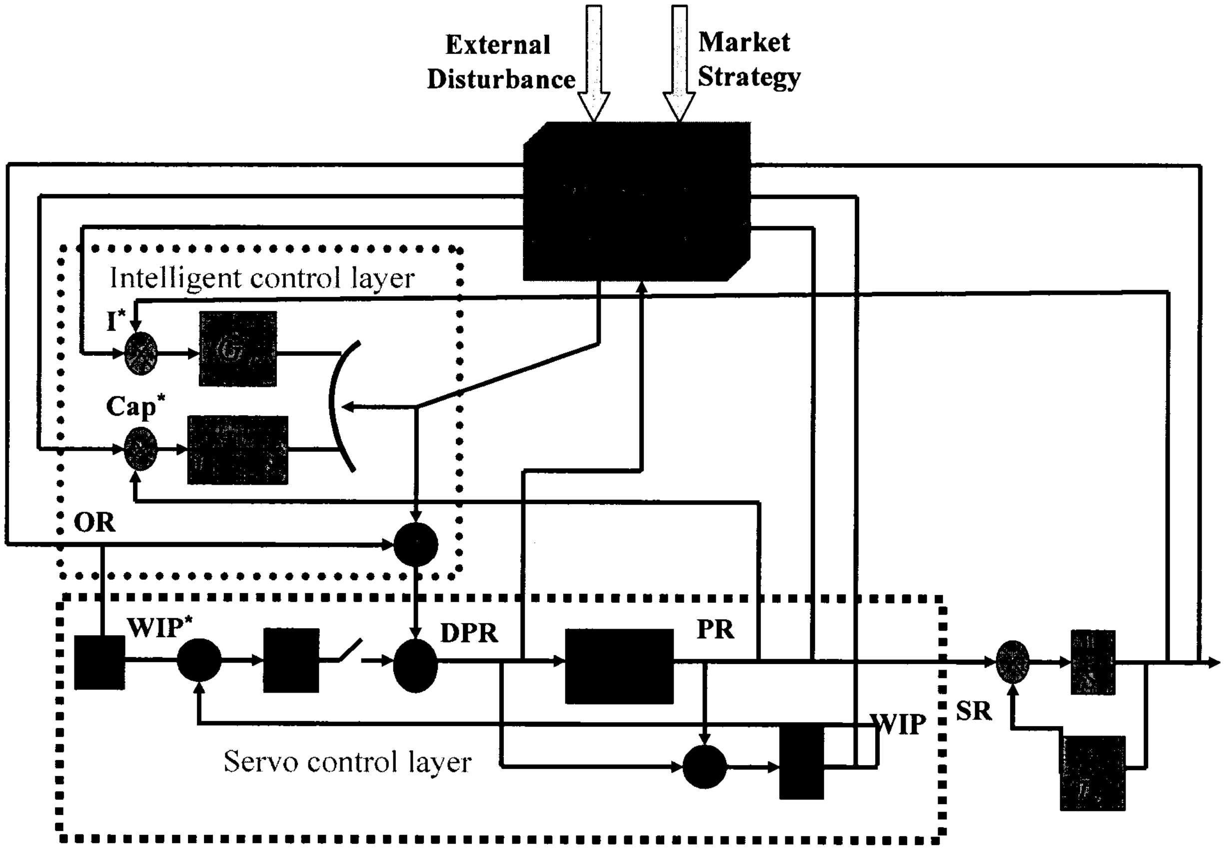


Figure 3.1 Agile MPC System

The main purpose of any manufacturing planning and control system is to set plans and group of control actions to adjust the desired production rate (DPR) to meet the demand patterns specified by marketing (Gangneux 1989).. Since DPR is the main decision rule in agile MPC system thus it is important to state the equations guiding this decision. The first equation (3.1) states that DPR is the sum of the expected losses (which in the manufacturing case are the expected order rates OR) plus adjustments in the production rate level APR. The adjustments can be in the WIP level, in the actual production rate PR level, in the finished inventory level, or any combination of the previous parameters based on the MPC policy selected by the decision logic unit. Another important equation is the one which ensures DPR to be nonnegative (since production can't be negative). A MAX function is introduced for this purpose when determining the DPR as shown in equation (3.2)

$$DPR = OR + APR \tag{3.1}$$

$$DPR = MAX(0, DPR) \tag{3.2}$$

The developed agile MPC model can be viewed as an extension of the known supply chain model by Sterman (1989) and the automatic pipeline inventory and order based production control system APIOBPCS model by John et al. (1994) where the model structure, control algorithm and its analysis were modified and enhanced. The new analysis approach is presented in details in chapter four and in Deif and ElMaraghy (2006-c). As for the structure; three major modifications were introduced to the model (Deif and ElMaraghy 2006-a). The first modification was considering capacity rate as a parameter and capacity rate as a correcting variable in the systems. This is valid in today's modern manufacturing systems like reconfigurable manufacturing system (RMS) and their enabling technologies such as modular designs and open control architectures. The use of the capacity rate controller was to overcome the problem of having high production rate (which can be unrealistic) when WIP is the correcting variable of the manufacturing system that aims to maintain a certain level of finished inventory. Also the assumption of the unlimited WIP values in the APIOBPCS model needs to be relaxed as each system in reality has a maximum limit of WIP to hold based on the system's configuration. Increasing capacity will alter that limit of WIP and thus the WIP controller can be reactivated. The second difference was in considering the shipment rate to be calculated through dividing the finished inventory level by average shipment time and establishing a relation between the order rate and the shipment rate. Third and major modification was the introduction of the decision logic unit as a supervisory controller where the real agility comes into the scene as will be explained in chapter five.

3.2.3.1 WIP Based MPC System

This configuration or policy is the default configuration in the agile MPC system and shown in figure 3.2. The WIP controller is connected while the other two controllers are disconnected. WIP is an important control parameter as it ties up capital and costs interest (Looding et al. 2003) and has direct relation with the production rate and production lead time. As mentioned before, production lead time is difficult to measure while WIP is easy to measure and therefore WIP can be and indicative and easy parameter to use for normal control of manufacturing system.

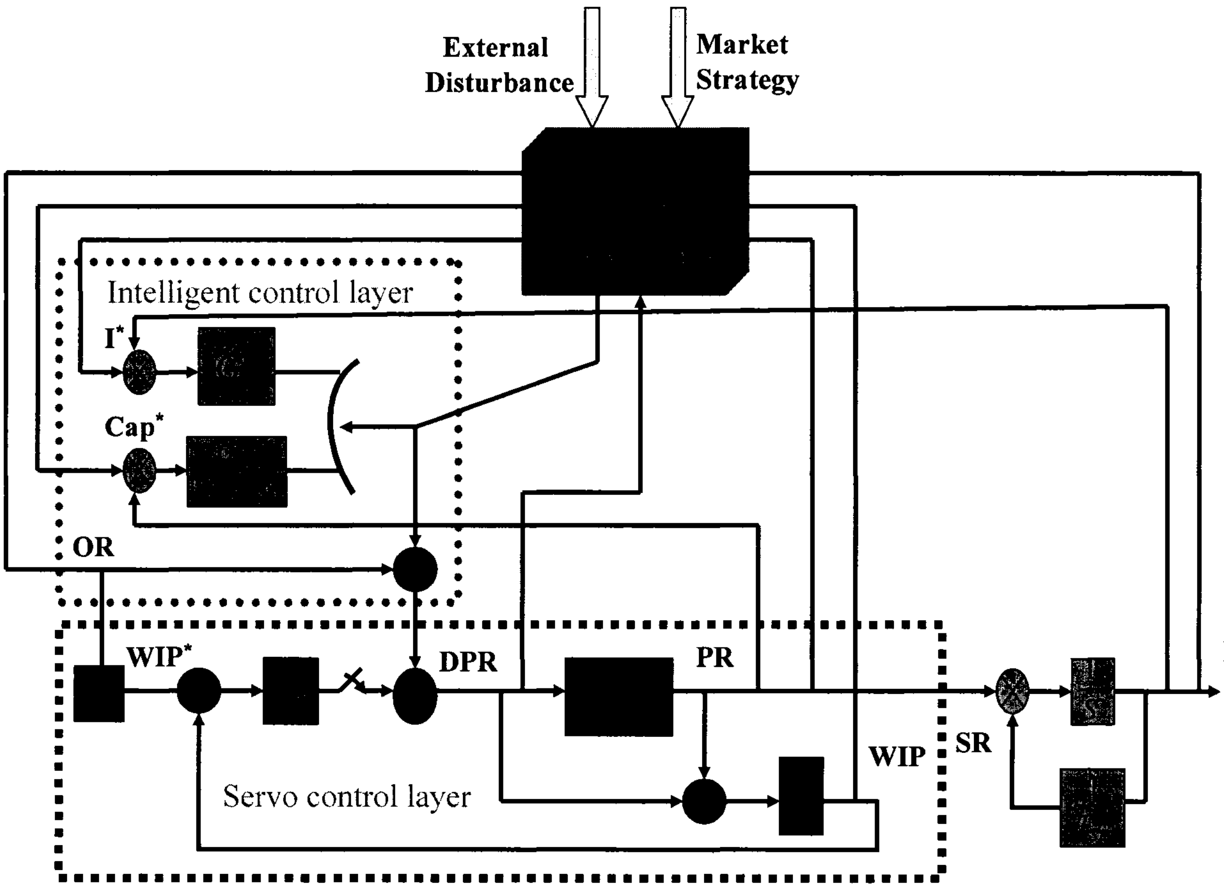


Figure 3.2 WIP based MPC System

This MPC system configuration observes the WIP level and compares it to a reference WIP level. Based on the error between the two levels the WIP controller adjusts the WIP level through a gain (G_W) and adds this amount together with the order rate OR to the desired production rate DPR level. WIP level is calculated as the difference between the desired production rate DPR and the actual production rate PR and the latter is due to an exponential time delay of the DPR based on the system's production lead time T_{LT} (John et al. 1994). This relation is presented in equations 3.3.

$$WIP = INTEGRAL\ (DPR - PR,\ WIP_{t=0}) \tag{3.3}$$

The desired WIP level is calculated as a product of multiplying the order rate OR with the estimated (ideal) lead time of the production system T_{LT}^{*} as indicated by Little's law (Sterman 1989, Hopp and Spearman 2000). The control gain (G_W) can be physically described as increasing or decreasing the input rate of work to the production system (Duffie 2002) since stocks, as in the case of WIP, are altered only by changes in their inflow and outflow rates (Sterman 2000). Exact WIP gain (G_W) values and the analysis of its effect on the system's performance will be discussed in chapter four.

3.2.3.2 Capacity Based MPC System

This configuration shown in figure 3.3 is achieved by only engaging the capacity controller into the system. Capacity based policy is very important in the cases when there is a highly varying input of orders caused by pre-fabrication or a frequently changing order situation (Pritschow and Wiendahl 1995). This configuration also suits the cases where exact capacity is needed and the capacity should match the demand without any backlog. This is also found when the value and carrying costs of inventory are very high as in the airplane manufacturing industries (Streman 2000). Ideally this configuration suits the make to order MPC strategy. Today's modern technology based on modularity and open architecture control enabled manufacturing systems to adjust their capacity much easier. A typical example of a manufacturing system adopting this MPC configuration is the reconfigurable manufacturing systems RMS.

Ideally in this MPC strategy, the production capacity should be adjusted to the demand in a continuous fashion, so as to always be in a profitable state. However, this type of policy is undesirable or impossible due to the fact that rate of demand variations is usually much higher than the rate at which capacity can be changed. So the desire of following the demand has to be balanced by the risk of losses due to over frequent changes in capacity (Farshid and Ulsoy 2004).

This MPC system configuration observes the production rate PR and compares it to a reference capacity rate. Based on the error between the two rates the capacity controller adjusts the capacity rate through a gain (G_C) and adds this amount to the desired production rate DPR level. The reference capacity rate is set to be equal to the order rate OR. A formula that can be used to calculate the reference capacity is shown in equation 3.4 (other formulas can also be used)

$$Cap^* = \frac{\text{Demands (parts)}}{\text{Due dates (days)} * \text{working hours (hours/day)}} \tag{3.4}$$

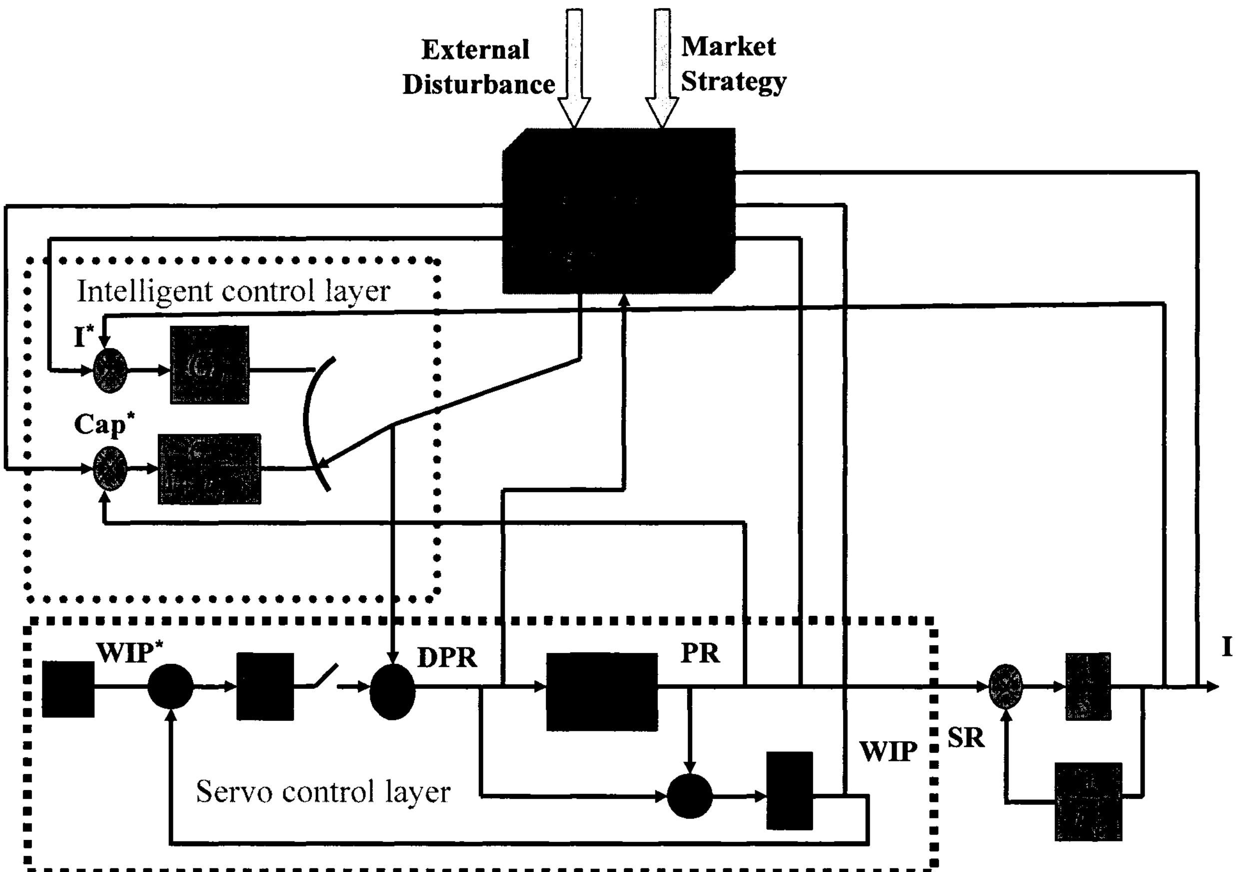


Figure 3.3 Capacity based MPC System

The data for the capacity reference are supplied by the decision logic unit. Sudden rush orders or any demand disturbance will immediately be reflected on the value of Cap^* and thus it's a dynamic parameter. The control gain (G_C) in a physical sense is for example adding or removing machines, adding or removing machines tools or components and adding or removing shifts (ElMaraghy 2006). Exact capacity gain (G_C)

values and the analysis of its effect on the system's performance will be discussed in chapter four.

3.2.3.3 Finished Inventory Based MPC System

The third policy of the Agile MPC model is based on controlling the finished inventory level. This is achieved in the model by engaging the inventory controller and disconnecting other controllers as shown in figure 3.4. One of the principle reasons used to justify investments in finished inventory is its role as a buffer to absorb demand variability (Baganha and Cohen 1998). In other words, finished good inventory is usually important for corporation which locates its market competitiveness position based on the high customer service level. Example of this case is the medical supplies market (Towill et al 1997). This configuration is typically suitable for companies adopting a push marketing strategy and a make to stock MPC approach where the fill rate is the major performance measure of the manufacturing system.

This MPC system configuration observes the finished inventory level I and compares it to a reference finished inventory level I^*. Based on the error between the two levels the inventory controller adjusts the inventory level through a gain (G_I) and adds this amount together with the order rate OR to the desired production rate DPR level. DPR level cannot be calculated based only on the gap between the desired inventory and the actual inventory. This will lead to a steady state error in the finished inventory level when the firm is in equilibrium i.e. production equals shipment rate (Sterman 2000). The finished inventory level is determined by having the difference between the production rate PR and the shipment rate SR as shown in equation 3.5.

$$I = INTEGRAL\ (PR - SR,\ I_{t=0}) \tag{3.5}$$

The shipment rate SR is calculated through dividing the previous finished inventory level by average shipment time and the later is determined by the higher management level based on the market strategy and shipments data. The control gain (G_I)

can be physically described as increasing or decreasing the input rate of work to the production system. Exact inventory gain (G_I) values and the analysis of its effect on the system's performance will be discussed in chapter four.

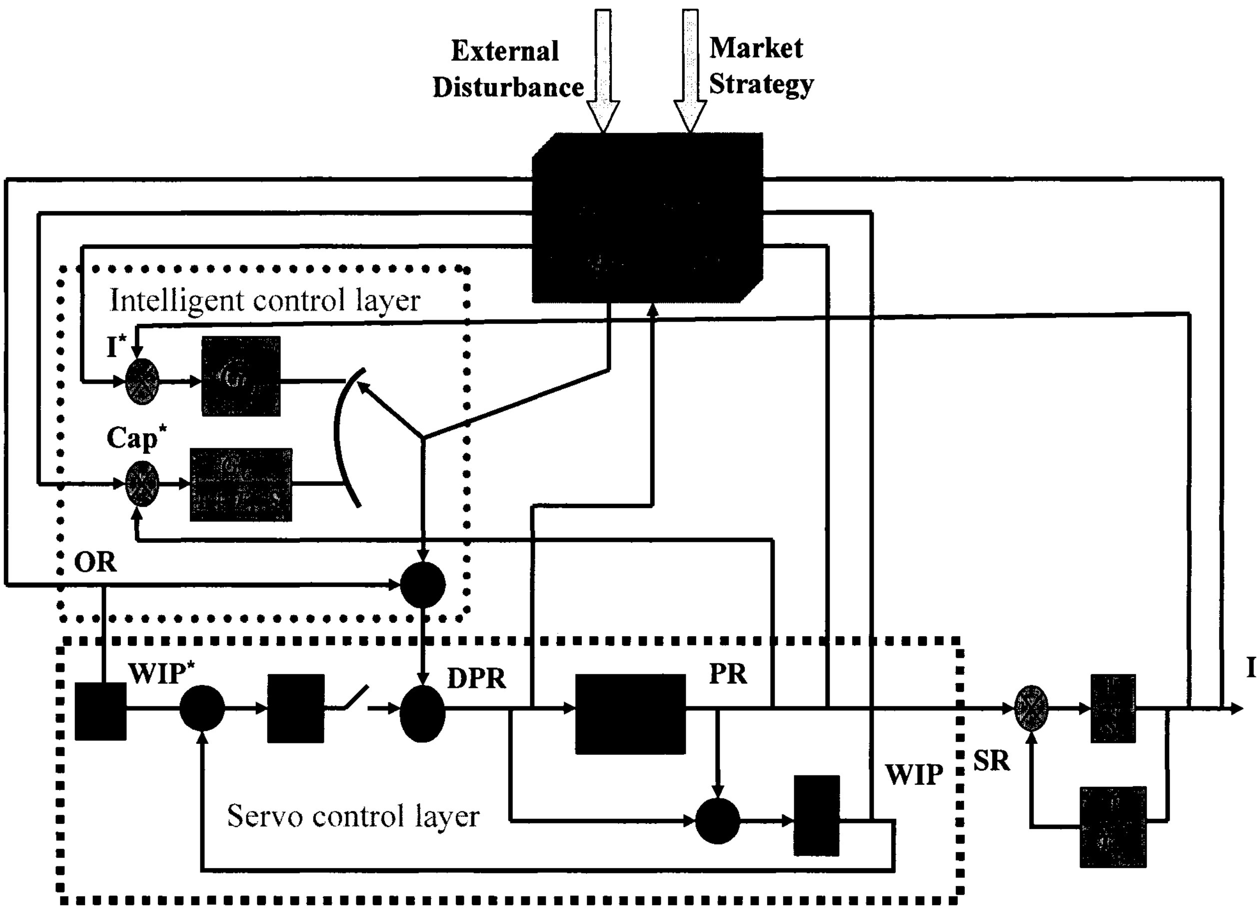


Figure 3.4 Inventory based MPC System

3.2.3.4 Capacity and WIP Based MPC System

The fourth policy of the Agile MPC model is based on controlling both the WIP level and the capacity rate. This is achieved in the model by engaging the WIP controller in the servo control layer together with capacity rate controller in the intelligent control layer and disconnecting the inventory controller as shown in figure 3.5. Accounting for WIP is very important as it decreases the oscillation of the system and affect the damping ratio of the system especially in the case of unanticipated shocks (rush orders). Further dynamic analysis of this configuration is discussed in chapter four. However, in reality any manufacturing system has a WIP increase limit which is the upper capacity limit of that system's configuration (Hopp and Spearman 2000). This limit is the maximum WIP point. To overcome this problem and keeping the advantage of having a WIP based MPC system, the system's capacity should be reconfigured (scaled). This is achieved through a capacity controller engaged in this configuration.

The WIP controller is appropriate for the normal production control below the maximum WIP point. If the lead time keeps growing due to any internal disturbances or if there is a rush order, the queue of waiting orders in front of the system (WIP level) can be diminished by decreasing the system's input rate through the WIP controller. However, if there is a due date limit (which is a typical case in agile manufacturing) then the input rate can't be reduced. The capacity controller only functions when the maximum WIP level of the system is reached and input rate cannot be decreased, as otherwise backlog does not arise. This point is indicated by the decision logic unit based on the current system's configuration limitation and the required utilization level.

On the other hand, if the capacity is increased by the capacity controller to compensate for the undesirable WIP increase and then the system is back into the stable state, the system can be in a state of unutilized capacity. The WIP controller will not detect this problem. Thus the capacity controller will also be used to resolve this undesired situation by observing production rate PR and comparing it to the capacity reference point. The capacity reference point is indicated based on a planned utilization level decided by the higher management level. For example, reconfigurable manufacturing systems aim (although this is very difficult) at having a utilization of almost 100 %. The automatic synchronization between the two controllers is the job of the decision logic unit.

This MPC system policy observes the WIP level and compares it to a reference WIP level. Based on the error between the two levels the WIP controller adjusts the WIP level through a gain (G_W) and adds this amount to the desired production rate DPR level.

Once the system reaches the maximum WIP point no more WIP gain can be added by the WIP controller and thus the capacity controller is activated to eliminate the backlog by reconfiguring the system to scale up the capacity. The new system configuration will introduce a new WIP maximum point and the system will be automatically set back to the WIP based control mode.

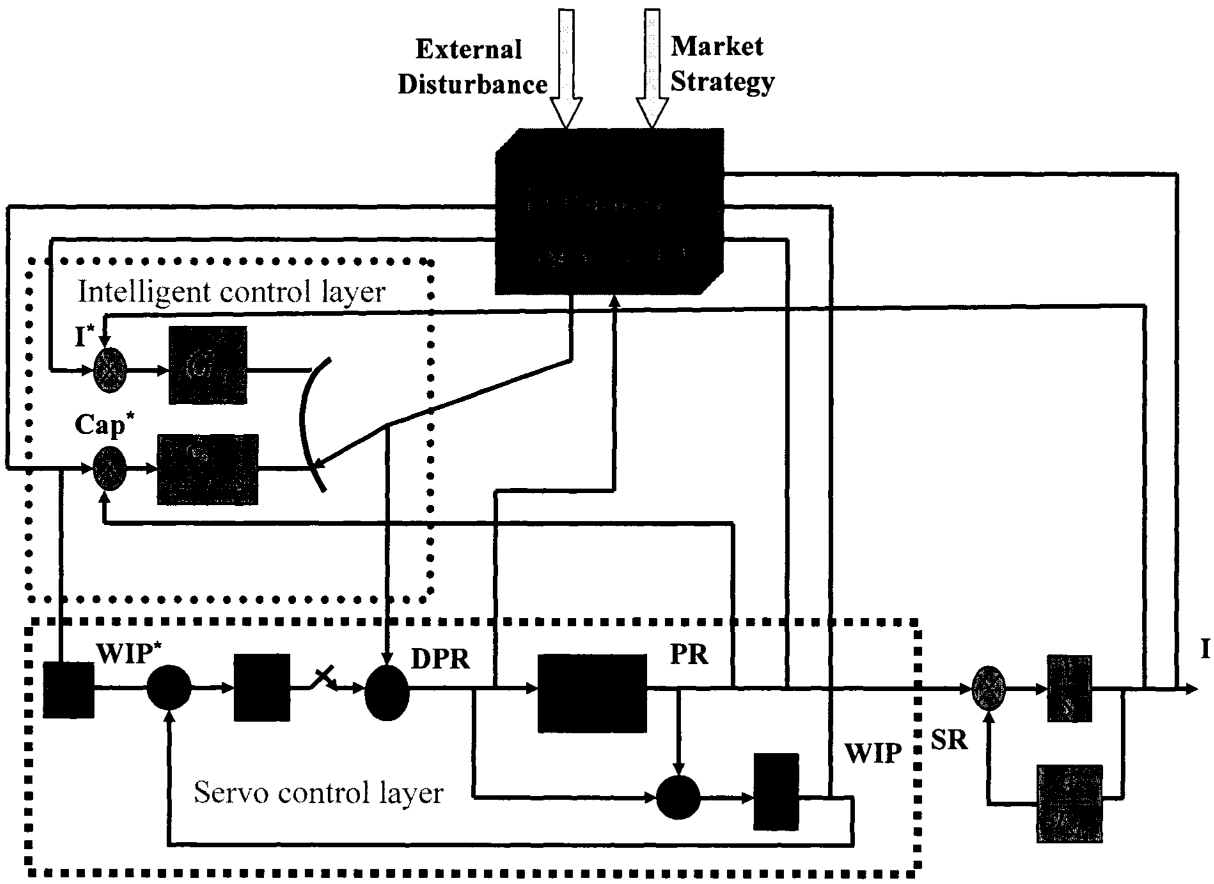


Figure 3.5 Capacity and WIP based MPC System

3.2.3.5 Finished Inventory and WIP Based MPC System

The fifth policy of the Agile MPC model is based on controlling both the WIP level and the inventory level. This is achieved in the model by engaging the WIP controller in the servo control layer together with inventory level controller in the intelligent control layer and disconnecting the capacity rate controller as shown in figure 3.6. This structure is usually used to have an optimal trade-off balance between the cost of inventory and production adaptation cost when considering the whole supply chain management problem.

If a perfectly leveled production rate is used then large inventory deviations are found and thus increasing the inventory cost or decreasing the service level. Conversely, if inventory deviations are minimized then high production variation (especially in terms of scheduling) will be realized leading to higher production cost. This trade-off problem has been illustrated using control theory by Simon (1952), Vassian (1955), Dezeil and Elion (1967), Towill (1982) and Disney and Towill (2003). This problem form a manufacturing planning and control perspective is approached in this agile MPC system through the implementation of the decision logic unit that optimizes between these two competing objectives based on the input data from the market and higher management level strategy.

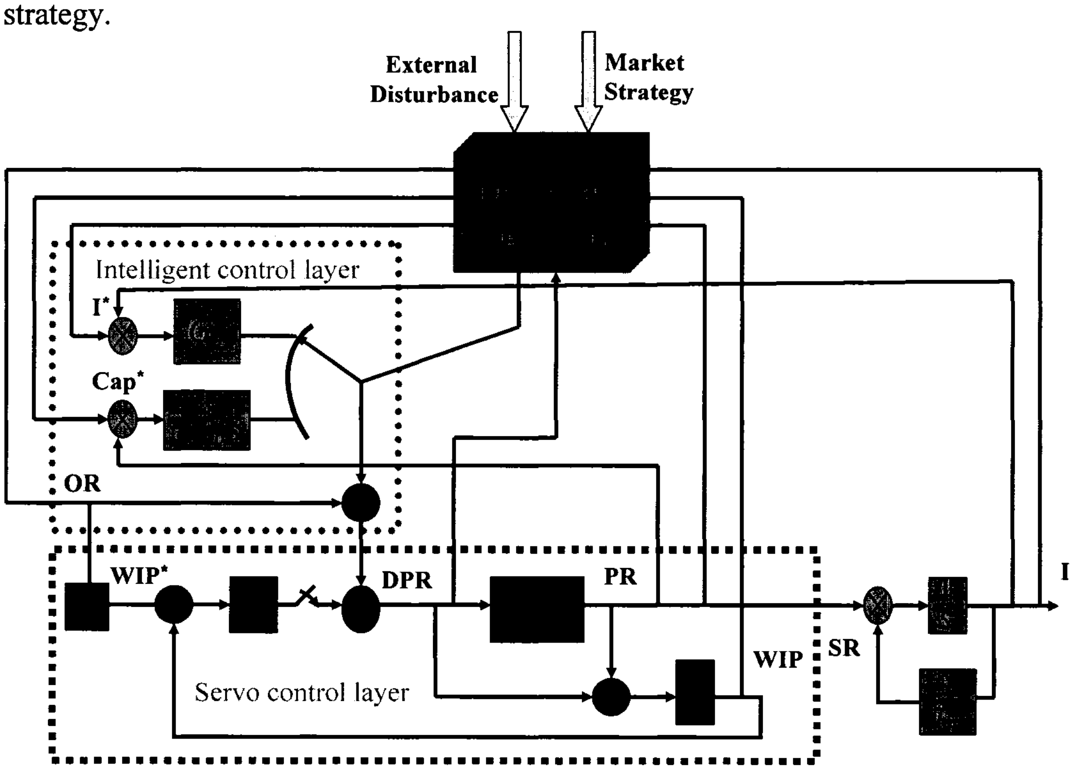


Figure 3.6 Inventory and WIP based MPC System

This MPC system configuration observes the finished inventory level I and compares it to a reference finished inventory level I^*. Based on the error between the two levels the inventory controller adjusts the inventory level through a gain (G_I) and adds this amount to the desired production rate DPR level. At the same time the system observes the WIP level and compares it to a reference WIP level. Based on the error between the two levels the WIP controller adjusts the WIP level through a gain (G_W) and adds this amount to the desired production rate DPR level. The addition of both gains to the production system is controlled by the decision logic unit.

3.3 Mathematical Formulation of Agile MPC Transfer Function

3.3.1 Model Assumptions:

- $T_{LT} = \delta\, T_{LT}^*$ where $0 \le \delta \le 1$ (Linear relation).
- $SR = \alpha\, OR$ where $0 \le \alpha \le 1$ (Linear relation).

Without loosing the generality of the model, for simplicity δ and α are assumed to be equal to one. These assumptions are made only for better understanding the problem and the proposed model does not have any limitations considering the case of any other values. Relaxation of these assumptions is discussed in chapter four.

The assumption of having SR = OR will make configuration 5 (Inventory and WIP based MPC system) very close to the model proposed by Sterman (2002). If α is set so that it can reflect the *average* order rate the same configuration will be equivalent to the APIOBPCS model presented by John et al. (1994). The difference between both assumptions is in determining the value of the desired work in process WIP^*. John et al. showed that setting the order rate equals to average order rate (based on market study) will eliminate the inventory offset problem. However, this will lead to production overshoot (John et al. 1994). The trade off decision (or deciding on the value of α) will be the task of the decision logic unit based on the data coming form the high management level and the market strategy.

The assumption of having the actual pipeline lead time T_{LT} equal to the expected lead time T_{LT}^* requires an accurate visibility of the pipeline. As indicated before this is not really practical but yet reflective to the basic dynamic behaviour of the MPC system. The exact value of δ is beyond the scope of this research.

Other assumptions to complete the whole picture are mentioned as follows. The model does not include scrap rates; if it did, production rate PR would have to exceed shipment rate by the scrap rate to achieve a balanced equilibrium. Also it is assumed that there is no raw materials inventory i.e. materials are always ample. This is assumed in order to have desired production start time equal to the production start time.

3.3.2 WIP Based MPC System:

This system is considered the first configuration of the developed agile MPC system. The configuration is shown in figure 3.2.

$$WIP = (DPR - PR)\frac{1}{S} \tag{3.6}$$

$$PR = DPR\left(\frac{1}{1+T_{LT}S}\right) \tag{3.7}$$

$$WIP = DPR\left(1-\frac{1}{1+T_{LT}S}\right)\frac{1}{S} \tag{3.8}$$

$$DPR = (WIP^{*} - WIP)G_{W} + OR \tag{3.9}$$

$$WIP = ((WIP^{*} - WIP)G_{W} + OR)\left(1-\frac{1}{1+T_{LT}S}\right)\frac{1}{S} \tag{3.10}$$

$$WIP = (WIP^{*} - WIP)\left(\frac{G_{W}T_{LT}}{1+T_{LT}S}\right) + \frac{\mathrm{OR}T_{LT}}{1+T_{LT}S} \tag{3.11}$$

$$OR = \frac{WIP^*}{T_{LT}^*} \tag{3.12}$$

$$T_{LT}^* = T_{LT} \tag{3.13}$$

$$WIP\left(1 + \left(\frac{G_W T_{LT}}{1 + T_{LT} S}\right)\right) = WIP^*\left(\frac{G_W}{1 + T_{LT} S}\right) + WIP^*\left(\frac{1}{1 + T_{LT} S}\right) \tag{3.14}$$

$$WIP\left(1 + \left(\frac{G_W}{1 + T_{LT} S}\right)\right) = WIP^*\left(\frac{G_W T_{LT} + 1}{(1 + T_{LT} S)}\right) \tag{3.15}$$

$$\frac{\mathrm{WIP}}{\mathrm{WIP}^*} = \left(\frac{G_W T_{LT} + 1}{1 + T_{LT}\ S + G_W T_{LT}}\right) \tag{3,16}$$

$$\frac{\mathrm{WIP}}{\mathrm{WIP}^*} = \left(\frac{G_W + T_{LT}^{-1}}{S + G_W + T_{LT}^{-1}}\right) \tag{3.17}$$

3.3.3 Capacity Based MPC System:

This system is considered the second configuration of the developed agile MPC system. The configuration is shown in figure 3.3.

$$PR = DPR\left(\frac{1}{1 + T_{LT} S}\right) \tag{3.18}$$

$$DPR = (Cap^* - PR)G_C\left(\frac{1}{1 + T_D S}\right) \tag{3.19}$$

$$PR = (Cap^* - PR)G_C\left(\frac{1}{1 + T_D S}\right)\left(\frac{1}{1 + T_{LT} S}\right) \tag{3.20}$$

$$PR\left(1 + \left(\frac{G_C}{1 + T_{LT} S}\right)\left(\frac{1}{1 + T_D S}\right)\right) = Cap^*\left(\frac{G_C}{1 + T_{LT} S}\right)\left(\frac{1}{1 + T_D S}\right) \tag{3.21}$$

$$\frac{PR}{Cap^*} = \left(\frac{G_C}{S^2 (T_{LT} T_D) + 1 + (T_{LT} + T_D) S + G_C} \right) \tag{3.22}$$

$$\frac{PR}{Cap^*} = \left(\frac{G_C T_{LT}{}^{-1} T_D{}^{-1}}{S^2 + S(T_{LT}{}^{-1} + T_D{}^{-1}) + (1 + G_C) T_{LT}{}^{-1} T_D{}^{-1}} \right) \tag{3.23}$$

3.3.4 Finished Inventory Based MPC System:

This system is considered the third configuration of the developed agile MPC system. The configuration is shown in figure 3.4.

$$I = (PR - SR)\frac{1}{S} \tag{3.24}$$

From equation 3.7

$$I = \left(DPR\left(\frac{1}{1 + T_{LT} S} \right) - SR \right) \frac{1}{S} \tag{3.25}$$

$$I = \frac{1}{S(1 + T_{LT} S)} (DPR - SR(1 + T_{LT} S)) \tag{3.26}$$

$$DPR = (I^* - I) G_I + OR \tag{3.27}$$

$$SR = \frac{I}{T_{SR}} \tag{3.28}$$

Substitute equations (3.27) and (3.28) into equation (3.26) and recall the assumption that $SR = OR$

$$I = \frac{1}{S(1+T_{LT}S)}((I^* - I)G_I - \frac{I}{T_{SR}}(T_{LT}S)) \tag{3.29}$$

$$I = \frac{G_I}{S(1+T_{LT}S)} I^* - I\left(\frac{G_I T_{SR} + T_{LT}S}{ST_{SR}(1+T_{LT}S)}\right) \tag{3.30}$$

$$I\left(1 + \frac{G_I T_{SR} + T_{LT}S}{ST_{SR}(1+T_{LT}S)}\right) = \frac{G_I}{S(1+T_{LT}S)} I^* \tag{3.31}$$

$$\frac{I}{I^*} = \frac{G_I T_{SR}}{(1+T_{LT}S)(T_{SR}S) + G_I T_{SR} + T_{LT}S} \tag{3.32}$$

$$\frac{I}{I^*} = \frac{G_I T_{LT}{}^{-1}}{S^2 + S(T_{LT}{}^{-1} + T_{SR}{}^{-1}) + G_I T_{LT}{}^{-1}} \tag{3.33}$$

3.3.5 Capacity and WIP Based MPC System:

This system is considered the fourth configuration of the developed agile MPC system. The configuration is shown in figure 3.5.

$$PR = DPR\left(\frac{1}{1+T_{LT}S}\right) \tag{3.34}$$

$$DPR = (WIP^* - WIP)G_W + (Cap^* - PR)G_C\left(\frac{1}{1+T_D S}\right) \tag{3.35}$$

$$WIP^* = Cap^* T_{LT}{}^* \tag{3.36}$$

$$T_{LT}{}^* = T_{LT} \tag{3.37}$$

From eqaution 3.3

$$WIP = DPR\left(1 - \frac{1}{1+T_{LT}S}\right)\frac{1}{S} \tag{3.38}$$

Substituteequations(3.36)and (3.38)in eqautiom(3.35)

$$DPR = \left(Cap^{*}T_{LT^{*}} - DPR\left(1 - \frac{1}{1+T_{LT}S}\right)\frac{1}{S}\right)G_W + (Cap^{*} - PR)G_C\left(\frac{1}{1+T_DS}\right) \tag{3.39}$$

Substitute(3.39)in (3.34)

$$PR = \left(\left(Cap^{*}T_{LT^{*}} - DPR\left(1 - \frac{1}{1+T_{LT}S}\right)\frac{1}{S}\right)G_W + (Cap^{*} - PR)G_C\left(\frac{1}{1+T_DS}\right)\right)\left(\frac{1}{1+T_{LT}S}\right) \tag{3.40}$$

$$PR(1+T_{LT}S) = Cap^{*}\left(T_{LT}G_W + \frac{G_C}{1+T_DS}\right) - PR\left(\frac{G_C}{1+T_DS}\right) - \left(\frac{DPR}{S}G_W\left(1 - \frac{1}{1+T_{LT}S}\right)\right) \tag{3.41}$$

From(3.32)

$$DPR = PR(1+T_{LT}S) \tag{3.42}$$

$$PR(1+T_{LT}S) = Cap^{*}\left(\frac{T_{LT}G_W + T_{LT}G_WT_DS + G_C}{1+T_DS}\right) - PR\left(\frac{G_C}{1+T_DS}\right) - (PRG_WT_{LT}) \tag{3.43}$$

$$PR(1+T_{LT}S) = Cap^{*}\left(\frac{T_{LT}G_W + T_{LT}G_WT_DS + G_C}{1+T_DS}\right) - PR\left(G_WT_{LT} + \left(\frac{G_C}{1+T_DS}\right)\right) \tag{3.44}$$

$$PR\left(1 + T_{LT}S + G_WT_{LT} + \left(\frac{G_C}{1+T_DS}\right)\right) = Cap^{*}\left(\frac{T_{LT}G_W + T_{LT}G_WT_DS + G_C}{1+T_DS}\right) \tag{3.45}$$

$$PR\left(\frac{1 + T_DS + T_{LT}S + T_{LT}T_DS^2 + G_WT_{LT} + G_WT_{LT}T_DS + G_C}{1+T_DS}\right) =$$
$$Cap^{*}\left(\frac{T_{LT}G_W + T_{LT}G_WT_DS + G_C}{1+T_DS}\right) \tag{3.46}$$

$$\frac{PR}{Cap^*}=\left(\frac{T_{LT}G_W+T_{LT}G_WT_DS+G_C}{1+T_DS+T_{LT}S+T_{LT}T_DS^2+G_WT_{LT}+G_WT_{LT}T_DS+G_C}\right) \tag{3.47}$$

$$\frac{PR}{Cap^*}=\left(\frac{T_{LT}G_W(1+T_DS)+G_C}{S^2T_{LT}T_D+S(T_D+T_{LT}+G_WT_{LT}T_D)+(G_WT_{LT}+G_C+1)}\right) \tag{3.48}$$

$$\frac{PR}{Cap^*}=\left(\frac{G_W(T_D{}^{-1}+S)+G_CT_{LT}{}^{-1}T_D{}^{-1}}{S^2+S(T_D{}^{-1}+T_{LT}{}^{-1}+G_W)+(G_WT_{LT}+G_C+1)T_{LT}{}^{-1}T_D{}^{-1}}\right) \tag{3.49}$$

3.3.6 Finished Inventory and WIP Based MPC System:

This system is considered the fifth configuration of the developed agile MPC system. The configuration is shown in figure 3.6.

From equation 3.25

$$I=\frac{1}{S(1+T_{LT}S)}(DPR-SR(1+T_{LT}S)) \tag{3.50}$$

$$DPR=(WIP^*-WIP)G_W+(I^*-I)G_I+\mathrm{OR} \tag{3.51}$$

$$WIP^*=OR\,T_{LT^*} \tag{3.52}$$

$$T_{LT^*}=T_{LT} \tag{3.53}$$

$$OR=\frac{I}{T_{SR}} \tag{3.54}$$

From eqaution 3.3

$$WIP=DPR\left(1-\frac{1}{1+T_{LT}S}\right)\frac{1}{S} \tag{3.55}$$

Substitute equations (3.52), (3.54) and (3.55) in (3.51)

$$DPR = (IT_{SR}{}^{-1}T_{LT})G_W - DPR\frac{G_W}{S}\left(1 - \frac{1}{1+T_{LT}S}\right) + I^*G_I - IG_I + IT_{SR}{}^{-1} \tag{3.56}$$

$$\text{DPR} = \frac{IT_{SR}{}^{-1}(1+T_{LT}G_W) + I^*G_I - IG_I}{\left(1+\frac{G_W}{S}\left(1-\frac{1}{1+T_{LT}S}\right)\right)} \tag{3.57}$$

$$\text{DPR} = \frac{IT_{SR}{}^{-1}(1+T_{LT}G_W) + I^*G_I - IG_I}{\frac{1+T_{LT}S+T_{LT}G_W}{1+T_{LT}S}} \tag{3.58}$$

Substitute(3.58)in (3.50)

$$I = \frac{1}{S(1+T_{LT}S)}\left(\frac{\left[(IT_{SR}{}^{-1}(1+T_{LT}G_W) + I^*G_I - IG_I)\right](1+T_{LT}S)}{1+T_{LT}S+T_{LT}G_W} - SR(1+T_{LT}S)\right) \tag{3.59}$$

$$I = \frac{I^*G_I - I(G_I + T_{SR}{}^{-1}T_{LT}S)}{S(1+T_{LT}S+T_{LT}G_W)} \tag{3.60}$$

$$I\left(1+\frac{G_I + T_{SR}{}^{-1}T_{LT}S}{S(1+T_{LT}S+T_{LT}G_W)}\right) = I^*\frac{G_I}{S(1+T_{LT}S+T_{LT}G_W)} \tag{3.61}$$

$$\frac{I}{I^*} = \frac{G_I}{S(1+T_{LT}S+T_{LT}G_W) + G_I + T_{SR}{}^{-1}T_{LT}S} \tag{3.62}$$

$$\frac{I}{I^*} = \frac{G_I}{S + T_{LT}S^2 + T_{LT}G_WS + G_I + T_{SR}{}^{-1}T_{LT}S} \tag{3.63}$$

$$\frac{I}{I^*} = \frac{G_IT_{LT}{}^{-1}}{S^2 + S(G_W + T_{LT}{}^{-1} + T_{SR}{}^{-1}) + (G_IT_{LT}{}^{-1})} \tag{3.64}$$

3.3.7 Summary of the dynamic models for the developed agile MPC system configurations:

Equations (3.65) - (3.69) list the dynamic models for the developed agile MPC system configurations (transfer functions). The analysis of these models is presented in the following chapter.

1. *WIP Based MPC System*

$$\frac{\text{WIP}}{\text{WIP}^*} = \frac{(G_W + T_{LT}^{-1})}{S + (G_W + T_{LT}^{-1})} \tag{3.65}$$

2. *Capacity Based MPC System*

$$\frac{PR}{Cap^*} = \frac{G_C T_{LT}^{-1} T_D^{-1}}{S^2 + S(T_{LT}^{-1} + T_D^{-1}) + (1 + G_C) T_{LT}^{-1} T_D^{-1}} \tag{3.66}$$

3. *Finished Inventory Based MPC System*

$$\frac{I}{I^*} = \frac{G_I T_{LT}^{-1}}{S^2 + S(T_{LT}^{-1} + T_{SR}^{-1}) + G_I T_{LT}^{-1}} \tag{3.67}$$

4. *Capacity and WIP Based MPC System*

$$\frac{PR}{Cap^*} = \frac{G_W (T_D^{-1} + S) + G_C T_{LT}^{-1} T_D^{-1}}{S^2 + S(T_D^{-1} + T_{LT}^{-1} + G_W) + (G_W T_{LT} + G_C + 1) T_{LT}^{-1} T_D^{-1}} \tag{3.68}$$

5. *Finished Inventory and WIP Based MPC System*

$$\frac{I}{I^*} = \frac{G_I T_{LT}^{-1}}{S^2 + S(G_W + T_{LT}^{-1} + T_{SR}^{-1}) + (G_I T_{LT}^{-1})} \tag{3.69}$$

3.4 Chapter Summary

The chapter introduced a dynamic model of an agile manufacturing planning and control MPC system. The architecture of the dynamic model is composed of two control layers. The first layer is a servo control layer which is responsible for keeping a desired WIP level for the manufacturing system via WIP controller. The second layer is an intelligent control layer that switches between two controllers based on the higher level strategies, external disturbances and finally the internal disturbances. The two controllers in this level are the inventory controller and the capacity rate controller. The reference points for each controller and the switching protocols between controllers are all executed through a decision logic unit which is directly linked to the higher management level.

Based on the developed architecture, it was shown that the system can have five MPC policies (WIP based, capacity based, inventory based, capacity/WIP based and inventory/WIP based) where each mode has its own structure. The description of each MPC policy and when it is used together with its block diagram and dynamic transfer function were presented.

The analysis of the developed agile MPC model and investigating the best parameters' setting are to follow in chapter four. As for the design of the decision logic unit and the reconfiguration (switching) protocol are to be discussed in chapter five.

Chapter Four

Agile MPC Dynamic Model Analysis

4.1 Introduction

Realistically, manufacturing planning and control is dynamic, non-linear, and a function of multiple interactions among manufacturing system parameters. Consequently, in order to understand MPC systems functionality, various dynamic analyses should be conducted. This chapter takes the initial steps of investigating MPC system performance in a changing demand environment (utilizing an RMS), by relating the factors that affect system responsiveness and stability performance to the different settings of both controllers' gains and system's time parameters.

First, the responsiveness of the system is examined as responsiveness is the major characteristic of agile manufacturing systems. The relationships between both the controllers gain values and the time variables and the different responsiveness measures from a dynamic perspective are explored. These measures include measuring step responses, rise time, settling time and time constants. In addition, a new approach to look to responsiveness is introduced by evaluating the effect of the previously mentioned parameters on the natural frequency and the damping ratio of the manufacturing system.

Second, the steady state error is also monitored while evaluating responsiveness as it plays a major role in realizing agility in terms of customer service level and on time delivery of products. This problem was significant in capacity based MPC policies and a control design approach was introduced to solve the problem

Third, the stability of the MPC systems' parameters is examined. It is essential to know when the MPC system is stable and when it is unstable. It is particularly important to understand system instability, as in such cases the system response to any change in input will result in uncontrollable oscillations of increasing amplitude and apparent chaos ensuing in manufacturing system. In our analysis we will aim to determine the limiting conditions for stability in terms of the different control gains values and the effect of the MPC system's time variables in increasing or decreasing these limits.

Finally, the utility of these analyses results will be demonstrated and used in the design and implementation of the supervisory controller which will act as the decision logic unit. This chapter generates a dynamical MPC system prescriptive which guides the decision logic unit to the optimal MPC policy required to satisfy higher level agile requirements.

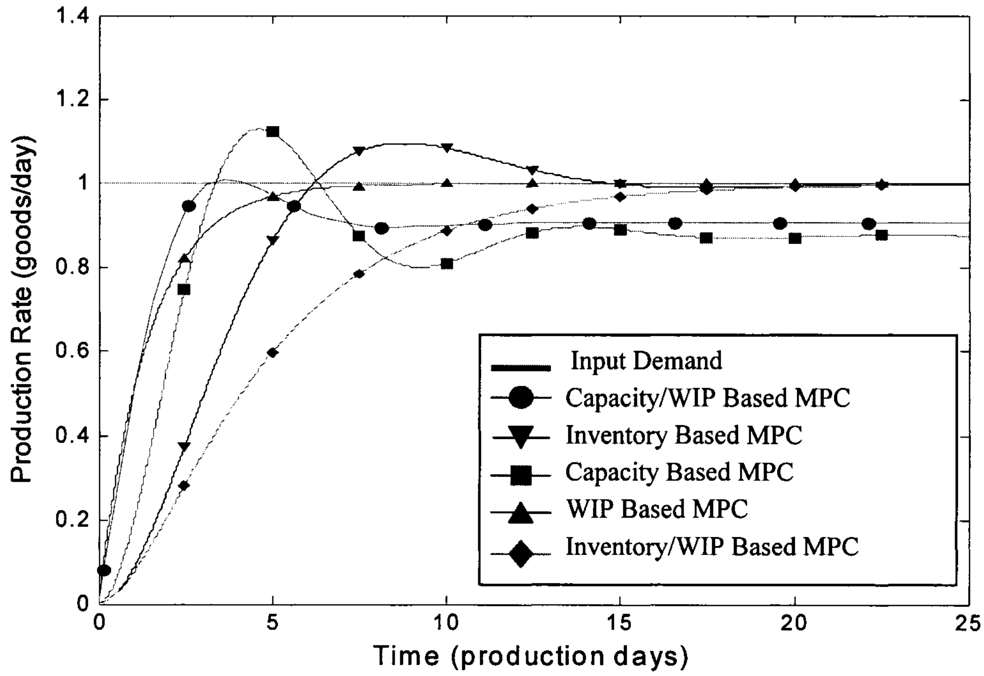
4.2 Transient Response

Since time is used as a major variable in MPC systems to examine the responsiveness of the system, it is interesting to evaluate the state and the output responses with respect to time. Transient response is defined as the part of the time response that goes to zero as time goes to infinity (Kuo and Golnaraghi 2004). Thus in agile MPC systems, the transient response (time to respond to demand changes) of the manufacturing system will play an important role in placing the enterprise in a better competitive market position. In this section the transient time response of the different MPC configurations will be analyzed by first examining the step response of the system and the effect of the different controllers' gains on that response and second by exploring the effect of MPC system's time variables on the responsiveness of the system.

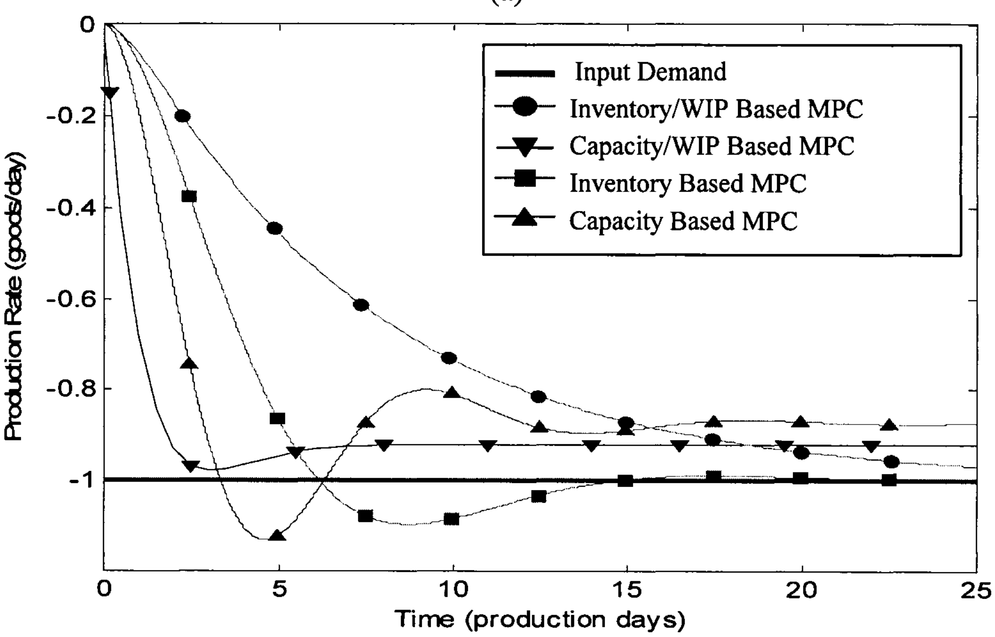
4.2.1 Step Response:

As is customary a deterministic step input is used to evaluate the system ability to cope with a sudden change in demand since this is a repeated scenario in an agile environment. The response to a step change in demand is of importance not only because it gives a shock to the system but additionally it is an input that is easily visualized and interpreted. It also determines the basic dynamic characteristics of the system (Coyle

1996). Figure 4.1 compares between the responses of the different MPC system configurations to a step change in demand with the given parameters setting. The data are arbitrarily selected without loosing the generality of the test (Deif and ElMaraghy 2006-c).



(a)



(b)

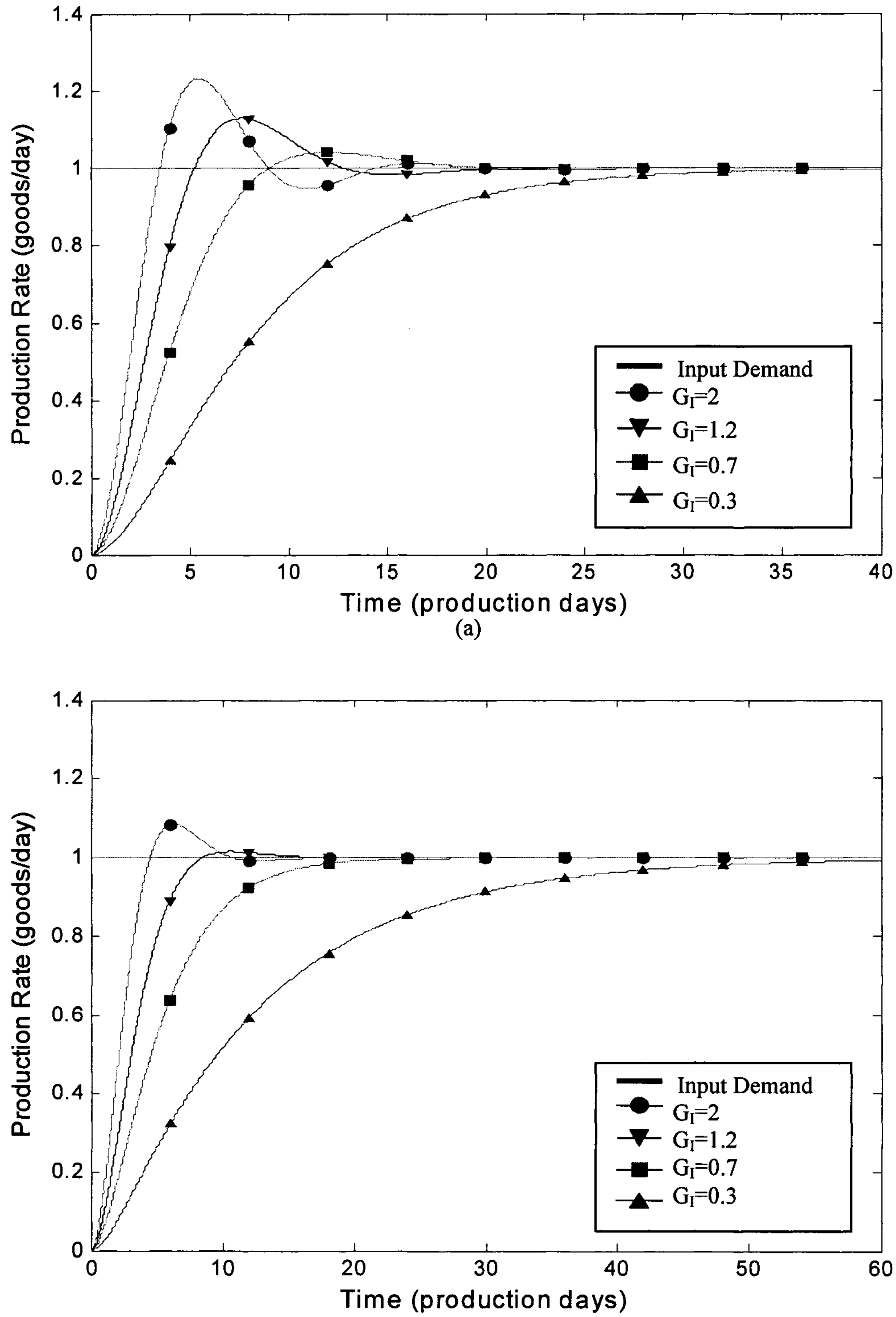
Figure 4.1: Response of the Different MPC Configurations for a Step Change in Demand (a) for Positive Step and (b) for Negative Step.
(T_{LT}=5 days, T_D=3 days, T_{SR}=3 days, G_W=1, G_I=1 and G_C=7)

Looking at figure 4.1 it is clear that the initial response to demand sudden change (whether it was an increase or decrease in this demand) is a production overshoot in all configurations except the default configuration (the WIP based MPC system). The overshoot in the WIP/Inventory based MPC system is not clearly seen due to the over-damping of the system with this setting of the WIP gain G_W. This is more explained later. This dynamic characteristic is very important when considering the level of the stability and cost a firm would like to have for its production.

This overshoot in production can be explained based on the MPC policy adopted. In the capacity based configurations (with or without WIP compensation), this overshoot reflects the increase (or decrease) of production level to chase the demand since this is the market objective of that policy. In the inventory based configurations (with or without WIP compensation), this overshoot reflects the desire to compensate for the loss (or gain) in the inventory level due to this demand change and keeping the target service level since this is the market philosophy of that policy.

4.2.1.1 The Effect of the Inventory Controller Gain

As mentioned earlier it is important to examine the effect of different controllers to guide the supervisory controller to the optimal settings of the MPC parameters. The first controller to be examined is the inventory controller which contributes to the system by increasing or decreasing the input rate. Figure 4.2 (a and b) shows the effect of different values of the inventory controller gain when the MPC system (whether it is inventory or inventory/WIP based) is subjected to a step change in demand. Analysis of the results shows that there are various competing objectives that need trade-off decisions (which are one of the tasks the supervisory controller based on the higher level market strategy). An insight about these trades-offs is as follows (Deif and ElMaraghy 2006-c):



(a)

(b)

Figure 4.2: Response of a) Inventory Based MPC Configuration b) Inventory/WIP Based MPC Configuration for a Step Change in Demand with Different Inventory Gain Values (T_{LT} =5 days, T_{SR} =3 days and G_W =0.25)

First, in both MPC policies, as the inventory control gain increases, the system is more responsive. However, this is at the expense of having a production overshoot which conforms to what was stated earlier in terms of the trade-off between decreasing costs of production and maintaining an acceptable customer service level. The production over shoot from a manufacturing point of view was explained earlier as the response of the system to compensate for the inventory level fall and reach the new demand level. From a dynamic analysis stand point, this can be also related to the structure of the MPC system model. The adjustment of inventory is actually a stock flow problem and thus there will always be amplification (overshoot) in the stock adjustment process (Sterman 2000). The only way for this structure to respond to changes is by having the production exceeds the demand change which means that the overshoot is inevitable. However, this amplification is related to the demand change in what is known as the amplification ratio which is the peak of the production overshoot divided by the demand change. This ratio depends on the adjustment time of the MPC system and at the same time reflects the production cost. Thus the trade off decision that should be taken by the supervisory controller is to decide on the amount of the controller gain value within the accepted amplification ratio set by the high level management and the required responsiveness level.

Second, at the same value of the inventory controller gain, the inventory based MPC policy has a lower rise time than inventory/WIP based MPC policy indicating more responsiveness. This is because in the later policy the production rate has to compensate for the required WIP level before matching the demand and thus takes longer time. However, the overshoot is less when WIP compensation is included due to its damping effect. Also the settling time of the inventory/WIP based MPC policy is longer than the inventory based one. Thus the same competing objectives (responsiveness versus reducing amplification or production cost) will also guide the decision of the supervisory controller whether or not to compensate for WIP when adopting an inventory based MPC policy.

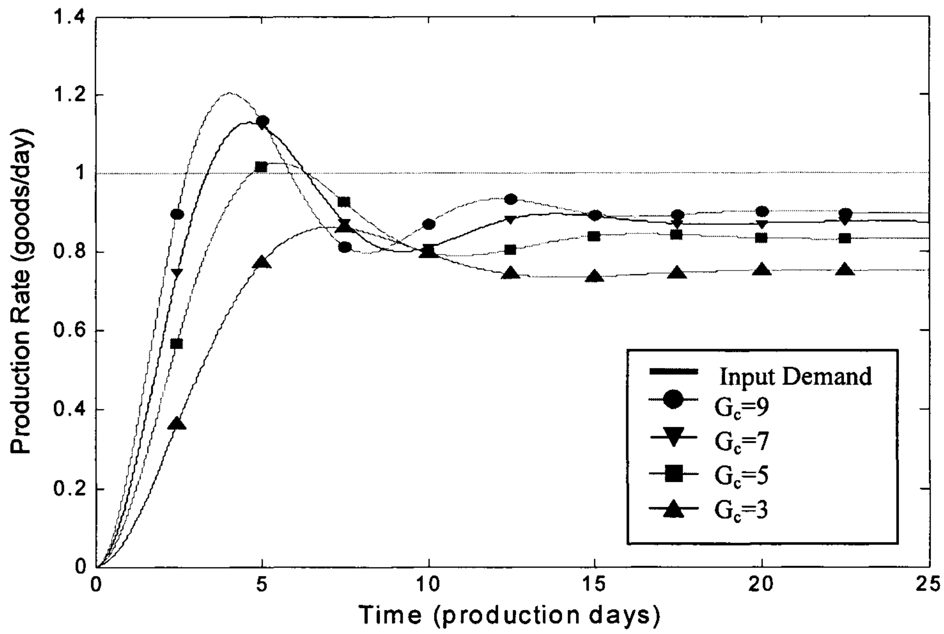
4.2.1.2 The effect of the capacity scalability controller gain

The value of the capacity gain controller is varied and the response of both capacity based MPC systems against a step change in demand is tested. The results for both systems are shown in figure 4.3 (a and b). Analyzing the results points to the following observations:

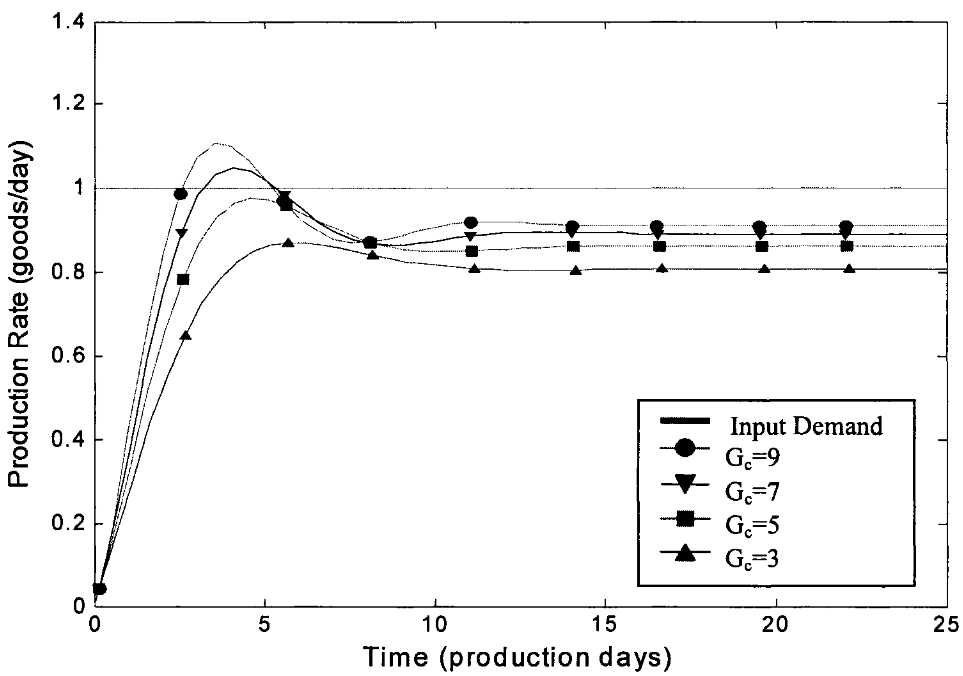
First, in both capacity-based MPC policies, no matter how much you increase the capacity controller gain, there will always be a production offset. This problem violates one of the main objectives of implementing a capacity based policy which is supplying exact capacity to match the demand. The solution for this problem is through redesigning the capacity scalability controller to include together with proportional component an integral parameter to account for all soft and hard activities associated with scaling the capacity and thus eliminating this offset. Details of these activities and the new design of the capacity controller were published in (Deif and ElMaraghy 2006-b) and will be explained in section 4.3.

Second, as the controller gain increases, the production offset decreases. This is obvious since this gain actually compensates for the difference between the production rate and the demand. However, the production overshoot increases with the increase of the gain leaving the trade-off decision for the supervisory controller to decide how to balance between supplying required capacity while maintaining an acceptable level of amplification or production cost.

Third, it is clear that the offset error with the capacity/WIP MPC policy is less than that with the capacity based policy. This is due to the contribution of the WIP controller to increase the production rate. The significant thing here when comparing both policies is that with capacity/WIP the overshooting is much less than that with capacity based while the level of responsiveness is almost the same (same rise time and even better settling time for the capacity/WIP MPC policy). This can lead to the conclusion that contrary to the case of inventory based policies, the capacity/WIP based policy is always superior over the capacity based MPC policy.



(a)



(b)

Figure 4.3: Response of (a) Capacity Based MPC and (b) Capacity Based MPC Configurations for a Step Change in Demand with Different Capacity Gain Values (T_{LT}=5 days and T_D=3 days and G_W=0.25)

4.2.1.3 The effect of the WIP controller gain

In this section we examine the effect of the WIP controller gain on the two general MPC policies, the inventory based and the capacity based policies. The same approach of varying the value of the WIP controller gain and testing the response of both policies against a step change in demand at different gain values is implemented. Figures 4.4 and 4.5 show the results for both systems. Analyzing the results of both MPC systems reveals the following points:

First, the damping effect of the WIP controller gain is very clear since production overshooting decreases as the value of that gain increases in both MPC systems. This can be also explained since WIP will keep production rate at a good level (in order not to stop) while adjusting the capacity rate (in case of capacity based MPC) or the input rate (in case of the inventory based MPC). From a dynamic stand point this can be explained by examining the damping ratio in the characteristic equation of two MPC models. As shown in equation (4.1) for the capacity/WIP MPC system and (4.2) for inventory/WIP MPC system that the major controllable factor that can increase the damping ratio ζ, and thus decreasing the overshooting, is the WIP control gain G_W. Other controllers' gains can share in this through affecting the natural frequency, ω_n, of the manufacturing system. However they are assumed to be fixed in order to highlight the effect of the WIP controller gain. Further analysis of the natural frequency and the damping ratio of the developed MPC system will be discussed in the next section.

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_D} + G_W\right) \quad \text{where} \quad \omega_n = \sqrt{\frac{G_W T_{LT} + G_C + 1}{T_{LT} T_D}} \tag{4.1}$$

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}} + G_W\right) \quad \text{where} \quad \omega_n = \sqrt{\frac{G_I}{T_{LT}}} \tag{4.2}$$

Second, the reduction of the production overshooting in inventory/WIP MPC system was at the expense of the rise time (i.e. system's responsiveness) while it was the opposite in the case of capacity/WIP MPC system. This can be explained through examining the rise time in equation (4.3) and realizing that the WIP control gain G_W positively affects the natural frequency of the capacity/WIP MPC system while it has no effect on the natural frequency of the inventory/WIP MPC system. This is why, in case of capacity/WIP MPC systems, when G_W increases; it damps the production overshooting and at the same time increases the system's natural frequency which in turns increases its responsiveness.

$$t_{r,10,90} \cong = \frac{0.8 + 2.5\xi}{\omega_n} \qquad 0 \le \xi \le 1 \qquad (4.3)$$

Third, observing the settling time for both MPC systems again emphasizes the fact that generally capacity based MPC systems are much more responsive than inventory based MPC systems.

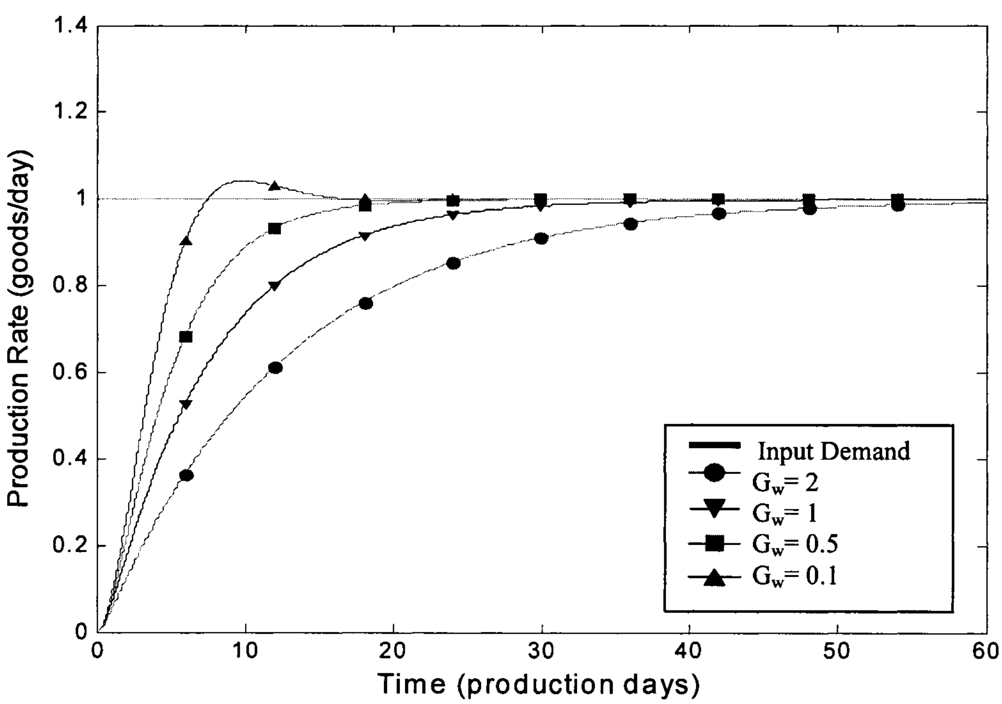


Figure 4.4: Response of the Inventory/WIP Based MPC Configuration for a Step Change in Demand with Different Inventory Gain Values (T_{LT}=5 days, T_{SR}=3 days and G_I=1)

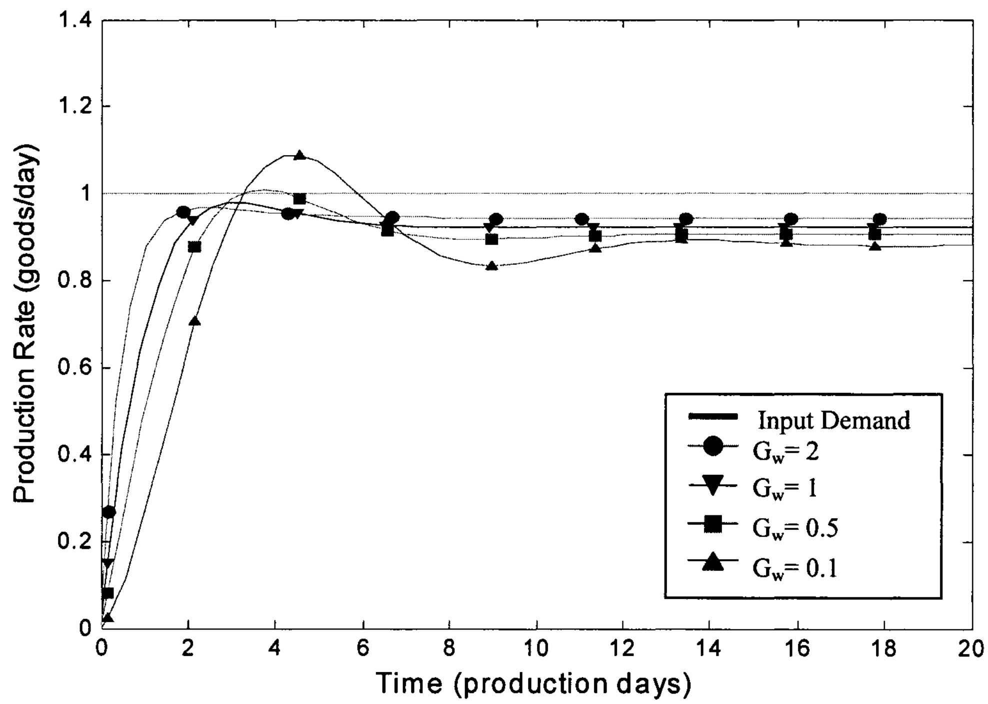


Figure 4.5: Response of the Capacity/WIP Based MPC Configuration for a Step Change in Demand with Different Capacity Gain Values (T_{LT}=5 days, T_D=3 days and G_C=7)

4.2.2 Agile MPC System Responsiveness Measures

In this section the time variables of the developed agile MPC system and their relation to the transient time (or responsiveness) measures are analyzed. The analysis covers the natural frequency and the damping ratio of MPC system which can be considered an imitative in this field. In addition, different response time measures like rise time, settling time and time constant are explored. Results of this analysis can be used to evaluate the agility of the MPC system in terms of responsiveness to fluctuating demand from a dynamical stand point.

The analysis will start by describing the different system's transient response measures and how they can be defined in terms of the MPC parameters. This will be followed by a simple sensitivity analysis to examine the effect of the different MPC system's time variables over these measures and in turn giving a clearer picture about MPC systems and the different parameters that affect these systems.

4.2.2.1 Natural Frequency

Natural frequency is the frequency of oscillation of the system without damping (Nise 2000). From a manufacturing stand point, the natural frequency of the system can be viewed as the mode (policy) of manufacturing or the parameters settings that lead to maximum productivity with the least effort. The term "manufacturing system's natural frequency" can be used also to measure the responsiveness of the system to external excitation (demand). The higher the natural frequency the more responsive the system is. This can be explained by examining the units of the manufacturing system's natural frequency which is *production cycles/production time* (time can be hours, days or shift). Thus the higher the manufacturing system's natural frequency means the less time a production cycle needs to be completed or in other words one production cycle gets completed more frequently and therefore higher system's responsiveness.

Equations (4.4) to (4.7) describe the natural frequency of each configuration or policy of the agile MPC system. Investigating these equations reveals that manufacturing system's natural frequency is basically determined by the inherited system's time variables, namely the production lead time and the capacity scalability delay time (in capacity based policies) and the shipment time (in inventory based policies). However it is also clear that the value of the manufacturing system's natural frequency can be altered and controlled via adjusting the values of the agile MPC system controllers. The previous observation is crucial in highlighting the importance of the supervisory controller (or the decision logic unit) which is responsible for selecting the optimal MPC policy and setting the values for the different controllers of the system.

Capacity based MPC system

$$\omega_{\mathrm{n}} = \sqrt{\frac{1+G_C}{T_{LT}T_D}} \tag{4.4}$$

Inventory based MPC system

$$\omega_{\mathrm{n}} = \sqrt{\frac{G_I}{T_{LT}}} \tag{4.5}$$

Capacity/WIP based MPC system

$$\omega_n = \sqrt{\frac{G_W T_{LT} + G_C + 1}{T_{LT} T_D}} \tag{4.6}$$

Inventory/WIP based MPC system

$$\omega_n = \sqrt{\frac{G_I}{T_{LT}}} \tag{4.7}$$

4.2.2.2 Damping Ratio

The damping ratio is used to describe the exponential decay frequency compared to the natural frequency (Nise 2000). From a manufacturing perspective, the damping ratio of the manufacturing system reflects the different system parameters that damp the production oscillation and can act as absorbers to sudden changes in demand or various internal disturbances (Deif and ElMaraghy 2005). In section 4.2.1.3 the analysis of the effect of the WIP controller gain highlighted the damping effect of the WIP in manufacturing systems and the major role of WIP controller to hedge for sudden demand changes in the developed agile MPC system. Also the damping ratio can provide a way to determine whether the production has been made over or under the desired production goal during the transient period (Fong 2004).

Equations (4.8) to (4.11) describe the damping ratio of each configuration or policy of the agile MPC system. In the next section we will examine the effect of the systems' time variables in determining the damping ratio of the manufacturing systems. This will also give a better picture about their role in maintaining a good level of production stability against different disturbances encountered in today's turbulent manufacturing environment.

Capacity based MPC system

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_D}\right) \tag{4.8}$$

Inventory based MPC system

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}}\right) \tag{4.9}$$

Capacity/WIP based MPC system

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_D} + G_W\right) \tag{4.10}$$

Inventory/WIP based MPC system

$$\xi = \frac{1}{2\omega_n}\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}} + G_W\right) \tag{4.11}$$

4.2.2.3 Rise Time

In control theory, it is known that it is difficult to have an exact analytical expression of the rise time. However the rise time can be approximately calculated using equation 4.12. By definition, the rise time is the time it takes the system to rise from 10% to 90% of its target value (Nise 2000). This responsiveness measure can be used as an indicator of how fast the manufacturing system can respond to 90% of the required demand and therefore the degree of its responsiveness.

Form figure 4.1, the rise time for the capacity based MPC configurations is much less than that for the inventory based MPC configurations indicating more responsiveness in adopting the first policy. This is because in the capacity based policies, the production directly follow the demand (exact capacity when needed and where needed). However in the inventory based policies, the production first has to fill the inventory gap due to the demand change and then match the demand level which leads to a phase lag that is reflected in the rise time.

Equations (4.13) to (4.16) describe the rise time of each configuration or policy of the agile MPC system. It is important to notice that rise time as well as the other response measures is dependent on the natural frequency and damping ratio of the system which gives both parameters a great importance in the dynamic analysis of MPC systems. From equation 4.12 the rise time is directly proportional to the damping ratio while it is inversely proportional to the natural frequency. This confirms the fact stated previously that increasing the natural frequency of the manufacturing system will increase the responsiveness (by decreasing the rise time required to meet the demand).

$$t_{r,10,90} \cong \frac{0.8 + 2.5\xi}{\omega_n} \qquad 0 \le \xi \le 1 \tag{4.12}$$

Capacity based MPC system

$$t_{r,10,90} \cong \frac{0.8 + 1.25\left[\dfrac{1}{\sqrt{\dfrac{1+G_C}{T_{LT}T_D}}}\left(\dfrac{1}{T_{LT}} + \dfrac{1}{T_D}\right)\right]}{\sqrt{\dfrac{1+G_C}{T_{LT}T_D}}} \tag{4.13}$$

Inventory based MPC system

$$t_{r,10,90} \cong \frac{0.8 + 1.25\left[\dfrac{1}{\sqrt{\dfrac{G_I}{T_{LT}}}}\left(\dfrac{1}{T_{LT}} + \dfrac{1}{T_{SR}}\right)\right]}{\sqrt{\dfrac{G_I}{T_{LT}}}} \tag{4.14}$$

Capacity/WIP based MPC system

$$t_{r,10,90} \cong \frac{0.8 + 1.25\left[\dfrac{1}{\sqrt{\dfrac{G_W T_{LT} + 1 + G_C}{T_{LT}T_D}}}\left(\dfrac{1}{T_{LT}} + \dfrac{1}{T_D} + G_W\right)\right]}{\sqrt{\dfrac{G_W T_{LT} + 1 + G_C}{T_{LT}T_D}}} \tag{4.15}$$

Inventory/WIP based MPC system

$$t_{r,10,90} \cong \frac{0.8+1.25\left[\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right]}{\sqrt{\frac{G_I}{T_{LT}}}} \tag{4.16}$$

4.2.2.4 Time Constant

Time constant is also another reflection of how the system can respond to a given input. Therefore, it can be used to measure how the production can respond to a given demand i.e. how long does it take the manufacturing system to totally (100%) meet the required demand.. The time constant can be found using equation (4.17). Equations (4.18) to (4.21) describe the time constant of each configuration or policy of the agile MPC system.

$$\tau = \frac{1}{\xi\omega_n} \tag{4.17}$$

Capacity based MPC system

$$\tau = \frac{2}{\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)} \tag{4.18}$$

Inventory based MPC system

$$\tau = \frac{2}{\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)} \tag{4.19}$$

Capacity/WIP based MPC system

$$\tau = \frac{2}{\left(\frac{1}{T_{LT}} + \frac{1}{T_D} + G_W\right)} \tag{4.20}$$

Inventory/WIP based MPC system

$$\tau = \frac{2}{\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}} + G_W\right)} \tag{4.21}$$

4.2.2.5 Settling Time (2% criteria)

Settling time is the time required for the transient's damped oscillations to reach and stay within 2% of the required target (Nise 2000). Investigating equation (4.22) which calculates the settling time show that it is a multiple of the time constant response parameter and thus it reflects the same aspect of system's responsiveness. However, the settling time gives the exact time by which the system will reach the target input within a certain percentage.

From a manufacturing stand point the settling time reflects the time required by the production to reach the target demand within the required service level (acceptable limit of deviation from the required demand level). Thus in inventory based MPC systems this percentage is determined based on the service level designated by the higher management level. As for capacity based MPC systems the settling time will reflect the acceptable degree (the % criteria) that the enterprise is willing to have for the production to chase the demand exactly. This will be reflected on the capacity scalability plans and schedules.

Kuo and Golnaraghi (2003) summarized the numerical relation between the settling time and both the damping ratio and the natural frequency of the system by indicating a value for the damping ratio ζ that controls that relation. If $\zeta < 0.69$ (in 5 %

criteria), the settling time will be inversely proportional to both the damping ratio and the natural frequency of the system. If $\zeta > 0.69$, the settling time will be proportional to the damping ratio and inversely proportional to the natural frequency of the system.

The previous observation opens the door to an interesting dynamic analysis approach to calculate that critical point for each manufacturing system based on its own parameters and thus control the settling time (and other response measures). This control will be through altering the natural frequency of the manufacturing system or basically increasing the natural frequency to reduce the settling time and thus increase the system's responsiveness.

The analysis of section 4.2.3 will show that this point in capacity based MPC policy is when the manufacturing lead time equals the capacity scalability delay time, while in inventory based MPC policy it is when the manufacturing lead time equals the shipment time

Equations (4.23) to (4.26) describe the settling time of each configuration or policy of the agile MPC system.

$$t_s = 4\tau = \frac{4}{\xi\omega_n} \tag{4.22}$$

Capacity based MPC system

$$t_s = \frac{8}{\left(\frac{1}{T_{LT}} + \frac{1}{T_D}\right)} \tag{4.23}$$

Inventory based MPC system

$$t_s = \frac{8}{\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}}\right)} \tag{4.24}$$

Capacity/WIP based MPC system

$$t_s = \frac{8}{\left(\frac{1}{T_{LT}} + \frac{1}{T_D} + G_W\right)} \tag{4.25}$$

Inventory/WIP based MPC system

$$t_s = \frac{8}{\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}} + G_W\right)} \tag{4.26}$$

4.2.2.6 Maximum Overshoot

The maximum overshoot or sometimes called the percent overshoot is the amount that the waveform overshoots the steady-state or final, value of the time required to reach maximum peak, expressed as a percentage of the steady-state value (Nise 2000). This response measure directly describes the maximum amount of excess production the system will encounter to respond to sudden change in demand.

The maximum overshoot should be determined by the manufacturing production planner based on the accepted level of excess production the enterprise can accept or the degree of deviation from the target production level since this is translated into production cost. It can be also considered as a measure for the relative stability of the manufacturing system against sudden market changes. Equation (4.27) calculates the percentage overshoot of dynamic systems

$$\%OS = e^{-(\xi\pi / \sqrt{1-\xi^2})} * 100 \tag{4.27}$$

Equations (4.28) to (4.31) describe the percentage overshoot of production in each configuration or policy of the agile MPC system.

Capacity based MPC system

$$\%OS = e^{-\left(\left(\frac{1}{\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)\right)\pi / \sqrt{1-\left(\frac{1}{\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)\right)^2}\right)} * 100 \tag{4.28}$$

Inventory based MPC system

$$\%OS = e^{-\left(\left(\frac{1}{\sqrt{\frac{GI}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)\right)\pi / \sqrt{1-\left(\frac{1}{\sqrt{\frac{GI}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)\right)^2}\right)} * 100 \tag{4.29}$$

Capacity/WIP based MPC system

$$\%OS = e^{-\left(\left(\frac{1}{\sqrt{\frac{G_W T_{LT}+1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)\right)\pi / \sqrt{1-\left(\frac{1}{\sqrt{\frac{G_W T_{LT}+1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)\right)^2}\right)} * 100 \tag{4.30}$$

Inventory/WIP based MPC system

$$\%OS = e^{-\left(\left(\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right)\pi / \sqrt{1-\left(\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right)^2}\right)} * 100 \tag{4.31}$$

4.2.3 Exploring the Effect of the MPC System's Time Parameters on Agility Objectives:

In section 4.2.1, the effect of manipulating the values of the different controllers' gains in the developed MPC system was demonstrated. In this section, the effect of the developed MPC system's time variables on the responsiveness (and in turn the agility) of manufacturing systems will be explored. This will be conducted using the different responsiveness measures and equations listed in section 4.2.2.

Although manufacturing system's time parameters in this dissertation are assumed to be constant, however, they can be changed based on higher level decisions. For example the production lead time can be changed by investing in the manufacturing systems in terms of machines or components. Also the shipment time can be altered by increasing or decreasing the market power or the sales rate. The objective of the analysis in this section is to give a better picture about the effect of each of the MPC system's time parameters and thus how the enterprise can strategically plan for improvement.

In the following analysis and simulation the systems controllers' gains and time parameters are set arbitrarily with certain constant values and then each time parameter explored will have different values to test for its effect on the different systems' response measures. The analysis will be conducted for each MPC system configuration.

Tables 4.1 through 4.8 display the values of the different responsiveness measure in each configuration or policy when the time variables of the MPC system at these configurations are changed. These results are plotted and discussed in the following sub-sections (Deif and ElMaraghy 2006-a).

1) Capacity Based MPC System:

G_W	T_{LT}	G_C	T_D	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	1	4	2	1.581139	0.474342	1.255964	1.3333333	5.333333	18.417259
1	2	4	2	1.118034	0.447214	1.715542	2	8	20.804518
1	3	4	2	0.912871	0.456435	2.126356	2.4	9.6	19.973056
1	4	4	2	0.790569	0.474342	2.511929	2.6666667	10.66667	18.417259
1	5	4	2	0.707107	0.494975	2.881371	2.8571429	11.42857	16.717618
1	6	4	2	0.645497	0.516398	3.239355	3	12	15.05453
1	7	4	2	0.597614	0.537853	3.588656	3.1111111	12.44444	13.488964

Table 4.1: The Effect of Manufacturing Lead Time (T_{LT}) on Response Time Measures for Capacity Based MPC System

G_W	T_{LT}	G_C	T_D	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	3	4	1	1.290994	0.516398	1.619677	1.5	6	15.05453
1	3	4	2	0.912871	0.456435	2.126356	2.4	9.6	19.973056
1	3	4	3	0.745356	0.447214	2.573313	3	12	20.804518
1	3	4	4	0.645497	0.451848	2.989355	3.4285714	13.71429	20.38406
1	3	4	5	0.57735	0.46188	3.385641	3.75	15	19.49187
1	3	4	6	0.527046	0.474342	3.767893	4	16	18.417259
1	3	4	7	0.48795	0.48795	4.139512	4.2	16.8	17.285307

Table 4.2: The Effect of Capacity Scalability Delay Time (T_D) on Response Time Measures for Capacity Based MPC System

2) Inventory Based MPC System:

G_W	T_{LT}	G_I	T_{ST}	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	1	4	3	2	0.333333	0.816667	1.5	6	32.95070114
1	2	4	3	1.414214	0.294628	1.086519	2.4	9.6	37.98026615
1	3	4	3	1.154701	0.288675	1.31782	3	12	38.80016751
1	4	4	3	1	0.291667	1.529167	3.42857143	13.71429	38.38651966
1	5	4	3	0.894427	0.298142	1.727761	3.75	15	37.50217613
1	6	4	3	0.816497	0.306186	1.917296	4	16	36.42444729
1	7	4	3	0.755929	0.31497	2.099967	4.2	16.8	35.27323943

Table 4.3: The Effect of Manufacturing Lead Time (T_{LT}) on Response Time Measures for Inventory Based MPC System

G_W	T_{LT}	G_I	T_{ST}	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	3	4	1	1.154701	0.57735	1.94282	1.5	6	10.85748705
1	3	4	2	1.154701	0.360844	1.47407	2.4	9.6	29.67389523
1	3	4	3	1.154701	0.288675	1.31782	3	12	38.80016751
1	3	4	4	1.154701	0.252591	1.239695	3.42857143	13.71429	44.05568956
1	3	4	5	1.154701	0.23094	1.19282	3.75	15	47.45924319
1	3	4	6	1.154701	0.216506	1.16157	4	16	49.84029277
1	3	4	7	1.154701	0.206197	1.139249	4.2	16.8	51.59857601

Table 4.4: The Effect of Shipment Time (T_{ST}) on Response Time Measures for Inventory Based MPC System

3) Capacity/WIP Based MPC System:

G_W	T_{LT}	G_C	T_D	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	1	4	2	1.732051	0.721688	1.503547	0.8	3.2	3.7866961
1	2	4	2	1.322876	0.755929	2.033315	1	4	2.662886
1	3	4	2	1.154701	0.793857	2.41157	1.0909091	4.363636	1.658687
1	4	4	2	1.06066	0.824958	2.698692	1.1428571	4.571429	1.0222677
1	5	4	2	1	0.85	2.925	1.1764706	4.705882	0.6303783
1	6	4	2	0.957427	0.870388	3.1083	1.2	4.8	0.3884394
1	7	4	2	0.92582	0.887244	3.259932	1.2173913	4.869565	0.2383132

Table 4.5: The Effect of Manufacturing Lead Time (T_{LT}) on Response Time Measures for Capacity Based MPC System

G_W	T_{LT}	G_C	T_D	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	3	4	1	1.632993	0.714435	1.583648	0.8571429	3.428571	4.0513804
1	3	4	2	1.154701	0.793857	2.41157	1.0909091	4.363636	1.658687
1	3	4	3	0.942809	0.883883	3.192278	1.2	4.8	0.2647757
1	3	4	4	0.816497	0.96959	3.948546	1.2631579	5.052632	0.0003957
1	3	4	5	0.730297	1.049802	4.689195	1.3043478	5.217391	Over Damped
1	3	4	6	0.666667	1.125	5.41875	1.3333333	5.333333	Over Damped
1	3	4	7	0.617213	1.195851	6.139898	1.3548387	5.419355	Over Damped

Table 4.6: The Effect of Capacity Scalability Delay Time (T_D) on Response Time Measures for Capacity/WIP Based MPC System

4) Inventory/WIP Based MPC System:

G_W	T_{LT}	G_I	T_{ST}	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	1	4	3	2	0.583333	1.129167	0.85714286	3.428571	10.48630131
1	2	4	3	1.414214	0.648181	1.711519	1.09090909	4.363636	6.905959544
1	3	4	3	1.154701	0.721688	2.25532	1.2	4.8	3.786696054
1	4	4	3	1	0.791667	2.779167	1.26315789	5.052632	1.709826591
1	5	4	3	0.894427	0.857159	3.290261	1.30434783	5.217391	0.537683268
1	6	4	3	0.816497	0.918559	3.792296	1.33333333	5.333333	0.067777131
1	7	4	3	0.755929	0.976408	4.287467	1.35483871	5.419355	6.81821E-05

Table 4.7: The Effect of Manufacturing Lead Time (T_{LT}) on Response Time Measures for Inventory/WIP Based MPC System

G_W	T_{LT}	G_I	T_{ST}	Natural Frequency	Damping Ratio	Rise Time	Time Constant	Settling Time	%OS
1	3	4	1	1.154701	1.010363	2.88032	0.85714286	3.428571	Over Damped
1	3	4	2	1.154701	0.793857	2.41157	1.09090909	4.363636	1.658687022
1	3	4	3	1.154701	0.721688	2.25532	1.2	4.8	3.786696054
1	3	4	4	1.154701	0.685603	2.177195	1.26315789	5.052632	5.196232157
1	3	4	5	1.154701	0.663953	2.13032	1.30434783	5.217391	6.154281441
1	3	4	6	1.154701	0.649519	2.09907	1.33333333	5.333333	6.840423808
1	3	4	7	1.154701	0.639209	2.076749	1.35483871	5.419355	7.354016978

Table 4.8: The Effect of Shipment Time (T_{ST}) on Response Time Measures for Inventory/WIP Based MPC System

4.2.3.1 Production Lead Time

As defined in chapter three, production lead time is the time of a given routing or line is the time allotted for production of a part on that routing or line (Hopp and Spearman 2002). In other words it is the span of time required to perform a process (or series of operations). The production lead time is composed of four different time elements for each step in a part routing: Queue time Setup time Run time Move time. With this detailed information, one can generate an accurate total lead time.

Lead time is an essential concept in studying the agility of manufacturing systems due to its impact on both costs, e.g. reduced lead times often lead to lower levels of in-process stock, and revenues, e.g. reduced lead times increase the competitive advantage due to increased flexibility. Also lead time is directly related to responsiveness as will be shown later. It is important to mention here that lead time in the developed MPC system is calculated using exponential delay as stated in chapter three; however, the exact calculation of lead time can be done using various techniques like using gamma distribution or Erlang-*k* distribution (Wikner 2003). The exact calculation of manufacturing lead time is beyond the scope of this dissertation and can be conducted in further research.

Figure 4.6 displays the effect of manufacturing lead time on the natural frequency of the different MPC system configurations. It is clear that as the lead time increases the natural frequency of the system decreases indicating a lower responsiveness level. As explained earlier in section 4.2.2.1, the natural frequency of the manufacturing system can be used to reflect the number of production cycles per unit time of manufacturing and this is why a large value of that metric indicates that less effort is required to produce more products.

Based on the previous analysis, it is obvious that increasing the manufacturing lead time will increase the duration of the production cycle leading to a decrease in the natural frequency of the system as shown by figure 4.6 (Deif and ElMaraghy 2006-a).

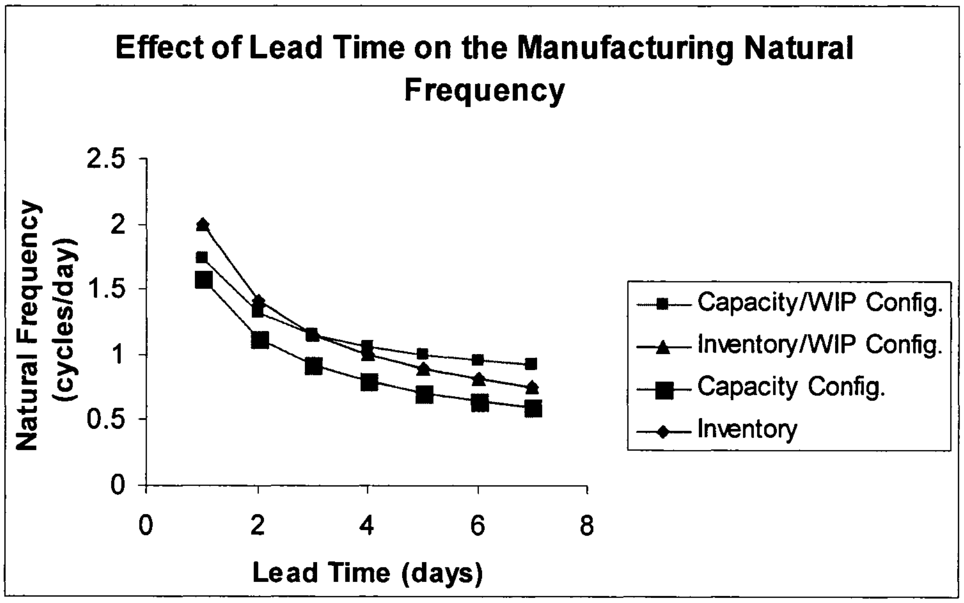


Figure 4.6: Effect of Manufacturing Lead Time on Different MPC Systems' Natural Frequency

The effect of manufacturing lead time on different MPC system's damping ratio is shown in figure 4.7. Investigating these results reveals three observations (Deif and ElMaraghy 2006-a):

First, the general trend is that as the manufacturing lead time increases the damping ratio also increases in all MPC system configurations. This can be explained by realizing that the damping ratio reflects the manufacturing system ability to hedge sudden changes in demand and damp production oscillation during this process. Thus the longer the lead time the manufacturing system encounters, the more time it has to compensate for the sudden change in demand i.e. damp this change. However, the increase trend is more significant with the MPC configurations (or policies) accounting for WIP. This was explained earlier while discussing the damping effect of WIP in manufacturing systems in section 4.2.1.3.

Second, in capacity based MPC configuration the damping ratio of the system decreases as the lead time increases when the lead time values are less than the capacity scalability delay time. The same observation applies for inventory based MPC system when manufacturing lead times are less than the shipment time. In both policies the damping ratio maintains its minimum when the manufacturing lead time is equal to the capacity scalability delay time (in case of capacity based MPC) or is equal to the shipment time (in case of inventory based MPC policy). This observation is important when designing the manufacturing system to have a certain lead time while considering the level of the stability (reflected by damping ratio) and cost (reflected by production overshooting) a firm would like to have for its production.

Third, in the inventory based MPC the minimum value of the damping ratio of the manufacturing system is maintained when the lead time equals the shipment time. This is the case of lean manufacturing since in this case the production rate is equal to the order rate and thus the just-in-time policy is adopted and no inventory or WIP are accumulated.

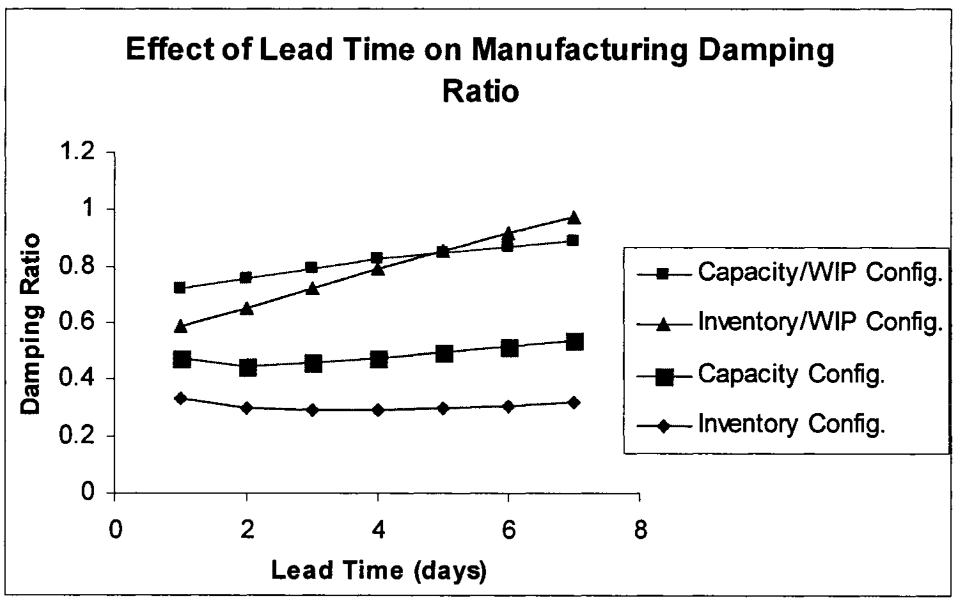


Figure 4.7: Effect of Manufacturing Lead Time on Different MPC Systems' Damping Ratio

Figure 4.8 shows the relation between the manufacturing lead time and the rise time of different MPC system configurations. As expected, the rise time increases as the lead time increases which in turns decreases the system's responsiveness. This confirms the known fact that agile MPC systems should work to decrease the lead times to maintain a good level of responsiveness to market demand in terms of how many days required to respond to that demand.

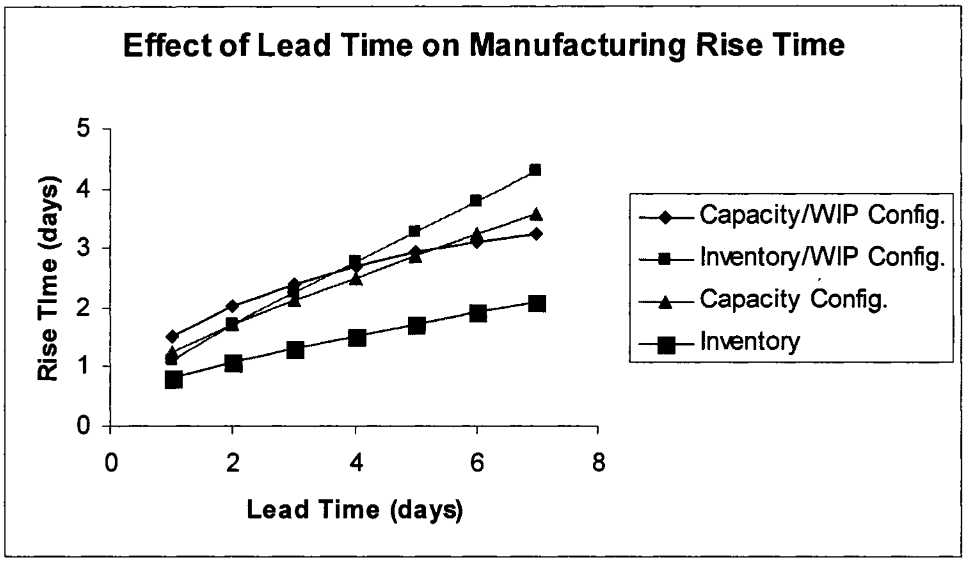


Figure 4.8: Effect of Manufacturing Lead Time on Different MPC Systems' Rise Time

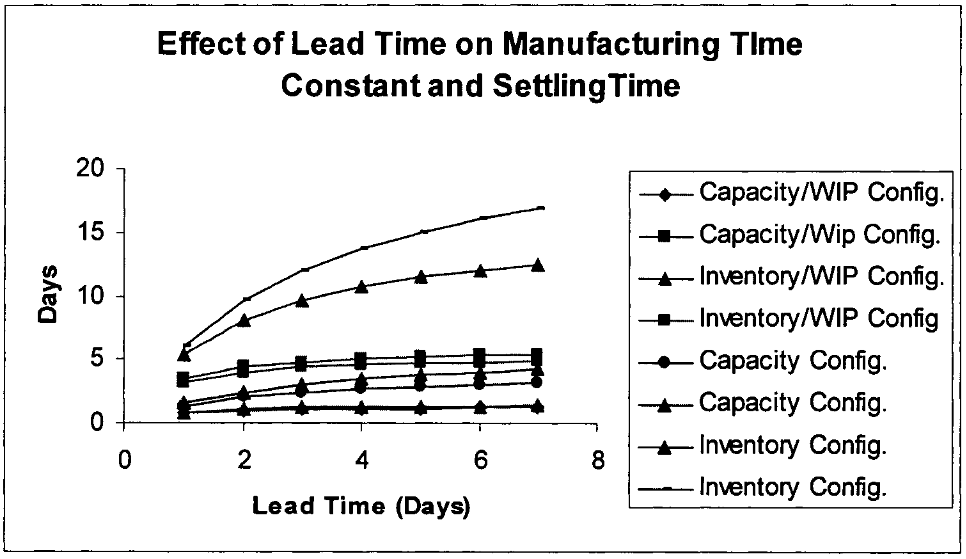


Figure 4.9: Effect of Manufacturing Lead Time on Different MPC Systems' Time Constant and Settling Time

Since manufacturing time constant and settling time are both multiples of each other they are plotted together versus the manufacturing lead time in figure 4.9. The result show that both time response measures increase when the lead time increase. This highlights the same conclusion reached before concerning the inverse relation between manufacturing lead time and manufacturing system responsiveness for all MPC system configurations (or policies). However, both response time measures increase with lead time increase more significantly in the policies with no WIP consideration due to the role that WIP plays in making manufacturing systems more stable in cases of sudden change in demand.

Figure 4.10 shows the relation between manufacturing lead time and production overshooting (Deif and ElMaraghy 2006-a). As explained in section 4.2.2.6 this response measure directly describes the maximum amount of excess production the system will encounter to respond to sudden change in demand. Therefore it relates to the production cost. It also can give an insight about the system stability (since it is function in the damping ratio).

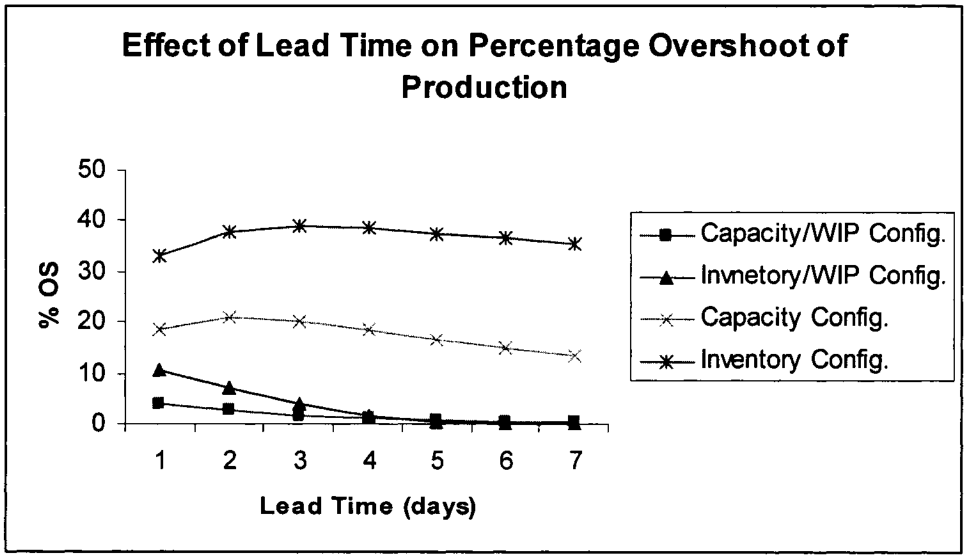


Figure 4.10: Effect of Manufacturing Lead Time on Different MPC Systems' Production Overshoot

Analysis of the figure reveals that generally as the manufacturing lead time increases the production overshoot percentage decreases. This is because longer lead times give more time to damp sudden oscillation due to market change. This allows us say that long lead time although they reduce responsiveness but they have the advantage of stabilizing the manufacturing system against sudden changes. A trade off decision between the costs of both market advantages is required in agile MPC systems.

Another observation is that the percentage overshoot in MPC policies that have no WIP compensation are much higher than those compensating for WIP due to the damping effect of the WIP as explained earlier.

Finally, similar to the damping ratio, the same relation between manufacturing lead time and capacity scalability delay time (in case of capacity based MPC policy) and shipment time (in case of inventory based MPC policy) exists. Thus the percentage overshoot in production can increase or decrease based on the value of the manufacturing lead time relative to the other time variables based on the adopted MPC policy. This conclusion has its impact on the system's design and parameters settings.

4.2.3.2 Shipment Time

The shipment time is used to express the shipment rate which is assumed (in this model) to be equal to the order rate. It is indicated based on the market strategy adopted by high level of the corporation and its sales power. It is subject to changes based on the market dynamics and sudden disturbances in demand such as rush orders. The function or the relation that can express these changes is normally used to relate the shipment rate to the order rate.

It is important to state that the exact or instantaneous shipment (or order) rate cannot be measured (Sterman 2000). Thus MPC systems measure average shipment rates or accumulated inventory over some finite interval which is called the shipment time. The actual shipment rate throughout the interval can vary. The shipment time can be days, weeks or even months, however in our model it is assumed to be days which is a relevant assumption for agile MPC systems.

The first observation to be stated concerning the shipment time in inventory based MPC policies is that it does not affect the natural frequency of the manufacturing system. This is because inventory based MPC systems are used when the enterprise is adopting a push market strategy and thus it is the company that decides on the amount to be pushed to the market and in turns the required production rate which reflects the natural frequency of the manufacturing system.

Figure 4.11 displays the effect of shipment time on the manufacturing system damping ratio (Deif and ElMaraghy 2006-a).

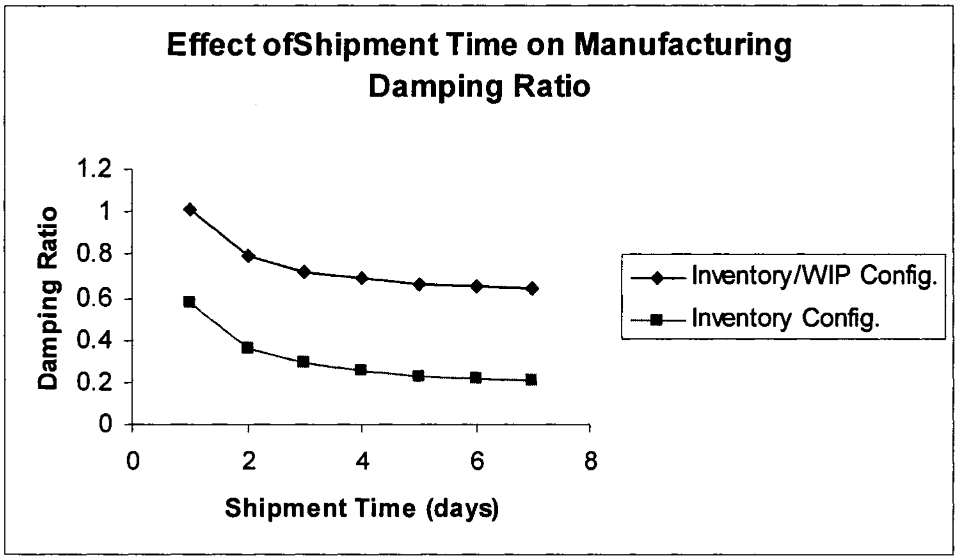


Figure 4.11: Effect of Shipment Time on Inventory Based MPC Systems' Damping Ratio

It is clear that as the shipment time increases, the damping ratio of the manufacturing system decreases indicating less effort to respond to market changes. The reason for this is that the longer the shipment time is the less the rate of goods or products to be pushed to market and this means that the system does not need high damping effort to market changes since there is enough time span for that.

Also it is shown that the decrease in damping ratio (in both MPC policies) is much higher when the shipment time is less than the manufacturing lead time (it is 3 days in this case). This observation help in designing the system parameters based on the required damping level.

Figure 4.12 shows the effect of shipment time on the manufacturing system's rise time. It can be easily seen that the trend in figure 4.12 is close to the trend in figure 4.11. This is because the rise time is basically function in both the natural frequency and the damping ratio, and since the shipment time does not affect the natural frequency of the manufacturing system, the rise time will follow a similar trend to the damping ratio in its relation with the shipment time.

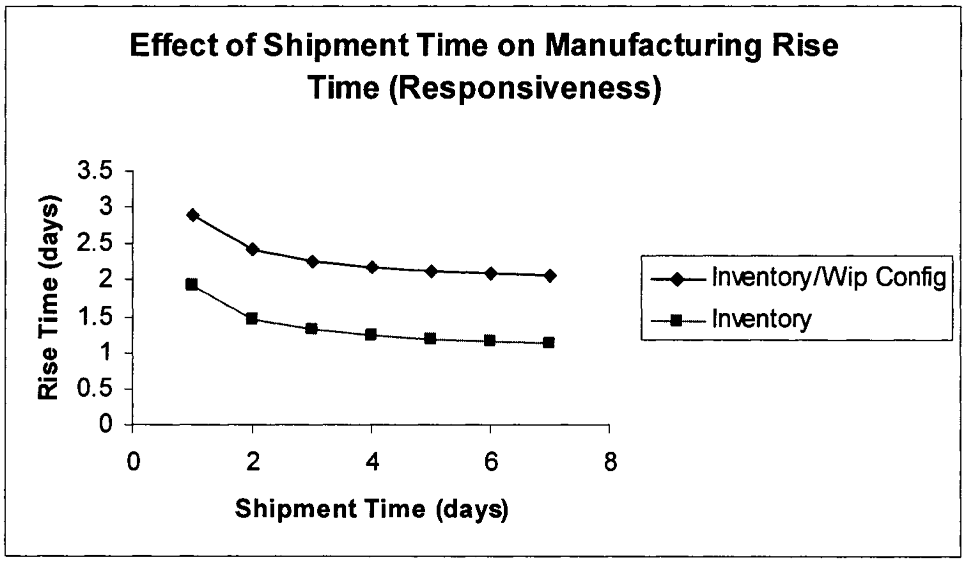


Figure 4.12: Effect of Shipment Time on Inventory Based MPC Systems' Rise Time

The rise time decreases as the shipment time increases due to the same fact that the system in a push policy does not need to have high rise times when the shipment rate is low as in the case of high shipment time.

Figures 4.13 and 4.14 outline the relation between the shipment time and both the manufacturing time constant and the manufacturing settling time respectively.

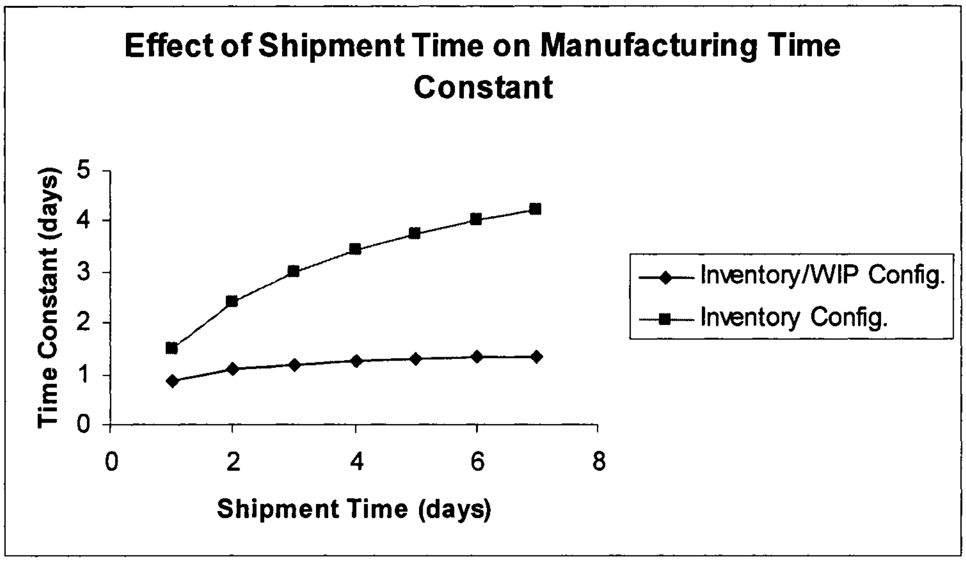


Figure 4.13: Effect of Shipment Time on Inventory Based MPC Systems' Time Constant

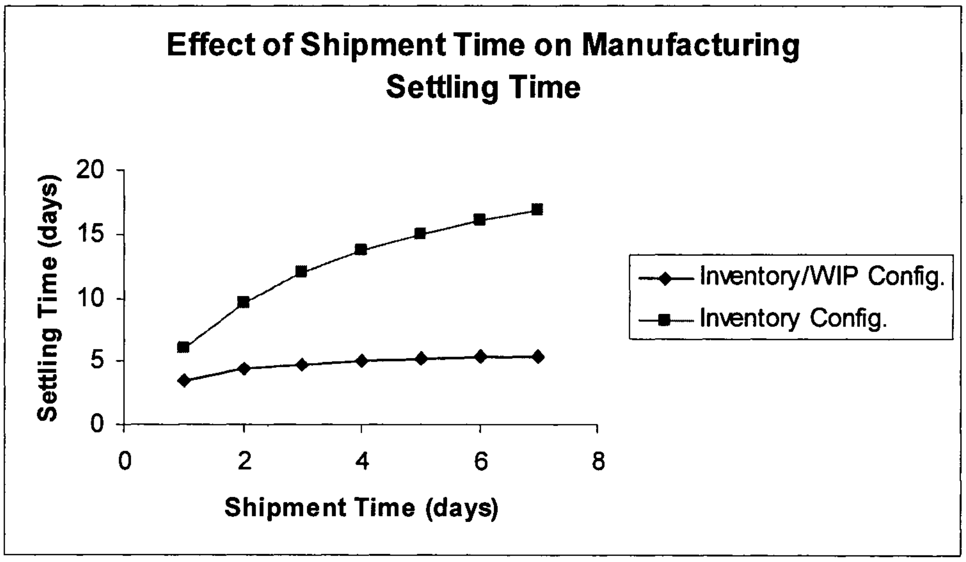


Figure 4.14: Effect of Shipment Time on Inventory Based MPC Systems' Settling Time

Since both time response measures are multiple of each others they reflect the same property and encounter the same analysis. Both measures indicate that the manufacturing system needs longer settling and constant times as the shipment time increases. This is because both measures describe the time required for the system to reach stability level in production and since the production can't be idle (production equals zero) even at low shipment rates, thus it will take longer time as the shipment time becomes longer.

Figure 4.15 shows the effect of shipment time on the manufacturing system's percentage overshoot of production. Increasing the shipment time leads to increasing the production overshooting since the damping ratio decreased as explained earlier.

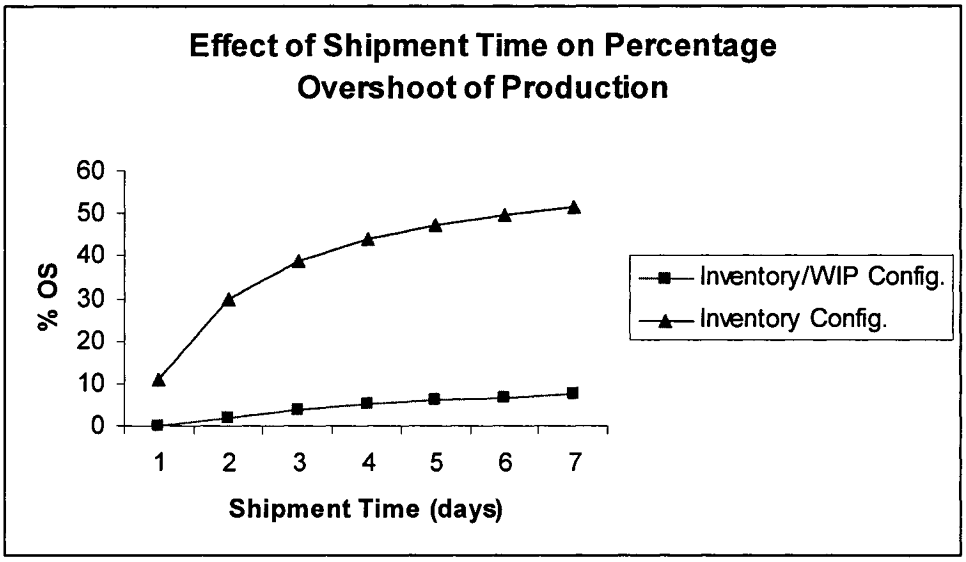


Figure 4.15: Effect of Shipment Time on Inventory Based MPC Systems' Percentage Overshoot of Production

The figure also shows how much the damping effect of WIP compensation is clearly recognized in MPC systems with inventory based policies. This is very obvious especially at large values of shipment time. For example at shipment time of 7 days the % OS of the inventory/WIP based MPC policy is less than 10% while it is 50% for the inventory based MPC policy. This leads to the conclusion that as the shipment time increases it is very important to account for WIP in the manufacturing system.

4.2.3.3 Capacity Scalability Delay Time

Ideally, in capacity based MPC policies, manufacturing systems aim to scale the capacity exactly when needed and thus theoretically there is no delay incurred in this scalability process. However, practically speaking, this is very difficult to achieve due to the different hard and soft activities associated with the scalability process. The effect of capacity scalability delay on manufacturing system's dynamics can be illustrated by comparing the response of two manufacturing systems; one with no capacity scalability delay (limit case) and the other incurs some delay while scaling the capacity (Deif and ElMaraghy 2006-b). To achieve this comparison, the characteristic equation of the developed capacity/WIP MPC system model expressed in equation (3.60) will be modified to eliminate the capacity delay component after the capacity scalability controller. The new characteristic equation of the no-delay MPC configuration is shown in equation (4.32):

$$\frac{PR}{Cap^{*}} = \frac{G_W + G_C T_{LT}^{-1}}{S + (G_W + G_C T_{LT}^{-1} + T_{LT}^{-1})} \qquad (4.32)$$

The responses of both systems to a sudden change in the demand are shown in figure 4.16. The system parameters were assumed arbitrarily to be as follows: the lead time = 5 days, the capacity scalability delay time = 3 days, the WIP control gain = 1 and the capacity scalability control gain = 7. The result shown in figure 4.16 shows that the manufacturing system with no capacity scalability delay has a shorter rise time indicating that it is more responsive to demand change. This can be easily understood due to the time difference between the two systems caused by the capacity scalability delay.

Another important fact shown by the figure is the presence of an overshoot in production only in the system with capacity scalability delay. This can be explained using control theory by realizing that the system with no capacity scalability delay is a first order system while the system with capacity scalability delay is a second order system. Also it can be related to the fact that any delay in the causal link of the negative feedback loop will lead to overshoot and oscillation. From a manufacturing stand point, the overshoot happens due to the desire of responding quickly to the sudden demand change.

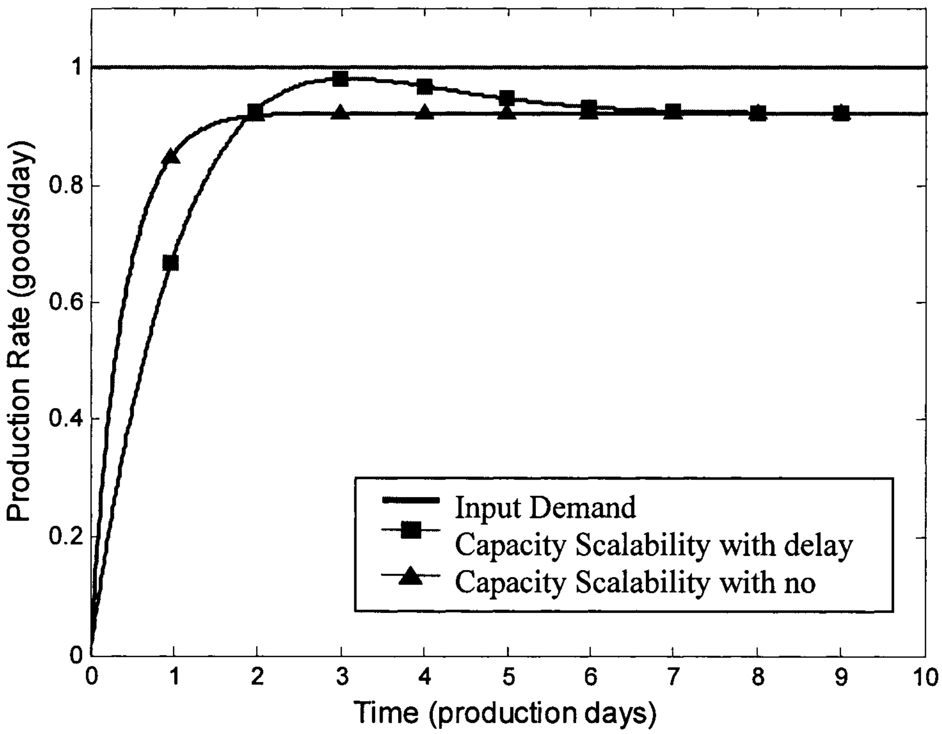


Figure 4.16: Capacity/WIP MPC System Responses with and without Capacity Scalability Delay

Figure 4.17 shows the effect of capacity scalability delay time on manufacturing system's natural frequency. It is clear that as the capacity scalability delay time increases the natural frequency of the manufacturing system decreases indicating more time to finish the production cycle. This is obvious since the capacity scalability time will increase the overall production time by its value and thus decreasing the system's responsiveness.

This confirms the known fact that to have successful implementation of capacity based MPC systems, as in the case of reconfigurable manufacturing systems, a lot of work should be done to decrease this delay and improve the ramp up time of new configurations.

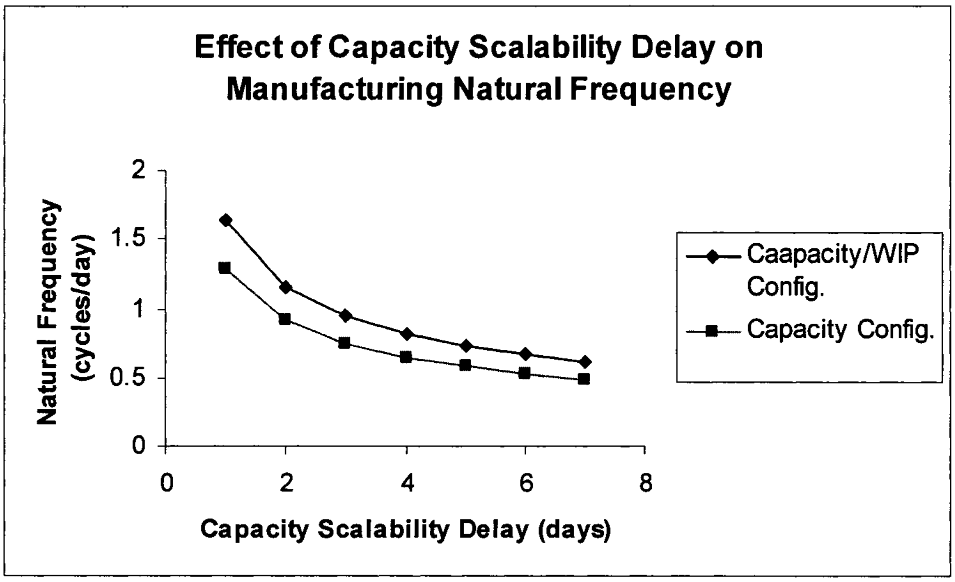


Figure 4.17: Effect of Capacity Scalability Delay Time on Capacity Based MPC Systems' Natural Frequency

Figure 4.18 shows the positive effect of increasing the capacity scalability delay time on increasing the damping ratio. From a manufacturing stand point this indicates that the system will have more relative stability because there will be enough time to adjust production to accommodate the sudden demand change. However, this will be at the expense of the manufacturing system's responsiveness.

The effect of capacity scalability delay time on the damping ratio is very significant in capacity/WIP based MPC systems rather than capacity based MPC system. This is due to of the damping effect of the WIP in the system.

Also it is shown again (as discussed in section 4.2.3.1) that in capacity based MPC system, this relation of the capacity scalability delay time with the damping ratio is reversed as long as this scalability delay time is less than the manufacturing lead time. This is because when the capacity scalability delay time is less than manufacturing lead time, the system will encounter to two feedbacks with delay and thus more oscillation will occur (Sterman 2000) leading to a decrease in the damping ratio. Once the delay of the capacity scalability feedback loop exceeds that of the manufacturing lead time, the system will practically face one dominant delay time of the production rate feedback loop.

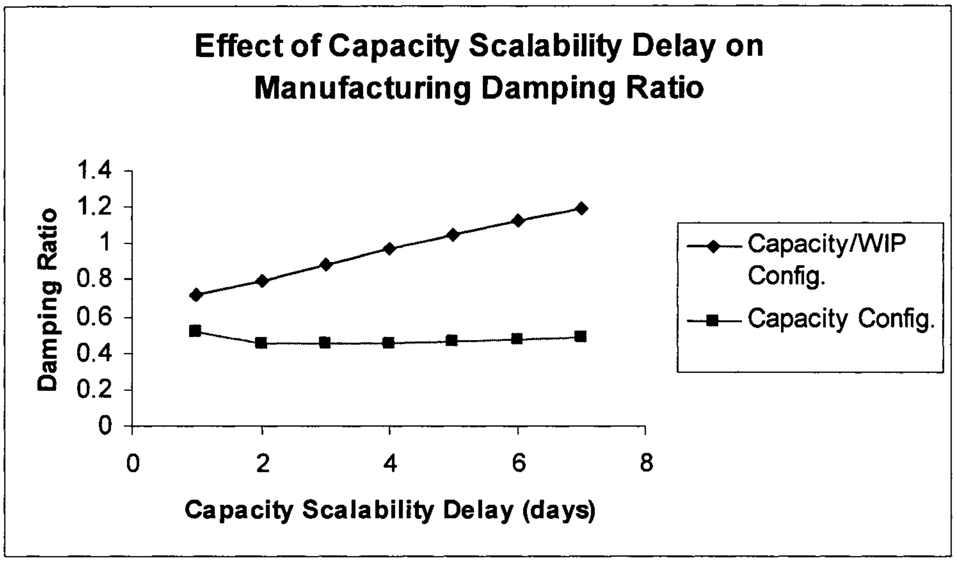


Figure 4.18: Effect of Capacity Scalability Delay Time on Capacity Based MPC Systems' Damping Ratio

Figures 4.19 and 4.20 displays different time response measures versus capacity scalability delay time in capacity based MPC system and capacity/WIP based MPC system respectively. The time response measures are rise time, time constant and settling time.

The first observation is that there is a general increase trend in all three time response measures as the capacity scalability delay time increases. This indicates that the responsiveness of the manufacturing system is negatively affected by the capacity scalability delay time.

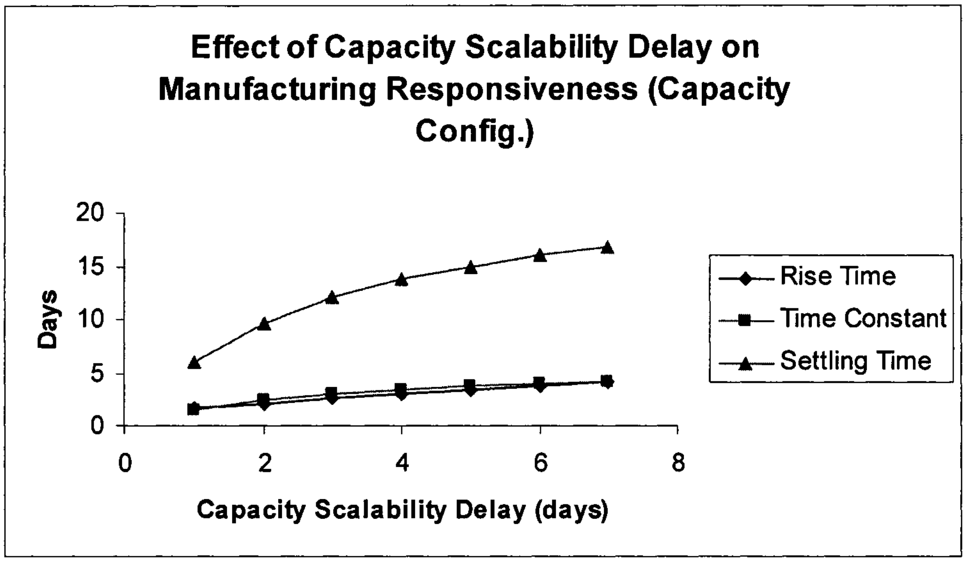


Figure 4.19: Effect of Capacity Scalability Delay Time on Different Time Response Measures in Capacity Based MPC System

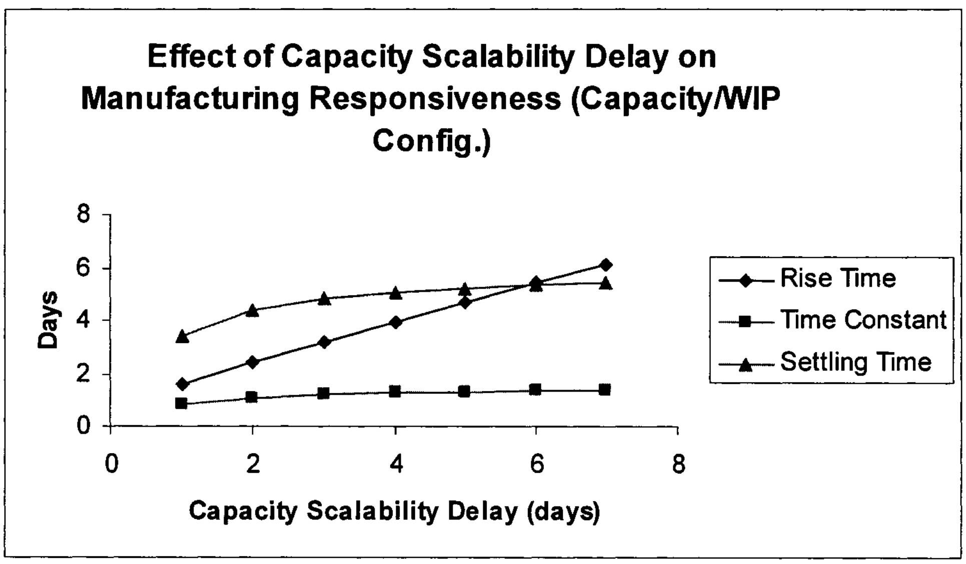


Figure 4.20: Effect of Capacity Scalability Delay Time on Different Time Response Measures in Capacity/WIP Based MPC System

Second, the rise time in capacity/WIP based MPC policy is more affected by the capacity scalability delay time than capacity based MPC policy. This is because when the capacity scalability controller action is delayed (due to capacity scalability delay time) the WIP controller will increase the WIP into the system via the WIP controller gain value which will lead to increasing the damping of the system and in turn increasing the rise time.

Third, both constant time and settling time are more affected in capacity based MPC policy by the capacity scalability delay time than capacity/WIP based MPC policy. This is due to the higher relative stability that capacity/WIP based MPC system has because of the WIP compensation process in these systems.

Figure 4.21 shows the effect of capacity scalability delay time on manufacturing percentage overshoot of production.

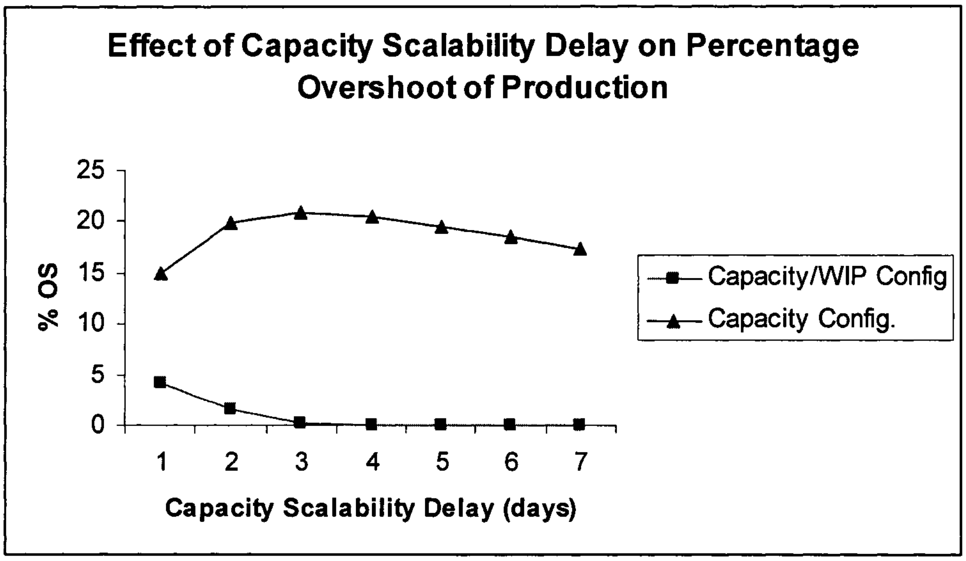


Figure 4.21: Effect of Capacity Scalability Delay Time on Capacity Based MPC Systems' Percentage Overshoot of Production

In capacity/WIP MPC system, as the capacity scalability delay time increases the production overshooting percentage decreases till the system reaches a point where it is over-damped and thus there is no production overshooting that will occur in response to any change in demand. Although this is a desirable output, however this will happen at the expense of the manufacturing system's responsiveness to these changes in demand. A trade-off decision should be made by the decision logic unit (supervisory controller) to decide on the best parametric settings for the damping ratio of the system.

As for capacity based MPC system, the overshoot in production is inversely proportional to the increase of capacity scalability delay time beyond the manufacturing lead time value and then the relation is reversed once the capacity scalability delay time value exceeds that of the manufacturing lead time. The reason for this was explained in the discussion about the effect of capacity scalability delay time on the capacity based MPC system's damping ratio.

Finally, the damping effect of WIP in manufacturing systems is very significant in figure 4.21 as it can be seen that the difference in production overshooting percentage between capacity/WIP and capacity MPC systems is very high. For example the production overshooting in capacity MPC system is almost 20% more than that of capacity/WIP MPC system at capacity scalability delay time of 3 days.

A conclusion that can be derived form the previous analysis is that capacity scalability delay plays an important role in the MPC system dynamics by causing an overshoot in the production of these systems when they are exposed to market disturbances. To overcome the production overshooting problem, a new capacity scalability controller design is suggested by Deif and ElMaraghy (2006-b).

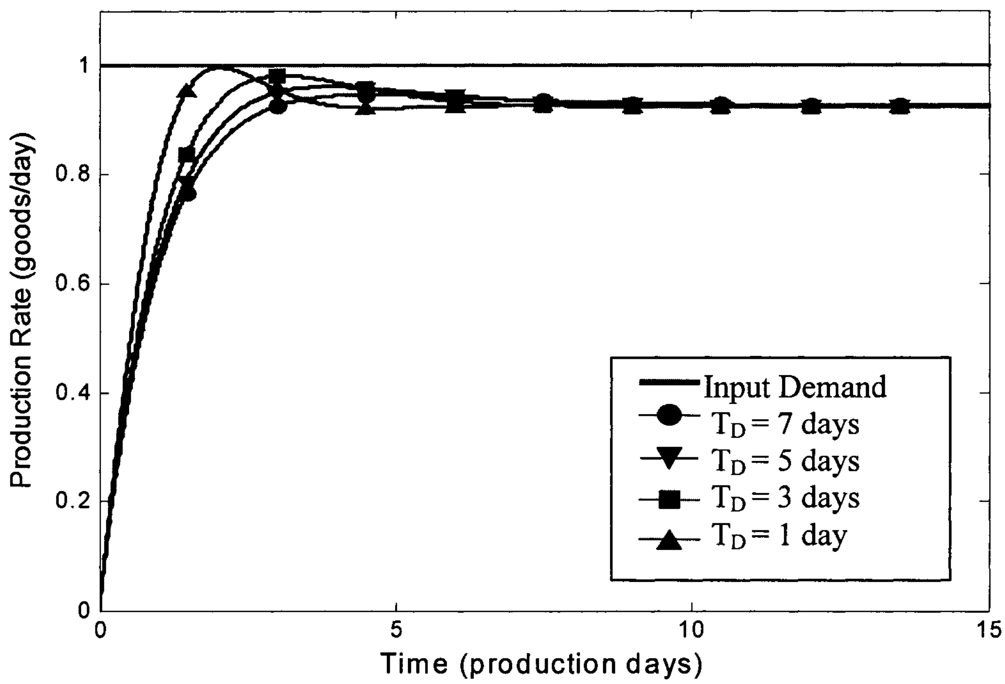
The new design includes a derivative component to change the controller type from proportional controller P to a proportional and derivative controller PD. The new control gain law of the capacity scalability controller will be Gc = Gc(1+*b*S), where *b* is the derivative controller gain. From a manufacturing point of view, the derivative part encounter for the extra time required for installing the extra capacity (which is indicated by the proportional gain) and the time for new system configuration to ramp up. The new characteristic equation for the capacity/WIP based MPC model after augmenting this ideal derivative compensator to the capacity scalability controller is shown in equation (4.33).

$$\frac{PR}{Cap^*} = \frac{S(G_W + G_C b T_{LT}{}^{-1} T_D{}^{-1}) + (G_W T_{LT} + G_C) T_{LT}{}^{-1} T_D{}^{-1}}{S^2 + S(T_D{}^{-1} + T_{LT}{}^{-1} + G_W + G_C b T_{LT}{}^{-1} T_D{}^{-1}) + (G_W T_{LT} + G_C + 1) T_{LT}{}^{-1} T_D{}^{-1}} \tag{4.33}$$

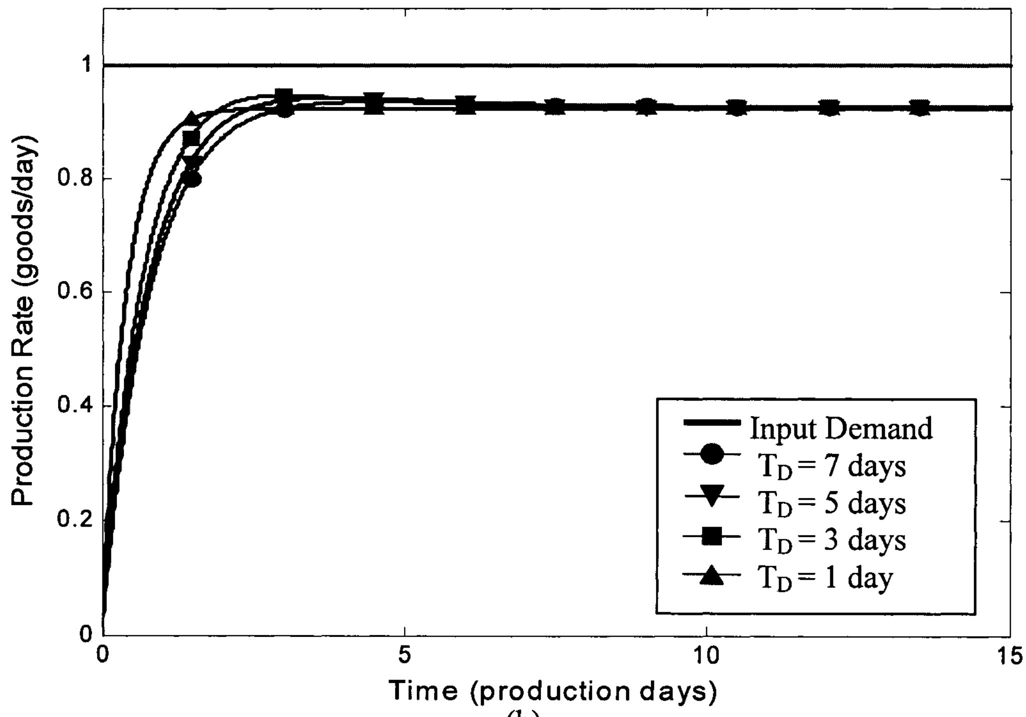
To examine the effect of the new controller design on the transient response of the manufacturing system (production overshoot), the response of both systems (with P and PD capacity scalability controller) with different scalability delay values will be plotted against a step change in the market demand. The same system parameters used in the previous simulation will be used except for setting b = 1 and varying the delay time. The results are shown in figure 4.22 (a) and (b).

The analysis of both figures reveals that the transient response measures of the manufacturing system with PD controller are much more improved than those of the system with the P controller indicating also a decrease in the production overshooting problem when demand is suddenly altered.

Similar to figure 4.21, figure 4.22 (a) shows that as the scalability delay time increases the amount of production overshoot decreases. This again highlights the trade off decision that should be made to balance between the responsiveness of the system and the production overshooting problem. This decision will be reflected in the values of the parameters settings especially the derivative controller gain, *b*.



(a)



(b)

Figure 4.22: Capacity/WIP based MPC System Responses with (a) a P Capacity Scalability Controller and (b) a PD Capacity Scalability Controller (T_{LT}=5 days, T_D=3 days, G_W=1 order/day, G_C=7 order/day)

4.3 Steady-State Response or Steady-State Error

Steady-state error is defined as the discrepancy between the output and the reference input when the steady state is reached (Kuo and Golnaraghi 2003). From a manufacturing stand point, it is considered one of the dynamic analysis elements that can be used to measure the offset of the production from the required level in case of capacity based MPC policies or level of the inventory drift in the inventory based MPC policies.

Steady-state errors in dynamic systems are usually caused by the combination of the control laws applied, the type of the system (especially, the presence of integrals) and the nonlinearities due to imperfections in the system's components. In addition, the system configuration itself and the applied input share in this error. Manufacturing systems are indeed nonlinear due to the many imperfect components in them and therefore drifts and offsets in inventories and production are expected. Examples of sources of imperfections (nonlinearities) in manufacturing systems are the different delay times and the soft activities associated with the decision making process in the enterprise. Also the sources manufacturing systems variability lead to nonlinear and even chaotic behaviour of these systems. Examples of causes of variability include random outages, setups, operator variability, recycles and natural variability due differences in machines and materials (Scmitz et al. 2002).

In the developed agile MPC model, some nonlinearities are accounted for through the exponential modeling of the lead time of both the manufacturing system and the capacity scalability delay time. However, it is beyond the scope of this thesis to investigate or account for all nonlinearities in manufacturing systems. Such approach can be a natural extension of this research work.

4.3.1 Inventory Based Agile MPC Policies

From figure 4.1, it is clear that there is no steady state error in inventory based MPC policies indicating that both inventory based MPC policies will maintain the required service level of inventories independent of the inventory controller gain value. This is given the previously considered assumption that the expected production lead time is equal to the actual lead time.

This can be explained by realizing that in the inventory based MPC policies, the desired production rate DPR is based on the adjusted error between the two levels of the inventory (through a gain G_I) together with the order rate OR. If the DPR level would have been calculated only based on the gap between the desired inventory and the actual inventory a steady state error in the finished inventory level would have occurred (Sterman 2000). The order rate here reflects the expected loss rate by the market demand which is the main source for the inventory drift (error) and therefore accounting for that loss in the dynamic structure of the MPC model prevents this error to occur.

Another reason that can lead to an inventory drift in inventory based MPC policies will be having a difference between the expected lead time T_{LT}^* and the actual lead time T_{LT}. This was proved by Disney and Towill (2005) through applying the final value theorem to their dynamic model that also expressed the production process using pipeline delay. The reason for the offset in that case is because the desired WIP level is based on the perception of the production lead time and the actual WIP is based on the actual production lead time.

4.3.2 Capacity Based Agile MPC Policies

It is clear from figure 4.1 that there is a production offset in the capacity based MPC policies. To explain this phenomenon, we should recall that the objective of this policy is to have the production exactly equal the demand. This implies that we aim to reach the state described in equation (4.34)

$$PR = Cap^* \quad \text{(since Cap}^* \text{ directly reflects the demand)} \tag{4.34}$$

However, in the capacity based MPC configurations, if we eliminate the WIP controller, then the desired production rate DPR will be equal to:

$$DPR = (Cap^{*} - PR)G_C \tag{4.35}$$

$$PR = Cap^{*} - DPR/G_C \tag{4.36}$$

From equations (4.34) and (4.36) (in steady state manufacturing)

$$PR = PR - DPR/G_C \tag{4.37}$$

It is clear from equation (4.36) that when exact chasing of demand in any capacity based MPC policy is targeted and if there is no WIP compensation involved in the system, there will be a production offset or drifts in state of equilibrium equals DPR/G_C. Thus, in case of capacity/WIP MPC policy, the WIP control gain value must be adjusted so that it does not only compensate for the difference between the target WIP level and the actual WIP level, but also to compensate for this production offset. However, this optimal solution for the design of the WIP gain G_w can not always be feasible due to the limitation on the values of the WIP gain.

Deif and ElMaraghy (2006-b) proposed a solution for this problem through redesigning the capacity scalability controller to include an integral gain to eliminate the production offset. The new control gain law of the capacity scalability controller will be Gc = Gc(1+a/S), where a is the integral controller gain. The role of this integral gain is to provide the system with a better ability to follow the target production level (tracking ability). This happens through the "accumulating" action of such component in dynamic systems. In the manufacturing context, this means that the controller will increase the scaled capacity beyond the error between the current production rate and the target capacity rate with an amount that accommodates the nonlinearities involved in the scalability process as explained before.

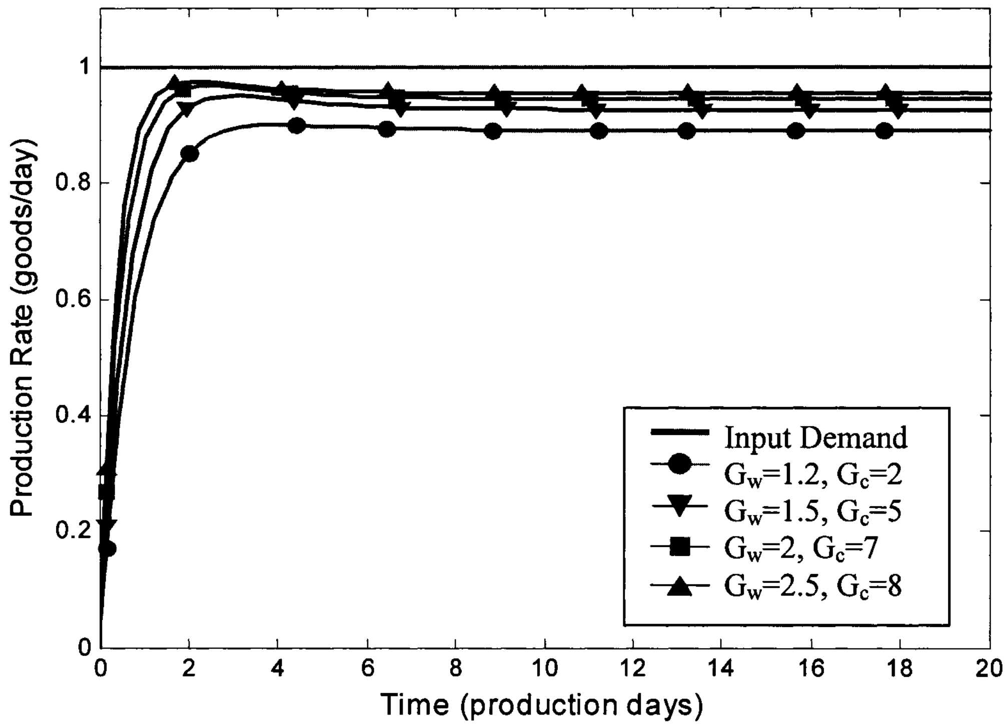
The new characteristic equation of the capacity/WIP MPC model after augmenting this ideal integral compensator to the capacity scalability controller is shown in equation (4.38). The new equation is of higher order which indicates that a greater effort is to be made to control the new system and in turn to eliminate the offset.

$$\frac{PR}{Cap^*}=\frac{S^2G_W+S(G_WT_D{}^{-1}+G_CT_{LT}{}^{-1}T_D{}^{-1})+G_CaT_{LT}{}^{-1}T_D{}^{-1}}{S^3+S^2(T_D{}^{-1}+T_{LT}{}^{-1}+G_W)+S(G_WT_{LT}+G_C+1)T_{LT}{}^{-1}T_D{}^{-1}+(G_CaT_{LT}{}^{-1}T_D{}^{-1})} \quad (4.38)$$

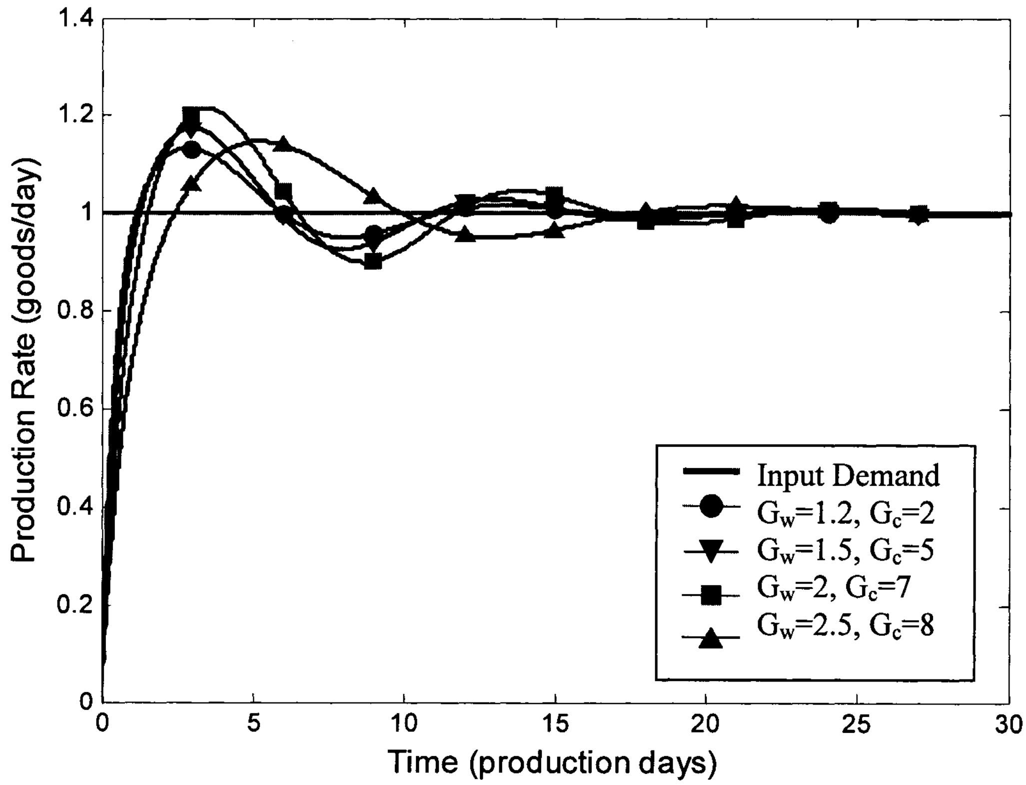
To examine the effect of the new controller on eliminating the production offset problem, the responses of both systems (with P and PI capacity scalability controller) at different capacity scalability and WIP gains values (G_c and G_w) will be plotted against a step change in the market demand. The same parameters settings will be used and the integral gain a = 2. The results are shown in figure 4.23 (a) and (b).

The analysis of figure 4.23 (a) shows that even if both controllers' gains are raised, the production offset problem will still exist. This problem disappeared in figure 4.23 (b) due to the existence of the new PI capacity controller design. Figure 4.23 (b) shows also the inherent destabilization effect of using integral control that appears in the overshooting and oscillation of the system before reaching the desired production rate. This problem is managed by the proportional controllers and it decreases as the values of both gains G_c and G_w increases. It should be noted, based on control theory, that the time required to reach the target state is determined by the ratio of the proportional to the integral time which highlights the importance of studying the optimal parameters settings for the developed model.

It is important to note that there is always a penalty in adding an integral component to a controller. The penalty is actually an increase in the overshoot of the system response. From a manufacturing perspective the trade-off of increasing the responsiveness of the system and eliminating its steady state error should be balanced with the extra cost that system designer will pay to that extra capacity (representing the integral component) to have that required performance.



(a)



(b)

Figure 4.23: Production offset in dynamic RMS model (a) with a P controller and (b) with a PI controller (T_{LT}=5 days, T_D=3 days, G_W=1 order/day, G_C=7 order/day)

4.4 Stability Analysis

Among the different performance specifications in the design of the dynamic systems, the most important requirement is that the system must be stable. An unstable system is generally considered to be useless. For analysis and design purposes we can classify stability as absolute stability and relative stability. Absolute stability refers to the condition whether the system is stable or unstable; it is a yes or no answer. Once the system is found to be stable, it is of interest to determine how stable it is and this degree of stability is a measure of relative stability (Kuo and Golnaraghi 2003).

One of the advantages of dynamic modeling of manufacturing systems using transfer functions is the ability to conduct a stability test for the system. It is essential to know when the MPC system is stable and when it is unstable. It is particularly important to understand system instability, as in such cases the system response to any change in demand will result in uncontrollable oscillations of increasing amplitude and apparent chaos ensuing in manufacturing system.

Stability can be calculated graphically by looking to the poles of the characteristic equation of each of the MPC system configuration or policy. If the poles are in the left half-plane of the S plane then the system is stable. This is because when the poles are located at that half-plane, the response of the system will have either pure exponential decay or damped sinusoidal natural responses and in these cases the bounded input will lead to a bounded output and the system is stable. The location of the poles can be found using equation (4.39) and equations (4.40) to (4.44) express the location of each of the MPC system configuration. The location of these poles can be altered (relative stability) by changing the values of the different controllers' gains in the MPC model.

$$S_{1,2} = -\xi\omega_n \pm j\omega_n\sqrt{1-\xi^2} \quad (4.39)$$

WIP based MPC system

$$-(G_W + T_{LT}{}^{-1}) \tag{4.40}$$

Capacity based MPC system

$$-\frac{1}{2\left(\dfrac{1}{T_{LT}}+\dfrac{1}{T_D}\right)} \pm j\sqrt{\frac{1+G_C}{T_{LT}T_D}}\sqrt{1-\frac{1}{4\left(\dfrac{1+G_C}{T_{LT}T_D}\right)}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)^2} \tag{4.41}$$

Inventory based MPC system

$$-\frac{1}{2\left(\dfrac{1}{T_{LT}}+\dfrac{1}{T_{SR}}\right)} \pm j\sqrt{\frac{G_I}{T_{LT}}}\sqrt{1-\frac{1}{4\left(\dfrac{G_I}{T_{LT}}\right)}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)^2} \tag{4.42}$$

Capacity/WIP based MPC system

$$-\frac{1}{2\left(\dfrac{1}{T_{LT}}+\dfrac{1}{T_D}+G_W\right)} \pm j\sqrt{\frac{G_W T_{LT}+1+G_C}{T_{LT}T_D}}\sqrt{1-\frac{1}{4\left(\dfrac{G_W T_{LT}+1+G_C}{T_{LT}T_D}\right)}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)^2} \tag{4.43}$$

Inventory/WIP based MPC system

$$-\frac{1}{2\left(\dfrac{1}{T_{LT}}+\dfrac{1}{T_{SR}}+G_W\right)} \pm j\sqrt{\frac{G_I}{T_{LT}}}\sqrt{1-\frac{1}{4\left(\dfrac{G_I}{T_{LT}}\right)}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)^2} \tag{4.44}$$

In our analysis for the stability we will aim to determine the limiting conditions for stability in terms of the different control gains values. However, we will adopt the Routh-Hurwitz algebraic method. This method will provide information about the absolute stability and how this stability condition can be through the different MPC controllers' gains.

Stability Analysis Using Routh-Hurwitz Method

The general Routh-Hurwitz method for 2^{nd} order systems can be explained using equation (4.45) and table 4.9 as follows (Nise 2000):

$$\frac{b_2 S^2 + b_1 S + b_0}{a_2 S^2 + a_1 S + a_0} \qquad (4.45) \quad \Rightarrow$$

The signs of the second column should always be the same

S^2	a_2	a_0
S^1	a_1	0
S^0	$\frac{(a_0 * a_1) - (a_2 * 0)}{a_1} = a_0$	0

Table 4.9: The General Routh-Hurwitz Method

Results of applying the Routh-Hurwitz method for the different MPC configurations or policies are displayed in tables 4.10 through 4.13. It is important here to remember that the manufacturing system's time variables (T_{LT}, T_{SR} and T_D) are always positive.

Capacity Based MPC

S^2	1	$\frac{1+G_C}{T_{LT}T_D}$
S^1	$\frac{1}{T_{LT}} + \frac{1}{T_D}$	0
S^0	$\frac{1+G_C}{T_{LT}T_D}$	0

Table 4.10: Routh-Hurwitz Method for Capacity Based MPC

Based on the Routh-Hurwitz method the system is stable. However, to keep the stability in an absolute condition the capacity scalability controller's gain should not be less than -1 ($G_C > -1$). The practical meaning of this limitation is that in case of down scaling the capacity rate, the value of capacity rate reduction must be greater than -1 goods/production time unit.

Inventory Based MPC

S^2	1	$\frac{G_I}{T_{LT}}$
S^1	$\frac{1}{T_{LT}}+\frac{1}{T_{SR}}$	0
S^0	$\frac{G_I}{T_{LT}}$	0

Table 4.11: Routh-Hurwitz Method for Inventory Based MPC

Based on the Routh-Hurwitz method the system is stable. However, to keep the stability in an absolute condition the inventory controller's gain should not be less than 0 ($G_I \geq 0$). Practically, this means that the MPC system when adopting inventory based policy cannot down rate the input rate to the system.

Capacity/WIP Based MPC

S^2	1	$\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}$
S^1	$G_W+\frac{1}{T_{LT}}+\frac{1}{T_D}$	0
S^0	$\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}$	0

Table 4.12: Routh-Hurwitz Method for Capacity/WIP Based MPC

Based on the Routh-Hurwitz method the system is stable. However, to keep the stability in an absolute condition the following limitation on the WIP controller's gain and the capacity scalability controller's gain should be satisfied

$$G_W > -\left(\frac{1}{T_{LT}} + \frac{1}{T_D}\right) \tag{4.46}$$

$$G_C > -\left(\frac{T_{LT}T_D}{G_W T_{LT} + 1}\right) \tag{4.47}$$

The limit for the WIP controller gain means that when down rating the input to the system value of this down rate should satisfy equation (4.46). The reduction of the WIP controller gain is function in the manufacturing system's lead time and capacity scalability delay time. As for the capacity scalability controller gain, the practical meaning of this limitation is that there is a limit to how much the system can reduce its capacity rate based on the lead time and delay time. It is important to note that the value for this limit can be decreased or increased using the WIP control gain which should be taken into consideration by the supervisory controller while optimally setting the MPC system's parameters

Inventory/WIP Based MPC

s^2	1	$\frac{G_I}{T_{LT}}$
s^1	$G_W + \frac{1}{T_{LT}} + \frac{1}{T_{SR}}$	0
s^0	$\frac{G_I}{T_{LT}}$	0

Table 4.13: Routh-Hurwitz Method for Inventory/WIP Based MPC

Based on the Routh-Hurwitz method the system is stable. However, to keep the stability in an absolute condition the following limitation on the WIP controller's gain and the inventory controller's gain should not be satisfied

$$G_I > 0 \tag{4.48}$$

$$G_W > -\left(\frac{1}{T_{LT}} + \frac{1}{T_{SR}}\right) \tag{4.49}$$

The same analysis as in the inventory based MPC policy and capacity/WIP policy applies for the meaning of the input rate reduction for both controllers' gains.

Overall Stability Concerns

Before ending the stability analysis, a very important principle should be noted. The developed agile MPC system includes distributed controllers that work and collaborate together, and thus two problems can be raised in a typical supervisory control system that affects the stability.

The first problem is that if a supervisory controller switches between two stable controllers in one policy, the resulting switched system can be unstable. However, this concern is not valid in the case of the developed MPC systems since polices that include more than one controller are expressed in one mathematical description (the transfer function) and thus the stability limit is calculated based on both controllers together.

The previous concern is clear examples of how important, when it comes to the application of control theoretic approaches in the system-level manufacturing design, a balance between pure control theory analysis and how this makes sense in the manufacturing domain at that level.

4.5 Chapter Summary

Dynamic analysis of the developed agile MPC system leads to a number of important points in realizing agility in manufacturing systems similar in design to the proposed MPC system:

- Any MPC policy needs a reaction time to respond to market changes. This time can be controlled through designing the suitable MPC system controllers' gains.
- Setting the optimal MPC system controllers' gains values involves multiple trade-off decisions. Results showed that achieving quick reaction time in both inventory based MPC systems via increasing the value of the inventory controller gain was always on the expense of production cost. In addition, reducing the production offset problem in both capacity based MPC systems through increasing the capacity controller gain was also on the expense of production overshooting. Finally the value of the WIP controller gain in inventory/WIP MPC system should be balanced with its effect of decreasing the responsiveness of the manufacturing system.
- Capacity based MPC systems (in the cases studied) showed more responsiveness to demand changes than inventory based MPC systems. This observation leads us to say that in agile manufacturing when delivery performance is an essential competitive component, it is better to adopt capacity based MPC policies.
- Accounting for WIP in MPC systems is very important. In inventory based MPC system the damping effect of the WIP controller gain was very significant and helped in decreasing production offset. However, as mentioned earlier this was at the expense of system's responsiveness. As for capacity based MPC system, the role of WIP controller gain is more significant. It does not only damp production overshooting, but also increases the system's responsiveness.
- Based on the previous result one can say that (in the cases studied) capacity/WIP based MPC policy is better than only capacity based MPC policy if the higher management level would like to adopt a capacity based MPC policy.

- The concept of the "natural frequency" of manufacturing systems was introduced as an approach to understand the dynamics of agile MPC systems. It can be used to give an insight about the agility of the system in terms of how fast it can respond to changes in market demand.
- The natural frequency of the developed agile MPC system is affected by different time variables of the system and the different gains of the controllers in the system. Optimal design of these parameters and variables can lead to the increase of the natural frequency of the system and in turn decrease the effort required to increase its productivity.
- The term damping ratio of manufacturing system was also discussed. It can be used to measure the relative stability of different MPC policies (configurations) when subjected to sudden demand change. It was obvious that MPC policies that compensate for WIP changes showed higher levels of stability.
- It is important to notice that rise time as well as the other response measures is dependent on the natural frequency and damping ratio of the system which gives both parameters a great importance in the dynamic analysis of MPC systems. A new manufacturing system design dynamic approach can be based on the manipulation of both these two system's parameters.
- Dynamic analysis of the effect of different time variables (in the cases studied) of the developed agile MPC system showed that generally as these variables increase in their values, the different response time measures indicate a decrease in the level of responsiveness of the system. This highlights the importance of working on reducing the different sources of time delays in agile manufacturing systems.
- The previous analysis also showed that there is always a trade-off between rise time (which is an indicative measure of system's responsiveness to demand changes) and production overshooting percentage (which is a measure of the excess production the system encounters to respond to demand change). In other words, a clear challenge facing agile MPC systems is how to balance between responsiveness and manufacturing cost.

- Same trade-off was shown from another perspective through observing that the natural frequency of the system is increased when the settling time of the manufacturing system is decreased.
- In inventory based MPC configuration (or policy) of the cases studied, it was shown that lean manufacturing policy can be realized when setting the shipment time (reflecting the order rate) equal to the manufacturing lead time of the system. This is considered a lean manufacturing since it's a typical just in time (JIT) policy where the production is exactly equal to the shipment rate and thus no inventory or WIP is accumulated.
- The dynamic analysis exploring the relation between the different agile MPC time variables in the cases studied, showed that when the lead time is greater than capacity scalability delay time the damping ratio of capacity based MPC system is decreased and the production overshooting percentage is increased. However, when the lead time is less than capacity scalability delay time this relation is reversed. Same observation was also realized in the relation between the lead time and the shipment time in inventory based MPC systems.
- An approach to decrease the capacity scalability delay time suggested in this chapter was by implementing a proportional plus a derivative PD controller when designing the capacity scalability controller to account for both the required capacity and the extra delay time. Results of comparing the two capacity scalability controllers (P and PD), showed a higher responsiveness to market changes when implementing the PD design in the capacity scalability controller. Also the PD controller improved the overshooting of production resulted form this capacity scalability delay time.
- Inventory based MPC systems (with the previous stated assumptions) does not suffer form production offset when reacting to demand changes like capacity based MPC systems. This means that if high service level is the competitive component in the agile manufacturing, it is better to adopt an inventory based MPC policy to hedge against demand changes.
- Initial investigations (in the cases studied) to examine how exact capacity scalability can be achieved showed that this is possible through eliminating

production offset or drift in its dynamic response to demand changes and accounting for different decisions associated with the capacity scalability process. In this chapter a proportional plus integral PI capacity scalability controller design was proposed to compensate for this production offset. To prove the preference of using this controller over the original proportional P controller of their model, their dynamic response to market change was compared. Results showed that even if the proportional gains of the model controllers were raised, only the integral component in the PI capacity scalability controller can eliminate the production offset. This result is very important when speaking about maintaining a high customer service level through adopting capacity based MPC policies.

- All MPC systems' policies (based on the stated time variables assumptions) showed a good level of stability.
- Caution should be taken when reducing the capacity scalability and WIP controllers' gains as not to go over the stability limit. As for the inventory gain, stability analysis showed that it can be reduced, i.e. no down rate for the input to the system via this gain. The stability limits of the capacity based MPC systems can be altered through manipulating the value of the WIP gain controller.

The analysis of the studied cases of the developed agile MPC model in this chapter showed that in order to manage the different MPC systems' configurations and to decide on the optimal parameters settings while adhering to the higher level market strategies and responding to external disturbances, there should be an overall control and decision making unit or a supervisory control. The good design of such supervisory control unit is an effective way to link high-level management to operational-level and thus maintaining real agility in manufacturing system. The design of this supervisory controller and the decision logic algorithm is addressed in chapter five.

Chapter Five

Design of the Decision Logic Unit for the Agile MPC System

5.1 Introduction

The underlying philosophy behind dynamical systems is that the behavior of a system is principally caused by factors endogenous to the system structure. That system structure not only includes the physical aspects of the system, but also the policies that govern the decision-making within the system. A policy within a system is a general statement of how the available information is used to generate a decision. Four concepts must be found within any policy statement:

1) A *goal*.
2) An *observed condition* of the system.
3) A method to express any *discrepancy* between the goal evaluation, prediction, and control of the procurement, and the observed condition.
4) *Guidelines* of which actions to take based on the discrepancy

Applying the previous facts to the developed agile MPC system, the main endogenous factors are the market demand and sudden changes in that demand. The decision to adopt a specific MPC policy (whether inventory based or capacity based) is governed by the higher market strategy or *goal*. This goal can be based on responsiveness and/or cost effectiveness as a market competitiveness strategy. Also that decision should take into account the physical aspects or parameters of the manufacturing system (lead time, scalability delay time and shipment time) and *observe* its current conditions (inventory level, WIP level and production rate). Based on the *discrepancy* between the observed conditions of the manufacturing system and required levels that achieve the specified marketing goals manufacturing control actions should be taken. The previous observation, evaluation and decision making *guidelines* in the developed agile MPC system are carried out by the decision logic unit (DLU). This decision unit acts as a supervisory controller that monitors and controls the whole manufacturing planning and control activities.

While dynamical modeling of systems is a powerful tool for predicting and evaluating the system to select the "right" system structure, it falls short of optimizing the system. To optimize the system, an optimization heuristic must be added to the system dynamics framework. By including optimization within system dynamics, it is possible not only to have the power to evaluate system behaviour, but also to select policies that will ensure that the system is operating at its optimum.

The various decisions conducted by the decision logic unit in the developed MPC system are based on various logical activities among them is how to optimally balance between competing objectives while deciding on the different controllers' gains in a specific MPC policy. This inclusion of optimization technique within the dynamical approach adopted in the analysis of agile MPC systems gives the approach proposed in this dissertation a distinctive ability to plan and control manufacturing systems in an agile environment.

This chapter describes the proposed design of the decision logic unit or the supervisory controller in the developed agile MPC system. The description will include the different logical activities associated with the planning and control decisions in each of the available MPC policies.

5.2 MPC System Decision Logic Unit (DLU) Design *(Deif and ElMaraghy, 2006-c and f)*:

Figure 5.1 shows the architecture of the proposed decision logic unit (DLU) of the agile MPC system.

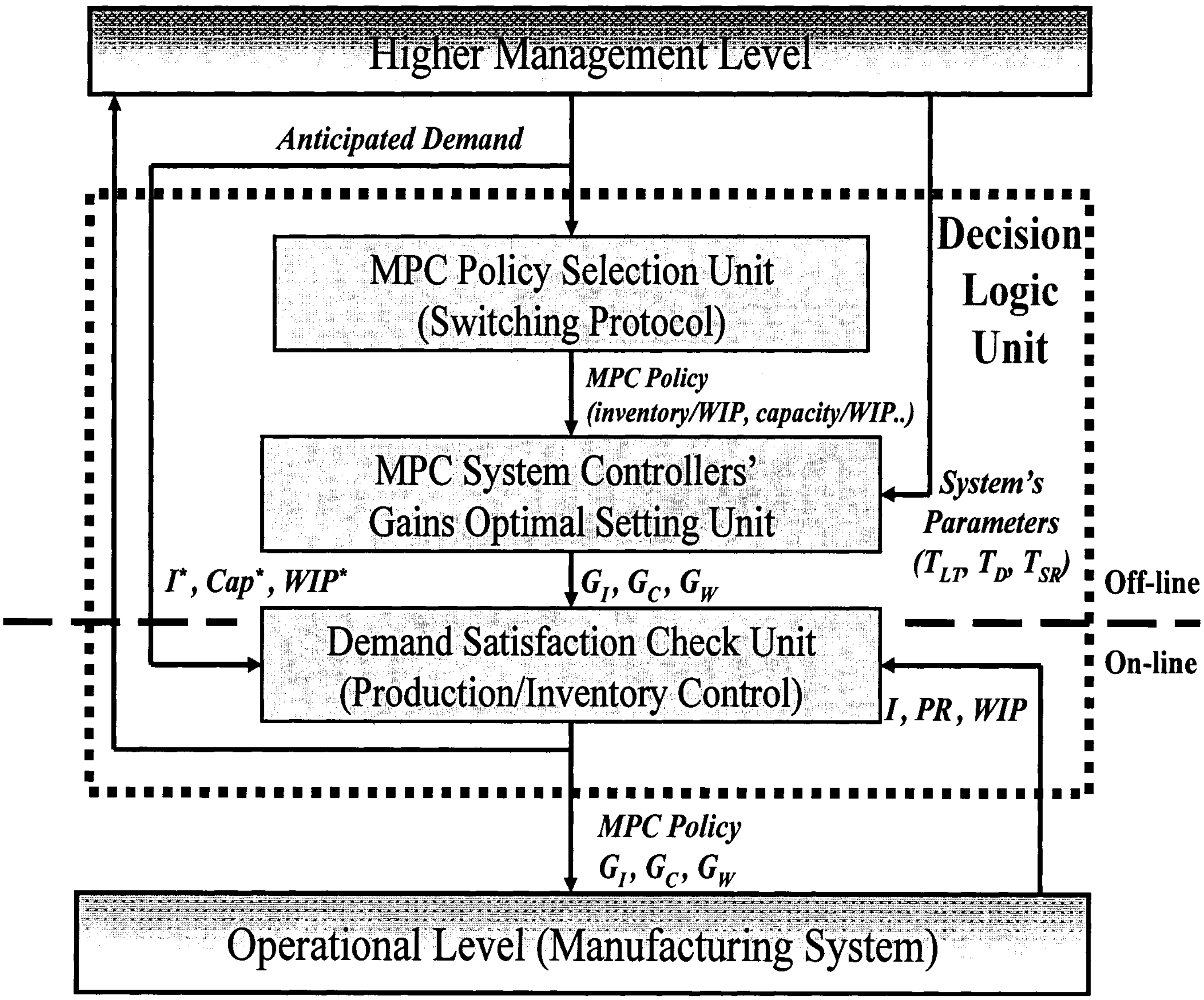


Figure 5.1: Architecture of the Proposed Decision Logic Unit (DLU)

The figure shows how the DLU unit links the higher management level with the operational level (manufacturing system) which is a basic requirement to realize agility in any manufacturing corporation. Such a detailed link, as stated previously, was always missing in previous MPC research work

The architecture of the DLU is composed of three hierarchal layers and thus it's a multi-layer unit. The first two layers function offline and the third layer is an online control layer. The first layer or unit is called MPC policy selection unit. This unit is responsible for analyzing the anticipated demand profile by the higher management level and its marketing expectation. Based on the analysis of the demand profile, the unit decides on which policy (or MPC configuration) to be adopted over which interval of time of that expected demand. In other words, the output would be a plan that indicates which MPC policy (inventory/WIP, capacity/WIP, or inventory) to be applied during which months of the year (if the demand profile was anticipated monthly). It is important to note that this unit can deal with sudden changes in the anticipated demand. Such ability is very important in agile manufacturing environments.

From a control perspective, this selection process can be considered the switching protocol that governs the engagement and disengagement of the different controllers involved in the developed agile MPC system as explained earlier in chapter three. The details of the analysis of the demand profile and how the selection process is carried out will be explained in the next section.

The second layer is called MPC system controllers' gains optimal setting unit. This can be considered the heart of the developed DLU. This unit is responsible for deciding on the optimal values of the different controllers' gains in the developed agile MPC system. By optimal, we mean the value of the gains that will satisfy the competing agility objectives of responsiveness and cost effectiveness. Based on the analysis of chapter four, it was clear that various trade offs should be carried out on deciding the settings of the controllers' gains. This unit is responsible for that task.

The optimization process is a function of the manufacturing systems parameters (lead time, scalability delay time and shipment time) and thus it can be altered (or changed) based on strategic decisions from higher level management to invest in the manufacturing systems or change market policy in order to change these parameters and in turn change the values of the optimal controllers' gains.

The MPC system controllers' gains optimal setting unit receives from the MPC policy selection unit the plan with the selected MPC policies and based on each policy (or configuration) it calls the model (or the transfer function) of that configuration as described in chapter three and manipulate it in the optimization process. The output of that unit is the optimal controllers' gain for each configuration based on the given manufacturing system's parameters. The details of the optimization process with its objective function and constraints will be discussed in section 5.4.

The last layer is called MPC demand satisfaction check unit. This layer is actually responsible for checking that the current production or inventory level satisfies the required demand and this is why it takes place online. The check is based on comparing the current production level with the required capacity rate, the current WIP level with the ideal WIP level and the current inventory level with the target inventory level (depending on which MPC policy is being adopted). These reference levels are actually calculated based on the anticipated demand as explained in chapter three and thus meeting these levels means satisfying the market demand.

Based on the discrepancy between the compared levels, a decision is made to compensate for that discrepancy through the previously calculated optimal control gains values. The decision indicates which gain is to be implemented and for how long in order to meet the required level. This process is carried out in an interactive manner with the operational level i.e. the manufacturing system updates this unit in the DLU with the current status of the system and based on the previously fed data of the demand, a control action is decided. Thus this unit is mainly responsible for what is known in the literature of MPC systems as production control. The details of this control process is explained in section 5.5

5.3 MPC Policy Selection Unit

The selection of the MPC policy is based on the demand profile. From a classical point of view the demand in the early manufacturing paradigms (mass production for example) used to be very well anticipated and thus the MPC policies were geared towards inventory based policies. As for modern market, demand is usually fluctuating and exposed to a lot of variation and thus MPC policies that are capacity based are rather preferred in these environments. In agile manufacturing, as explained earlier, both market profile trends are expected and thus the question becomes which is better to hedge for demand variations; capacity or inventory? The proposal in this dissertation is that real agility of manufacturing system stems from the flexibility and the ability to adopt both policies optimally when needed.

Based on the previous analysis, inventory based MPC policies are best when the demand profile experiences a period of a steady or quasi-steady trend. This trend can be increasing, decreasing or constant. On the other hand, capacity based MPC policies are a better candidate when the demand profile experiences a significant fluctuating trend.

The first challenge that faces the DLU is how to understand the anticipated demand and select the best MPC policy based on that. This challenge is addressed by the first layer of the DLU which is responsible for selecting the required MPC policy over different demand periods. From the developed agile MPC system perspective, this is the unit assigned for switching between the different controllers engaged in the system (capacity scalability, inventory and WIP controllers) and thus its algorithm is the switching protocol of these controllers.

The MPC selection unit's algorithm is based mainly on what is called moving regression analysis. Regression analysis is a method that fits a straight line to a set of data. The algorithm receives the set of anticipated demand data from the higher management level and starts with first three points (or months) and tests the absolute error of these points with their calculated regression line. If the error is relatively small this means that the demand within this range is of a steady trend and thus an inventory based policy is selected. On the other hand if this error shows high values this means that the demand experiences great variations and thus a capacity based policy is better to hedge against these variations in this demand period.

After the decision was taken for the first three demand data points, the algorithm will check the next two data points with the last point of the previously tested three points and the same regression analysis is carried out. The analysis will keep on exploring the demand data till the whole planning period (all anticipated demand) is covered and divided into different regions where a specific MPC policy is applied to each grouped demand points or regions. The output of this unit will be a plan that indicates which policy will be adopted by the manufacturing system over which demand period from the anticipated demand profile given by the higher management level.

It is important to note two things here. First, the value of the error limit of the regression analysis explained earlier (on which the switching decision is based) is function in the degree to which the enterprise would like to be sensitive to variation. This degree is usually relative form one business to another depending on the market competitiveness strategy. Thus the DLU expects to receive this value from the higher management level and this is another form of linking the operational level with the higher management level to maintain agility in manufacturing systems. In this dissertation the error is arbitrarily selected to have the value of 10 % as an average accepted value.

Second, the algorithm selected to analyze the demand profile can be replaced by any other data recognition algorithms found in the literature which gives the approach a wider opportunity for improvement. Also it is possible for the higher management level to decide to skip this analysis step and dictate directly the MPC policy that it feels better for the market now and goes directly to the second layer of the developed DLU. Figure 5.2 shows the flow chart of the MPC selection unit's algorithm.

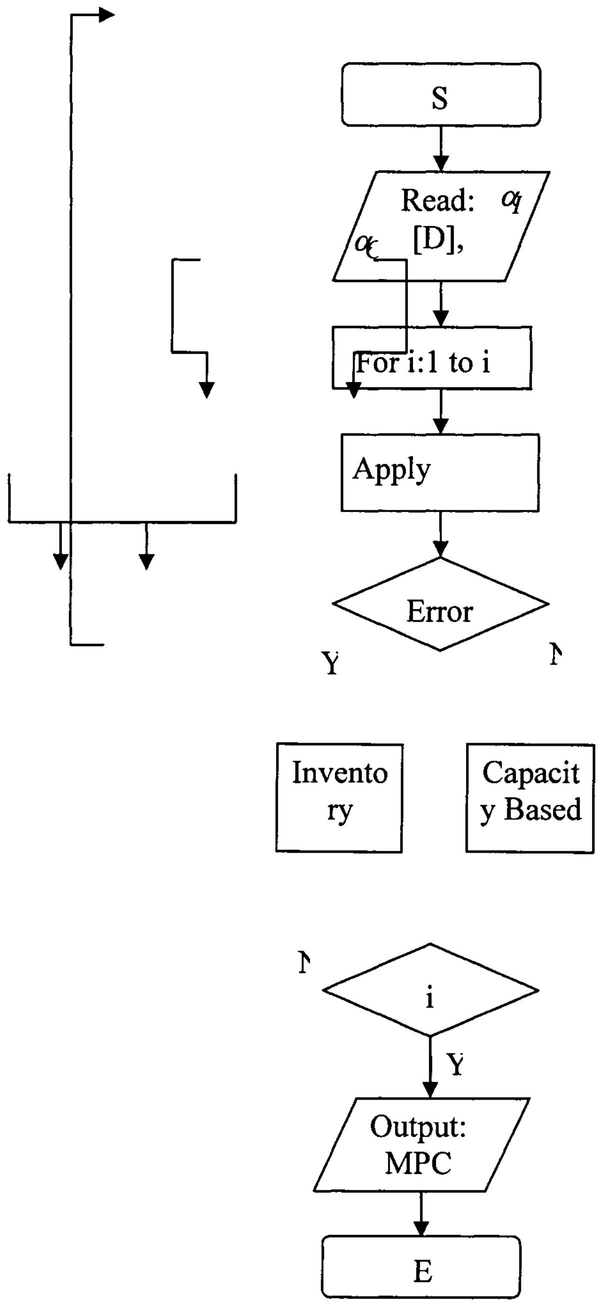


Figure 5.2: Flow Chart of the MPC Selection Unit's Algorithm

5.4 MPC System Controllers' Gains Optimal Setting Unit

As described earlier in this chapter, this unit is responsible for deciding on the optimal values of the different controllers' gains in the developed agile MPC system. The decision is made through a multi objective optimization approach that tends to make a trade off between responsiveness and cost effectiveness. No doubt that both agility goals are important to any enterprise, however, the importance degree of each of these goals is relative form one business to another. This relativity is indicated by the higher level management and is described in the multi objective function of the optimization approach in the DLU through the weighting variable "α".

From the dynamic analysis of chapter four the responsiveness of the developed MPC system can be expressed by the rise time of the system, while the cost of deviating from the target production level can be reflected in the value of the production overshoot measure as explained earlier. The objective function thus will aim to minimize the rise time (to increase responsiveness) and at the same time minimize the production overshoot (to decrease that cost) and each objective will take a specific weight "α" based on the policy adopted and the strategy of the higher level management.

It is important to recall here that all the previous measures are expressed in terms of the natural frequency and damping ration of the MPC system. Thus there will be four different objective functions for each MPC policy (or configuration). Also it is important to realize that both measures (natural frequency and damping ratio) are composed of the system's parameters (lead time, scalability delay time and shipment time) and the controllers' gains. Since the system's parameters are assumed to be fixed for each configuration, thus the optimization decision variable will be the controllers' gains of each policy.

5.4.1 Optimization Algorithm:

Consideration of more than one objective function in an optimization problem introduces additional degrees of freedom. Unless these degrees of freedom are constrained, mathematical theory indicates a set of solution points rather than a single, optimal point. In the case of the DLU, preferences dictated by the higher management level together with the stability and system constraints provide enough constraints to find a single optimal value for each controller gain in the developed agile MPC system. The most common approach to imposing such constraints is to develop a utility function which includes the different competing objectives.

The selection of the multi objective optimization (MOO) technique or method to be adopted is very important. Coello (2003) lists different methods for multi-objective optimization. The most commonly used method is the Weighted Sum Method where all the objective functions are added together using different weights and the utility function (U) is given as follows:

$$U = \sum_{i=1}^{k} w_i F_i(x) \tag{5.1}$$

where w is the weight for each objective function F(x) ($\sum_{i=1}^{k} w_i = 1$) and k is the number of the objective functions.

The main advantage of this method is that if all the weights are positive (as in the case of the DLU), the minimum of equation (5.1) is Pareto optimal (Zadeh 1963); i.e., minimizing equation (5.1), as in the case for the DLU objective, is sufficient for Pareto optimality. The general objective function is shown in equation (5.2).

$$Min\ : \alpha\left(\frac{0.8 + 2.5\xi}{\omega_n}\right) + (1-\alpha)\left(e^{-(\xi\pi / \sqrt{1-\xi^2})} * 100\right) \tag{5.2}$$

Equations (5.3) – (5.6) display the objective function for each MPC policy or configuration.

Inventory Based MPC:

$$MIN{:}\ \alpha\left[\frac{0.8+1.25\left[\frac{1}{2\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)\right]}{\sqrt{\frac{G_I}{T_{LT}}}}\right]+(1-\alpha)e^{-\left(\left(2\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)\right)\pi/\sqrt{1-\left(\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}\right)\right)^2}\right)}*100 \tag{5.3}$$

Capacity Based MPC:

$$MIN{:}\ \alpha\left[\frac{0.8+1.25\left[\frac{1}{2\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)\right]}{\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\right]+(1-\alpha)e^{-\left(\left(\frac{1}{2\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)\right)\pi/\sqrt{1-\left(\frac{1}{\sqrt{\frac{1+G_C}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}\right)\right)^2}\right)}*100 \tag{5.4}$$

Inventory/WIP Based MPC:

$$MIN{:}\ \alpha\left[\frac{0.8+1.25\left[\frac{1}{2\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right]}{\sqrt{\frac{G_I}{T_{LT}}}}\right]+(1-\alpha)e^{-\left(\left(2\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right)\pi/\sqrt{1-\left(\frac{1}{\sqrt{\frac{G_I}{T_{LT}}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_{SR}}+G_W\right)\right)^2}\right)}*100 \tag{5.5}$$

Capacity/WIP Based MPC:

$$MIN\,\alpha\left[\frac{0.8+1.25\left[\frac{1}{2\sqrt{\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)\right]}{\sqrt{\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}}}\right]+(1-\alpha)e^{-\left(\left(\frac{1}{2\sqrt{\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)\right)\pi\Big/\sqrt{1-\left(\frac{1}{2\sqrt{\frac{1+G_C+G_W T_{LT}}{T_{LT}T_D}}}\left(\frac{1}{T_{LT}}+\frac{1}{T_D}+G_W\right)\right)^2}\right)}*100$$

(5.6)

As for the constraints of the optimization process that constrain the different controllers gains (decision variables), they are mainly three constraints. First, the stability constraints described earlier in the stability analysis of the developed agile MPC system in chapter four for each MPC policy.

Second, the damping ratio is always constrained between 0 and 1 in order to have an under-damped system since an over damped MPC system (where the damping ratio is greater than 1) will decrease the system responsiveness dramatically while a negatively damped MPC system (where the damping ration is less than 0) will make the system unstable.

The final constrain is in the case of capacity based MPC systems where the upper limit for the capacity scalability controller gain is limited by the max capacity that can be supplied to the system since the capacity is assumed not to be infinite. The units of the calculated optimal gains values are daily rates

In any multi objective optimization (MOO) process, attention should be paid to two critical issues. The first issue is the determination of the weights in the objective function. Misinterpretation of the theoretical and practical meaning of the weights can make the process of intuitively selecting non-arbitrary weights an inefficient chore. There are different methods to calculate the value of these weights (see Yoon 1981 for a survey on these methods). In this dissertation, the weights will be determined by the higher management level depending on the adopted market strategy. This is another manifestation of how this agile MPC system links the operational level with the higher management level.

The second issue in MOO is the problem of the difference in the order of magnitude between the different objectives. A solution proposed to that is normalization where all objectives are transformed to have values from 0 to 1. This is especially true with secularization methods that involve a priori articulation of references as the one adopted in this layer of the DLU. In this unit, the most robust approach to normalize the objective functions regardless of their original range is used and it is given in the following equation (Koski 1984, Koski and Silvennoinen 1987, Rao and Freiheit 1991):

$$F_i = \frac{F_i(x) - F_i^*}{F_i^{\max} - F_i^*} \tag{5.7}$$

where Fi is the objective function, i is the number of objective functions, F* is the optimal objective function at the utopia point (optimal point) and F^{max} is value of the objective function at the maximum point of the range (in the cases of a minimization problems as in our case).

Figure 5.3 shows the flow chart of the optimization algorithm in this MPC System controllers' gains optimal setting unit. A MATLAB code is used to implement this algorithm and plot the decision variables to indicate the optimal points.

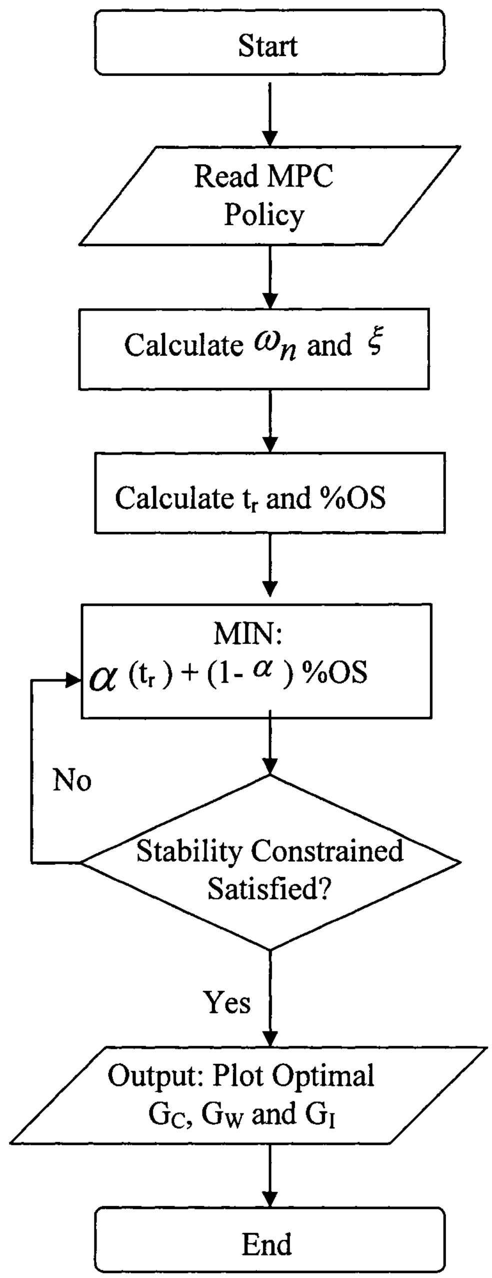


Figure 5.3: Flow Chart of the Optimization Algorithm MPC System Controllers' Gains Optimal Setting Unit

5.4.2 Simple Sensitivity Analysis of the Competing Objectives and Optimization Variables:

It is important to study the sensitivity degree of each of the optimization objectives (rise time and production overshoot) with the decision variables (controllers' gains). Such study will give a better understanding of the nature of the problem and which are the real effective objectives with each MPC policy and the same for the decision variables.

To carry out this study the previous developed optimization algorithm is implemented with different values for the weights and the time parameters are arbitrarily to be as follows: $T_{LT} = 1$ day, $T_D = 2$ days and $T_{SR} = 4$ days. The maximum capacity rate constraint is 10 orders/day while the maximum feasible input rate is 5 orders/day. In addition, to better visualize the problem, the objective function is plotted against the decision variables.

5.4.2.1 Inventory Based MPC Policy

Figures 5.4 to 5.6 show the objective function versus the inventory controller gain "G_I" at different values of "α". The feasible calculated range of G_I is [0.4-1.4] K RAM/day. Analysis of these figures leads to the following conclusions (Deif and ElMaraghy 2006-e):

- When both objectives have equal weights (figure 5.4), the competitiveness between both objectives is obvious. The rise time minimization objective is trying to increase the value of G_I while the minimization of the overshooting objective is trying to do the opposite.
- However, the same figure shows that the change in the overshooting objective with the change in the G_I values is higher than that of the time rise objective across the G_I domain. This leads to the conclusion that minimization of the

overshooting (or partial cost) objective is more sensitive to the inventory controller gain G_I than minimization of the rise time objective (1/responsiveness).

- The weights of the objective function play a significant role in determining the optimal value of the inventory controller gain G_I as shown in figures 5.5 and 5.6. When the responsiveness objective is of higher importance (α= 0.7), the optimal value tends to fall near the upper boundary of the inventory controller gain range, while when the cost objective is of higher priority (α= 0.3), the optimal value tends to fall near the lower boundary of that range. This is obvious since the weights acts in the favorite of one of the objectives and each of these objectives tries to push the value of G_I to one of the limits.
- Based on the previous observation, it is clear that the higher management strategy plays an important role on determining the policy of inventory control in the operational level. This again highlights how important the link between these two levels is in order to improve the enterprise performance.

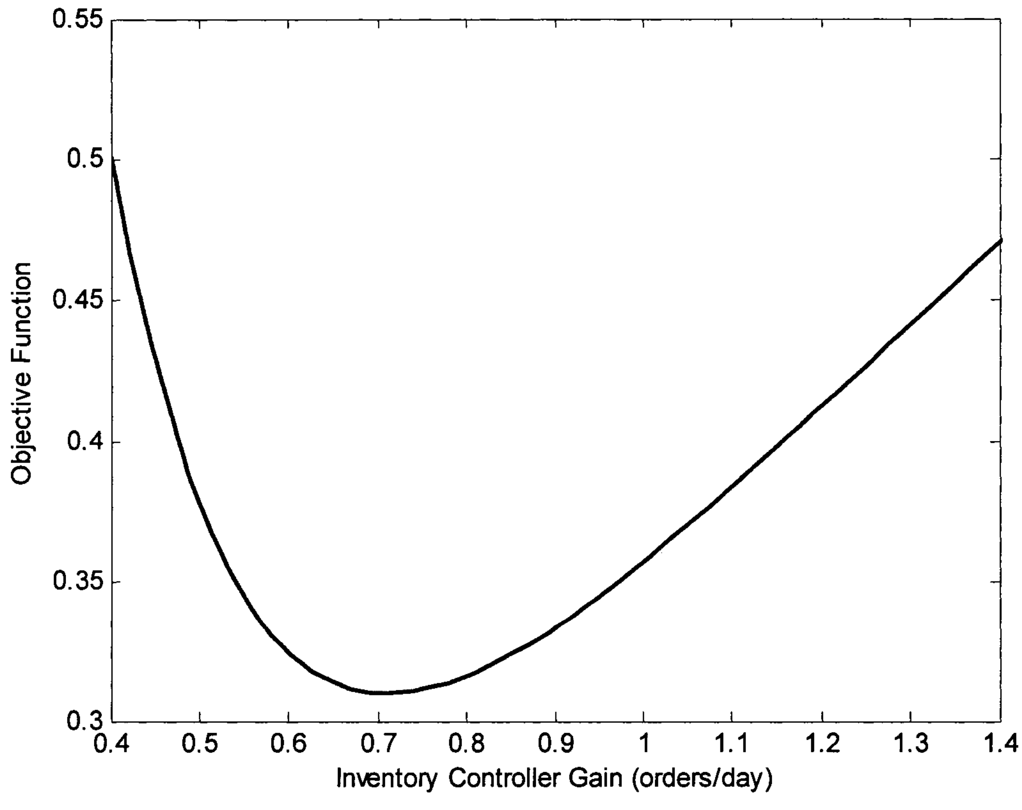


Figure 5.4: The Objective Function versus the Inventory Controller's Gain at α = 0.5

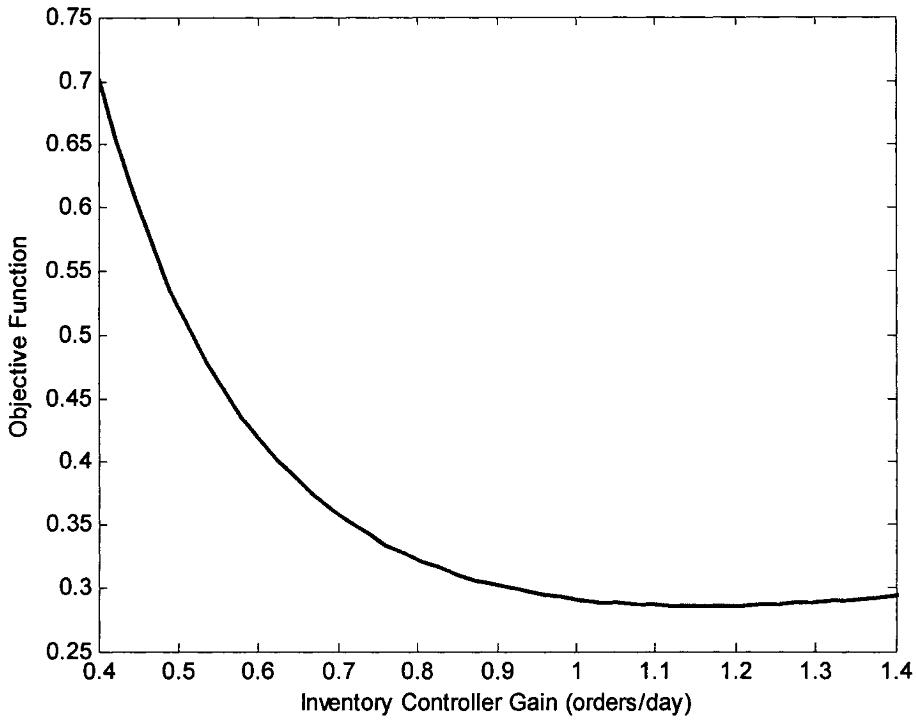


Figure 5.5: The Objective Function versus the Inventory Controller's Gain at $\alpha = 0.7$

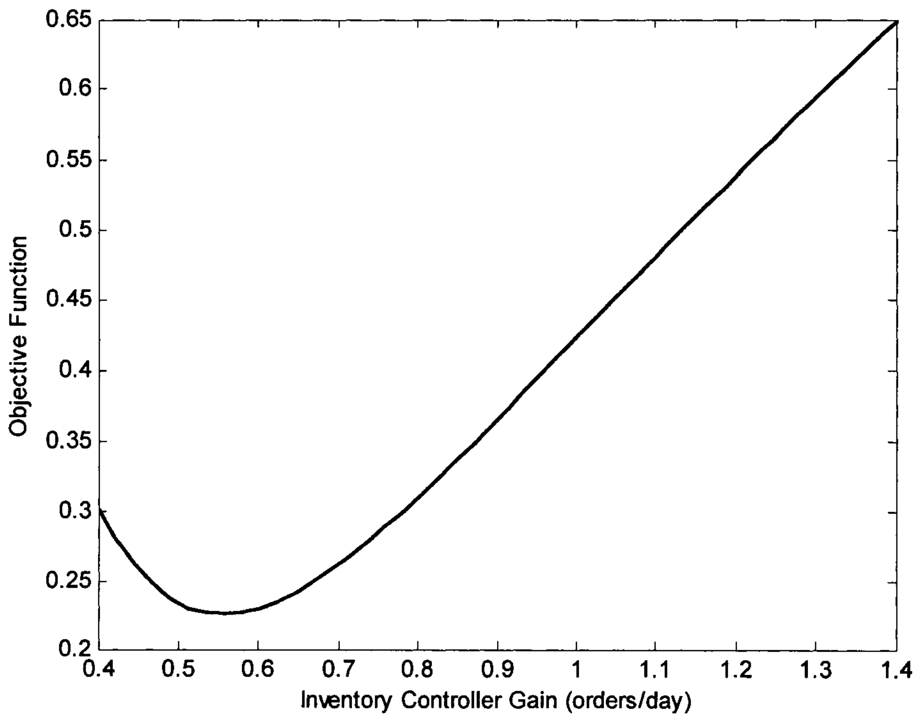


Figure 5.6: The Objective Function versus the Inventory Controller's Gain at $\alpha = 0.3$

5.4.2.2 Capacity Based MPC Policy

The same analysis is carried out for the capacity based MPC system with the same variety in the values of the weights. The feasible range of G_C is [0-7]. Results are shown in figures 5.7 to 5.9 and can be analyzed as follows:

- From figure 5.6, the competitiveness between both objectives is obvious at α= 0.5 in the same fashion as for the previous inventory based MPC system.
- Also the same figure shows that the minimization of the overshooting (or the cost) objective is more sensitive to the capacity scalability controller gain G_C than the minimization of the rise time objective (1/responsiveness).
- The weights of the objective function play similar role in determining the optimal value of the capacity scalability controller gain G_C as shown in figures 5.7 and 5.8. When the responsiveness objective is of higher importance (α= 0.7), the optimal value tends to fall near the upper boundary of G_C, while when minimization of partial cost objective is of higher priority (α= 0.3), the optimal value tends to fall near the lower boundary of the same range as explained earlier.

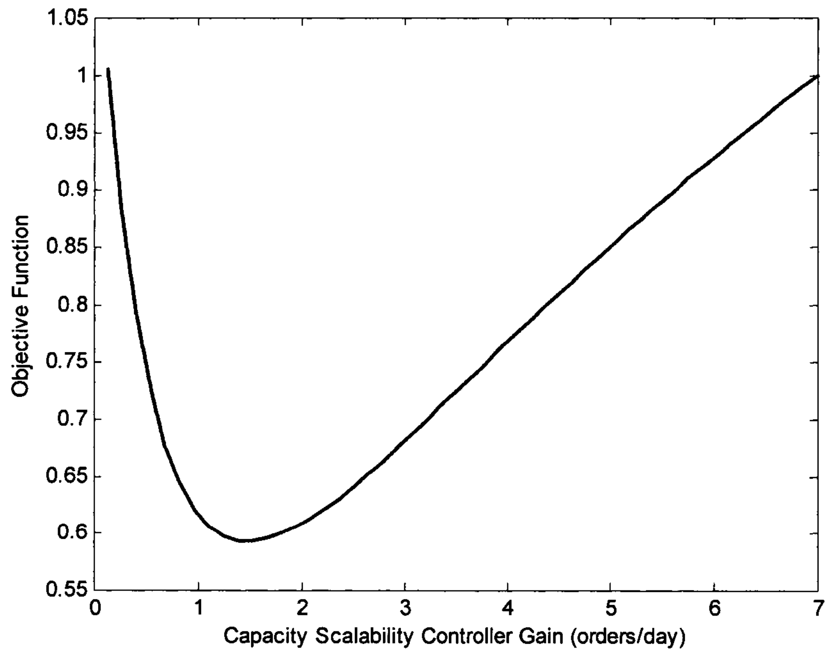


Figure 5.7: The Objective Function versus the Capacity Scalability Controller's Gain at α = 0.5

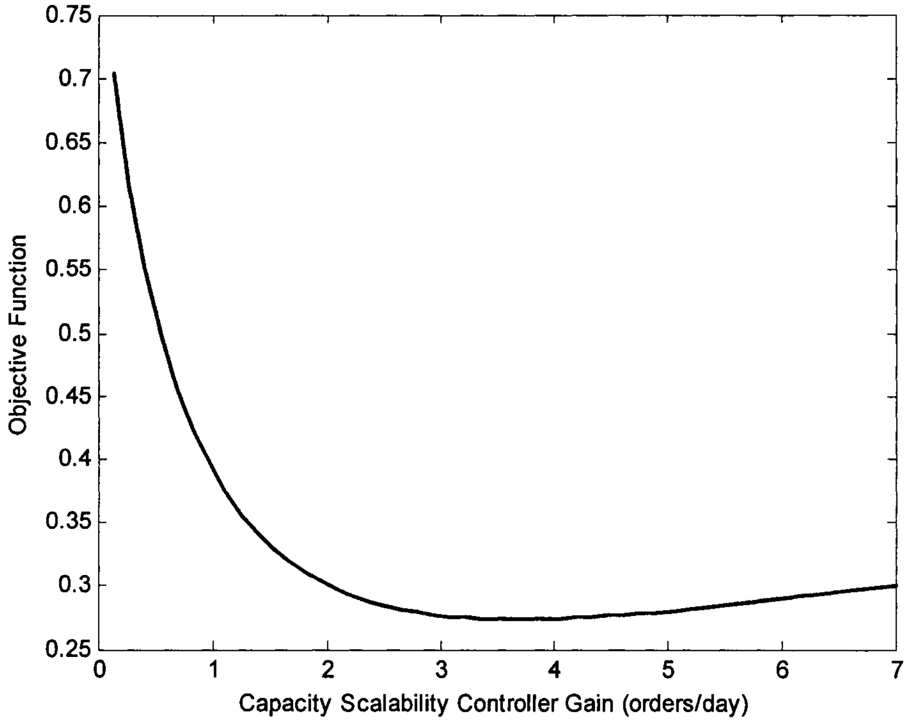


Figure 5.8: The Objective Function versus the Capacity Scalability Controller's Gain at $\alpha = 0.7$

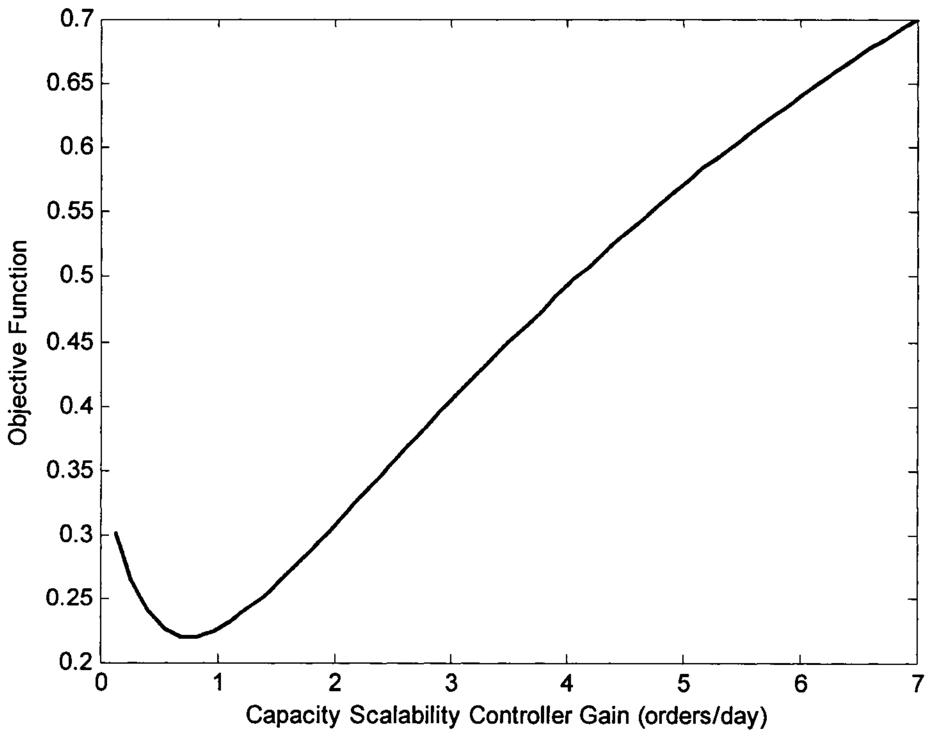


Figure 5.9: The Objective Function versus the Capacity Scalability Controller's Gain at $\alpha = 0.3$

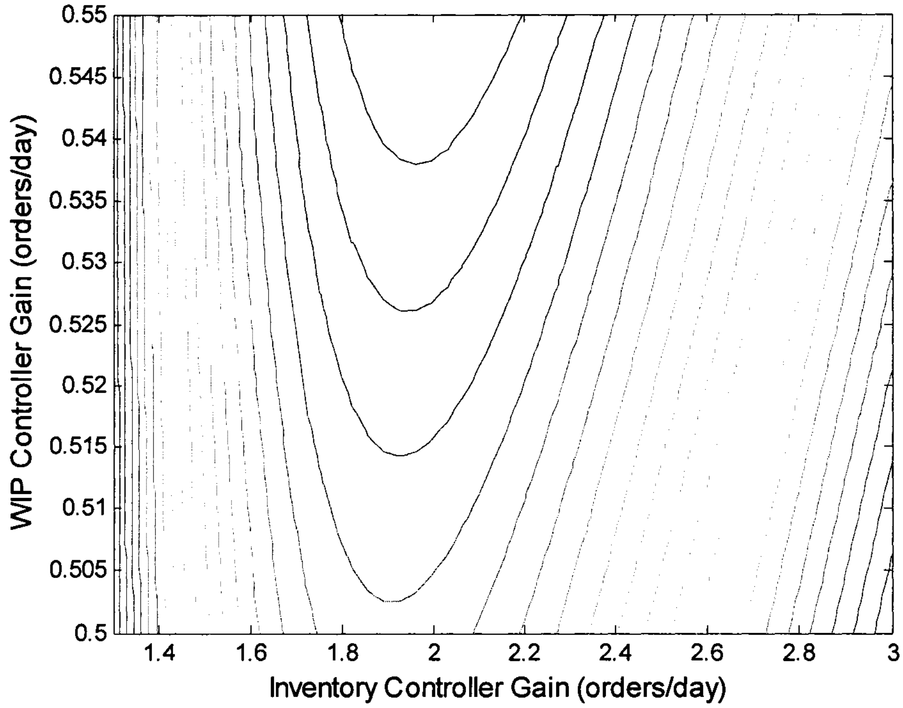
5.4.2.3 Inventory/WIP Based MPC Policy

The analysis of this policy is different from the previous two policies since two decision variables are considered (the inventory controller gain G_I and WIP controller gain G_W). The feasible range for G_I is calculated to be [1.3-5] K RAM/day and for G_W is [0-1] K RAM/day.

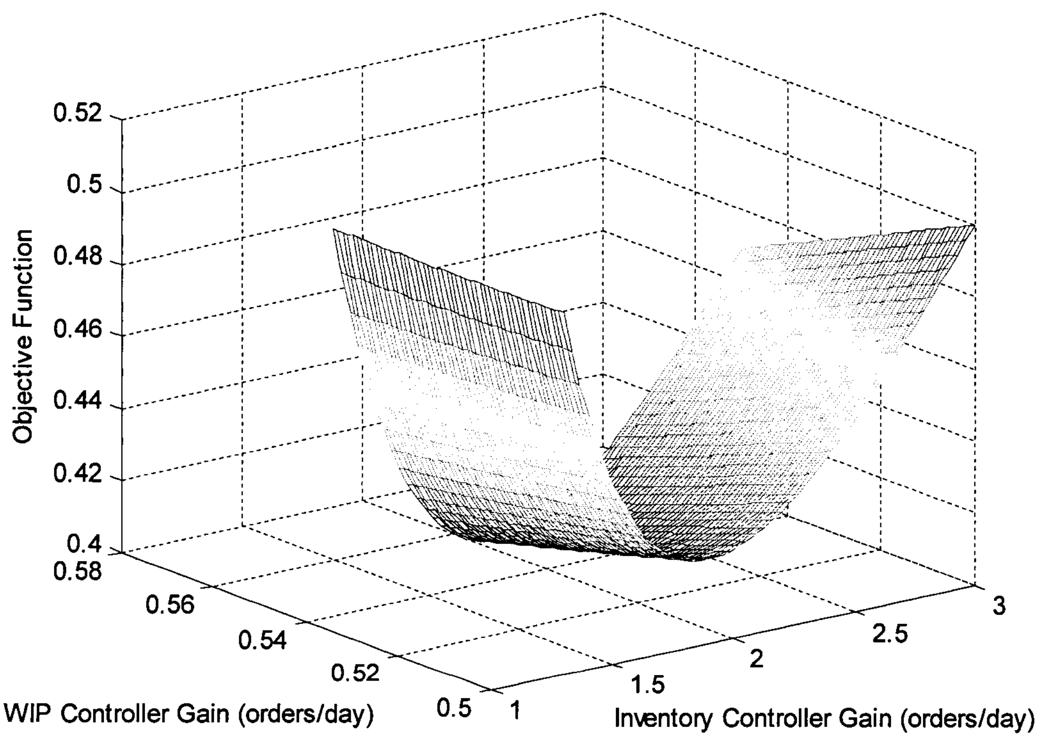
In order to sense the degree of competition of both objectives with each of the decision variables, the first analytical approach will consider one of the decision variables constant while the other will change along its feasible range. Figure 5.10 (a and b) shows the objective function versus different values of G_I while G_W varies in a very small range at its average value. Same results were obtained when G_W has different values (see table 5.1). The results in the figure emphasize the competition of both objectives without dominance of G_W over G_I.

Figure 5.11 (a and b) shows the objective function versus different values of G_W while G_I varies in a very small range at its minimum value. The results in the figure again emphasize the competition of both objectives. However, only at low values of G_I, G_W showed that behaviour. When G_I has higher values, G_W is always at its maximum range showing the dominance of G_I over G_W in this MPC configuration or policy (see table 5.2).

Furthermore, when both variables are considered simultaneously with equal weights ($\alpha = 0.5$), the optimal value for WIP controller's gains is found to be at the upper boundary as shown in figure 5.12 (a and b). Meanwhile the optimization process is carried out to decide on the optimal value of the inventory controller gain. The general insensitivity of the WIP controller gain is mainly due to damping limits or constraints.

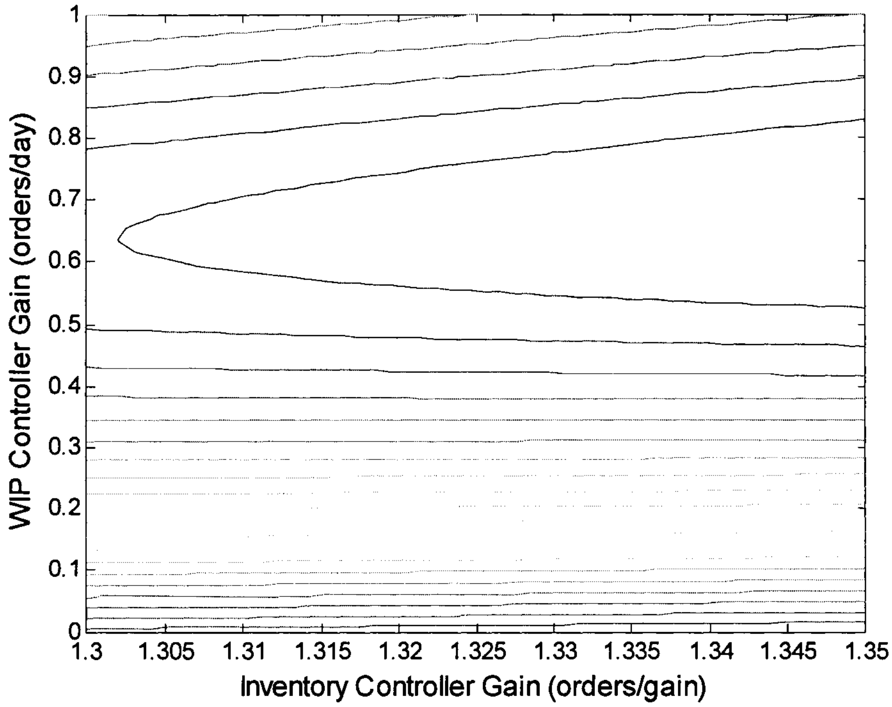


(a)

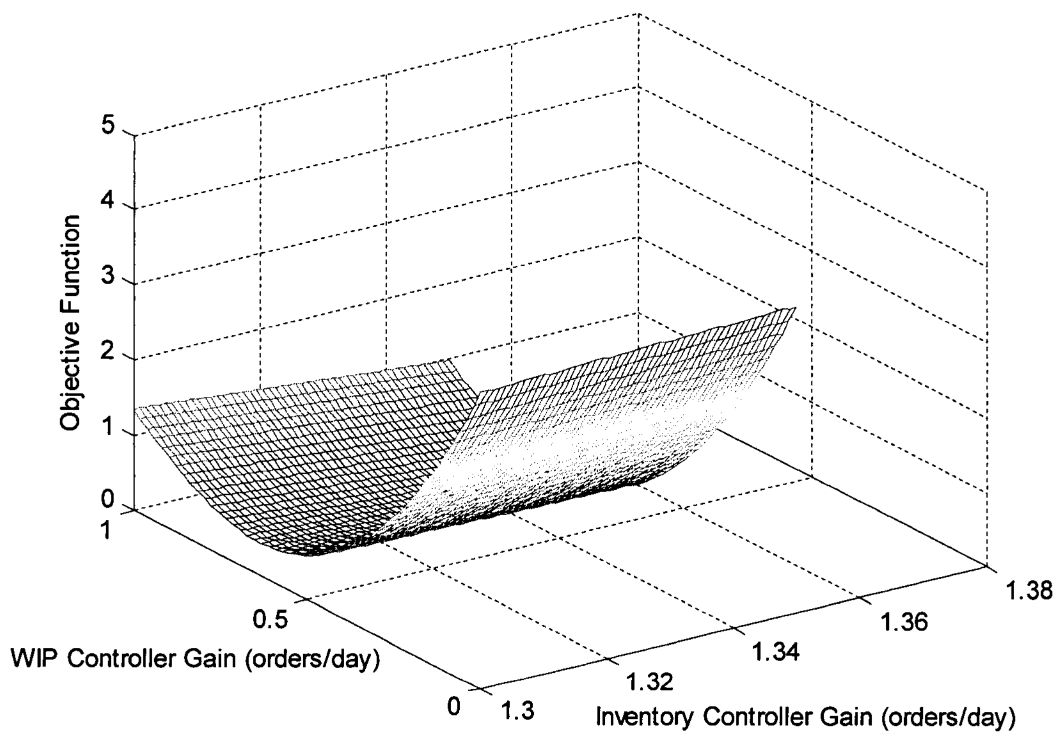


(b)

Figure 5.10: The Objective Function in Inventory/WIP Based MPC System versus the Inventory Controller's Gain at G_W = (0.5 to 0.58)

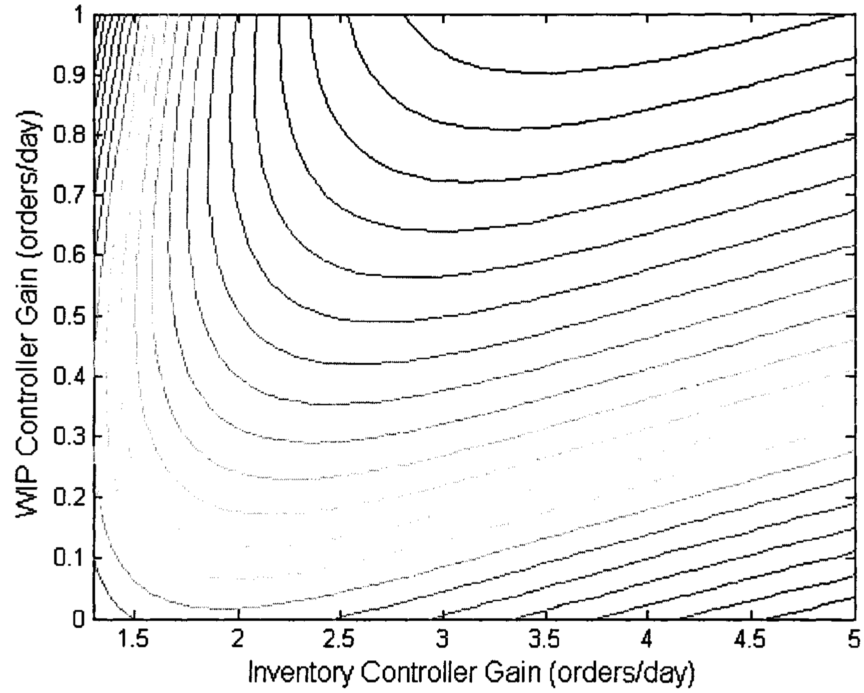


(a)

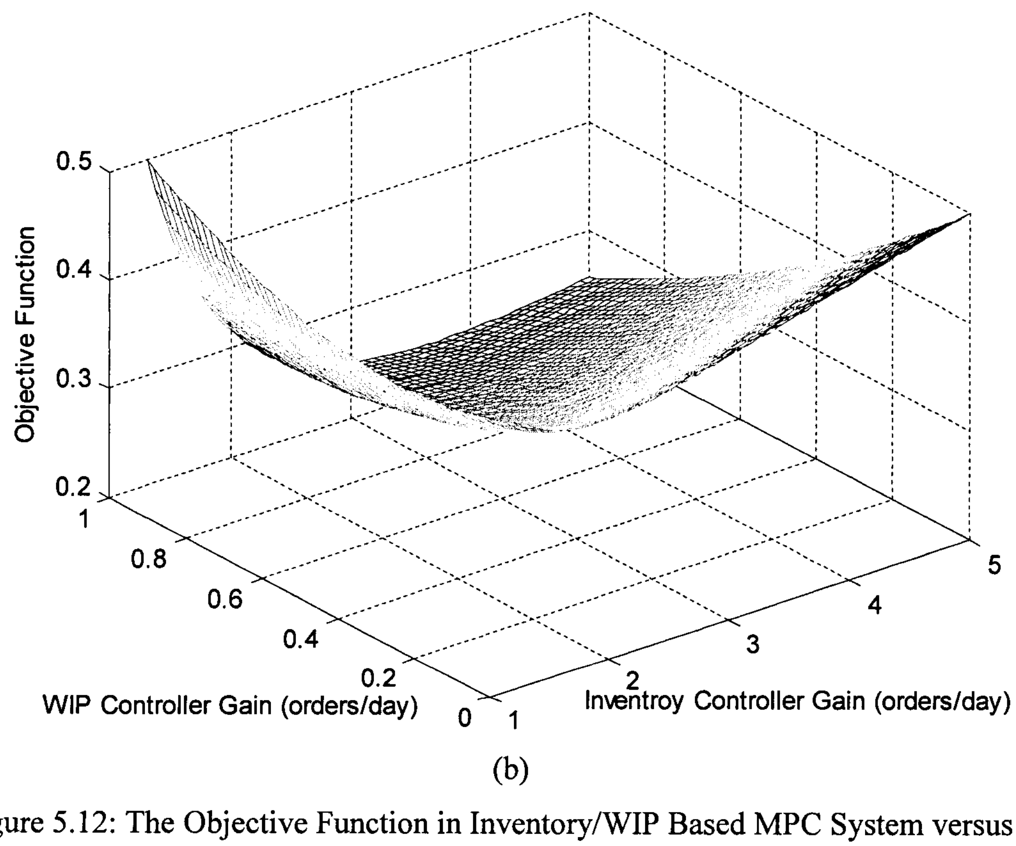


(b)

Figure 5.11: The Objective Function in Inventory/WIP Based MPC System versus the WIP Controller's Gain at G_I = (1.3 to 1.38)



(a)



(b)

Figure 5.12: The Objective Function in Inventory/WIP Based MPC System versus the Inventory Controller's Gain and WIP Controller's Gain at $\alpha = 0.5$

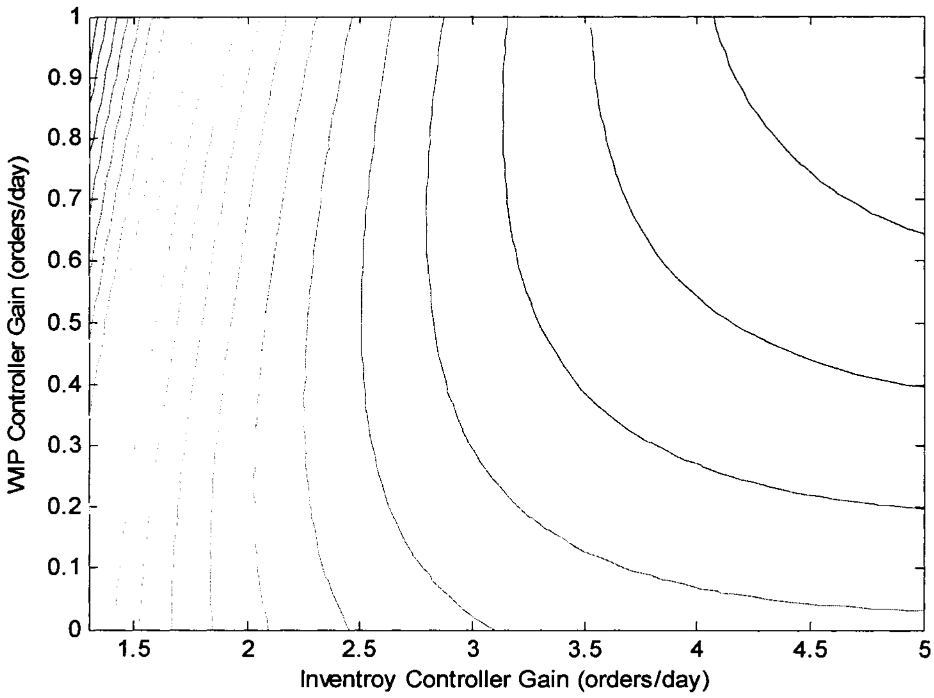
Value for G_W	Corresponding Optimal Value for G_I	Objective Function
0	1.6	0.44922
0.3	2	0.36192
0.7	2.7	0.27456
0.9	3	0.24275
1	3.3	0.22391

Table 5.1: Some Results for Sensitivity Analysis for Optimal Values of G_W

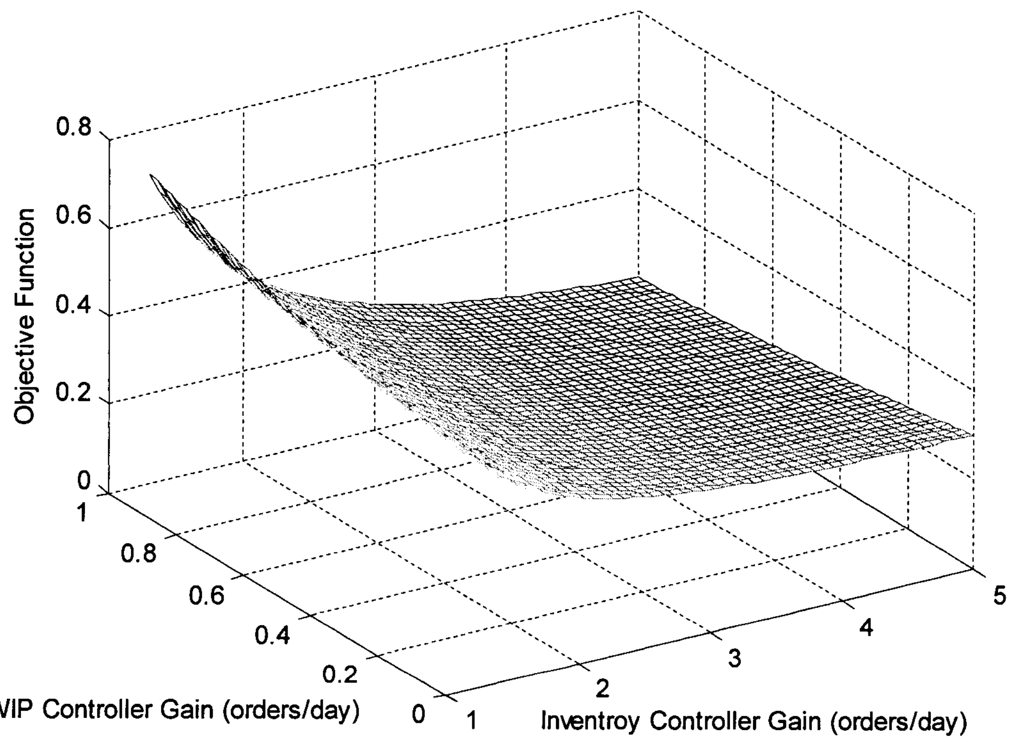
Value for G_I	Corresponding Optimal Value for G_W	Objective Function
1.5	0.6	0.367176
2	0.9	0.288936
3	1	0.225935
4	1	0.230974
5	1	0.254253

Table 5.2: Some Results for Sensitivity Analysis for Optimal Values of G_I

The effect of the weights is highlighted by choosing the weight "α" to be equal to 0.7 and 0.3 as shown in figures 5.13 (a and b) and 5.14 (a and b) respectively. It is clear that when responsiveness is of higher importance, G_I will always tend to be at its upper boundary (figure 5.13) while G_W gets a bit sensitive to the optimal solution. The case is reversed when the partial cost is of higher importance where G_I will tend to go to its minimum limit while G_W is again insensitive to the optimal solution (figure 5.14). This can be explained since the weights gear the problem to one of the two objectives and in the responsiveness case the system will always try to have maximum G_I and decrease the damping effect of G_W while in the case of partial cost the system will always try to have maximum G_W to decrease overshooting and decrease the instability effect of G_I.

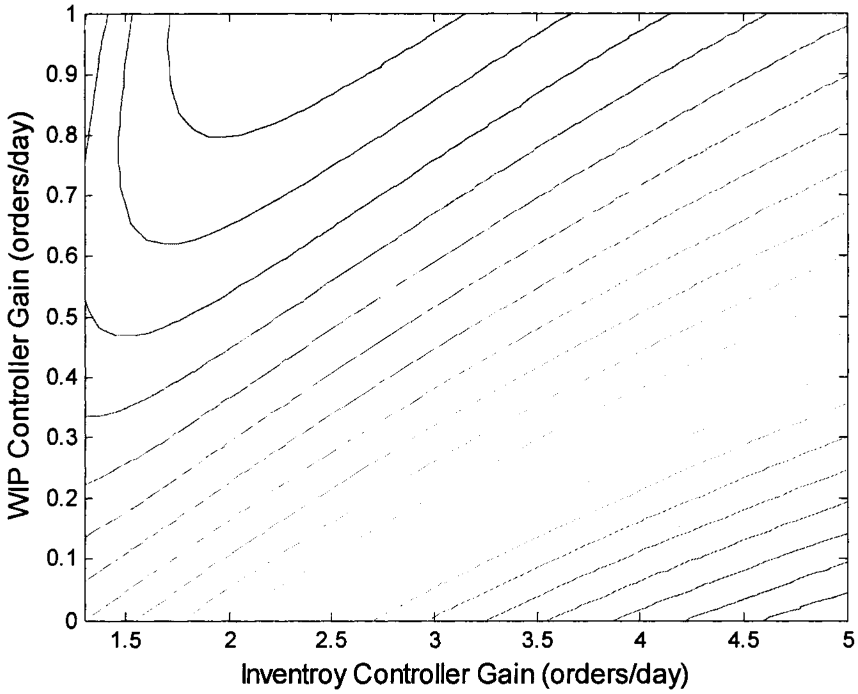


(a)

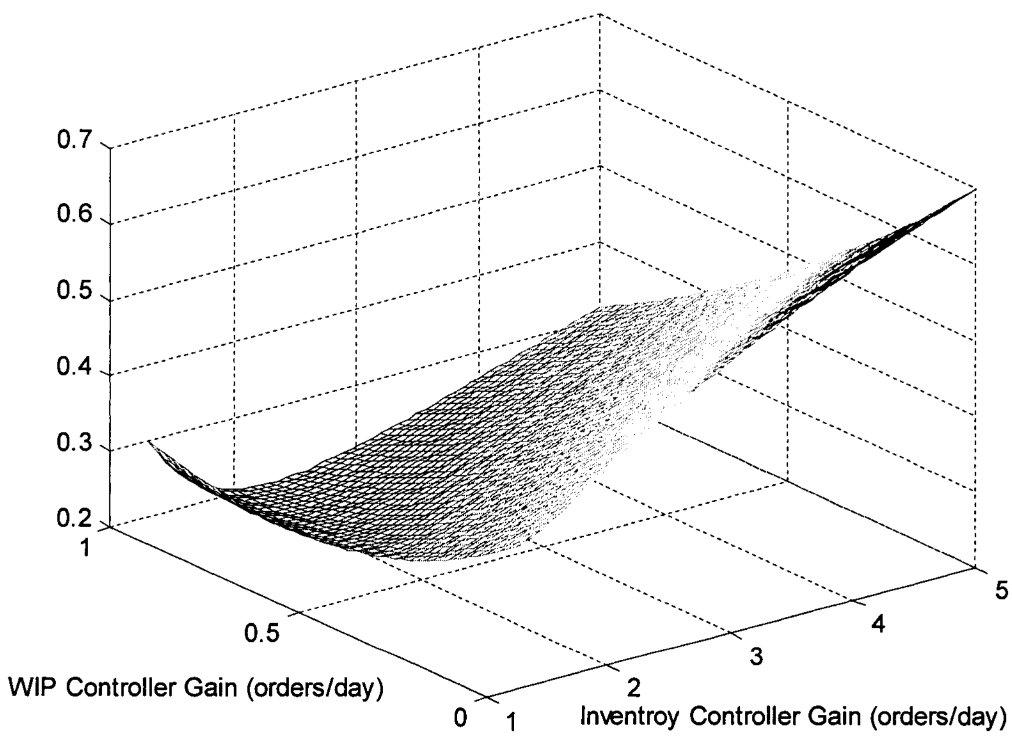


(b)

Figure 5.13: The Objective Function in Inventory/WIP Based MPC System versus the Inventory Controller's Gain and WIP Controller's Gain at $\alpha = 0.7$



(a)



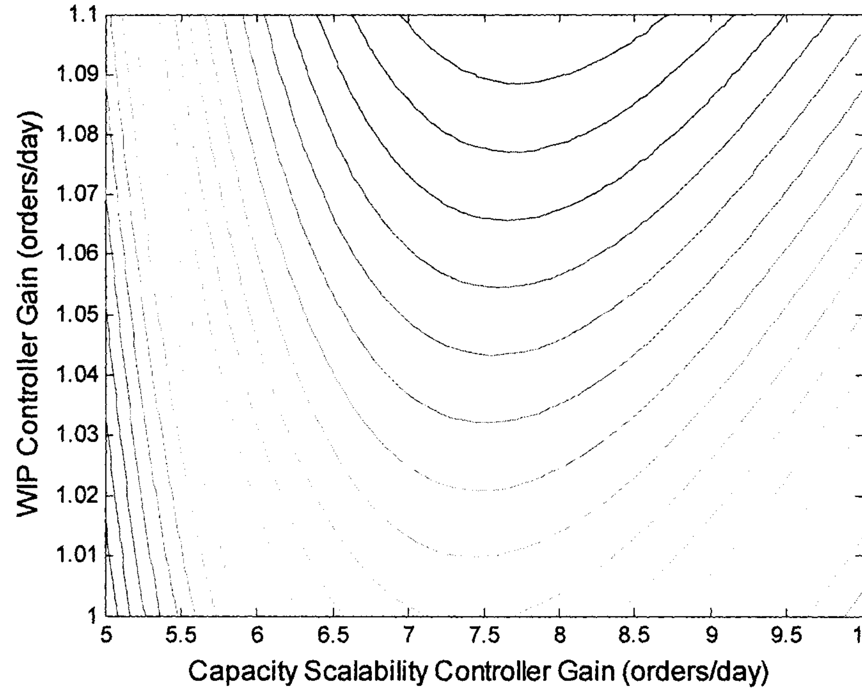
(b)

Figure 5.14: The Objective Function in Inventory/WIP Based MPC System versus the Inventory Controller's Gain and WIP Controller's Gain at $\alpha = 0.3$

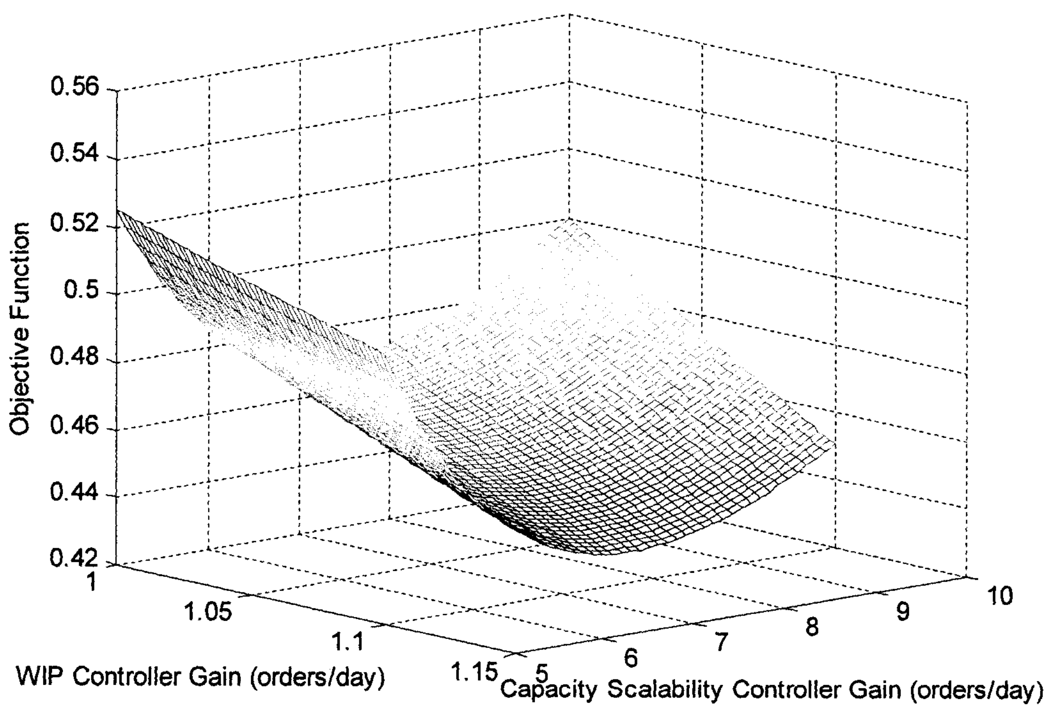
5.4.2.4 Capacity/WIP Based MPC Policy

A similar analysis to the previous inventory/WIP based MPC policy is carried out since both have two decision variables (where the capacity scalability controller G_C will replace G_I). The feasible range for G_W is calculated to be [-1.4 - 2.3] K RAM/day and for G_C is [5-10] K RAM/day. Figures 5.15 to 5.19 revealed the following points:

- The competitiveness of both agility objectives with each of the decision variables (controllers' gains) is clearly shown in figures 5.14 and 5.15 where one of the decision variables is changed across the feasible range while the other is slightly changing.
- However, figure 5.16 show that when both decision variables are considered, the system decision logic unit tends to optimize only the WIP controller gain while the capacity scalability controller gain is always at its upper boundary. This declares the dominance of the WIP controller gain as a decision variable over the other variable in the multi objective optimization for this configuration. This can be explained by realizing that as the capacity rate increases, the limit of the maximum WIP increases as well (due to the increase in the production limit) and thus problem becomes (unless capacity is restricted at each stage) to find the optimal WIP gain value across all available WIP levels. A practical solution for this problem is to have this layer in the DLU displays the optimal G_W at each capacity scalability increment (or limit) across the G_C range.
- The previous observation is still valid even when the weights were altered towards both objectives as shown in figures 5.17 and 5.18. For example, when the responsiveness (or minimization of rise time) is given a higher weight, the optimization process tends to minimize the value of G_W to decrease its damping effect while G_C is at its maximum limit. In the case of cost being of higher priority, the optimization process tends to push G_W to its maximum value to decrease overshooting while G_C is also kept at it upper boundary.



(a)



(b)

Figure 5.15: The Objective Function in Capacity/WIP Based MPC System versus the Capacity Controller's Gain at G_W = (1 to 1.1)

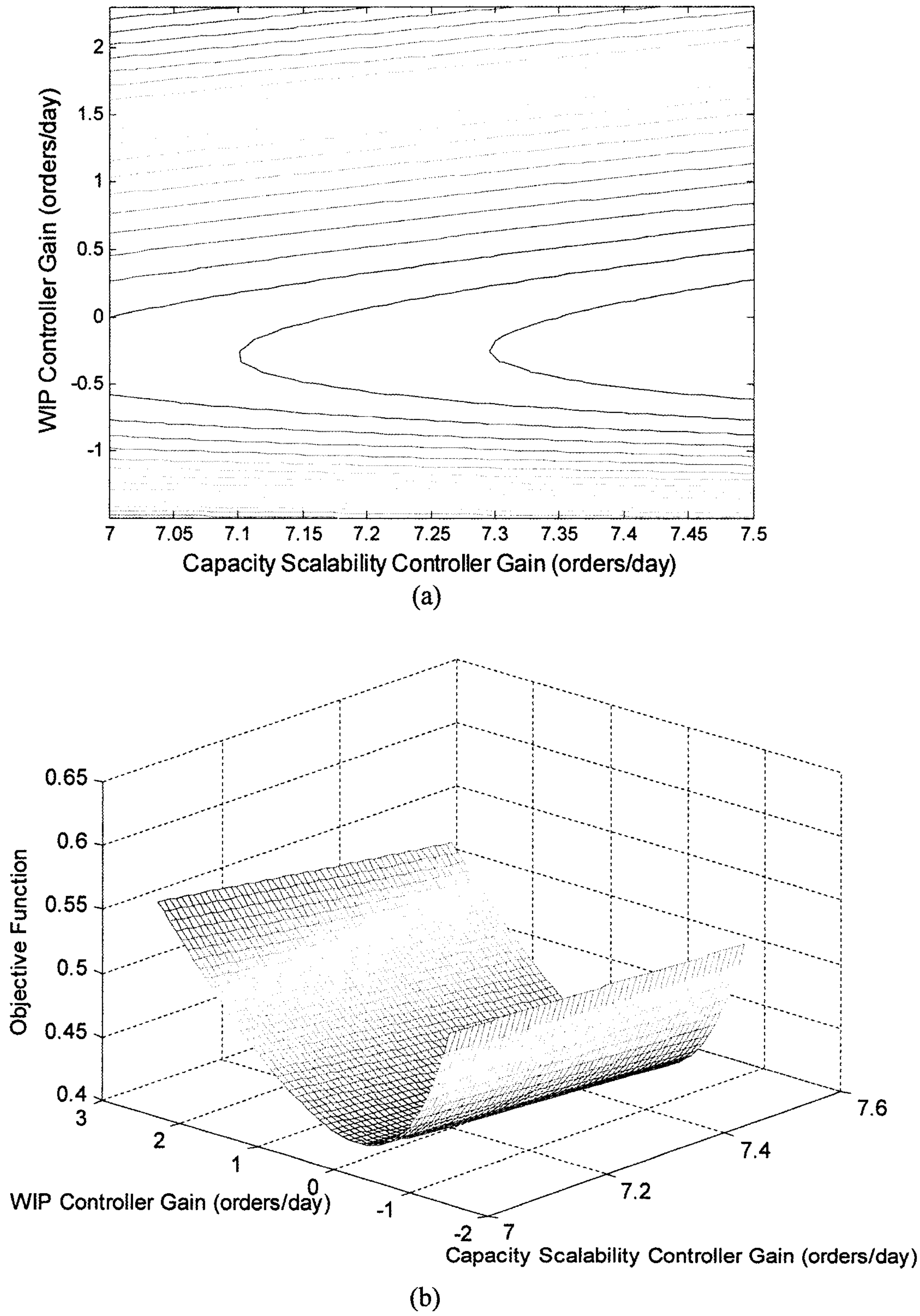


Figure 5.16: The Objective Function in Capacity/WIP Based MPC System versus the WIP Controller's Gain at G_C = (7 to 7.5)

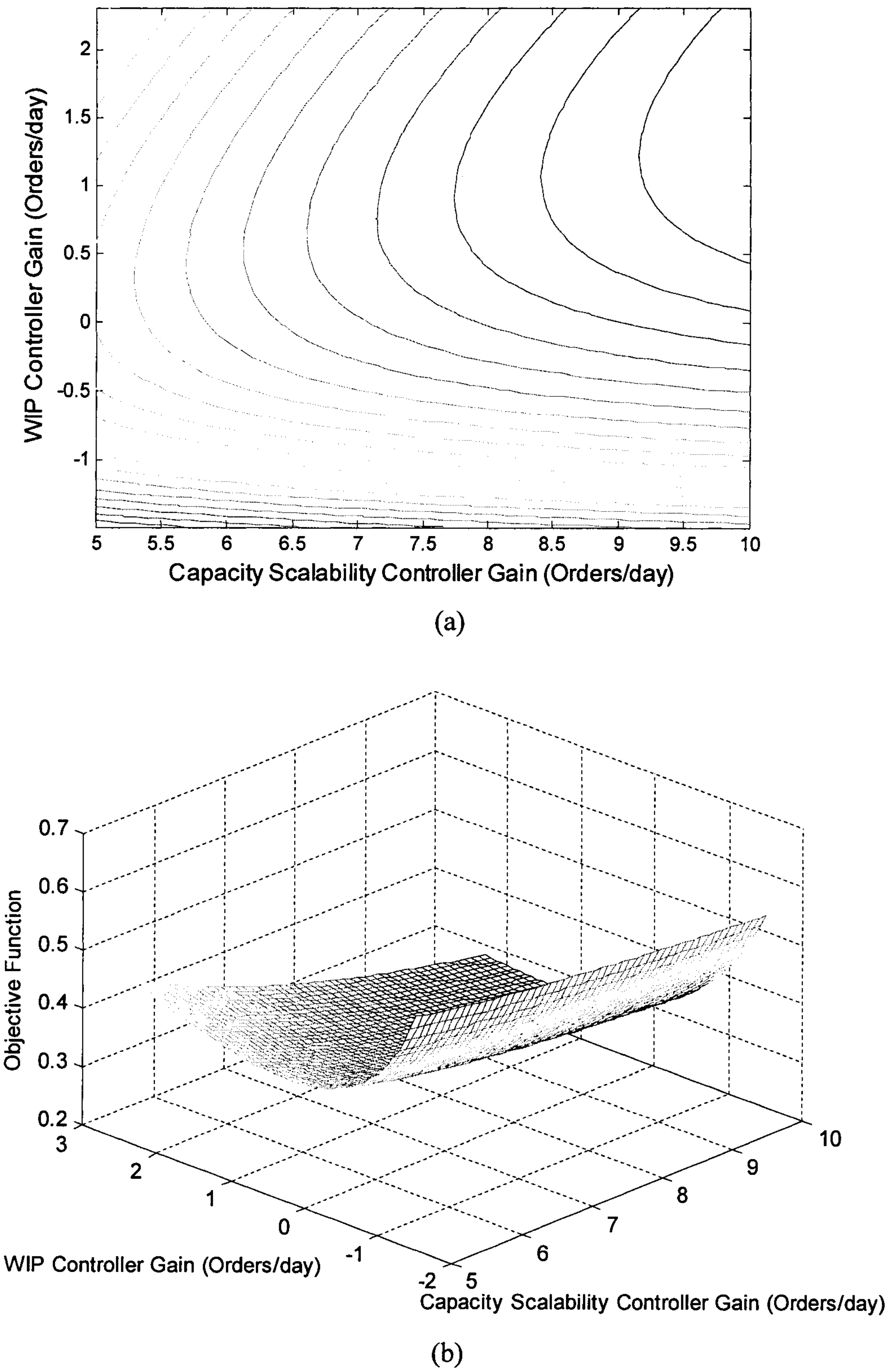
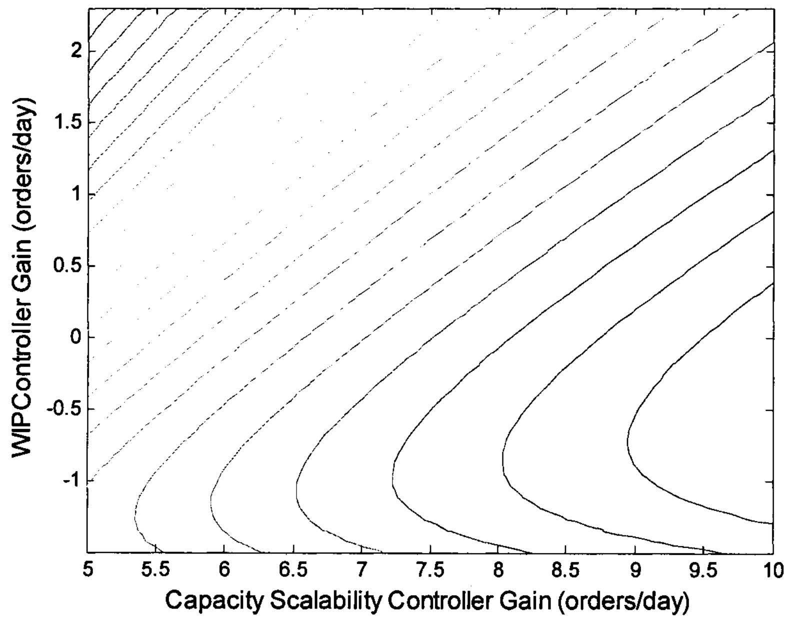
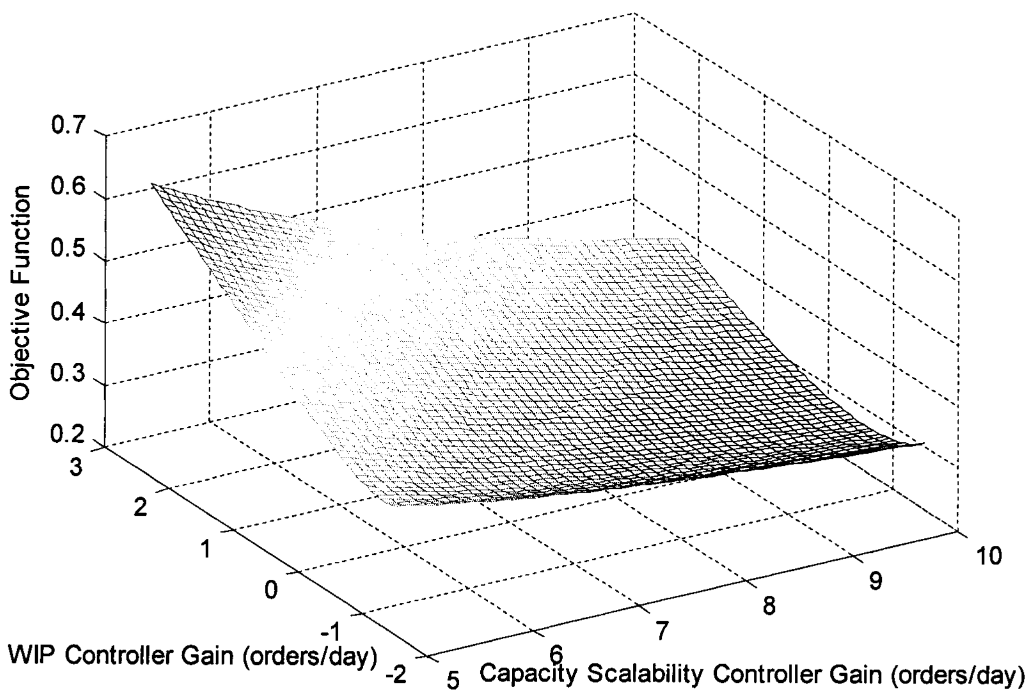


Figure 5.17: The Objective Function in Capacity/WIP Based MPC System versus the Capacity Controller's Gain and WIP Controller's Gain at $\alpha = 0.5$

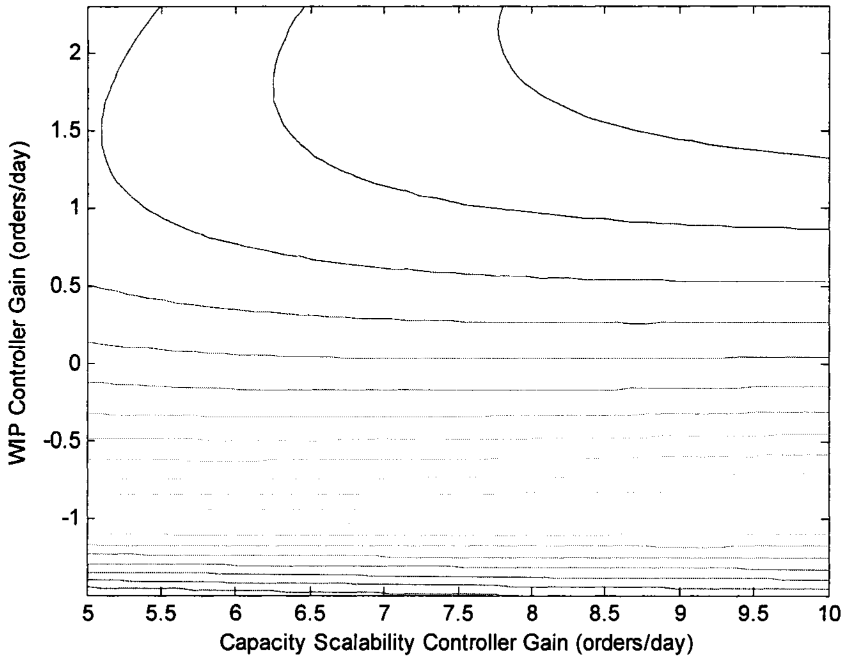


(a)

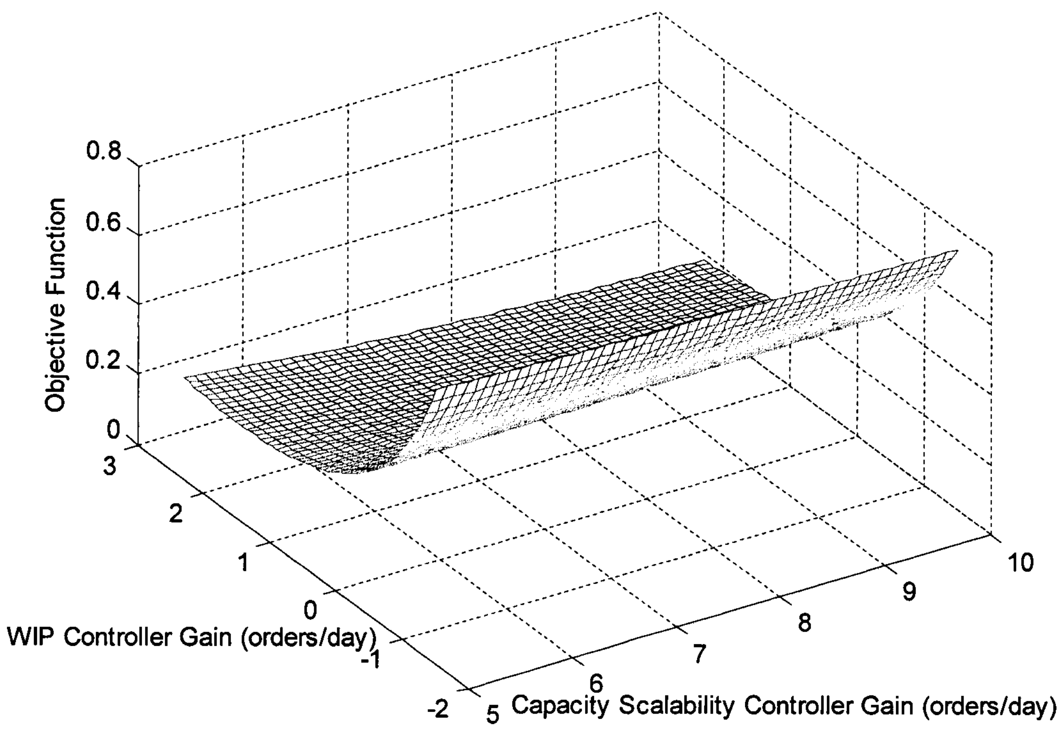


(b)

Figure 5.18: The Objective Function in Capacity/WIP Based MPC System versus the Capacity Controller's Gain and WIP Controller's Gain at $\alpha = 0.7$



(a)



(b)

Figure 5.19: The Objective Function in Capacity/WIP Based MPC System versus the Capacity Controller's Gain and WIP Controller's Gain at $\alpha = 0.3$

5.5 MPC Demand Satisfaction Check Unit

After deciding on the optimal controllers' gains values the system will observe the current status of the manufacturing system, specifically the production rate, WIP level and inventory level. The observation process is interactive with the operational level or the manufacturing system, i.e. the DLU is updated with these levels on a monthly basis and the reference levels are also updated on a monthly basis based on the anticipated demand. The update is followed by a checking process (production control process) where the measured levels are compared with their respective target levels to check for demand satisfaction as will be explained next.

The production rate is compared to the desired capacity rate in any of the capacity based MPC policies. The reference capacity rate is set to be equal to the order rate OR which reflects the monthly demands that are anticipated by the higher management level. It is important to note that both rates are monthly rates. Based on the discrepancy between the two levels, the demand satisfaction check unit will decide on the required capacity scalability decision (increase or decrease) through scaling the capacity by the previously determined optimal capacity scalability controller's gain.

Since the optimal capacity scalability gain is a daily rate value, this unit will also determine the duration for the application of the scalability decision. In other words the output from this unit to the operational level will be to scale the capacity by this amount (optimal capacity scalability gain) and through this duration (number of days in the next month).

As for the inventory level in inventory based policies, it is compared to the reference inventory level which can be determined by one of two ways. The first way is a preset service level that is determined by the higher management level where a minimum level of finished inventory should always be available in the warehouse.

The second way is to calculate the average demand in the months where the inventory policy is implemented and setting this average value as the reference inventory level. Based on the discrepancy between the two levels the same process as in determining the capacity scalability decision is applied to determine the amount of inventory gain (input rate) and for how long.

Finally, the WIP level in the MPC policies accounting for WIP is compared to the ideal WIP level. The ideal WIP level is calculated as a product of multiplying the order rate OR with the estimated (ideal) lead time of the production system T_{LT}^* as indicated by Little's law (Sterman 1989, Hopp and Spearman 2000). The discrepancy between the two levels is compensated by the demand satisfaction check unit using the previously calculated optimal WIP controller's gain (input rate) and in the same manner as in the cases of production rate and inventory.

Figure 5.20 shows the flow chart of the algorithm in this MPC system demand satisfaction check unit.

The final outcome of the whole decision logic unit (DLU) after its three hierarchical units have processed their functions as discussed earlier is what is called agile MPC plan. The operational level (manufacturing system) receives a yearly plan indicating which MPC policies will be applied during which periods and also a continuously updated monthly production control decisions to increase or decrease the production levels, WIP levels and/or inventory levels for a specific period of time in order to satisfy the demand anticipated by the higher level management.

The full switching protocol, optimization and control algorithms of the developed decision logic unit are being developed using MATLAB programming tool.

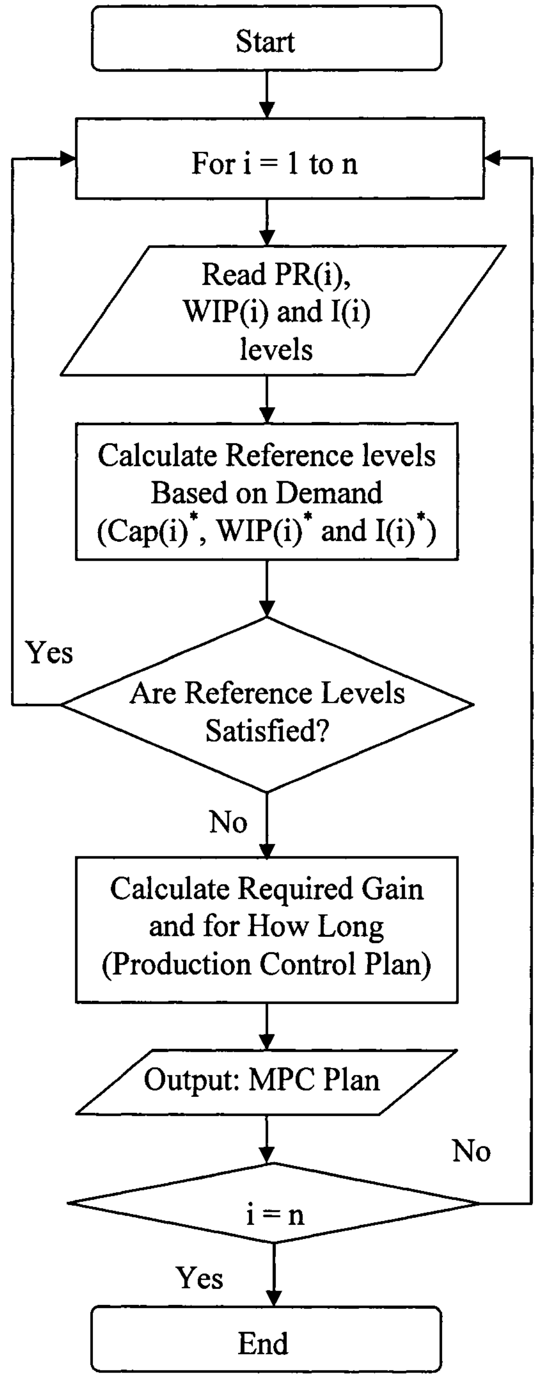


Figure 5.20: Flow Chart of the Algorithm for MPC Demand Satisfaction Check Unit

5.6 Chapter Summary

The design of the decision logic unit or the supervisory controller was conducted in this chapter. The following points summarize the main observations and conclusions that were realized during the design and the numerical analysis process:

- The design of the decision logic unit (DLU) was achieved through the development of a hierarchical architecture composed of three layers each layer resembles a unit that carry out a certain task.
- The decision logic unit succeeded in linking the higher management level with the operational level. This linkage was mainly through aligning the marketing strategy with the manufacturing strategy via the generated MPC plan. This alignment appears in the selection of various decision parameters like the weights for the optimization process that balances between responsiveness and cost effectiveness (based on the market strategy) and also in the selection of the regression error that reflects the sensitivity degree accepted by the company to demand variation based again on its market strategy. Such linkage and alignment is the proposed research approach to realize agility in today's manufacturing systems.
- The first layer in the DLU was the MPC policy selection unit. This unit is responsible for analyzing the anticipated demand profile and based on regression analysis the unit decides which MPC policy to be applied during which demand period.
- The second layer of the DLU is the MPC system controllers' gains optimal setting unit. This unit receives the selected MPC polices and based on the previously developed models for each MPC policy or configuration it optimally select the controllers' gains values for that policy or configuration. The optimization is basically a trade off decision between the two competing objectives of agility, responsiveness and cost effectiveness and thus a multi objective optimization approach was adopted.

- The adopted multi objective optimization technique was the weighted sum as a Pareto optimal value is guaranteed. To avoid a problem in the order of magnitude, a normalization approach was implemented and as for the weights of the objective function, their selection was guided by the market strategy.
- The optimization process is constrained by the stability constraints investigated earlier in chapter four as well as the manufacturing system's constraints and the damping ratio constraints. These constraints determined the range of the decision variables (controllers' gains).
- A sensitivity analysis was carried out to better understand the nature of the competing objectives and their relation with the decision variables. A number of observations were found for the studied cases. In the non-WIP compensation MPC systems, the minimization of the overshooting objective is more sensitive to the values of the controllers' gains than the minimization of the rise time objective. Also the values of optimal controllers' gains were highly affected by the weights of the objective function.
- In WIP compensation MPC systems, although the competitiveness of both agility objectives was clear with each of the decisions variables individually, when both variables are considered simultaneously the results showed a degree of dominance of inventory gain over the WIP gain and WIP gain over capacity scalability gain.
- In case of Inventory/WIP based MPC systems, when both objectives are given equal weights, the optimal decision is sensitive to the value of the inventory controller gain while the WIP controller gain tends to be at the upper boundary. However, when the responsiveness objective is given a high weight, the inventory controller gain is at its maximum limit while the WIP controller gain is being optimized and the case is reversed between these variables when the cost objective is given a higher weight.
- In the case of capacity/WIP the WIP controller gain is always dominating over the capacity scalability controller gain in the optimization process.
- The previous sensitivity analysis results are very important when considering which MPC policy to adopt and which decision variables are of importance to better control the manufacturing system.

- After deciding on the optimal controllers' settings, the third layer which is called the demand satisfaction check unit takes the responsibility of production control. This control process is based on comparing the current capacity, inventory and WIP levels of the manufacturing system with the reference values of these levels that are continuously calculated based on the demand data. Based on the discrepancy between the compared levels this unit decides on which of the previously calculated optimal gains of each policy to be used and for how long in order to compensate for that discrepancy.
- The output of the DLU is an MPC plan that indicates on a yearly basis which MPC policy to be applied during which demand period of that year and on a monthly basis (interactively with the manufacturing system) which controller gain to be used and for how many days in that month
- The developed agile MPC system approach considers the planning on a monthly level (since it is in the mid managerial level), however the developed model and DLU can be extended with some modification to a daily MPC systems.
- The DLU updates the higher management level with the performance of the manufacturing system and the developed MPC plan. An approach to improve the performance of the agile MPC system in case that the optimal controllers' gains fails to satisfy the market strategy and needs, is by the higher management level to decide to change the MPC system's parameters (lead time, capacity scalability time and shipment time). These decisions involve investments to alter these time variables and also changing market strategies. A natural extension of this research is to study the inclusion of changing these parameters in the optimization process in the DLU.
- The algorithm of the developed DLU was coded using MATLAB computer package. The algorithm efficiency can be improved using other approaches in both pattern recognition adopted in the first layer (to analyze demand pattern) and other optimization techniques than that adopted in the second layer. The comparison of the efficiency of different approaches in the design of the DLU can be carried out in future research.

Chapter Six

Agile MPC Dynamic Model Application and Validation

6.1 Application of the Developed Agile MPC System to Automatic PCB Assembly Industry:

The developed agile MPC system with its decision logic unit (supervisory controller) is illustrated using a real industrial case study in an automatic PCB assembly factory. The objective of this case study is to highlight the applicability of the developed approach in a very turbulent market that can resemble the agile environment which is the electronics market and in a manufacturing system that is an ideal candidate for agile manufacturing which is the automatic PCB assembly line (Deif and ElMaraghy 2006 a and d).

6.1.1 Automatic PCB Assembly Line

Traditional printed circuit board (PCB) automatic assembly line (sometimes called surface mount technology SMT), consists of a loader/unloader magazine for loading the PCB into and from the line, a screen printing machine for printing the solder paste over the PCB to hold the electronic components, automatic pick and place machines to place or assemble the components over the PCB (this is the heart of the line) through different types and sizes of feeders and nozzles, reflow oven for solidifying the solder paste to maintain robust connectivity for the components over the PCB (this is achieved through providing a pre-designed thermal profile) and finally some inspection devices like the ICT (in-circuit tester) inline or at the end of the line.

The automatic assembly process (which constitutes the lead time of the system T_{LT}) simply starts by printing the solder paste (highly conductive martial) over the PCB in the designated solder pads for the of the components, then followed by placing the different components over these pads through the automatic pick and place machines and finally solidifying the viscous paste under the components through the oven to firmly fix the components over the PCB. Inspection and quality checks are carried out in the line and after the assembly process through microscopic or any vision tool to check for the shape and quality of the paste and an in-circuit tester ICT is also used to check for the electronic circuit functionality (open and closed circuits) and the conditions of the assembled components of the assembled PCB. Figure 6.1 is a typical PCB assembly line.

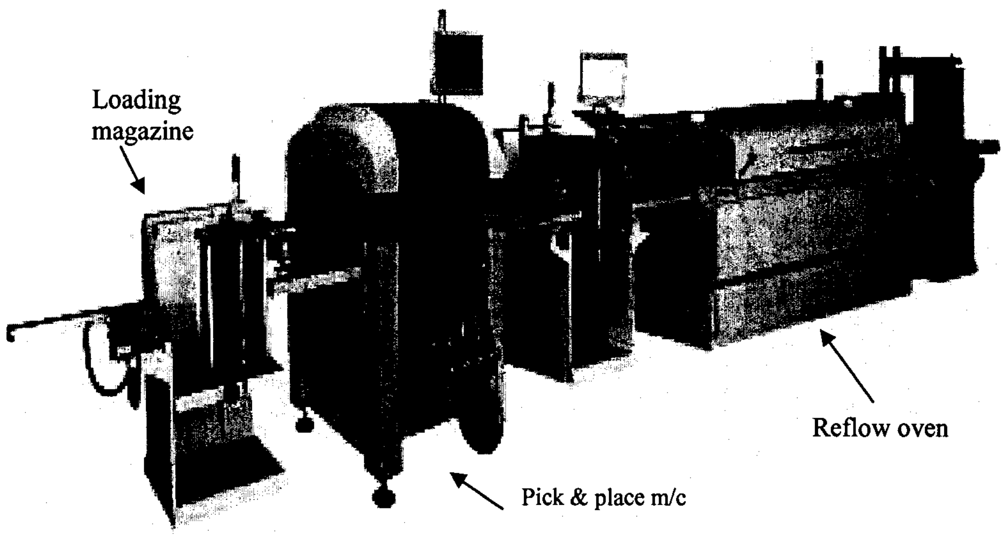


Figure 6.1: PCB Automatic Assembly Line

In a reconfigurable PCB automatic assembly line (which is typical for an agile manufacturing enterprise), the previous components of the line are designed to be reconfigurable. PCB automatic assembly line has great potential for modular design especially for some of its critical parts that will enable the scalability of the line's capacity and functionality. This is why such a system, on the contrary to mass production system, can produce different PCB cards with different volumes.

On the system level, the reconfiguration of these assembly systems would be through the addition or removal of machines. Practically speaking the machines that are added or removed are the automatic pick and place machines as they are the bottle neck of any automatic PCB assembly line. Other types of machines could be added based on the capacity needed. To have a smooth reconfiguration of these lines on the system level, the infra-structure of the line should be also designed to accommodate these changes in terms of the pneumatic and electrical facilities. The ramp up time (which is a major component of the capacity scalability delay time T_D) of the changes of these assembly systems is mainly consumed in aligning the conveyors and the cameras of the installed machines.

On the machine level, the automatic pick and place machines are designed to assemble different types of electronic components and IC chips by its modular design that can accommodate different types of cameras, according to the size of the components and chips and different types and sizes of nozzles to pick these components and chips. Also these machines are designed to assemble different volumes of PCB through adding and removing different numbers and kinds of components feeders. This is assisted by a reconfigurable open control system of those machines that can compensate for these different parts.

The printing machine is also modularly designed to be reconfigured to act as screen printing machine for the solder paste or as a glue dispenser (in case of double PCB side assembly) according to the application by just adding the required dispensing modules.

The reconfiguration of the reflow oven is done through reprogramming the settings of the thermal profile according to the type of the paste and product (logic or soft reconfiguration). For the ICT machine it is reconfigured through modular design of the jigs and testing probes. Finally the material handling devices (loaders, unloaders and conveyors) are sizeable according to the product in the line.

The input for this system is mainly the bare PCB and the surface mount electronic devices SMD together with solder paste required to solder the SMD over the bare PCB. Also some sub-assemblies (partially assembled PCB) can be delivered to the system to complete the assembly process of the PCB. This is important to understand what is meant by increasing the input rate when talking about both inventory and WIP controllers' gain in the developed agile MPC system.

6.1.2 Agile MPC System Applied to an Automatic PCB Assembly Line

The line considered for the application of the developed Agile MPC system is dedicated to assembly of RAM (random access memory) modules; however other computer peripherals can be easily assembled on the same line by some reconfiguration as explained earlier. The RAM module is selected as a product to highlight the application of the agile MPC system in an agile environment since RAM chips are known to be having a very dynamic and unstable market.

The data listed below are real data gathered from an automatic PCB assembly line. The factory considered works for 2 shifts (16 hours) for 20 days per month and the maximum nominal capacity for the existing line is 26K RAM modules per day. However the actual production rate of the current line is 20K RAM modules per day. The products are in the form of panels each panel includes 10 RAM modules. Figure 6.2 shows a sample of the produced RAM modules.

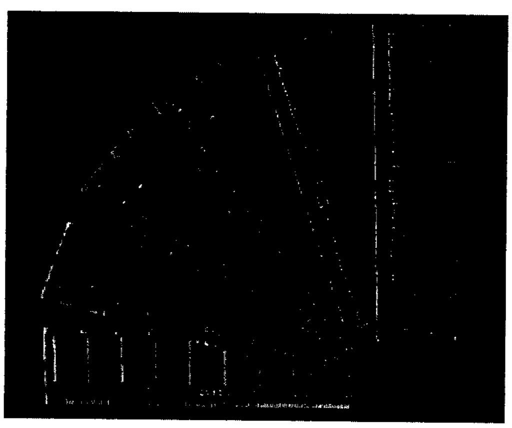


Figure 6.2: Sample of the Produced RAM Modules

6.1.2.1 Input Data for the DLU of the Developed Agile MPC System:

Time Parameters

Lead time (T_{LT}): The assembly line produces the RAM modules in batches of 40K per batch as this is the best scheduling policy with the suppliers in terms of kitting especially the TSOP micro chips of the RAM. Thus the lead time for that line is 2 days.

Capacity scalability delay time (T_D): The main capacity scalability mechanism in this line is the addition of an extra pick and place machine. The average time for installing the machine in the line and calibrating its camera and conveyor with the line's conveyor plus the ramp up time is 3 days (without stopping the line).

Shipment time (T_{SR}): The marketing plan dictates that the factory should ship 100K of RAM modules at least every week. Thus the shipment time is 5 days.

System Limits

Input rate: The maximum input rate that the systems can handle is the difference between the maximum available capacity (26K/day) and the current production rate (20K/day), i.e. 6K/day of RAM modules' raw materials, PCB and SMD components.

Capacity rate: The shop-floor of the factory is composed of 2 lines. Each line contains 4 pick and place machines. The pick and place machines are of two types (2 of each per line); one type is a chip shooter (high capacity) with average production rate of 3.2K/day and another type (medium capacity) with average production rate of 1.8K/day. The factory works 2 shifts/day. Due to space limitations of the shop floor, only one pick and place machine of the medium capacity type can be added for each of the assembly lines. Thus the maximum capacity rate that can be added to the factory is 3.6K/day. The monthly production rate is 400K of RAM (20K/day * 20 days).

WIP: The WIP in the PCB assembly line is mainly bare PCBs ready to be assembled or partially assembled PCBs. These PCB are normally stacked in trays offline ready to feed any starving pick and place machine or waiting for any blocked machine to be empty. The maximum WIP that can be stacked in the trays of the considered PCB assembly line is 2K. Since the lead time of the batch is 2 days, thus the max WIP rate is 1k/day. Also WIP can refer to the assembled RAMs before they are stocked as finished inventory.

Market Strategy

The market strategy reflects the competitive advantage that the enterprise would like to have over a certain period and while adopting a certain MPC policy. The weights of the multi objective optimization function in the second layer of the DLU represent that strategy. In this case study the weight α_C is the weight when capacity based MPC policies are implemented while α_I is the weight when inventory based MPC policies are implemented. Table 6.1 displays the different weights for the two agility objectives with the different MPC policies

MPC Policy	Responsiveness Objective	Cost Objective
Inventory/WIP (α_I)	0.3	0.7
Capacity/WIP (α_C)	0.7	0.3

Table 6.1: Weights of the Multi-objective Optimization Function for each MPC Policy

Another market strategy input required for the implementation of the agile MPC system is the degree of sensitivity to market demand fluctuation. This degree is used by the first layer of the DLU to switch between capacity based MPC policies and inventory based MPC policies through regression analysis of the demand data. In this case study the only capacity/WIP and Inventory/WIP policies are considered (since WIP is important to account for in this type of industry). The maximum accepted regression error that will keep the MPC policy inventory/WIP based policy is 10 % since this reflects a sort of stable market trend. If the error exceeds that limit, the policy is switched to capacity/WIP policy.

Demand Forecast

The higher management layer feeds the DLU with the anticipated yearly demand whether this demand was anticipated by stochastic or deterministic techniques. In this case study the yearly demand similar to a previous year is anticipated as shown in table 6.2. It is important to recall that the developed MPC system is agile enough to respond to any disturbances in these demand values via the different controllers engaged in the agile MPC system.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Demand (in 1000)	400	425	390	410	460	380	300	410	470	400	420	430

Table 6.2: Anticipated Market Demand for the RAM Modules

6.1.2.2 DLU Results (Offline):

The previous input data were given to the DLU (or the supervisory controller) of the developed agile MPC system. The output of the different layers of the DLU, as explained earlier, can be classified into results that are calculated offline and ahead of the production plan while other results are calculated online i.e. during production. The offline results are the outputs from the first two layers indicating which policy to adopt during which months and the optimal controllers' gains values for each MPC policy.

Table 6.3 indicates the MPC policy to be adopted in each month based on the regression analysis of the anticipated demand with the sensitivity to market turbulence indicated by the higher managerial level.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Demand (in 1000)	400	425	390	380	460	380	300	410	470	400	420	430
MPC Policy	Inventory/WIP				Capacity/WIP					Inventory/WIP		

Table 6.3: The Output of the First Layer of the DLU Indicating which MPC Policy to be Adopted each Month

As for the optimal controllers' gains values, the second layer of the DLU calculated the feasible range for these values that satisfy the stability, damping and system's constraints. This was followed by a multi-objective optimization that was carried out to have a value that balanced between the two competing agility objectives with the weights designated for each objective at each MPC policy by the higher management level as explained earlier. The results for each MPC policy are shown in table 6.4.

MPC Policy	Optimal Controllers' Gains Values
Inventory/WIP	$G_I = 5$ K RAM/day
	$G_W = 1$ K RAM/day
Capacity/WIP	$G_C = 3.6$ K RAM/day
	$G_W = 0.8$ K RAM/day

Table 6.4: Optimal Controllers' Gains Values for each MPC Policy as Obtained by the Second DLU Layer

6.1.2.3 Manufacturing System Control (Online):

After determining the policies to be adopted with optimal controllers' gains for each policy, it is the role of the DLU as a supervisory controller to use these results to control the production based on the continuous feedback of the status of the system's parameters. Based on the developed MPC system model, these parameters are mainly the WIP level, inventory level and the production rate. According to the discrepancy in the levels or the backlog from the target levels which are also calculated by the same layer from the demand data, the DLU takes a monthly action to correct or compensate for these discrepancies or backlog. The action is taken each month based on the status of these parameters form the previous month using the previously calculated optimal gains of each policy.

In the considered case study of the RAM assembly lines the production results of a previous year were taken as if they were currently occurring to demonstrate the online action of this layer in the DLU. Results are shown in table 6.5. It is important to notice that there is some rounding off in terms of the compensation for the discrepancy of the different levels in order to stick to the exact optimal value of the controllers' gains as in the case of the last three columns of row six in the table in the inventory/WIP policy (e.g. 2.5 days was rounded to 3 days).

Table 6.5 is considered a summary of all the deliverables of the designed DLU or the supervisory control which is the heart of the developed agile MPC system proposed in this dissertation.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Demand (in 1000)	400	425	390	380	460	380	300	410	470	400	420	430
MPC Policy (offline)	***Inventory/WIP*** $G_I = 5$ and $G_W = 1$				***Capacity/WIP*** $G_C = 3.7$ and $G_W = 0.8$					***Inventory/WIP*** $G_I = 5$ and $G_W = 1$		
MPC Action (online)	I^*=405 WIP^*=40.5				Cap^*=460 WIP^*=46	Cap^*=380 WIP^*=38	Cap^*=300 WIP^*=30	Cap^*=410 WIP^*=41	Cap^*=470 WIP^*=47	I^*=417 WIP^*=41.7		
	Current I = 400	Current I = 400	Current I = 400	Current I = 400	Current PR = 400	Current PR = 380	Current PR = 300	Current PR = 400	Current PR = 400	Current I = 400	Current I = 400	Current I = 400
	Action: G_I (**1**days)	Action: G_I (**1**days)	Action: G_I (**1**days)	Action: G_I (**1**days)	Action: G_C (**13**days)	Action: G_C (**0**days)	Action: G_C (**0**days)	Action: G_C (**3**days)	Action: G_C (**19**days)	Action: G_I (**3**days)	Action: G_I (**4**days)	Action: G_I (**3**days)
	Current WIP = 40	Current WIP = 40	Current WIP = 39	Current WIP = 38	Current WIP = 42	Current WIP = 39	Current WIP = 27	Current WIP = 40	Current WIP = 42	Current WIP = 39	Current WIP = 40	Current WIP = 41
	Action: G_W (**1**days)	Action: G_W (**0**days)	Action: G_W (**2**days)	Action: G_W (**2**days)	Action: G_W (**5**days)	Action: G_W (**0**days)	Action: G_W (**2**days)	Action: G_W (**2**days)	Action: G_W (**6**days)	Action: G_W (**3**days)	Action: G_W (**1**days)	Action: G_W (**0**days)

Table 6.5: The Output of the DLU Unit.

6.2 Verification of Agile MPC Policy Using a Comparative Cost Analysis Approach:

In this section we conduct a cost analysis comparison between different policies to show how each policy, including the agile MPC developed, can handle different demand scenarios for the same discussed industrial case (Deif and ElMaraghy 2006-d). The objective of this comparison is to highlight the efficiency of the developed agile MPC approach and its superiority especially in mixed demand patterns.

The policies considered are inventory based MPC policy, capacity based MPC policy and finally the agile MPC policy (that can adopt both policies when needed). The demand patterns investigated are quasi or semi stable demand (demand with small fluctuations), fluctuating demand and demand patterns that are mix between previous two demands.

6.2.1 Capacity Based MPC Case Cost Calculations

As stated earlier in section 6.1, the normal productivity of the automatic PCB assembly line is 400K of RAM per month using 2 shifts. The available capacity scalability (physical and logical) options are shown in table 6.6:

Capacity Scalability Option	Production Rate (1000 RAM)
Normal (2 lines) with 2 shifts/day	400
1 m/c with productivity of 1.8 K in one line	472
2 m/c with productivity of 1.8 K in each line	544
3 shifts with normal production	600
3 shifts with 1 m/c with productivity of 1.8 K in one line	708
3 shifts with 2 m/c with productivity of 1.8 K in each line	816

Table 6.6: Capacity Scalability Options for the Automatic PCB Assembly Line

The monthly cost for each capacity scalability option will be calculated using Capital Recovery analysis [Fraser et al. 2006]. The input data for this analysis are as follows:

- The capital cost (P) for the smaller m/c (1.8K capacity) is $100,000.
- The interest rate (i) is 1% accumulated monthly.
- Depreciation period (N) is 8 years
- Salvage value (D) will be equal to 10% of the capital cost and the declining balance method will be used to calculate the salvage value.

The monthly cost (A) for having the smaller pick and place (1.8K capacity) machine will be calculated through adding the capital recovery cost minus the sinking fund factor as shown in equation (6.1):

$$A = \left[P\left(\frac{i(1+i)^N}{(1+i)^N - 1} \right) \right] - \left[P(1-D)^N \left(\frac{i}{(1+i)^N - 1} \right) \right] \tag{6.1}$$

From the previous data and using equation (6.1), the monthly cost of this machine will be A = $1300

The cost of each other machine in the line is calculated in the same manner with the same data except for the capital cost for each machine which is as follows:

- Reflow Oven m/c capital cost (P) = $50,000 and A = $650.
- Solder Paste Printing m/c capital cost (P) = $50,000 and A = $650.
- Pick and Place Chip Shooter m/c capital cost (P) = $150,000 and A = $2000.

As for the labour cost, it is $3000/shift each month (1 worker for every line each shift with $1500/month as salary).

The overall monthly cost of normal production for the two PCB automatic lines to produce the 400K monthly based on the previous analysis will be:
$6000 (labor for 2 shifts) + $1300 (2 printing m/c) + $1300 (2 reflow m/c) + $2600 (2 small pick and place m/c) + $4000 (2 chip shooters pick and place m/c) = $15200

Table 6.7 shows the capacity scalability options with the cost of each option based on the previous calculations. It should be mentioned here that these monthly costs reflect the cost of the physical unit only. However a more comprehensive calculation would be through considering the reconfiguration costs (Deif and ElMaraghy 2006(b) and 2007) and the share of each scalability option on the monthly overhead cost of the facility. These considerations are omitted for simplicity and also because they are beyond the scope of this calculation and will not affect the validity of the approach.

Capacity Scalability Option	**Production Rate (1000 RAM)**	**Cost ($)**
Normal (2 lines) with 2 shifts/day	400	15200
1 m/c with productivity of 1.8 K in one line	472	15200+1300
2 m/c with productivity of 1.8 K in each line	544	15200+2600
3 shifts with normal production	600	15200+3000
3 shifts & 1 m/c with productivity of 1.8 K/line	708	15200+4300
3 shifts & 2 m/c with productivity of 1.8 K/line	816	15200+5600

Table 6.7: Monthly Costs for Capacity Scalability Options for the Automatic PCB Assembly Line

The last cost parameter that should be considered in capacity scalability cost analysis is the under-utilized capacity cost or sometimes referred to as capacity loss cost. Although there is no well accredited or standard formula for that cost, however an accepted assumption would be treating the underutilized capacity cost as a holding cost where you pay for the unused capacity portion as function of the overall cost of the capacity unit. For example, in this case, if the monthly capacity scalability cost of adding a pick and place machine is $1300 and the utilized capacity of this machine is only 75% of the overall capacity, then the monthly cost of underutilized capacity would be: (1300/4) = $325.

6.2.2 Inventory Based MPC Case Cost Calculations

In any inventory cost analysis there are three important cost parameters that should be considered. First, is the holding cost which reflects the interest charge for the unsold goods (incorporating costs of capital, taxes, insurance, storage and breakage). Stock out cost or backlog cost is the second cost and it reflects the penalty the manufacturer pay for late delivery to the customer (incorporate the cost of the customer service level) and also the loss of good will cost (reflects the customer dissatisfaction cost). The last cost is the setup cost which is the cost for putting a production order (incorporating management activities, paper work…etc). In this section each cost parameter will be calculated for the purpose of this analysis and further validation analysis using the following data:

- Monthly interest rate for held inventory items (i) is 0.2% (typical value in low interest inventory cases, Nahmias 2001). It is important to note here that this interest value plays a very important role in such cost analysis. Thus the analysis results can be highly altered if this value changes. However, the effect of interest rate variation is a wide research area in the field of economics and beyond the scope of this research.
- Actual cost of the RAM (Pr) is equal to the manufacturing cost + the components' costs (SMD, chips and solder paste). The manufacturing cost can be calculated by dividing the monthly production with monthly cost (from table 6.7): Mfg. Cost = 400000/15200 = $26/RAM.

  The components cost based on the priced bill of material (BOM) is approximately $4/ RAM. Thus the cost of the RAM = $30.
- The average selling price (P_S) of the considered RAM module is $100
- Based on the market strategy and customers contracts, the penalty for instantaneous unmet demand or backlog (P_B) for each RAM module is 0.01% of the selling price.
- Based on the market competitiveness estimations, the estimated cost for loss of good will (C_{LGW}) for instantaneous unmet demand is also 0.01% of the selling price.

- The monthly production order set up cost (K) = \$10/order (\$120 yearly).
- The reference inventory level will be calculated using the classical approach of summing all the anticipated demand over the year and then dividing the total by 12 to have the monthly inventory level as shown in equation (6.2)

$$I^* = \frac{\sum Demand}{12} \tag{6.2}$$

6.2.3 Comparative Cost Analysis Calculations

Based on the previous data for both policies the following cost parameters are calculated to be used later in the analysis of each policy with different demands:

For capacity based MPC policy:

- The cost for capacity scalability each month will be calculated using table 6.7.
- The cost of underutilized capacity will be calculated as stated previously

For inventory based MPC policy

- The holding cost (C_H) will be calculated by first calculating the quantity of un-sold RAM/month (Q_H) and then multiplying this quantity by the holding cost using the following equations:

$$Q_H = Production - Demand \tag{6.3}$$

$$C_H = Q_H * i * Pr \tag{6.4}$$

In this example: $C_H = Q_H*0.002*30$ (6.5)

- The backlog cost (C_B) will be calculated for each month first by calculating the backlog quantity (Q_B) and then multiplying this quantity by the backlog penalty (P_B) and the cost of loss of good will (C_{LGW}) as shown in the following equations:

$$Q_B = Demand - (Production + Q_H) \tag{6.6}$$

$$C_B = Q_B * (P_B + C_{LGW}) * P_S \tag{6.7}$$

In this example: $C_B = Q_B* (0.0001+0.0001)*100$ (6.8)

For Agile MPC policy

As stated earlier, the main philosophy behind the developed agile MPC approach was the ability to deal with all demand patterns through combining the previous two policies and applying the most suitable one to any demand pattern. Thus in this analysis in quasi-stable demand patterns the agile MPC policy will adopt the inventory based MPC policy with all its calculations. In the fluctuating demand the capacity based MPC policy will be adopted. Finally in the mixed demand a mix between the two policies (hybrid policy) will be used in accordance to demand segmentation approach stated earlier. The previous activities are carried out by switching between different controllers in the agile MPC model and being supervised by the first layer in the DLU of the developed approach as explained in details in chapter 5.

The demands patterns considered in this analysis and their values are shown in figures 6.3 to 6.5. Based on the previous cost calculations for each policy and the three considered demand patterns, tables 6.8 – 6.10 were developed to calculate the cost details for adopting each of the previous MPC policies to the different demand patterns.

It is important to note that the mixed demand patterns in figure 6.5 will be divided by the DLU in the agile MPC policy into three zones. The first zone from month 1 to 3 and will adopt inventory based policy since it has a semi-stable trend, the second zone from months 4 to 9 will adopt a capacity based policy due to the clear demand fluctuations and finally the last zone from months 10 to 12 will again adopt an inventory based policy for the same reasons as the first zone. Analysis of these figures leads to the following observations (for the studied and similar cases):

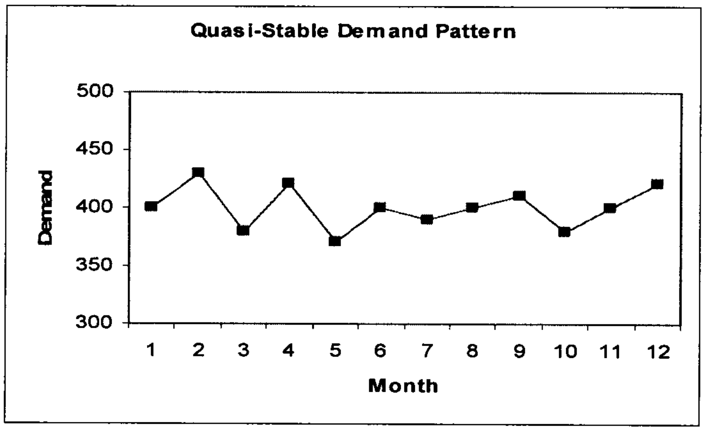


Figure 6.3:Quasi Stable Demand Pattern

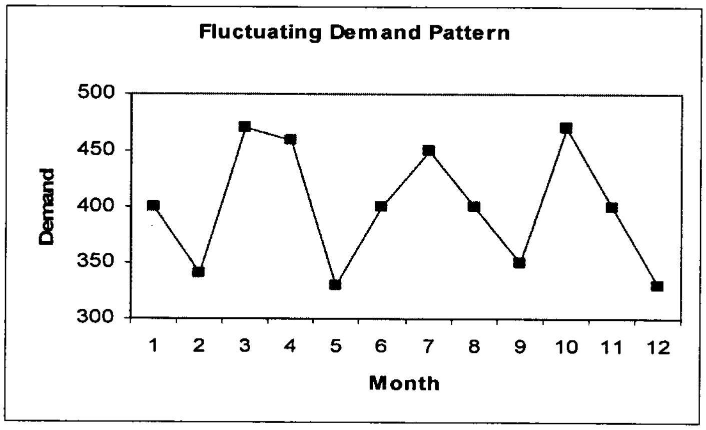


Figure 6.4: Fluctuating Demand Pattern

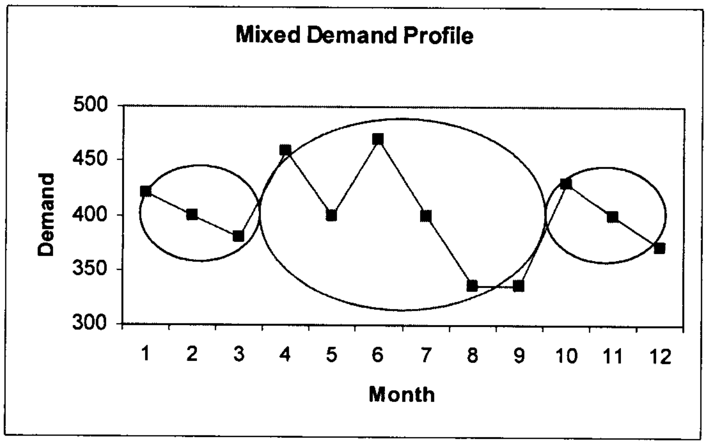


Figure 6.5: Mixed Demand Pattern

	Month	1	2	3	4	5	6	7	8	9	10	11	12	Sub-Total Cost	Total
Policy	**Demand (in 1000)**	***400***	***430***	***380***	***420***	***370***	***400***	***390***	***400***	***410***	***380***	***400***	***420***		
Inventory-Based Only	**Production Rate**	400	400	400	400	400	400	400	400	400	400	400	400		
	Backlog Qty	0	30	10	30	0	0	0	0	0	0	0	0	1400	
	Holding Qty	0	0	0	0	0	0	10	10	0	20	20	0	3600	5000
Capacity-Based Only	**Production Rate**	400	430	380	420	370	400	410	400	390	420	400	380		
	Scaling Cost	0	1300	0	1300	0	0	1300	0	0	1300	0	0	5200	
	Under-utilization Cost	0	800	0	1000	0	0	1200	0	0	1000	0	0	4000	9200
Agile MPC	**Production Rate**	400	400	400	400	400	400	400	400	400	400	400	400		
	Backlog Qty	0	30	10	30	0	0	0	0	0	0	0	0	1400	
	Holding Qty	0	0	0	0	0	0	10	10	0	20	20	0	3600	5000

Table 6.8: Cost Calculation for each MPC Policy with Quasi Stable Demand Pattern

	Month	1	2	3	4	5	6	7	8	9	10	11	12	Sub-Total Cost	Total
Policy	**Demand**	***400***	***340***	***470***	***460***	***330***	***400***	***450***	***400***	***350***	***470***	***400***	***330***		
Inventory-Based Only	**Production Rate**	400	400	400	400	400	400	400	400	400	400	400	400		
	Backlog Qty	0	0	10	70	0	0	50	50	0	70	70	0	7800	
	Holding Qty	0	60	0	0	0	0	0	0	0	0	0	0	3600	11400
Capacity-Based Only	**Production Rate**	400	470	340	460	330	400	450	400	350	470	400	330		
	Scaling Cost	0	1300	0	1300	0	0	1300	0	0	1300	0	0	5200	
	Under-utilization Cost	0	0	0	200	0	0	400	0	0	0	0	0	600	5800
Agile MPC	**Production Rate**	400	470	340	460	330	400	450	400	350	470	400	330		
	Scaling Cost	0	1300	0	1300	0	0	1300	0	0	1300	0	0	5200	
	Under-utilization Cost	0	0	0	200	0	0	400	0	0	0	0	0	600	5800

Table 6.9: Cost Calculation for each MPC Policy with Fluctuating Demand Pattern

Policy	Month	1	2	3	4	5	6	7	8	9	10	11	12	Sub-Total	Total
	Demand	***420***	***400***	***380***	***460***	***400***	***470***	***400***	***335***	***335***	***430***	***400***	***370***		
Inventory-Based Only	**Production Rate**	400	400	400	400	400	400	400	400	400	400	400	400		
	Backlog Qty	20	20	0	60	60	130	130	65	0	30	30	0	10900	
	Holding Qty	0	0	0	0	0	0	0	0	0	0	0	0	0	10900
Capacity-Based Only	**Production Rate**	420	400	380	460	400	470	400	335	335	430	400	370		
	Scaling Cost	1300	0	0	1300	0	1300	0	0	0	1300	0	0	5200	
	Under-utilization cost	1000	0	0	200	0	0	0	0	0	800	0	0	2000	7200
Agile MPC	**Production Rate**	400	400	400	460	400	470	400	335	335	400	400	400		
	Backlog Qty	20	20	0	0	0	0	0	0	0	30	30	0	2000	
	Holding Qty	0	0	0	0	0	0	0	0	0	0	0	0	0	
	Scaling Cost	0	0	0	1300	0	1300	0	0	0	0	0	0	2600	
	Under-utilization cost	0	0	0	200	0	0	0	0	0	0	0	0	200	4800

Table 6.10: Cost Calculation for each MPC Policy with Mixed Demand Pattern

Note:

As mentioned earlier, the calculations can be altered with the variation of the interest rate value for the holding cost. A simple sensitivity analysis was conducted for the results of the previous comparison if the interest rate is changed. Analysis showed that the same results are obtained if the interest rate varies up to 0.5%/monthly and if the rate is over this value then the holding cost becomes very high and capacity based policies would always be better. This analysis however does not affect the conclusion of the ability of agile MPC systems to efficiently handle different demand patterns through adopting different policies.

Figures 6.6 to 6.8 plot the overall costs of each MPC policy with the three considered demands.

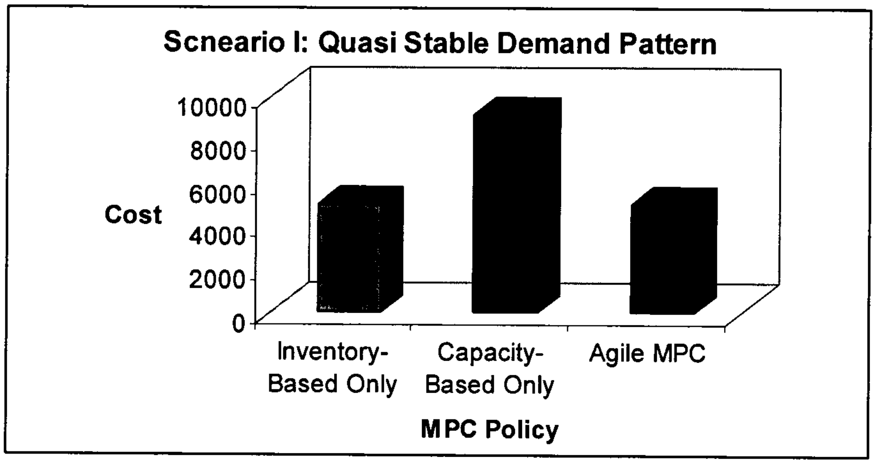


Figure 6.6: Cost of Different MPC Policies with Quasi Stable Demand Pattern

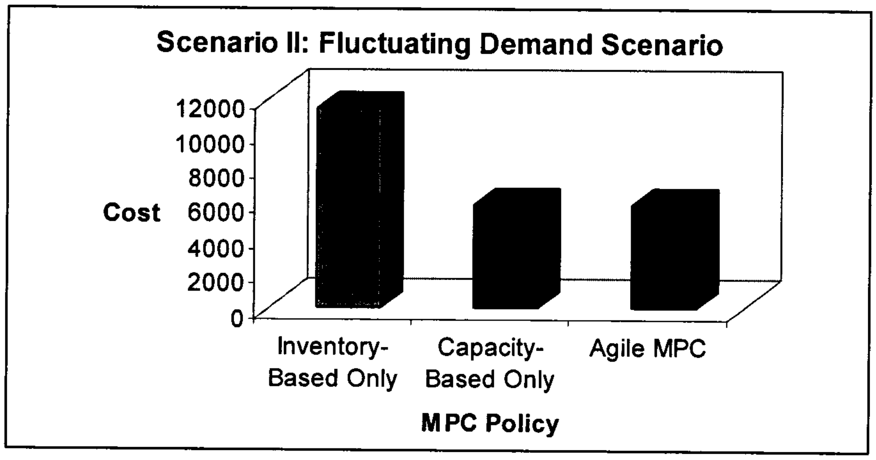


Figure 6.7: Cost of Different MPC Policies with Fluctuating Demand Pattern

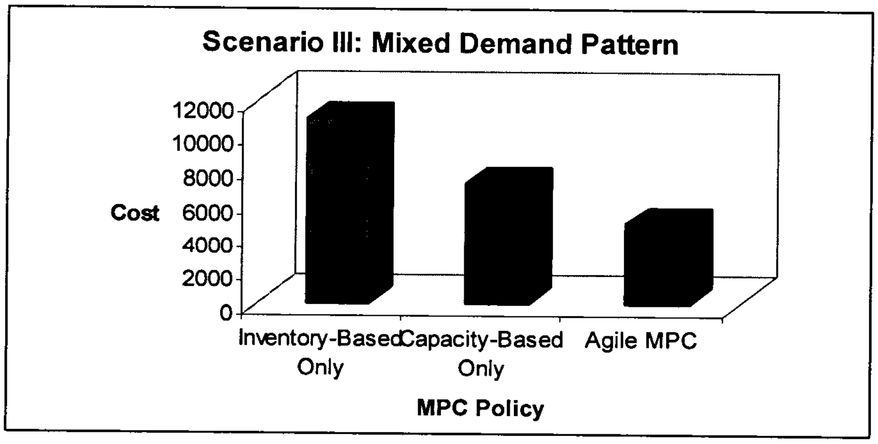


Figure 6.8: Cost of Different MPC Policies with Mixed Demand Pattern

- With quasi-stable demand, inventory based MPC policy shows a better performance in terms of cost since the variations of demand from the target inventory level is limited and thus both the holding cost as well as the backlog cost is minimal. As for the capacity based policy, the cost to handle that demand pattern is quite higher since capacity is usually scaled to high values that need high demand variation to avoid paying for underutilized capacity or capacity loss as in this case.
- With Fluctuating demand, the opposite scenario was found where capacity based MPC policy showed a better cost performance in handling this kind of demand. The reason for that is the huge variation in demand (around 30%) values which justifies the usage of extra capacity (capacity scalability) in cases of demand increase. At the same time, these demand variations lead to high levels of accumulated inventory (holding cost) and sometimes shortage in the level of available inventory (backlog cost) leading to higher cost for inventory based policy.
- The developed agile MPC approach showed the best performance all over the three considered demand patterns. In quasi stable demand pattern the agile MPC approach adopted an inventory based policy by engaging the inventory controller and this is why it was as cost efficient as the classical inventory based policy. In fluctuating demand, the DLU of the agile MPC approach disengaged the inventory control and switched to the capacity controller to have the same cost effective performance as the typical capacity based MPC policy. However, in the mixed demand pattern, the agile MPC approach was far superior to the other two policies due to its ability to handle each period in the demand pattern with the suitable policy manipulating its switching ability between different controllers as explained in chapter 5 while talking about the first layer of the designed DLU.

The cost analysis conducted in this section verified the fundamental philosophy of agile MPC system proposed in this dissertation by showing that in a typical dynamic market environment, MPC system should maintain its agility by the ability to efficiently react to different demand patterns. Also the analysis validated the ability of the algorithm of the first layer in the developed DLU of the model to handle different demand patterns and to switch between different controllers (switching protocol).

6.3 Validation of Inventory Based Policy in the Developed Agile MPC System through Comparison with Traditional EOQ Approach:

The previous section verified in a general sense the use of the developed agile MPC approach. In this section the validation process will take more in depth approach where the performance of the inventory based MPC policies in the agile MPC approach will be compared with the most famous inventory based policy known as Economic Order Quantity (EOQ) approach [Hanssmann 1961, Wagner 1962 and Scarf et al. 1963].

6.3.1 Comparison Data

The data considered for this analysis will depend mostly on the same data of the previous section for the automatic PCB assembly line. The data are as follows:

- Annual interest rate (i) = 10% (0.85 % monthly)
- Cost of the RAM module (Pr) = $30
- Selling price (Ps) = $100
- Setup cost (K) = $120/year ($10/month)
- Penalty for backlog (P_B) = 0.25% of the RAM selling price/RAM
- Cost of loss of good will (C_{LGW}) = 0.25% of the RAM selling price/RAM
- Demand over the year in 1000 RAM [D] = [400, 380, 360, 400, 380, 380, 360, 360, 380, 400, 380, 350]. $\Sigma D = \lambda = 4510k$

6.3.2 Comparison Calculations

The EOQ Model:

The EOQ model is the simplest and the most fundamental of all inventory models. It describes the trade off between fixed order costs and holding costs and it is usually used to calculate the quantity of inventory which the company should always order to maintain the required service level. In MPC field, the EOQ model is usually used to indicate the target inventory level and sometimes applied to calculate the desired production rate.

In this analysis the EOQ model will determine the required inventory level (I^*) based on the previous data and then two scenarios will be considered. The first scenario adopts inventory based policy to satisfy the required demand and the second scenario will adopt inventory based policy using the developed agile MPC system (incorporating inventory controller). The analysis will show the difference in the overall cost efficiency between adopting the EOQ model only and when this model is adopted through the agile MPC system to show the superiority of the developed agile MPC policy over the classical inventory approach.

The economical order quantity (or the target inventory level in our case) is determined using equation (6.9):

$$EOQ = I^* = \sqrt{\frac{2K\lambda}{h}} \; where\; h = (i * \Pr) \tag{6.9}$$

Using the available data:

$$I^* = \sqrt{\frac{2*120*4510000}{3}} \approx 19k \text{ RAM} \tag{6.10}$$

The above values are calculated based on the annual data. To calculate the required monthly inventory levels, we need first to determine the cycle time over the year using equation (6.11)

$$T = \frac{I^*}{\lambda} = \frac{19K}{4510K} = 0.0045 \text{ year} \tag{6.11}$$

No. of production days = 20 days/month * 12 =240 days/year (6.12)

Multiplying equations (6.11) and (6.12) it is found that the daily required inventory level is 19K RAM and thus the average monthly inventory level required will be equal:

$$I^*_{monthly} = 19 * 20 = 380K \text{ RAM} \tag{6.13}$$

The EOQ augmented with the Agile MPC Model (Agile EOQ):

The previous EOQ model will be augmented with the developed agile inventory based MPC policy. This means that the EOQ model will be used to calculate the required inventory level and the inventory controller will account for the positive deviation or backlog between the demand and the calculated inventory level through the gain G_I (note that in this analysis, G_I can't take negative values due to stability constraints).

The optimal value for G_I will be calculated by the second layer in the DLU of the Agile MPC system. The management policy in the inventory based MPC system (as stated in chapter 5) will give cost a higher weight than responsiveness in the multi-objective optimization process ($\alpha = 0.3$). The value of the optimal inventory gain delivered by the DLU based on all previous data and utilizing the developed multi-objective optimization algorithm is G_I=0.8K RAM/day. The calculation of the monthly holding and backlog costs are based on the equations listed in section 6.2.3 as follows:

$$C_H = Q_H * 0.0085 * 30 \tag{6.14}$$

$$C_B = Q_B * (0.0025 + 0.0025) * 100 \tag{6.15}$$

The analysis will consider the previous models with two market scenarios. The first scenario will assume the anticipated demand information was perfect, and the second scenario will assume that there was an error in this information (imperfect anticipation) with a value of 5% extra than the original data. The second scenario is very likely to happen in an agile environment and this is why it will give a good indication of the efficiency of both models in dealing with such environment.

6.3.3 Comparison's Results and Analysis

Tables 6.11 to 6.14 display the cost calculations for each scenario. Figures 6.9 and 6.10 show the costs of the inventory policy of each model.

Demand	400	380	360	400	380	380	360	360	380	400	380	350	Total	Sub-total Cost	Total Cost
EOQ	380	380	380	380	380	380	380	380	380	380	380	380			
Holding Qty	0	0	0	0	0	0	0	20	20	0	0	30	70	17500	
Backlog Qty	20	20	0	20	20	20	0	0	0	0	0	0	100	50000	67500

Table 6.11: Cost Calculations for EOQ Model with Perfect Anticipated Demand Information

Demand	400	380	360	400	380	380	360	360	380	400	380	350	Total	Sub-total Cost	Total Cost
EOQ	380	380	380	380	380	380	380	380	380	380	380	380			
Holding Qty	0	0	20	0	0	0	20	40	40	20	20	50	210	52500	
Backlog Qty	4	0	0	0	0	0	0	0	0	0	0	0	4	2000	54500
No. of Days for G_l	20	5	0	0	0	0	0	0	0	0	0	0			

Table 6.12: Cost Calculations for Agile EOQ Model with Perfect Anticipated Demand Information

Demand	420	400	378	420	400	400	378	378	400	420	400	368	Total	Sub-total Cost	Total Cost
EOQ	380	380	380	380	380	380	380	380	380	380	380	380			
Holding Qty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Backlog Qty	40	60	76	116	136	156	154	152	172	212	232	220	1726	863000	863000

Table 6.13: Cost Calculations for EOQ Model with Imperfect Anticipated Demand Information (5% Demand Increase)

Demand	420	400	378	420	400	400	378	378	400	420	400	368	Total	Sub-total Cost	Total Cost
EOQ	380	380	380	380	380	380	380	380	380	380	380	380			
Holding Qty	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Backlog Qty	24	28	10	34	38	42	24	6	10	34	38	26	314	157000	157000
No. of Days for G_l	20	20	20	20	20	20	20	20	20	20	20	20			

Table 6.14: Cost Calculations for Agile EOQ Model with Imperfect Anticipated Demand Information (5% Demand Increase)

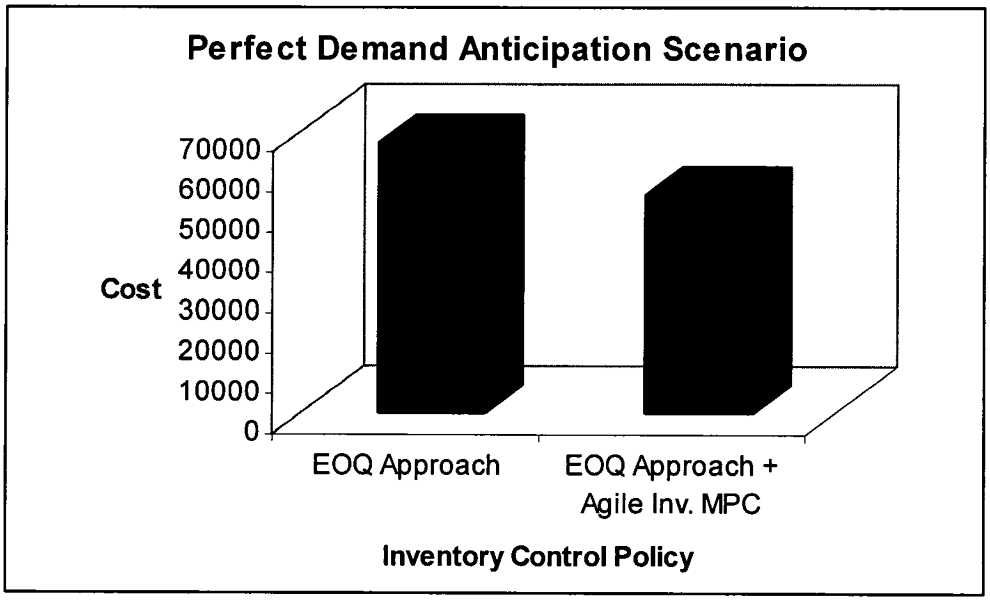


Figure 6.9: Cost of EOQ and Agile EOQ Inventory Control Policies with Perfect Demand Anticipation Scenario

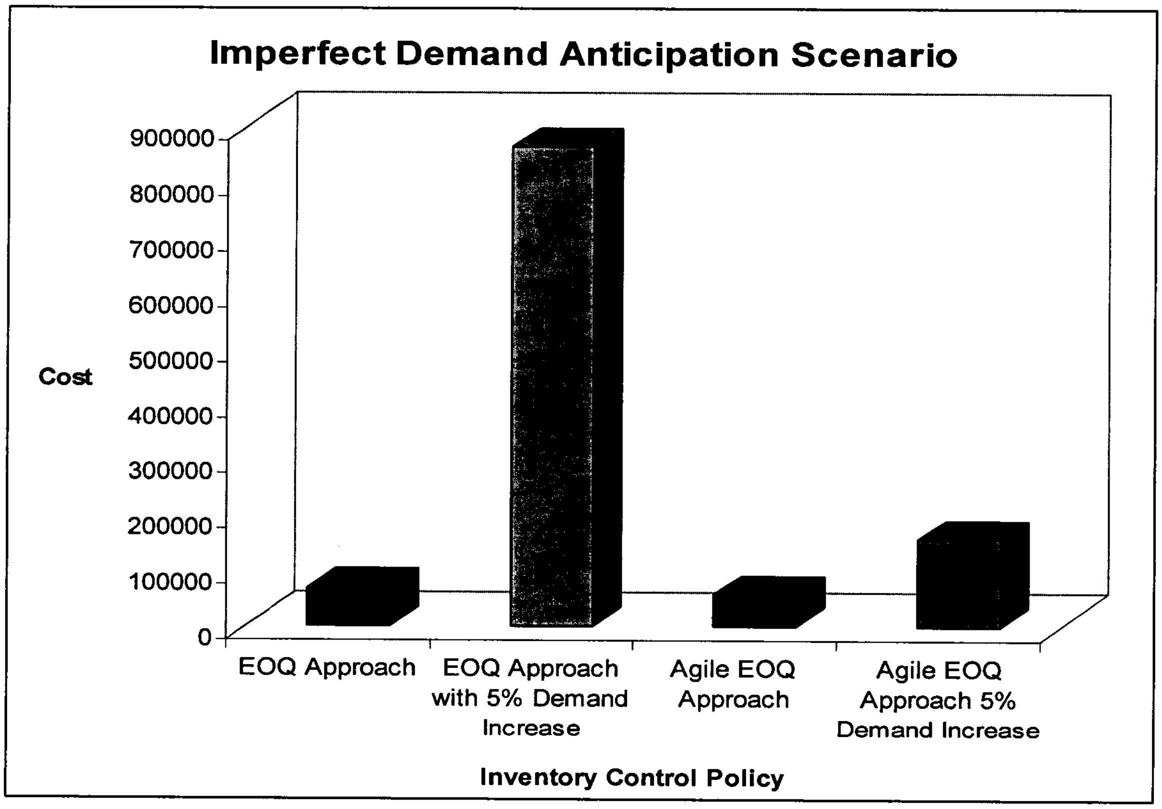


Figure 6.10: Cost of EOQ and Agile EOQ Inventory Control Policies with Imperfect Demand Anticipation Scenario

Analysis of the previous figures reveals the following observations (for the studied and similar cases):

- The EOQ with the Agile MPC model (Agile EOQ) is more cost effective due to the ability to decrease the backlog quantity using the inventory controller.
- The EOQ model was significantly in-efficient in dealing with imperfect demand anticipation information. The extra costs that the EOQ model showed when subjected to 5% increase in demand was over 12 times more than the original cost. This is due to the high cost of the backlog penalty. In market environment where backlog is accepted or has a low penalty, this extra cost would have been much less.
- The Agile EOQ model showed a clear ability to handle imperfect demand anticipation and sudden increase in demand in an acceptable cost effective way. In the previous example the increase in cost was 3 times less than that of the original cost.
- The conducted comparison revealed that the inventory based policy in the developed agile MPC system is better than the classical EOQ inventory based policy which validates the efficiency proposed approach.

Before ending this section, it is important to note that the results of the previous analysis can be altered when considering different parameters especially the interest rate value and both the costs of backlog penalty and loss of good will cost. However, this does not affect the objective of this analysis which was to show the efficiency of the developed approach compared with classical approaches.

6.4 Validation of Capacity Based Policies in the Agile MPC System using Numerical Simulation of Exogenous and Endogenous Disturbance Scenarios:

In the previous section, the efficiency of the inventory based policy in the developed agile MPC system was validated. To complete the validation of the efficiency of the developed agile MPC, the capacity based policies should also be investigated. In this section, numerical simulation experiments are conducted to examine the efficiency of these policies in different exogenous and endogenous disturbances (Deif and ElMaraghy 2007 a and b).

It is important to note that numerical simulation is favoured to classical discrete event simulation (DES) in this analysis due to the level of abstraction of the model which is oriented to the tactical level. The tactical and strategic levels of MPC systems are rather simulated with continuous approaches because they offer a better understanding of the complex dynamic behaviour and show the impact of decisions on the enterprise level. The DES systems would have been a better option if the proposed agile MPC model deals with the operational level since DES systems require various detailed data about the machines and other equipments.

The use the commercial PPC package "SAP AG" in this simulation analysis was explored, however, it was disregarded due to the fact that "SAP AG" is suitable only for the workflow analysis on the shop floor level not on the aggregate level of the proposed approach.

For the purpose of this analysis and in the considered case study, a typical exogenous disturbance would be a "rush order" scenario while the endogenous disturbance would be represented by a machine failure scenario. The manufacturing system will be subjected to a sudden change in demand due to rush order or a sudden drop in capacity rate due to machine failure and it is required to respond to these changes. A simulation comparison will be held between systems with no controlled capacity scalability and system implementing the agile capacity based MPC policy. This comparison will be carried out for both agile MPC capacity based policies that account and does not account for WIP.

6.4.1 Numerical Simulation Data

The data used in this experiment is mainly based on the same case study conducted in this chapter for the automatic PCB assembly factory. However, we will consider different time variables for each agile capacity based MPC policy to test for different cases. The data are as follows:

- Normal capacity (or production rate PR): 20K RAM/day
- Demand rate: 19K RAM/day.
- Capacity utilization level (based on demand) is 95%.
- Capacity scalability delay time (T_D) for capacity based MPC policy = 2 days and for capacity/WIP = 3 days.
- Production lead time (T_{LT}) for capacity based MPC policy = 1 day and for capacity/WIP = 2 days.
- Target WIP level = PR * T_{LT} = 20*2 =40K RAM
- The market strategy gives responsiveness and cost equal weights, thus $\alpha = 0.5$
- The optimal capacity scalability gain (G_C) delivered by the second layer in the DLU of the agile MPC system was calculated to be 1.5K RAM/day for capacity based MPC policy and for capacity/WIP based MPC policy it was 3.6K RAM/day

6.4.2 Numerical Simulation Algorithm

The numerical simulation algorithm was developed and coded using VISUAL BASIC language. The flowcharts for the used algorithms for different scenarios are shown in figures 6.11 to 6.14.

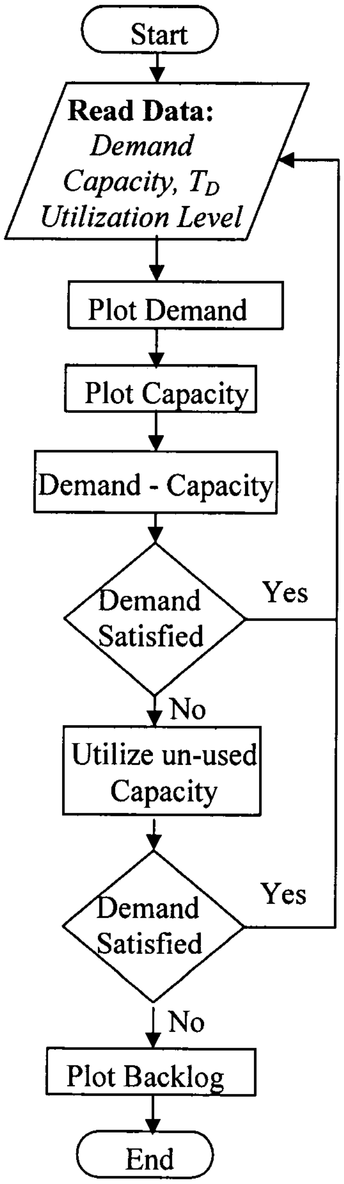


Figure 6.11: Flowchart for Uncontrolled Capacity Based MPC System Simulation

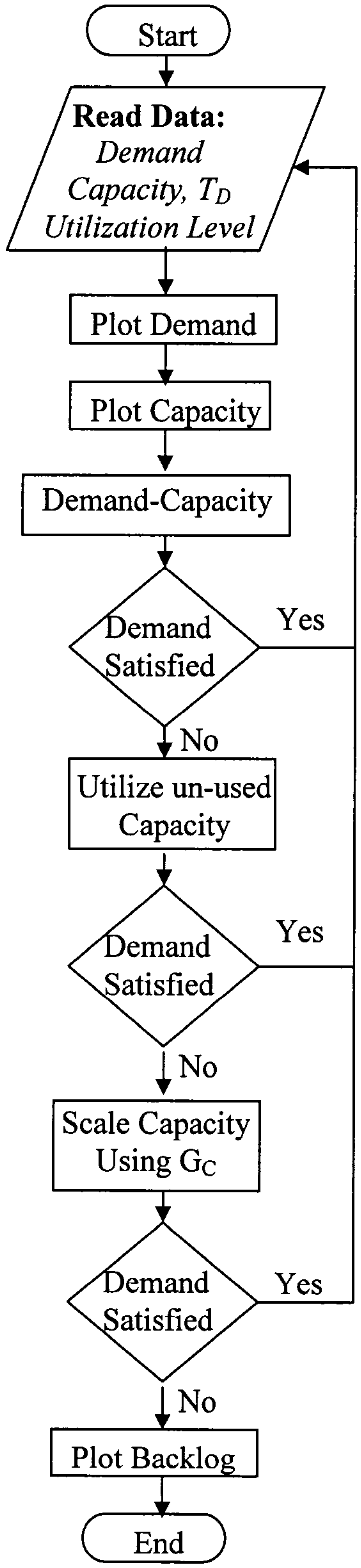


Figure 6.12: Flowchart for Controlled Capacity Based MPC System Simulation

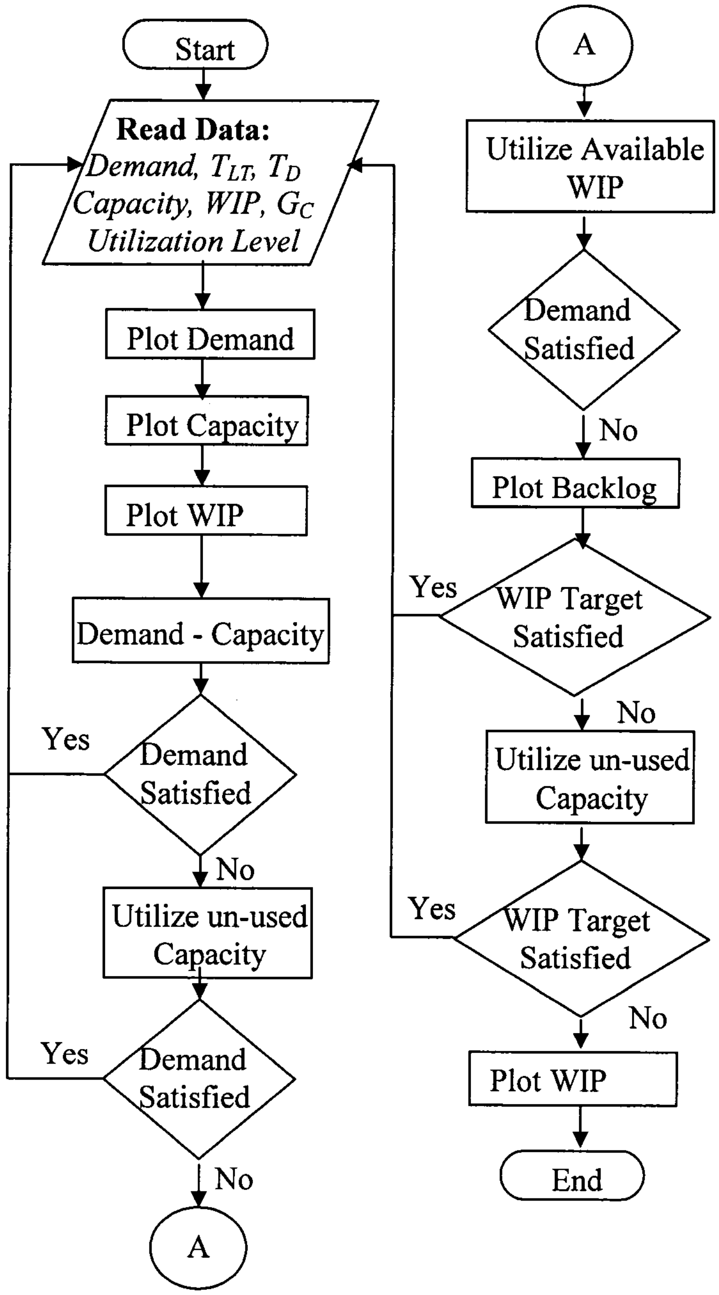


Figure 6.13: Flowchart for Uncontrolled Capacity/WIP Based MPC System Simulation

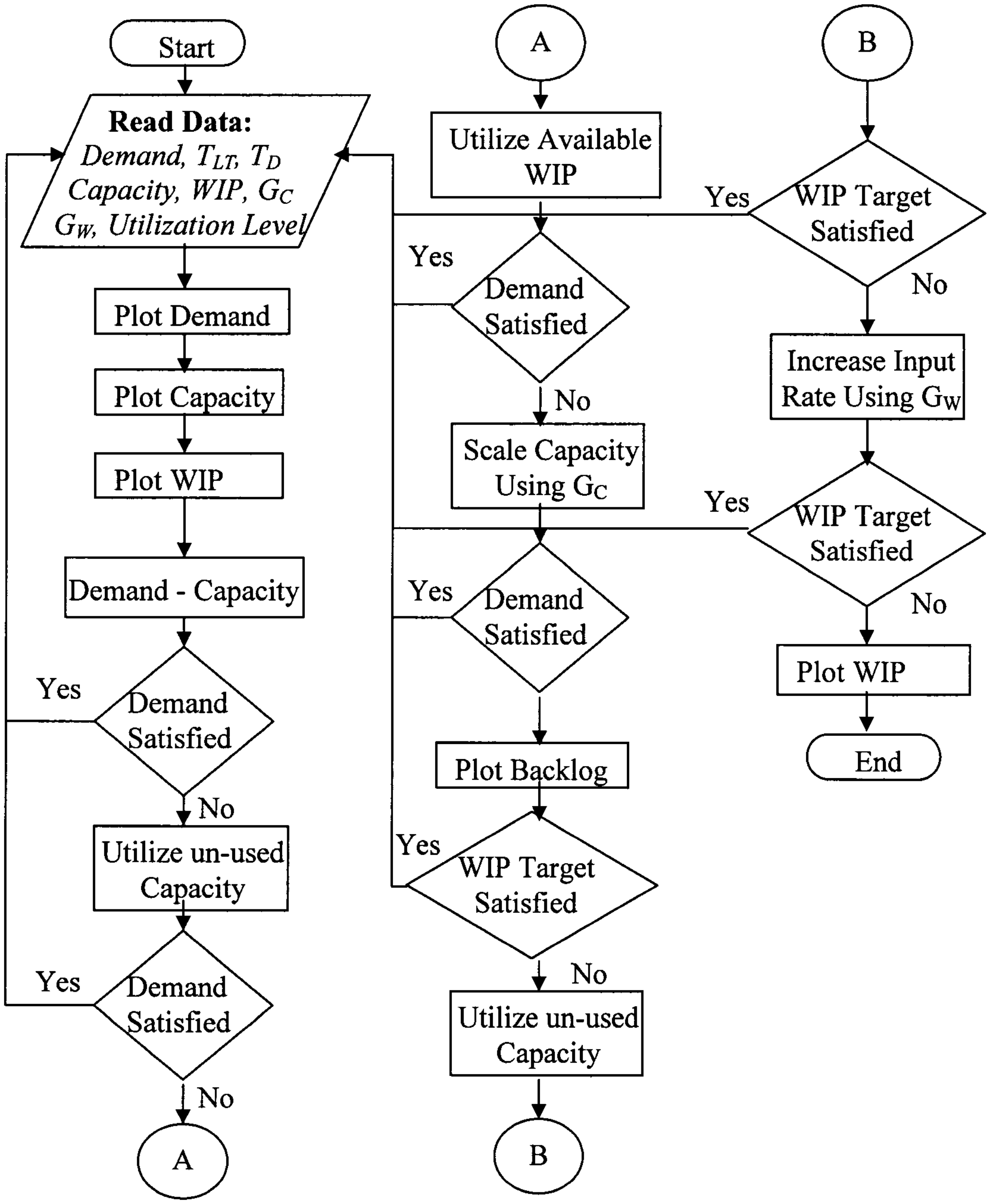


Figure 6.14: Flowchart for Uncontrolled Capacity/WIP Based MPC System Simulation

A sample of the GUI (graphical user interface) for the developed numerical simulation is shown in figure 6.15. The developed simulation gives the user flexibility to change any of the developed capacity based MPC system's parameters. The results of the different scenarios were plotted in the following figures using EXCEL for clarity.

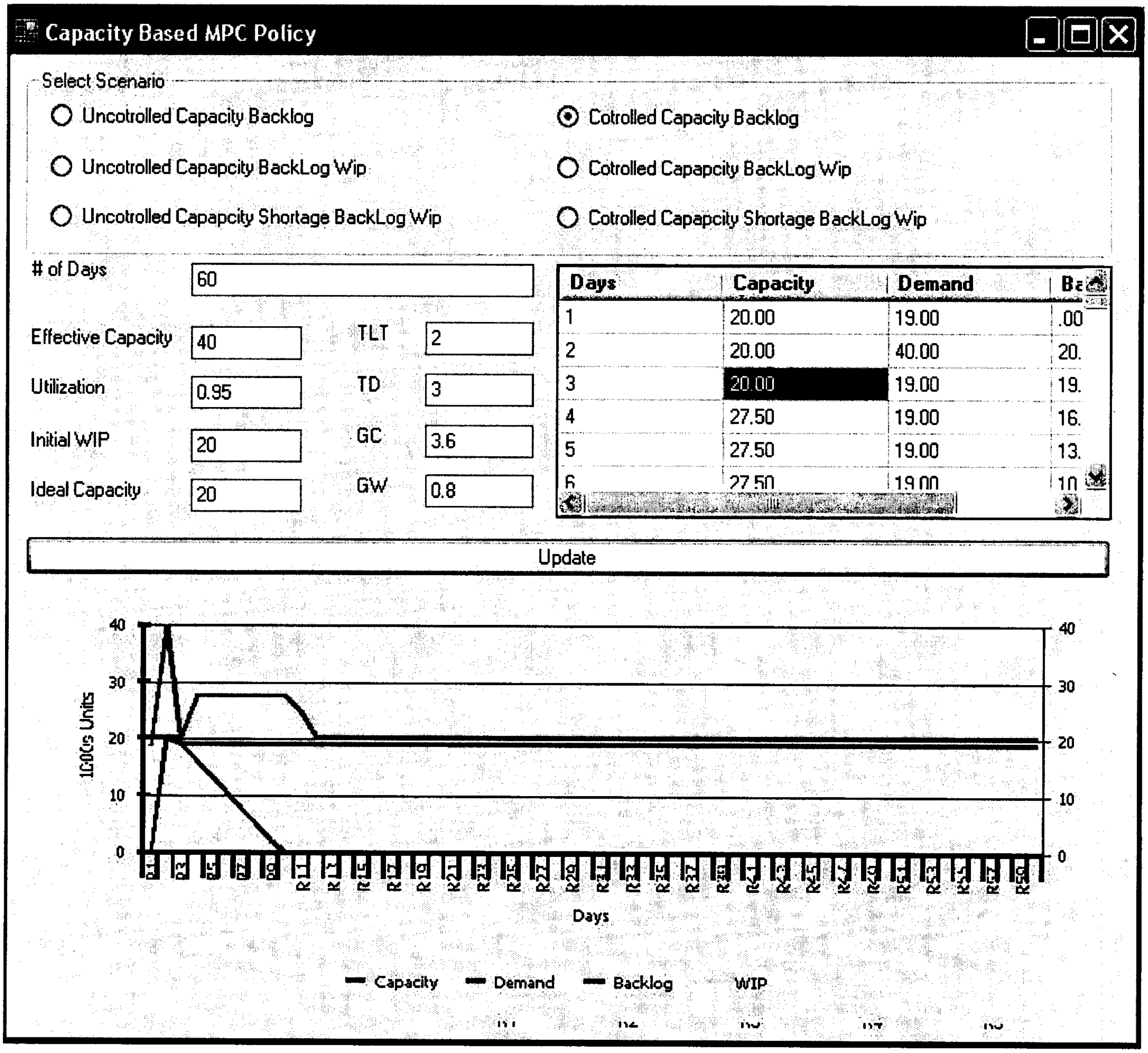


Figure 6.15: GUI of the Developed Simulation Algorithm using Visual Basic

6.4.3 Numerical Simulation Results and Observations

The previous data and the developed simulation package were used to produce the simulation comparison results. Figures 6.16 and 6.17 compare between the cases of uncontrolled and controlled (agile MPC system) capacity policies when subjected to rush order. Analysis of the two figures reveals the following observations (for the studied and similar cases):

- The uncontrolled capacity based MPC system needed 19 days to balance the disturbance and eliminate the backlog caused by the rush order. The controlled capacity based MPC system needed 9 days to respond to the same rush order.
- The unplanned short term with high priority demand (rush order) is very likely to happen in an agile environment and thus it gives a very good indicative about the agility of the system. Based on this fact together with the previous observation, it is clear that developed controlled capacity based MPC system is more agile than normal capacity based MPC systems.
- The controlled capacity required the application of the controller gain G_C for 7 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding temporarily one small pick and place machine as indicated in table 6.5.
- The controlled capacity based MPC system reacted two days later after the rush order due to capacity scalability delay time. The responsiveness of the system can increase if this delay time decrease as stated in the analysis of chapter four and in Deif and ElMaraghy (2006-b)
- If the system was driven with higher utilization it would have taken the uncontrolled capacity based MPC system much more time to eliminate the backlog. This is important to note when enterprises are considering high utilization strategies versus slack capacity strategies in agile environment and also highlights the importance of adopting the developed agile capacity based MPC system with such strategies.

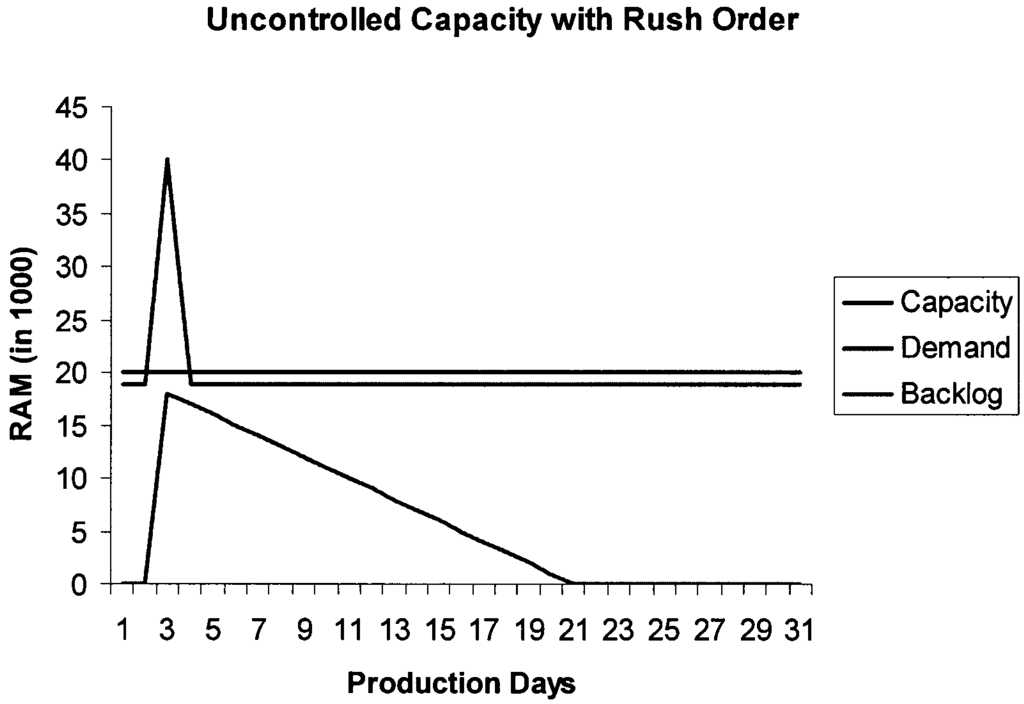


Figure 6.16: Uncontrolled Capacity with Rush Order

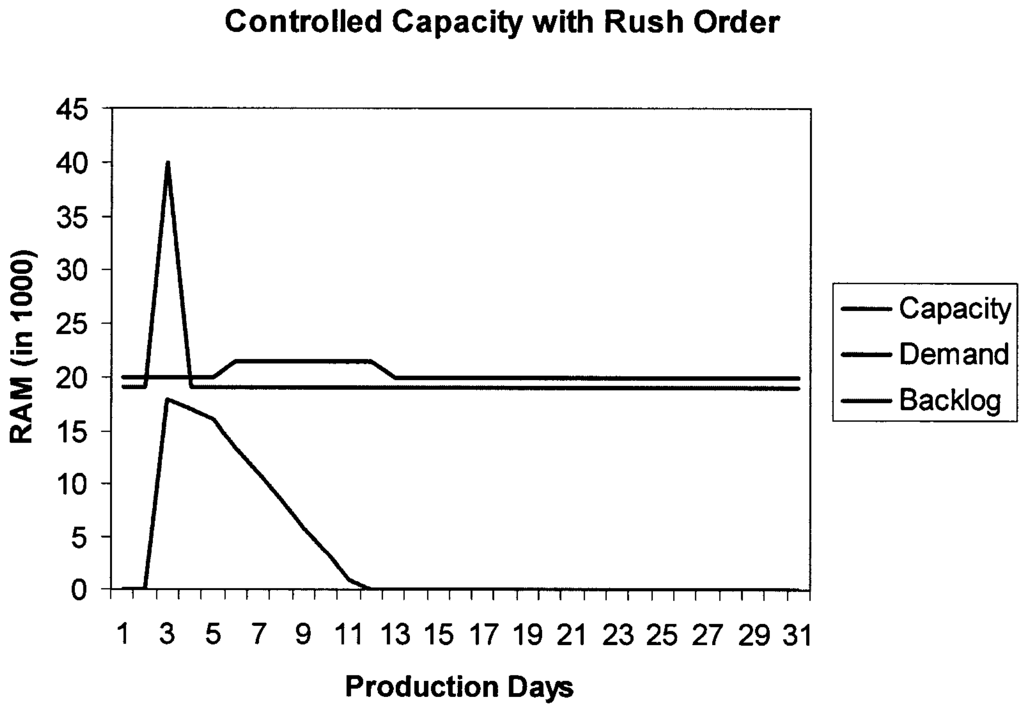


Figure 6.17: Controlled Capacity with Rush Order

Comparing the Developed Capacity Based Agile MPC Model with another PPC Model in a Similar Environment:

To validate the developed capacity based MPC policy and its simulation, they are compared with the simulation results of another PPC model developed by (Wiendahl and Breithaupt 2000) in a similar environment of sudden rush order.

Comparison Validity:

In order to judge on the comparison as a fair one we need to examine how similar both systems are in terms of their parameters and the approach for capacity scalability. Table 6.15 compares both systems:

Comparison item	Developed agile capacity based MPC system	PPC system by (Wiendahl and Breithaupt 2000)
System Structure	Based on feedback control theory.	Based on feedback control theory.
System Parameters	T_{LT} = 1 day. T_D = 2 days. Utilization level: 87%.	T_{LT} = 1 day. T_D = 2 days. Utilization level: 87%.
Controlled Parameters	Backlog: Difference between demand and capacity.	Backlog: Difference between demand (reflected in WIP level) and capacity.
Units of Capacity	Time (in days)/ Production units	Time (in days)/ Production order
Capacity Scalability Approach	As discussed earlier, the capacity scalability controller gain is based on an optimal trade-off between responsiveness and cost of excess production. In this case G_C = 1.5 orders/day.	In their approach they try to balance between responsiveness and cost of supplying excess capacity (cost of un-utilized capacity). In this case G_C = 2 orders/day.

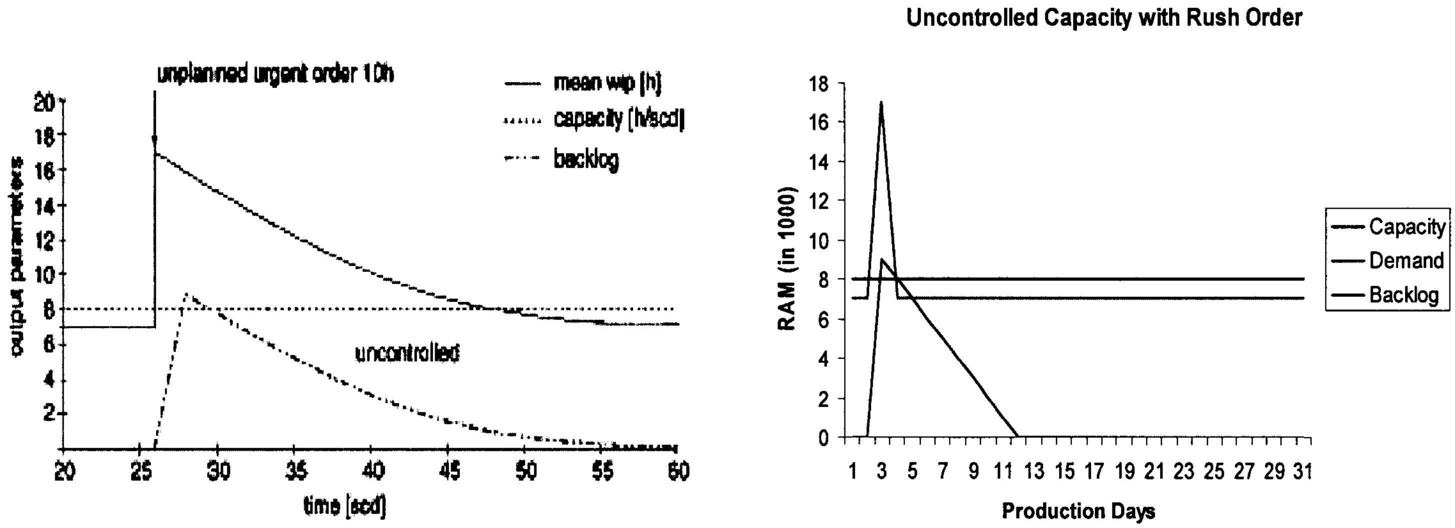
Table 6.15: Comparison between Capacity Based Agile MPC System and PPC System Developed by (Wiendahl and Breithaupt 2000)

On the other side, the differences between both systems are mainly the following:

- The techniques for deciding on the value of G_C are different. In the developed agile MPC systems, multi objective optimization technique is conducted by the DLU to balance between responsiveness and partial cost. While for the PPC model by (Wiendahl and Breithaupt 2000), a backlog controller decides on the value of G_C based on flexibility curves that were discussed earlier in chapter two which indicates the capacity scalability level with its associated reaction and delay times.
- The general control strategy adopted in both systems is different. In the developed capacity based agile MPC system the DLU hold the demand data and compares the current production rate with the required demand and based on the difference a decision to scale the capacity is taken. In the PPC model by (Wiendahl and Breithaupt 2000) the demand is translated into a WIP level. The WIP controller decides on the release of the orders based on the WIP level and that level can be altered by scaling the capacity by a capacity controller. The previous strategy is explained in the funnel model by (Wiendahl and Breithaupt 1999) in chapter 2.

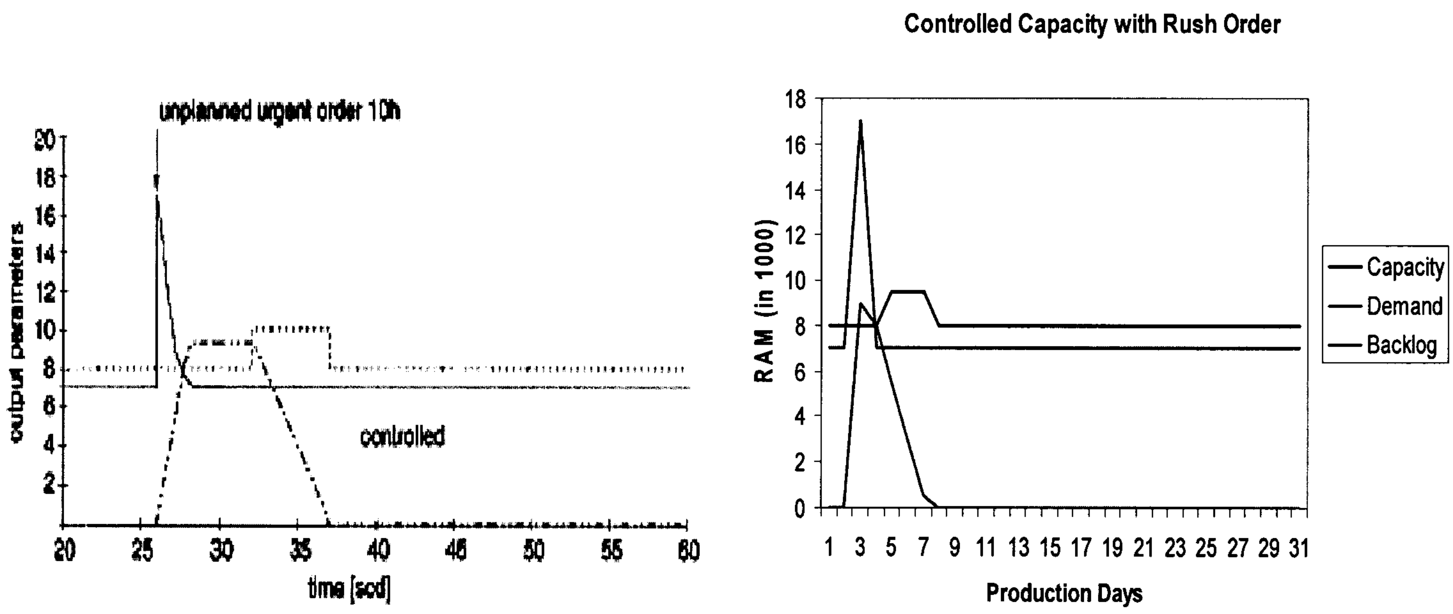
The simulation results of both systems in a rush order environment are shown in figure 6.18 for the uncontrolled case and in figure 6.19 for the controlled case. Analysis of both figures reveals two observations:

- The results in a holistic sense look similar. This can be considered a validation for the developed capacity based agile MPC model and the developed simulation.
- The developed agile MPC system in this scenario has a better performance than the PPC system by (Wiendahl and Breithaupt 2000) in terms of time required for eliminating backlog (6 days in case of the agile MPC and 10 days in the other PPC system). However, this can not be an absolute judgment due to the differences in the control strategy and system structure as discussed earlier.



(a) (b)

Figure 6.18: Backlog due to Rush Order in both (a) PPC system by (Wiendahl and Breithaupt 2000) and (b) Capacity based Agile MPC System with Uncontrolled Capacity Scalability



(a) (b)

Figure 6.19: Backlog due to Rush Order in both (a) PPC system by (Wiendahl and Breithaupt 2000) and (b) Capacity based Agile MPC System with Controlled Capacity Scalability

Figures 6.20 and 6.21 compare between the cases of uncontrolled and controlled (agile MPC system) capacity/WIP policies when subjected to rush order. Analysis of the two figures reveals the following observations (for the studied and similar cases):

- The uncontrolled capacity/WIP based MPC system also needed 19 days to balance the disturbance and eliminate the backlog caused by the rush order. The controlled capacity/WIP based MPC system needed 9 days to respond to the same rush order. This validates again the agility of the developed agile MPC system.
- Although the rush order in this scenario was double the amount of the previous scenario, the backlog was eliminated in equal time. This is due to the existence of WIP in the system which absorbed an amount of the required demand. This conclusion confirms the damping effect of the WIP and highlights the importance of accounting for WIP in a turbulent demand environment when stability of the system is of concern.
- The uncontrolled capacity/WIP based MPC system needed 57 days to recover the WIP level to its target value. The controlled capacity/WIP based MPC system needed 50 days to get back to the same level. This time difference (due to WIP controller gain G_W contribution) validates again the agility of the developed agile MPC system and its ability to perform better in changing demand environment.
- The controlled capacity required the application of the controller gain G_C for 4 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding 2 small pick and place machines as indicated in table 6.5.
- Same observations in the previous scenario can be stated for the effect of utilization level and capacity scalability delay time on the responsiveness level of the manufacturing system.

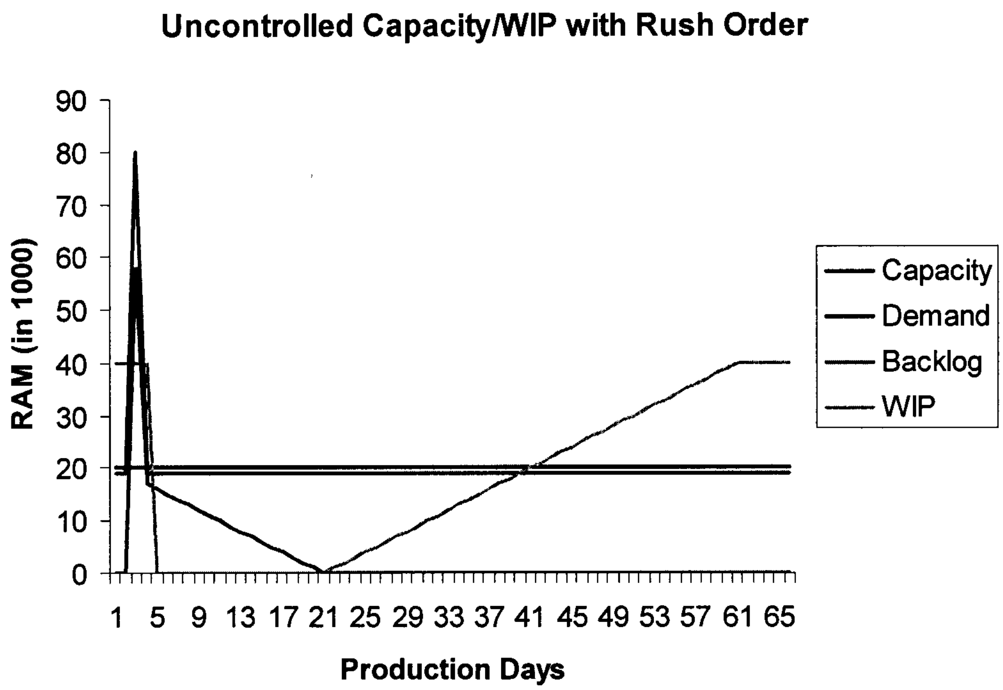


Figure 6.20: Uncontrolled Capacity /WIP with Rush Order

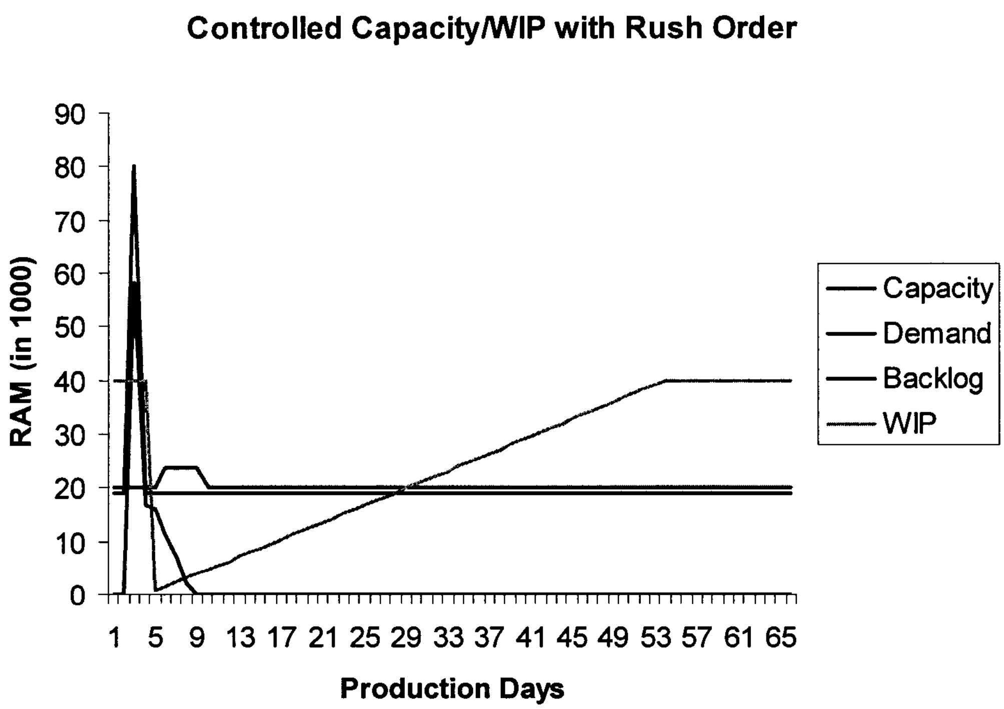


Figure 6.21: Controlled Capacity/WIP with Rush Order

Figures 6.22 and 6.23 compare between the cases of uncontrolled and controlled (agile MPC system) capacity/WIP policies when subjected to machine failure for 1 week (5 days) with different lead time (T_{LT} = 1 day). Analysis of the two figures reveals the following observations (for the studied and similar cases):

- The uncontrolled capacity/WIP based MPC system needed 30 days to balance the disturbance and eliminate the backlog caused by the machine failure. The controlled capacity/WIP based MPC system needed 19 days to respond to the same problem indicating higher level of agility.
- The role of WIP in damping such internal disturbances is very clear as it eliminated the backlog for the first two days. However, the backlog level was raised again due to the long time of the machine failure. Accounting for WIP is crucial for manufacturing stability.
- The uncontrolled capacity/WIP based MPC system needed 46 days to recover the WIP level to its target value. The controlled capacity/WIP based MPC system needed 25 days to get back to the same level. This time difference (due to WIP controller gain G_W contribution) validates again the agility of the developed MPC system and its ability to perform better in turbulent manufacturing environment.
- The controlled capacity required the application of the controller gain G_C for 3 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding 2 small pick and place machines as indicated in table 6.5.
- Capacity scalability delay time in cases of machine failure plays an important role in indicating the level of capacity backlog since failure times are usually short. If the delay time is long, the real effect of capacity scalability will not be realized.

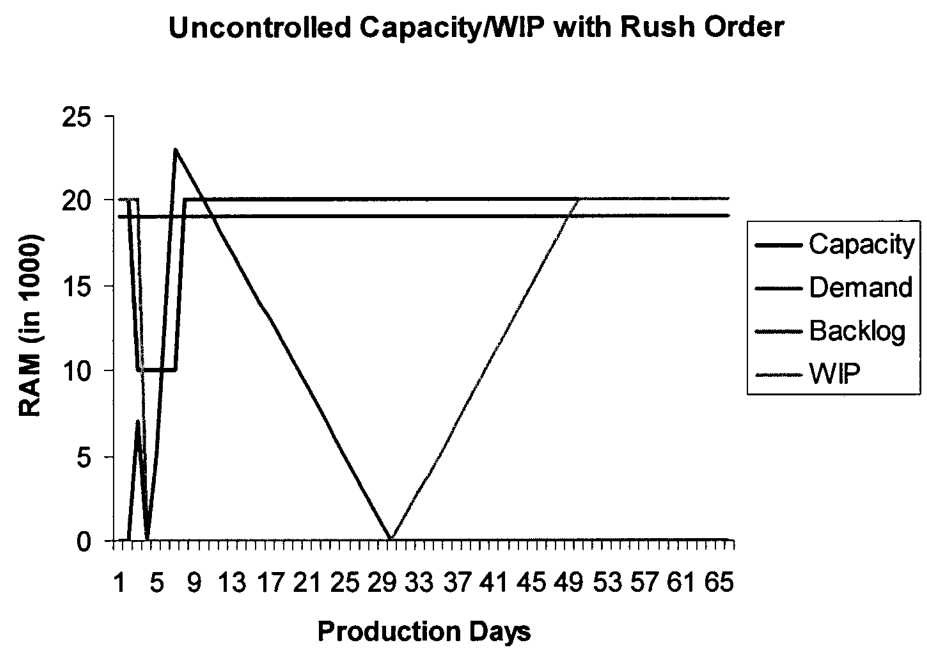


Figure 6.22: Uncontrolled Capacity /WIP with M/C Failure

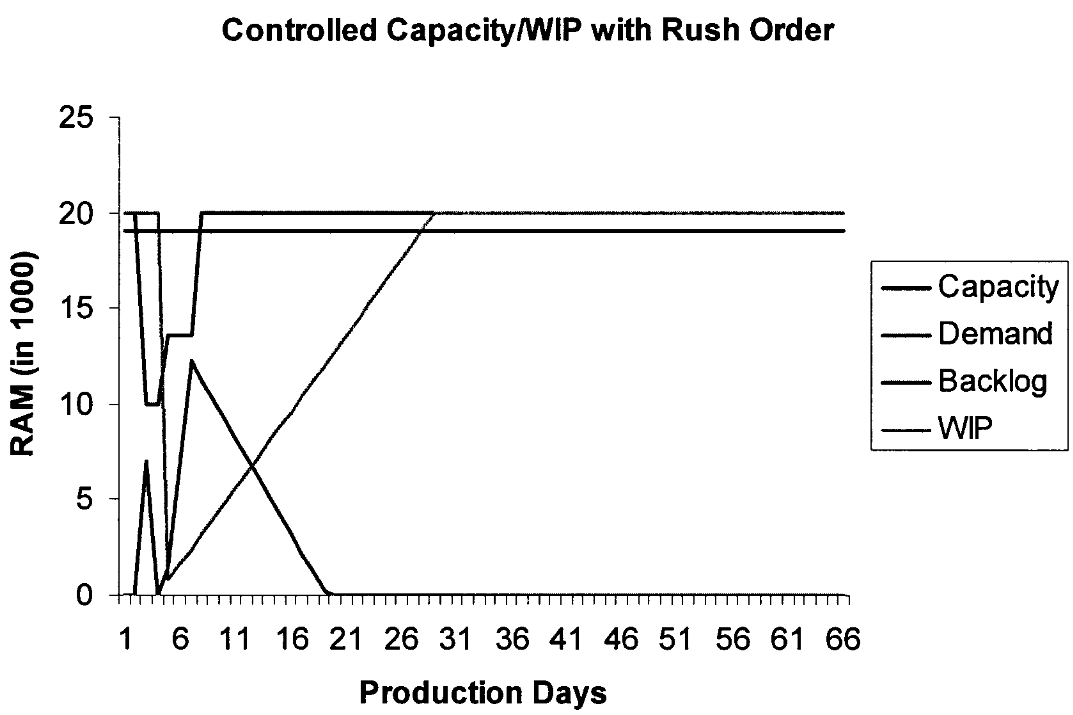


Figure 6.23: Controlled Capacity/WIP with M/C Failure

6.5 Chapter Summary

This chapter applied the developed agile MPC system to a case study and considered different approaches to validate and highlight the efficiency of the developed system. The approaches included cost analysis and comparison to classical approaches to validate the efficiency of the developed MPC system together with numerical simulation to some cases where the developed MPC system showed superior performance over other MPC approaches. Summary of the application and different validation approaches are listed as follows:

- The developed agile MPC system was applied to an automatic PCB assembly line producing RAM modules. The different manufacturing system characteristics and limitations together with the market strategy and the anticipated demand were delivered to DLU or the supervisory controller of the MPC system. The DLU in turn (offline) selected the MPC policy suitable for each demand period followed by computing the required optimal values of the controllers' gains for each policy.
- The DLU also managed to control the production line and its selected parameters online i.e. on a monthly basis using the previous optimal values of the controllers of each of these parameters. A final MPC sheet was produced to summarize the MPC approach in the selected factory.
- The case study highlighted the applicability of the developed approach and at the same time the capability of the developed MPC system to switch between inventory based MPC policies and capacity based policies in an optimal manner based on market need. Also it highlighted how the DLU of the MPC system acts as a linkage between the higher managerial level and the operational level of the production system. Such capabilities will help the manufacturing enterprise to gear towards real agility.
- With quasi stable demand, inventory based MPC policy shows a better performance in terms of cost since the variations of demand from the target inventory level is limited and thus both the holding cost as well as the backlog cost is minimal. As for the capacity based policy, the cost to handle that demand pattern is quite higher since

the capacity is usually scaled to high values that need high demand variation to avoid paying for underutilized capacity or capacity loss as in this case.

- With Fluctuating demand, the opposite scenario was found where capacity based MPC policy showed a better cost performance in handling this kind of demand. The reason for that is the huge variation in demand values which justifies the usage of extra capacity (capacity scalability) in cases of demand increase. At the same time, these demand variations leads to high levels of accumulated inventory (holding cost) and sometimes shortage in the level of available inventory (backlog cost) leading to higher cost for inventory based policy.
- The developed agile MPC approach showed the best performance all over the three considered demand patterns. In quasi-stable demand pattern the agile MPC approach adopted an inventory based policy by engaging the inventory controller and this is why it was as cost efficient as the classical inventory based policy. In fluctuating demand, the DLU of the agile MPC approach disengaged the inventory controller and switched to the capacity controller to have the same cost effective performance as the typical capacity based MPC policy. However, in the mixed demand pattern, the agile MPC approach was far superior to the other two policies due to its ability to handle each period in the demand pattern with the suitable policy manipulating its switching ability between different controllers as explained in chapter 5 while talking about the first layer of the designed DLU.
- When comparing the classical EOQ model with the same model augmented with the developed agile MPC system, the EOQ with the agile MPC model (Agile EOQ) is more cost effective due to the ability to decrease the backlog quantity using the inventory controller.
- The classical EOQ model was significantly in-efficient in dealing with imperfect demand anticipation (inaccurate). The extra costs that the EOQ model showed when subjected to 5% increase in demand was over 12 times more than the original cost.
- The Agile EOQ model showed a clear ability to handle imperfect demand anticipation and sudden increase in demand in an acceptable cost effective way. In the previous example the increase in cost was less than 3 times than that of the original cost.

- The conducted comparison revealed that the inventory based policy developed agile MPC system is better than the classical EOQ inventory based policy which validates the efficiency of the proposed approach.
- Simulation experiments were conducted to compare uncontrolled and controlled capacity based MPC policy in a rush order scenario. The simulation validated the efficiency of the developed capacity based MPC systems through various observations.
- The uncontrolled capacity based MPC system needed 19 days to balance the disturbance and eliminate the backlog caused by the rush order. The controlled capacity based MPC system needed 9 days to respond to the same rush order.
- The unplanned short term with high priority demand (rush order) is very likely to happen in an agile environment and thus it gives a very good indication about the agility of the system. Based on this fact together with the previous observation, it is clear that developed controlled capacity based MPC system is more agile than normal capacity based MPC systems.
- The controlled capacity required the application of the controller gain G_C for 7 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding 1 small pick and place machine as indicated in table 6.5.
- The controlled capacity based MPC system reacted two days later after the rush order due to capacity scalability delay time. The responsiveness of the system can increase if this delay time decreases as stated in the analysis of chapter four and in Deif and ElMaraghy (2006-b)
- If the system was driven with higher utilization it would have taken the uncontrolled capacity based MPC system much more time to eliminate the backlog since the available unused capacity would be much less. This is important to note when enterprises are considering high utilization strategies in agile environment and also highlights the importance of adopting the developed agile capacity based MPC system with such strategies.
- The uncontrolled capacity/WIP based MPC system also needed 19 days to balance the disturbance and eliminate the backlog caused by the rush order. The controlled

capacity/WIP based MPC system needed 9 days to respond to the same rush order. This validates again the agility of the developed agile MPC system.

- Although the rush order in this scenario was double the amount of the previous scenario, the backlog was eliminated in equal time. This is due to the existence of WIP in the system which absorbed an amount of the required demand. This conclusion confirms the damping effect of the WIP and highlights the importance of accounting for WIP in a turbulent demand environment when stability of the system is of concern (Deif and ElMaraghy 2006-a and b).
- The uncontrolled capacity/WIP based MPC system needed 57 days to recover the WIP level to its target value. The controlled capacity/WIP based MPC system needed 50 days to get back to the same. This time difference (due to WIP controller gain G_W contribution) validates again the agility of the developed agile MPC system and its ability to perform better in changing demand environment.
- The controlled capacity required the application of the controller gain G_C for 4 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding 2 small pick and place machines as indicated in table 6.5.
- Same observations in the previous scenario can be stated for the effect of utilization level and capacity scalability delay time on the responsiveness level of the manufacturing system.
- The uncontrolled capacity/WIP based MPC system needed 30 days to balance the disturbance and eliminate the backlog caused by the machine failure. The controlled capacity/WIP based MPC system needed 19 days to respond to the same problem indicating higher level of agility.
- The role of WIP in damping such internal disturbances is very clear as it eliminated the backlog for the first two days. However, the backlog level was raised again due to the long time of the machine failure. Accounting for WIP is crucial for manufacturing stability.
- The uncontrolled capacity/WIP based MPC system needed 46 days to recover the WIP level to its target value. The controlled capacity/WIP based MPC system needed 25 days to get back to the same level. This time difference (due to WIP controller

gain G_W contribution) validates again the agility of the developed agile MPC system and its ability to perform better in turbulent manufacturing environment.

- The controlled capacity required the application of the controller gain G_C for 3 days. This in a practical context requires the manufacturing system to be reconfigured to scale up the capacity with this amount by adding 2 small pick and place machines as indicated in table 6.5.
- Capacity scalability delay time, in cases of machine failure, plays an important role in indicating the level of capacity backlog in cases where failure times are usually short. If the delay time is long, the real effect of capacity scalability will not be realized. This is because the unutilized capacity level will probably be able to compensate for the lost capacity due to the machine failure.

Chapter Seven

Summary and Future Work

7.1 Research Summary

This work was concerned with the dynamic analysis of agile manufacturing planning and control (MPC) systems. After studying different definitions and explanations for agility and agile manufacturing, agile MPC system was defined as: "The ability to accomplish rapid and feasible dynamic changeover between the adoption of different manufacturing policies, mainly inventory based and capacity based policies, (utilizing essentially a reconfigurable manufacturing system) in order to adhere to the higher level management strategies dictated by market needs or trends."

To study such dynamic systems a review for dynamic modeling and analysis of manufacturing systems was conducted. The review revealed the need to develop a comprehensive dynamic manufacturing planning and control model. The model required (in order to show real agility) should be able to adopt efficiently different MPC policies based on the market needs. In order to achieve that, the model should include work in process (WIP), capacity and inventory and how they are related together. Also the model should include a link to the higher management level.

To fulfill the previous needs, a dynamic model of an agile manufacturing planning and control MPC system using control theoretic approaches was developed. The architecture can have five operation policies (WIP based, capacity based, inventory based, capacity/WIP based and inventory/WIP based) where each policy has its own structure or configuration. The description of each planning and control policy and when it is best used were presented. The block diagram and dynamic transfer function for each MPC policy were also derived.

After developing the dynamic agile MPC system's model, the model was analyzed. The analysis included transient time response, stability, sensitivity and steady state error analysis. The analysis helped to understand various characteristics and behaviour of agile MPC systems from a dynamic perspective. The major observations of the previous analysis (for the studied cases) are listed as follows:

- The concept of the "natural frequency" of manufacturing systems was introduced as an approach to understand the dynamics of agile MPC systems. It can be used to indicate the agility of the system in terms of how fast it can respond to changes in market demand.
- The natural frequency of agile MPC system is affected by different time variables of the system and the different gains of the controllers in the system. Optimal design of these parameters and variables can lead to the increase of the natural frequency of the system and in turn decrease the effort required to increase its productivity.
- The term damping ratio of MPC system was also discussed. It can be used to measure the relative stability of different MPC policies (configurations) when subjected to sudden demand change. It was obvious that MPC policies compensating for WIP changes showed higher levels of stability.
- In inventory based MPC configuration (or policy), it was shown that lean manufacturing policy can be realized when setting the shipment time (reflecting the order rate) equal to the manufacturing lead time of the system.
- Various control theoretic approaches were suggested to improve the performance of the agile MPC system. A proportional plus a derivative PD controller was recommended to decrease the capacity scalability delay time. A proportional plus integral PI capacity scalability controller design was proposed to compensate for production offset.
- All MPC systems' policies (based on the stated time variables assumptions) showed a good level of stability.

Based on the analysis of the developed dynamic agile MPC system, the decision logic unit or the supervisory controller of the system was designed. The main points concerning the design of that unit and its performance are stated as follows:

- The design of the decision logic unit (DLU) was based on a hierarchical architecture composed of three layers. Each layer resembles a unit that carry out a certain task.
- The first layer in the DLU was the MPC policy selection unit. This unit is responsible for analyzing the anticipated demand profile and based on regression analysis, the unit decides which MPC policy to be applied during which demand period.
- The second layer of the DLU is the MPC system controllers' gains optimal setting unit. This unit receives the selected MPC polices and based on the previously developed models for each MPC policy or configuration it optimally select the controllers' gains values for that policy or configuration. The optimization is basically a trade off decision between the two competing objectives of agility, responsiveness and cost effectiveness and thus a multi objective optimization approach was adopted.
- A sensitivity analysis was carried out to better understand the nature of the competing objectives and their relation with the decision variables.
- After deciding on the optimal controllers' settings, the third layer which is called the demand satisfaction check unit takes the responsibility of production control. This control process is based on comparing the current capacity, inventory and WIP levels of the manufacturing system with the reference values of these levels that are continuously calculated based on the demand data. Based on the discrepancy between the compared levels this unit decides on which gains (of the previously calculated optimal gains of each policy) to be used and for how long in order to compensate for that discrepancy.
- The output of the DLU is an MPC plan that indicates on a yearly basis which MPC policy should be applied during which demand period of that year and on a monthly basis which controller gain to be used and for how many days in that month
- The DLU updates the higher management level with the performance of the manufacturing system and the developed MPC plan.

Different approaches were considered to demonstrate and validate the efficiency of the developed agile MPC system. The approaches included:

- An application to an automatic PCB assembly line producing RAM modules. The different manufacturing system characteristics and limitations together with the market strategy and the anticipated demand were delivered to DLU. The DLU in turn (offline) selected the MPC policy suitable for each demand period followed by computing the required optimal values of the controllers' gains for each policy. The DLU also managed to control the production line and its selected parameters (online).
- A comparative cost analysis between the developed agile MPC system and classical MPC systems. The comparison investigated the cost (holding cost and backlog cost) of implementing each MPC system in different demand patterns. The developed agile MPC system showed the best performance with all considered patterns.
- A comparative cost analysis between the classical EOQ model and the same model augmented with the developed agile MPC system (Agile EOQ system). The Agile EOQ system showed a far better ability to handle imperfect demand anticipation and sudden increase in demand in an acceptable cost effective way.
- Numerical simulation experiments using a developed simulation tool. The agile MPC system was first validated by comparing the simulation results to another similar PPC simulation by (Wiendahl and Breithaupt 2000) in the same environment. The numerical simulation experiments explored the performance of the different capacity based polices in the agile MPC system with uncontrolled capacity MPC systems. The performance measures were the time to eliminate backlog and time required for the WIP to reach its target level. The simulation scenarios included cases of rush orders and machines breakdown. Results showed a better performance for the developed agile MPC system in all considered scenarios.

7.2 Research Conclusions:

The major conclusions that can be derived from the various modeling, analysis, design and validation approaches in this dissertation can be stated as follows:

- Dynamic analysis using control theoretic approaches gives a better understanding of the behaviour of agile MPC systems in today's turbulent market environment.
- Setting the optimal MPC system controllers' gains values involves multiple trade-off decisions. Results (for the studied cases) showed that achieving quick reaction time and reducing production offset were always at the expense of partial production cost. Also, although accounting for WIP was important for manufacturing system stability, a balance between the damping effect of WIP and its effect on decreasing the responsiveness of the manufacturing system should be considered.
- Dynamic analysis of the effect of different time parameters of agile MPC system showed that generally as these parameters increase in their values, the different response time measures indicate a decrease in the level of responsiveness of the system. This highlights the importance of working on reducing the different sources of time delays in agile manufacturing systems.
- The decision logic unit succeeded in linking the higher management level with the operational level. This linkage was mainly through aligning the marketing strategy with the manufacturing strategy via the generated MPC plan. Such linkage and alignment is the core of the proposed approach to realize agility in today's manufacturing systems.
- The case study highlighted the applicability of the developed approach and at the same time the capability of the developed MPC system to switch between inventory based MPC policies and capacity based policies in an optimal manner based on market need.
- The developed agile MPC approach showed a better performance over classical MPC inventory and capacity approaches (in the studied cases) in terms of cost and responsiveness. This conclusion was validated using both comparative cost analysis and numerical simulation results for different exogenous and indigenous disturbances.

7.3 Agile MPC System's Limitations

The developed approach was intended to maintain agility in manufacturing systems through a dynamic MPC system and at the same time understand the general dynamic behaviour of such systems. Although the approach succeeded in this objective, it has the following limitations:

- The first limitation is an abstract one that deals with the background of this research. This dissertation attempted to combine the field of manufacturing systems with the field of control engineering to understand the dynamic nature of manufacturing systems and thus drive it to be more agile. However, this combination cannot be considered a full combination due to the difference in the fundamentals of both disciplines. Consequently, it is important to state (at the end of this work) that not all dynamic analysis and results in control theoretic approaches would make sense from a manufacturing system stand point. Such a fact was a continuous challenge and limitation throughout the development of the agile MPC system and its analysis.
- Generally, any dynamic analysis is limited to the boundaries that maintain the stability of the dynamic model. In this approach the stability limits had a great impact in restricting the values of the parameters settings and thus limiting their ranges.
- The cost considered in the agility analysis and in the multi-objective optimization dealt exclusively with the cost of deviating from the target production level or extra production. This is a crucial cost parameter and it gives a fair idea about the cost profile, however, for such cost assessment to be complete a more detailed analysis is required.
- The dynamic analyses and behaviours presented in this dissertation are limited to the middle level in agile enterprises that links the higher management level with the production operational level. The results and conclusions derived cannot be directly applied beyond this level without further dynamic analysis.

7.4 Future Work

There are many potential extensions to the proposed work in this dissertation. Among the suggested future research are:

- Extending the developed agile MPC model to fully integrate with both the strategic and operational levels to have a complete model for MPC systems. A suggestion would be through modeling the strategic level using system dynamics and the operational level using discrete event simulation and having a DLU for each of these levels. Finally a general MPC supervisory unit would be responsible for these distributed DLUs to manage the overall system.
- Relaxing some of the modeling assumptions like investigating the effect of having a nonlinear relation between the ideal production lead time and the actual lead time. Also exploring the exact relation between the shipment rate and the order rate and how can this be related through the higher level management and its relation with the whole supply chain management.
- Extending the sensitivity analysis to include the effect of controllers' gains on the different response and stability measures. Such analysis will help to give a better understanding of the effect of these control actions which will lead to better controllability of manufacturing systems.
- Examining the effect of involving the system's time parameters as variables in the optimization process done by the DLU. Such involvement will reflect both production control actions (in terms of setting the optimal controllers' gains as discussed in this dissertation) and also strategic manufacturing planning actions (in terms of where and how to invest in the manufacturing system to improve its efficiency and agility).
- The MPC system controls the manufacturing process based on responsiveness and cost effectiveness objectives from a dynamic stand point. A more comprehensive approach would be through involving other static control parameters or extending the existing ones to have better decisions. An example of that is to extend the cost

as an optimization objective from not only being reflected in the production overshooting parameter to a more detailed cost structure expression.

- Other techniques can be used to design the DLU unit. An example of that is using a fuzzy control approach or an agent based approach to design the three layers of the developed DLU architecture.
- The existing design of the DLU unit can be enhanced by using other techniques for each layer in the unit. Other pattern recognition techniques can be used to better analyze the anticipated market demand profile better than the regression analysis adopted in this thesis. Also other optimization techniques can be used to reach better optimal values for the controllers' gains other than that adopted in the second layer as shown previously.
- More industrial applications would illustrate more the use of the developed agile MPC system.

7.5 Summary of Contributions in this Research

In summary, the presented research provided enhancement and contributions to the existing knowledge about dynamic analysis of MPC systems on both theoretical and practical levels. The major contributions in this research can be summarized as follows:

- First comprehensive dynamic MPC model that can adopt different policies based on market strategy by integrating capacity rate, inventory level and WIP level in one model.
- A complete approach and a mathematical model to link higher management level with operational production level to realize agility in manufacturing enterprises using supervisory controller.
- Novel attempts to dynamically understand various manufacturing systems behaviours. The attempts included introducing new terms such as MPC natural frequency and damping ratio.
- Integrating dynamic analysis with optimization techniques to not only understand the MPC system behaviour but also to optimally design the system parameters based on that behaviour.

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VITA AUCTORIS

NAME: Ahmed Mahmoud Deif

PLACE OF BIRTH: Cairo - Egypt

YEAR OF BIRTH: 1976

EDUCATION:

University of Windsor, Windsor, Ontario 2004-2007 Ph.D.

University of Windsor, Windsor, Ontario 2002-2004 M.A.Sc.

The American University in Cairo, Egypt 1995-1999 B.Sc.