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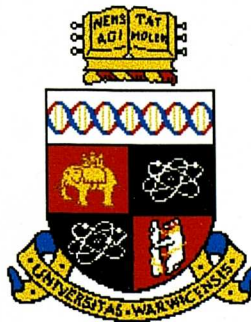
An Investigation into Sources of Uncertainty within Industrial Supply Chains; Amplification, Deterministic Chaos & Parallel Interactions.

By

Richard David Wilding

Submitted to the University of Warwick for the award of

Doctor of Philosophy



University of Warwick

Department of Engineering

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I dedicate this work to Janice, Ben and Emma. They have made many sacrifices to enable me to complete this research. Their love, patience and prayers have been ever present during the “highs” and “lows” of the past five years.



“My son, there is something else to watch out for. There is no end to the writing of books, and too much study will wear you out.

After all this, there is only one thing to say: Have reverence for God, and obey his commands, because this is all that man was created for.”

Ecclesiastes: Chapter 12, Verses 12 & 13.
(The Good News Bible)

Declaration

I declare that I am the sole author of this work and that it has not been submitted for any other award. All sources of published information have been acknowledged in the text by the use of references.

Summary

*“An Investigation into Sources of Uncertainty within Industrial Supply Chains;
Amplification, Deterministic Chaos & Parallel Interactions.”*

By

Richard David Wilding.

The objective of this research was to investigate the generation of uncertainty within industrial supply chains. Since the late 1950's it has been recognised that the systems used internally within supply chains can lead to oscillations in demand and inventory as orders pass through the system. The uncertainty generated by these oscillations can result in late deliveries, order cancellations and an increased reliance on inventory to buffer these effects. Despite the best efforts of organisations to stabilise the dynamics generated, industry still experiences a high degree of uncertainty from this source. Greater understanding of the generation of uncertainty within the supply chain could result in improved management of the systems and consequently competitive advantage being gained by organisations.

The investigation used simulation models of real industrial supply chains to identify possible sources of uncertainty. The complexity of the models was adjusted by increasing the number of echelons and the number of channels in the supply chain. One source of uncertainty investigated was the generation of deterministic chaos and a methodology was developed to detect and quantify this within the supply chain. Parallel interactions, which occur between suppliers in the same tier in the supply chain, were also modelled and quantified.

In addition to demand amplification, which has been recognised as a source of uncertainty by both academics and industrialists, two additional sources of uncertainty were identified: namely deterministic chaos and parallel interactions. The relationship between these causes of uncertainty was established and the original concept of the “supply chain complexity triangle” is proposed. The “average prediction horizon” was calculated by the use of Lyapunov exponents and was used to quantify the amount of chaos experienced by supply chain members. This chaos was found to be dependent on the number of echelons, which also impacts on the amount of chaos experienced by all members of the supply chain, both up and down stream. Parallel interactions impact on all the members of the supply chain resulting in reduced performance. However, the number of channels in the supply chain modelled had little effect on the amount of chaos. Implications for reducing supply chain uncertainty either by managing or removing these effects is also discussed.

Chapter 1

Introduction

1.1 Background to research.

Today's market place is increasingly dynamic and volatile. Customer responsiveness is generally the key differentiator in markets today [Hill, 1993]. Globalisation is resulting in many organisations experiencing market pressures that are forcing a fundamental rethink of the way business is conducted. Trade-offs between for example labour costs, transportation costs, inventory costs and response time to customer are becoming increasingly complex [Sharma, 1997]. It is no longer seen as possible only to focus on one's individual organisation to gain competitive advantage. It has been recognised that the success of the individual organisation is dependent on the performance and reliability of its suppliers and also customers.

Christopher [Christopher, 1992] emphasises this by stating:

“Competition in the future will not be between individual organisations but between competing supply chains”

One key issue known to impact on the effectiveness of a supply chain is that of uncertainty [Davis, 1993]. Uncertainties in supply and demand are recognised to have a major impact on the performance of the manufacturing function. Uncertainty results in increased inventory, poor utilisation of resources, continual rescheduling all of

which contribute to manufacturing management being in a constant state of flux. Traditionally improved planning within the manufacturing function was seen as key to the reduction of uncertainty [Vollmann, Berry, & Whybark, 1992].

Materials Requirements Planning (MRP) is one planning tool that has been used by the majority of industry over the past three decades. Improved planning has resulted in a number of organisations gaining benefits. However, many western organisations have experienced few improvements and some even a detrimental impact on their operations [Womack & Jones, 1996 p.110]. MRP systems have been superseded by Manufacturing Resources Planning (MRP2) and other systems such as Optimised Production Technology (OPT) [Lundigran, 1986]. As each new system is developed it is recognised that to improve the planning process increasing amounts of information about the use of manufacturing resources need to be processed. MRP2 requires information on capacity, OPT needs further information on resources to identify bottlenecks. It is generally believed that the more information about the manufacturing environment that can be used in the planning process the better the plans will be. However, the requirement for increasing levels of accuracy in information about the manufacturing environment has highlighted the high levels of uncertainty resulting from areas outside manufacturing influence.

Recognising that just focusing on local operations did not result in reductions in uncertainty and improvements in customer service expected, managers now seek benefits by attempting to manage the total supply chain. Again this has been tackled by the implementation of improved planning and control systems. Similar planning processes have subsequently been applied to the remainder of the organisation's

supply chains. Distribution Resources Planning (DRP) and Enterprise Resources Planning (ERP) are examples of such approaches [Johnson & Wood, 1993].

Benefits have been gained by removal of duplication of stock and improved understanding of customer requirements but high levels of uncertainty are still present.

The complexity of many every day products now requires the expertise of a multitude of organisations in the delivery to the customer of a finished product. Due to the increasingly competitive nature of the global business environment organisations are specialising on core business competencies [Hill, 1993]. This introduces further complexity into the supply chain, as organisations have to manage a multitude of relationships with suppliers. This trend seems to be accelerating further with the concept of the “virtual organisation” encouraging organisations to join forces to gain competitive advantage for limited periods of time in focused markets [Purchase & Alexander, 1997 pp.41-44]. It is therefore increasingly important to understand how uncertainty occurs within the supply chain.

Uncertainty is generally accepted as the result of random events from sources outside the control of the individual organisation. However research in early 1960's by Forrester [Forrester, 1961] demonstrated that amplification of demand variation occurred as a result of the systems structure. This resulted in periodic fluctuations in demand and inventory over periods of time. These, it is thought, could be interpreted by managers as seasonal trends or cycles. Time compression and other initiatives have been able to reduce the amplification effect and many benefits have been experienced. However uncertainty has by no means been eliminated. In the manufacture of complex engineering products, (for example cars) the sources of

uncertainty are often blamed on the large number and variety of suppliers all contributing to a single end product. Managers also claim that the systems and planning tools used within the supply chain can generate uncertainty within the system.

Demand uncertainty has also resulted from the increase in product variety expected in the market place. Consumer markets are becoming increasingly segmented and organisations are tailoring products to increasingly smaller market sectors. These drivers have resulted in the concept of “mass customisation” [Saisse & Wilding, 1997]. Suppliers responding to this complex market place also experience uncertainty generated by their customers requiring shorter lead-times and demanding changes to the product configuration within the delivery lead-time. The factors detailed result in forecasting horizons decreasing and the complexity of the forecasting task increasing.

Pressures from all stakeholders in the business are resulting in many companies instigating re-engineering initiatives that often result in cuts in resources, such as manpower, inventory and capacity. Inventory and capacity have been seen as the traditional buffers to uncertainty within an organisation, and so reductions often result in a reduction of responsiveness. The organisation is therefore caught between the often conflicting requirements of increasing responsiveness to their customers and reducing the inventory and capacity buffers that cope with uncertainty.

1.2 The research problem

The overall research problem addressed by this thesis is:

What are the sources of uncertainty generated internally by systems within the supply chain and what is their impact on supply chain performance?

This question will be addressed by the use of a number of simulations of supply chain systems and subsequent analysis of the data. Two sources of uncertainty will be focused on particularly. The impact of uncertainty generated by the interaction of a number of companies supplying one key manufacturing customer, and the uncertainty generated by the supply chain systems used. The analysis of the data will use standard statistical methods, but will also employ new tools developed for the analysis of non-linear systems. Three interacting effects appear to generate uncertainty. These are amplification of demand, “parallel interactions” within the supply network and deterministic chaos generated by the supply chain’s internal systems.

1.2.1 The research questions.

The research questions addressed in this thesis are detailed and supported in Chapters 2, 3 and 4. However the key issues are listed below:

- Is a significant amount of uncertainty generated by the internal processes within the supply chain?
- How is uncertainty generated by internal processes?

-
- Does deterministic chaos {“Random behaviour generated by law” [Stewart, 1989]} contribute to the uncertainty within the supply chain?
 - Can these effects be quantified for a given system?

We now know a great deal about amplification within the supply chain [Towill, 1996]. This can be classified as a “serial effect” in that the effect is accumulated in sequence as orders pass from customer to supplier down a supply chain.

Parallel effects and interactions between supply chains have received little attention. Some analogies can be drawn to work undertaken in Job shop environments, however a Job shop is generally under the control of one organisation. A supply chain network is under the control of many organisations and thus individual control is rarely achieved.

Little quantitative analysis of deterministic chaos within the supply chain has been undertaken. The work giving the greatest insight into chaos within the supply chain has focused on the human decision making behaviour of participants playing the Beer game, a simple supply chain hand simulation.

Once an understanding of the sources of uncertainty has been gained it may be possible to remove, reduce or control the generators of uncertainty. Managers working within supply chain environments may be required to work in a particular way to minimise the effects of uncertainty.

1.3 Motivation for research

1.3.1 Importance of research to supply chain management.

In the USA alone it is estimated that the total inventory in all supply chains amounts to some \$750 billion. [Sharma, 1997]

Uncertainty in late deliveries and order cancellation leads to increased inventory. Research at Intel [Oliver & Houlihan, 1986] investigating the match between actual call off and the actual forecast, estimated that supply and demand were in equilibrium for 35 minutes in 10 years! This comment further emphasises the degree of uncertainty being experienced by commercial organisations. This has a major impact on capacity planning and resources utilisation within the supply chain.

The alternate periods of stockout and surpluses result in increased total costs. Hewlett Packard have found simple statistical techniques can calculate inventory required in a single company but that uncertainty tends to propagate through a manufacturing network [Davis, 1993]. Currently there is no clear analytical way to calculate inventory required within a network so organisations traditionally rely on a combination of intuition and experience. Typically 25 % reduction in inventory is possible in even the best-run supply chains if proper tools and understanding can be applied.

Hill [Hill, 1996] has undertaken an analysis of the forecast vs. actual demand. It was found that the correlation between the forecast and actual call off of items was small and in some cases negligible. This uncertainty requires “gambles” to be made on scheduling, capacity management and inventory in order to meet demand. This further emphasises the uncertainty experienced by organisations.

Jones and Towill [Jones & Towill, 1996] state that the design of systems that dampen uncertainty is a key priority for logistics research in next few years.

In summary the need to understand possible sources of uncertainty within the supply chain is essential to improve supply chain performance. More effective use of resources can result in competitive advantage being gained by all organisations participating in the supply chain.

1.3.2 Overview of research undertaken to date.

The first piece of work undertaken to understand the dynamic behaviour of simple linear supply chains was carried out by Jay Forrester of MIT [Forrester, 1961]. One of the key outputs of Forrester's work is a practical demonstration of how various types of business policy create disturbances which are often blamed on conditions outside the system. Random, meaningless sales fluctuations can be converted by the system into apparently annual or seasonal production cycles thus sub-optimising the use of capacity and generating swings in inventory. A change in demand is amplified as it passes between organisations in the supply chain. This amplification effect can explain some of the uncertainty experienced in the supply chain but does not explain the complex dynamics experienced in practice.

Forrester's work has been further developed by Towill [Towill & Naim, 1993; Towill, 1996], who has investigated ways of reducing demand amplification and demonstrated the impact of current supply chain strategies such as just-in-time, vendor integration and time-based management on reducing the amplification effect. [Berry, Towill, & Wadsley, 1994]

Davis [Davis, 1993] has focused on the propagation of uncertainty through a supply network, analogous to Forrester's demand amplification. Davis an employee of HP has developed a methodology which has been found to reduce the uncertainty. Davis cites performance measurement, the control of uncertainty and planning changes by modelling supply chains as essential requirements in any supply chain re-engineering methodology.

Mosekilde, Larson and Sterman [Mosekilde, Larsen, & Sterman, 1991] produced a detailed discussion of chaos in human decision making. The paper produced results that provided direct experimental evidence that chaos can be produced by the decision making behaviour of real people in simple managerial systems. The system used for the investigation was the Beer Game based on the Forrester supply chain.

More recently Levy [Levy, 1994] proposed chaos theory as a useful theoretical framework for understanding the dynamic evolution of industry and the complex interactions between industrial players.

In summary, there is little investigative research being carried out into the sources and generation of uncertainty within the supply chain. The general approach has been to accept uncertainty within the supply chain rather than focus on its reduction or removal. The research documented in this thesis gains an insight into a further two causes of uncertainty and associated methods of reduction and removal.

1.3.3 Overview of methodologies used to date.

A systems dynamics methodology has been used for the majority of investigations into supply chain dynamics. This was originally used by Forrester [Forrester, 1961] and

more recently by Towill [Towill, 1996]. In all this work simple linear supply chains were investigated and simulated over relatively short time periods. Little work has been carried out on the simulation of more complex supply networks with multiple branches.

Davis [Davis, 1993] used a stochastic simulation methodology for his investigation into the propagation of uncertainty. Many authors advocate either the use of stochastic or deterministic simulation methodologies. This has generated much discussion between researchers (see for example [Morecroft, 1984; Heyl & Callarman, 1984]). For the research undertaken in this thesis both techniques were used. Stochastic methods tend to hide internally generated uncertainty but do emphasis interactions between organisations. Deterministic simulations however can give insight into internally generated uncertainty but can be less effective at highlighting interactions between organisations.

Analysis of supply chain simulation results generally uses statistical methods. The use of non-linear analysis is very much in its infancy with little published work being available that is directly relevant to supply chain simulations.

1.3.4 Potential application of research findings.

Initially it is assumed that the research to be undertaken and documented in this thesis will find and quantify additional sources of uncertainty within the supply chain. If parallel interactions and deterministic chaos are found to have a significant impact on the dynamics of the supply chain it may be possible to investigate methods to remove, reduce or control their effects.

The buffering of parallel interactions by the use of inventory is one possible approach. The drive of organisations to reduce inventory and implement Just-in-time systems has often resulted in an organisation being very susceptible to uncertainty. Optimising inventory holding at certain points in the supply chain may facilitate reductions in the uncertainty. If supply chains do prove to be chaotic, research into chaotic systems have revealed that under certain conditions the system may perform in a stable manner. If these “Islands of stability” could be identified for a particular supply chain it may be possible to exploit this by optimising batch sizes or control variables to operate the supply chain in regions of stability. It is anticipated that this research may result in guidance on supply chain design and recommendations of how management can be most effective in operating in supply chains to minimise uncertainty generated by these mechanisms.

The non-linear analysis tools to be used have not been applied previously to the type of supply chains to be investigated. It is hoped that the techniques can be assessed for use by practitioners in supply chain management and therefore be applied by organisations while carrying out re-engineering of supply chains.

1.4 Methodology

A simulation approach was undertaken, as this was an effective way to gather the quantity of data required for analysis.

When this investigation was started various approaches to organisations were made for data but little was available. A search of the Internet was also undertaken, but

very little data was available, and was mainly related to the financial sector such as stock market data.

However previous work in the Department of Engineering, University of Warwick [Roy & Meikle, 1995; Hill, 1996; Grinsted, 1990; Jones, 1990] has gathered information and distributions for the building of realistic simulations. Two simulation approaches were used for investigating the various effects. Both simulations were subjected to validation by the author, engineers and scientists within the University of Warwick and also external practitioners and academics. The simulations enabled the generation of large quantities of “clean” data that could be used in any further analysis. The author also collaborated in the development of a simulator used by industry for the simulation of warehouse supply chains. This package has been used successfully by Black & Decker and ICI for supply chain improvement projects, and was found to mimic with good accuracy the actual supply chains simulated.

The data was analysed using standard statistical methods and various non-linear analysis techniques that have only become available in recent years. The non-linear analysis methodology was adapted from Abarbanel, Kaplan and Glass, and Sprott and Rowlands [Abarbanel, 1996; Kaplan & Glass, 1995; Sprott & Rowlands, 1995]. A search for such tools was undertaken and due to the pace of development in this area the Internet is the main source of such tools. One well-proven commercial package co-authored by a colleague at the University of Warwick [Sprott & Rowlands, 1995] was identified and was subsequently used for much of the non-linear analysis undertaken by the author.

1.5 Outline of thesis

The thesis has been divided into four parts. Part One, the current chapter, provides an introduction to the thesis and an overview of the research problem to be addressed.

Part Two, the literature survey section, provides a theoretical foundation to the thesis and identifies key research questions. It consists of four chapters; Chapter Two, outlines the issues and current trends in supply chain management. The literature has been classified under two headings: Drivers and Requirements for supply chain management. Chapter Three progresses to look in detail at work focusing on the generation of uncertainty within the supply chain and the dynamics produced. This chapter identifies the majority of the research questions, which this thesis addresses. Chapter Four proceeds to give an explanation of non-linear dynamics and chaos. This subsequently gives an overview of the application of non-linear dynamics and chaos theory within business and the supply chain environment. Some examples from other discipline areas such as biology are also referenced to see if analogies can be drawn with business and supply chain systems. Chapter Five, presents a survey and explanation of the tools used for non-linear analysis and the investigation of chaos. The analysis methodology used in this work is developed and described.

Part Three of the thesis, describes the experimental methodology and outlines the results gained. Chapter Six describes the simulation methodology and the experimental procedures used to identify if deterministic chaos is a possible cause of uncertainty within a simulated warehouse supply chain. The results of the analysis are presented and discussed. Chapter Seven describes the simulation and analysis

methodology used in the investigation of “Parallel interactions” within the supply network. The results of this work are presented and discussed.

Part Four of the thesis discusses the findings and concludes the research undertaken. Chapter Eight, discusses the implications of the research for addressing uncertainty within the supply chain. The implications of the research for management policy and practice are also discussed.

Chapters Nine and Ten summarise the main conclusions of the thesis and further work that the author perceives is required.

1.6 Definitions

The definitions adopted by researchers are often not uniform. This section defines two key terms to establish positions taken in this thesis. These terms will be explored in more detail in the relevant literature review section.

1.6.1 *Chaos*

The term chaos is currently much used within the management literature. The Collins English dictionary describes chaos as meaning “complete disorder and confusion”. The term chaos has been used in this context to describe the seemingly random disorder of customer demands for products as described by Womack and Jones [Womack & Jones, 1996 p.81] and by Tom Peters [Peters, 1988] in his book “Thriving on chaos” to describe disorganised yet responsive business structures that rapidly adapt and gain competitive advantage. Chaos is also used as a metaphor to describe how a small change can be amplified to have a large effect on the system.

This has resulted from the popularisation of the “butterfly effect” (see section 4.2.4). Authors (for example [Jones & Towill, 1996; Womack & Jones, 1996 p.87]) describing amplification within the supply chain have used the term chaos in this context.

Peitgen et al [Peitgen, Jurgens, & Saupe, 1992 p.9] emphasise the danger of the casual use of the term chaos but also highlight the positive effects of the popularisation of the term, they state:

“Chaos theory is occasionally in danger of being overtaxed by being associated with everything that can be even superficially related to the concept of chaos. Unfortunately, a sometimes extravagant popularisation through the media is also contributing to this danger; but at the same time this popularisation is also an important opportunity to free areas of mathematics from their intellectual ghetto and to show that mathematics is as alive and important as ever.”

Within this thesis the term chaos describes deterministic chaos. The definition used in this thesis is adapted from that proposed by Kaplan and Glass [Kaplan & Glass, 1995 p.27] and Abarbanel [Abarbanel, 1996 p.15]:

Chaos is defined as aperiodic, bounded dynamics in a deterministic system with sensitivity dependence on initial conditions, and has structure in phase space.

Aperiodic means that the same state is never repeated twice.

Bounded means that on successive iterations the state stays in a finite range and does not approach plus or minus infinity.

Deterministic means that there is a definite rule with no random terms governing the dynamics.

Sensitivity to initial conditions means that two points that are initially close will drift apart as time proceeds.

Structure in Phase Space. Non-linear systems are described by multidimensional vectors. The space in which these vectors lie is called phase space (or state space). The dimension of phase space is an integer [Abarbanel, 1996]. Chaotic systems display discernible patterns when viewed. Stacey [Stacey, 1993a p.228] emphasises this by defining chaos as;

“order (a pattern) within disorder (random behaviour)”.

Section 4.4 defines chaos in more detail.

1.6.2 Parallel Interactions

Serial interactions in supply chains occur between each echelon in the supply chain i.e. a single customer and a supplier. An example of a serial interaction would be demand amplification [Forrester, 1961]. The term “Parallel interaction” has been defined to describe interactions that occur between different channels of the same tier in a supply network. An example of Parallel interactions occurs when a 1st tier supplier cannot supply a customer, this results in re-scheduling within the customer organisation resulting in the customer changing its requirements on other 1st tier suppliers. This results in uncertainty being generated within the supply network. The supplier is affected by an occurrence in a parallel supply chain, which at first would seem unrelated. Figure 1.1 shows a diagrammatic representation of these effects.

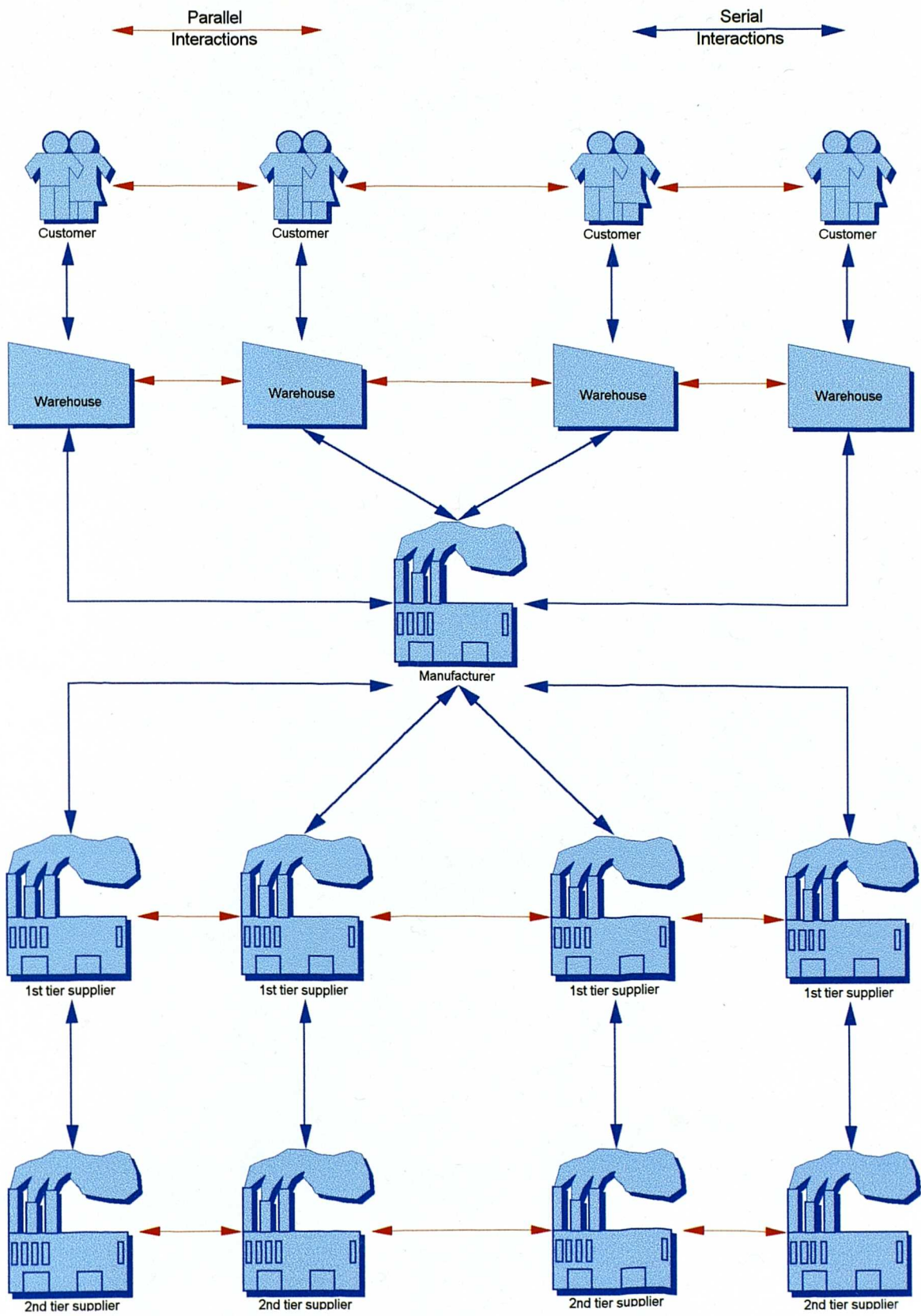


Figure 1.1 – Serial and Parallel interactions in supply network.

1.7 Delimitations of scope and key assumptions

The simulations used in this research are based on real supply chains. However the simulation process does simplify the system to some degree. The simulations have been subjected to a careful validation procedure and have been shown to mimic with good accuracy the types of supply chains studied. The simulations have been based on the author's experiences of engineering supply chains and it is accepted that there may be differences in the logic used by managers in different product supply chains such as food, maintenance or service industry. However it is believed that the key principles investigated in this thesis can be applied to other supply chain environments.

The simulations have been run for long periods of time during validation and subsequently long periods (3000 time units) during the analysis. In the real environment this would equate to 8 years worth of readings taken daily. It can be argued that human intervention or other external events would occur within this time frame thus impacting on the future decisions. However, these decisions may have a further detrimental impact on the sources of uncertainty [Sterman, 1989a].

1.8 Conclusion to Chapter 1

This chapter has given an overview of the thesis. It has introduced the research problem and research questions to be addressed. The research has been justified and the methodology briefly described and justified. The structure of the thesis has been outlined and the limitations of the research have been documented. From this chapter,

it can be seen that the research is expected to contribute to our understanding of uncertainty in supply chains and to result in practical recommendations for improved supply chain management.

Chapter 2

The Supply chain and its management.

2.1 Introduction.

In this chapter the concept of the supply chain will be presented and the strategic drivers and requirements for the successful application of this approach will be presented and briefly discussed. It is not the intention of this chapter to discuss every facet of logistics and supply chain management but to set the remainder of this work in context. A fuller discussion of all areas of logistics and supply chain management is found in Christopher [Christopher, 1992] and Bowersox and Closs [Bowersox & Closs, 1996]. Uncertainty generation by the internal supply chain processes will be discussed in chapters 3 and 4.

2.1.1 Definitions of Logistics and supply chain management.

A supply chain has been defined by Stevens [Stevens, 1989] as:

“A supply chain is a system whose constituent parts include material suppliers, production facilities, distribution services and customers linked together via a feedforward flow of materials and the feedback flow of information.”

This definition emphasises the linkage between organisations and the movement of material and information between them.

The term supply chain is a simplification of reality. A complex network of organisations is generally present, organisations are frequently part of many different supply chains or channels. Harland et al [Harland, Williams, & Fitzgerald, 1993], investigating automotive supply chains demonstrate that component suppliers are part of many chains with differing characteristics due to the customers being served. Automotive components are not just supplied to the automotive manufacturers, but also parts and service providers. Parts and service providers then supply a number of distinctly different markets and through a variety of supply chains, these include fleet garages, the DIY market, motor factors etc. Complex interactions occur within this supply network. For example, the author recently came across a supply problem of air conditioning units to an automotive manufacturer caused by the automotive manufacturer's dealers ordering large quantities of units for fitting to vehicles after they had been purchased. This resulted in a shortage of units for the manufacturer to fit to vehicles on the production line and subsequently the lead-time to delivery of air-conditioned vehicles increased dramatically resulting in a loss of sales.

Supply chains exhibit many complex interactions between organisations and ultimately the end customer and market that customer represents.

The management of the supply chain is accomplished through logistics. The British Standard definition of logistics is as follows [British Standards Institute, 1997]:

“Logistics is the planning, execution and control of the movement of people, goods and related support in order to achieve an objective within a system”

Harland et al [Harland, Williams, & Fitzgerald, 1993] define supply chain management as:

“The management of the flow of goods and services to end customers to satisfy their requirements”

The British standard definition raises two questions; what is the system and what is the objective? Wild [Wild, 1989] defines an operating system as:

“A configuration of resources combined for the function of manufacture, transport, supply or service.”

The above definition of a system would also make an excellent definition for a supply chain.

Harland’s definition provides the objective of “satisfying the customers requirements”. This is often achieved through ensuring the right products are in the right place, at the right time and at the right price. To achieve this objective we require effective logistics management.

The Institute of Logistics, U.K. summarises this relationship as follows [Institute of Logistics, 1997]:

“The management of logistics makes possible the optimised flow and positioning of goods, materials, information and all other resources of an enterprise.

The supply chain is the flow of materials through procurement, manufacture, distribution, sales and disposal, together with the associated transport and storage.

The application of logistics is essential to the efficient management of the supply chain”

2.1.2 The fundamental elements of Logistics and supply chain management.

Supply chain management differs from traditional material control in a number of key areas. Jones and Riley [Jones & Riley, 1985] suggest that fundamental to effective supply chain management is the need for organisations to integrate by:

- Recognising end customer service level requirements.
- Defining where to position inventories along the supply chain, and how much to stock at each point.
- Developing the appropriate policies and procedures for managing the supply chain as a single entity.

✓ Christine Jones [Jones, 1989] emphasises the importance of focusing on the end customer. She argues that if all members of the supply chain do not focus on the end customer, improvements made in one link of the supply chain will not necessarily improve the overall competitive position of the organisations in the supply chain. By achieving “supply chain synergy” additional benefits are gained from managing a supply chain as a whole rather than its individual elements. }

Oliver and Webber [Oliver & Webber, 1982] identify four fundamental differences between the supply chain approach and traditional approaches to management. These can be summarised as follows:

- The supply chain is viewed as a single entity.
- An emphasis on strategic decision making is required.
- Inventories are viewed with a different perspective; inventories are used as a last, not first resort.
- A focus on systems integration is required, not systems “interfacing”.

A key element of both Oliver and Webber’s and Riley and Jones’s is the need for effective inventory management within the supply chain. This is driven from the recognition that within most manufacturing organisations 70-80% of total annual costs are spent on materials [Christopher, 1992 p.205], the effective management of this resource is therefore a focal point of many organisations.

In summary, effective logistics and supply chain management is characterised by an emphasis on the end customer, the integration of systems, policies and inventory within the supply chain, thus achieving a “synergy” where all organisations gain competitive advantage and subsequently prosper. \

2.1.3 Classification of Literature

The diversity of literature on aspects of supply chain management is a result of large numbers of activities that impact on the efficiency of the supply chain. The author has classified the subject area under two main headings. These are:

1. The drivers for supply chain management. These are the issues that result in organisations recognising the need for the application of supply chain management techniques. The drivers are generally the need to gain competitive advantage and/or the need for cost reduction.
2. The requirements and methods for supply chain management. These are the policies and systems that must be in place to undertake effective management and thus the integration of the supply chain. These policies and systems relate to five broad areas; material logistics, information systems, time compression, quality of products and service and finance and costing systems.

In the following sections an overview of these areas will be presented.

2.3 Drivers for supply chain management

2.3.1 *Competitive advantage*

When gaining an understanding of drivers for supply chain management it is first necessary to look at the nature of competitive advantage. Ohmae [Ohmae, 1983] defines a useful framework within which to view competitive advantage. This is depicted in figure 2.1.

The objective of a business is to make a profit by delivering more value to a customer at a similar cost to the competition, or the same value as the competition at a lower cost.

Value is based on customer perception and is a mixture of tangible and intangible benefits, specific product features and also image, reputation and responsiveness (see Figure 2.2). As the old marketing saying states “Customers don’t buy products they buy benefits”.

If a business is very effective it might be possible to achieve differentiation (more value) and cost-leadership (lower cost) at the same time. Expert in competitive strategy, Professor Michael Porter, argues that there are irreconcilable differences in approach between these two objectives, and achieving both over a long time-scale is unlikely [Porter, 1985 pp. 17-18].

However experience shows that supply chain management can support both the drive to add more value and the drive to produce at lower cost.

The success or failure of any firm depends on its ability to define an effective strategy, to achieve the elusive goal of sustainable competitive advantage. Unfortunately strategic advantages rarely last. The competition learn, understand the approach, apply it and it becomes the industry norm. As a result approaches have evolved over time and companies have moved through a range of strategies.

It has been proven that companies that seek and exploit innovation in business strategy grow faster and are more profitable than their competitors [Stalk & Hout, 1990 p.4]. This is probably more a reflection on the ability of senior management to review and adapt their current strategy rather than the fact that all new strategy is good strategy. A word that is increasingly used to describe such organisations is “Agile”.

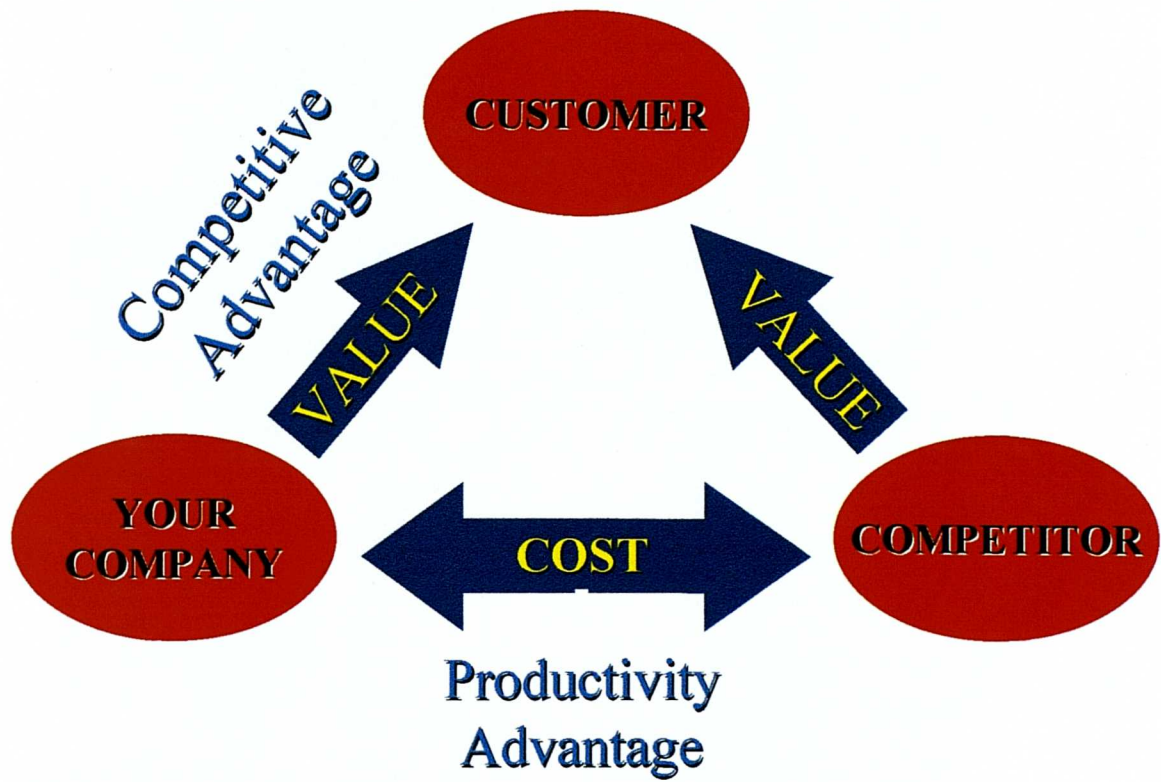


Figure 2.1 – The Strategic Three “C’s”.

Adapted from Ohmae, K. “The mind of the strategist” Penguin, 1983.

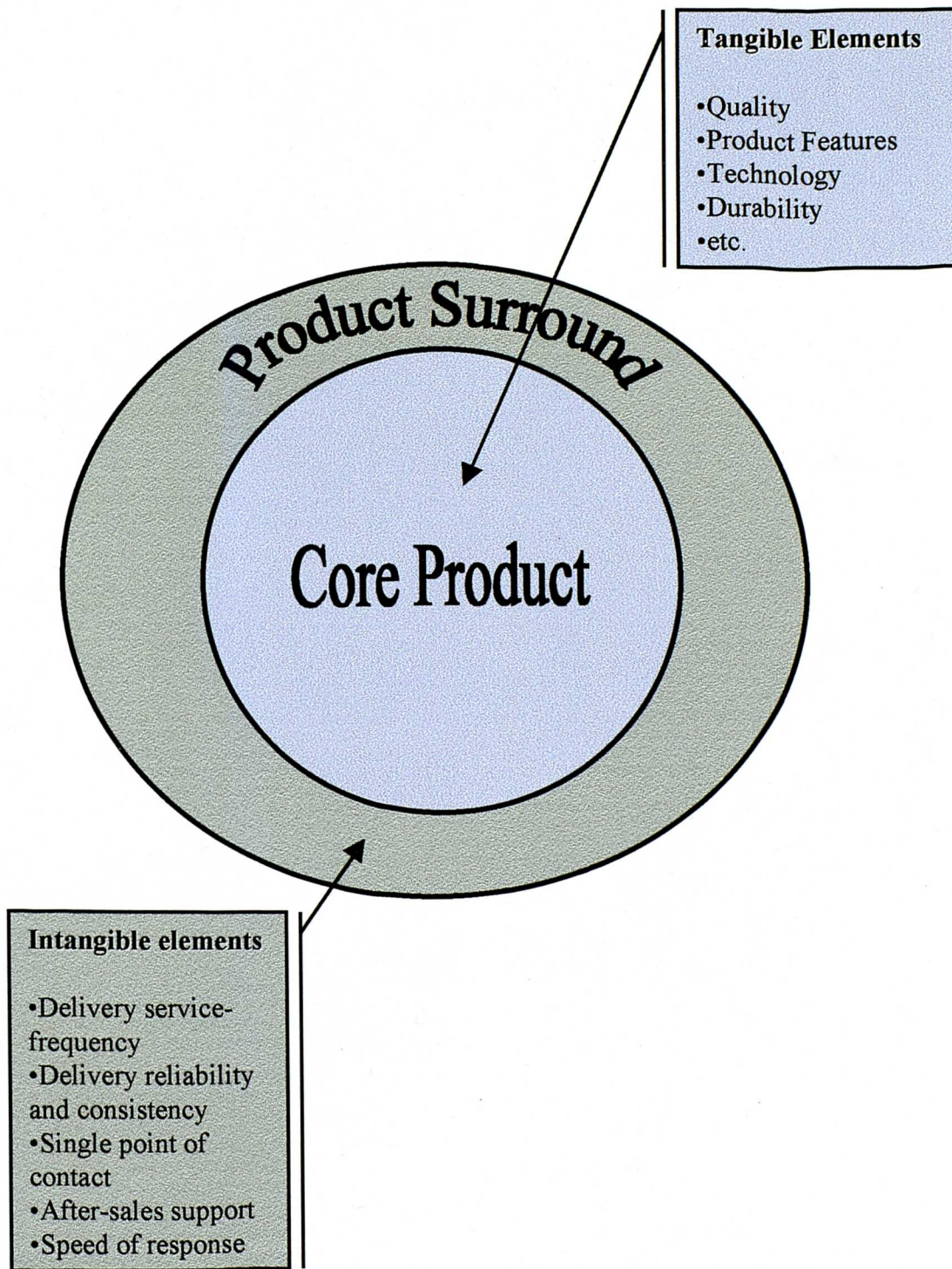


Figure 2.2 – The customer product perception.

Adapted from Christopher, M. "Logistics and Supply Chain Management" Pitman, 1992.

Agile competition demands that the supply chain processes that support the creation, production and distribution of goods and services are centred on the customer perceived value of products. Successful agile companies therefore know a great deal about individual customers and interact routinely and intensively [Goldman, Nagel, & Preiss, 1995 pp.3-7].

2.3.1.1 Customer Service

Defining what is meant by customer service is dependent on the expectations of each individual customer. However, all attempts to define customer service tend to focus on relationships at the buyer/seller interface [Christopher, 1992 p.26].

Effective customer service requires three key elements to be in place. These are customer focused systems, measurements and people [Wilding, 1995]. These elements are all interrelated, and each element requires the other elements to be in place to achieve the customer service levels expected. For example, a computer system developed to aid customer service requires trained personnel to operate it. The effectiveness of the systems operation requires measurement, and the effectiveness of people also needs to be measured.

The author witnessed a recent example of these relationships with a leading telephone banking organisation. After many months of exceptional service the author, who was the customer, noticed that it was becoming difficult to contact the organisation. After complaining about the situations the organisation explained that due to a recent advertising campaign the number of customers had increased dramatically, this resulted in the response time (a key measure for the organisation) increasing. The organisation responded by increasing the number of telephone lines and improving

communication systems, however this resulted in increased stress on the telephone banking assistants resulting in errors occurring (another key measure for the organisation). This led to the recruitment and training of new telephone banking assistants. The service the author now experiences has returned to the high level witnessed prior to the advertising campaign. This example demonstrates the importance to customer service of systems (the telephone system) people (telephone banking assistants) and measurements; response time (a systems measure) and error rate (a people measure).

LaLonde and Zinszer, [LaLonde & Zinszer, 1976] suggest that the requirements to achieve customer service can be categorised as:

- Pre-transaction elements.
- Transaction elements.
- Post-transaction elements.

Pre-transaction elements relate to policies and programmes within the organisation such as written statements of service policy and adequate organisational structure. The transaction elements are those focussing on order processing and delivery of the product. Post-transaction elements are generally in support of the product after purchase, for instance service call out time, warranty length, customer complaints handling.

For effective customer service organisations need to ensure that for each of these key categories the systems, measurements and people are in place to respond to each customer group or market.

The driver of improving customer service and hence competitive advantage results in the re-engineering of the supply chain. Christopher [Christopher, 1992 p.34] states that the role of logistics is the provision of systems and the supporting co-ordination process to ensure the customer service goals of an organisation are met. Supply chain management can enable all organisations to focus on the customer through integrating activities and policies. This can result in a reduction of non-value adding activity within the supply chain resulting in cost reduction.

2.3.2 Cost Reduction

From the definitions of supply chain management described in section 2.1.1 it is concluded that inventory management across the supply chain is a key emphasis. This is due to the fact that this is a major area where cost reduction can be achieved for all players in the supply chain. It is estimated that typically a 25% reduction in inventory is possible in the best-run supply chains if proper tools and understanding can be applied [Davis, 1993]. It is recognised that the supplier's finished goods stock becomes the customers raw material stock, and by working together organisations can remove this duplication and locate the inventory at the best location to benefit the end customers and subsequently the organisations in the supply chain.

Further cost benefits are achieved by effective supply chain management. Some of these costs are easily quantified by current accounting techniques; some however are less easy to quantify. Savings can be made within the ordering process by electronic data interchange and in design and life time costs by involving suppliers in the design phase for new products. Concurrent engineering with a focus on the supply chain can also benefit ownership and service costs for products. This may be the result of

careful engineering to reduce the complexity of the products and subsequently the supply chain [Wilding R.D. & Yazdani, 1997]. These areas will be discussed in more detail in later sections.

Cost reduction through supply chain management is often a major driver for organisations. However, both competitive advantage and cost reduction can be achieved concurrently by applying a holistic approach to the management of the supply chain.

2.4 ✓ Requirements and Methods for Supply chain management

The implementation of effective supply chain management requires an organisation to focus on a number of key areas, which can be categorised as follows:

- Material logistics: - This focuses on the movement and management of material and the physical processes undertaken on the material. It is planned and controlled by a number of functions within an organisation from purchasing and manufacturing through to distribution. Supply chain management requires that the movement and processing of material should be as seamless as possible.
- ✓ Information requirements: - Information is passed between organisations and within organisations within the supply chain. This may take the form of orders, invoices and schedules; the accuracy and timeliness of this information is critical to the effective management of the supply chain. The electronic transmission of information is having a major impact on the effectiveness of supply chains and can enable a more detailed picture of customer requirements and habits to be gathered.

-
- Time Compression is becoming a widely used approach enabling the integration of the supply chain and subsequently gaining competitive advantage. Time compression focuses on maximising the proportion of added value time that is spent on key resources such as materials and information.
 - Quality of products and service is essential to the effective management of the supply chain. In section 2.3.1.1 the importance of customer service was discussed, customer service requires both quality in the tangible product and intangible product.
 - Costing systems also require reviewing when undertaking effective supply chain management. Total lifecycle costing, focusing not just on the initial purchase costs but also the service and ultimately disposal costs of a product, may be applied such as Activity based costing.

In the following sections each of these areas will be discussed in relation to the management of the supply chain.

2.5 Material Logistics

2.5.1 Capacity, Inventory and Scheduling

The effective management of a supply chain system may be considered as dependent on three interacting factors. The factors are scheduling, capacity management and inventory management [Wild, 1989]. Figure 2.3 depicts the relationship between these areas. These areas are closely related; decisions made to address problems in one area may have a major (and sometime detrimental) impact on another area.

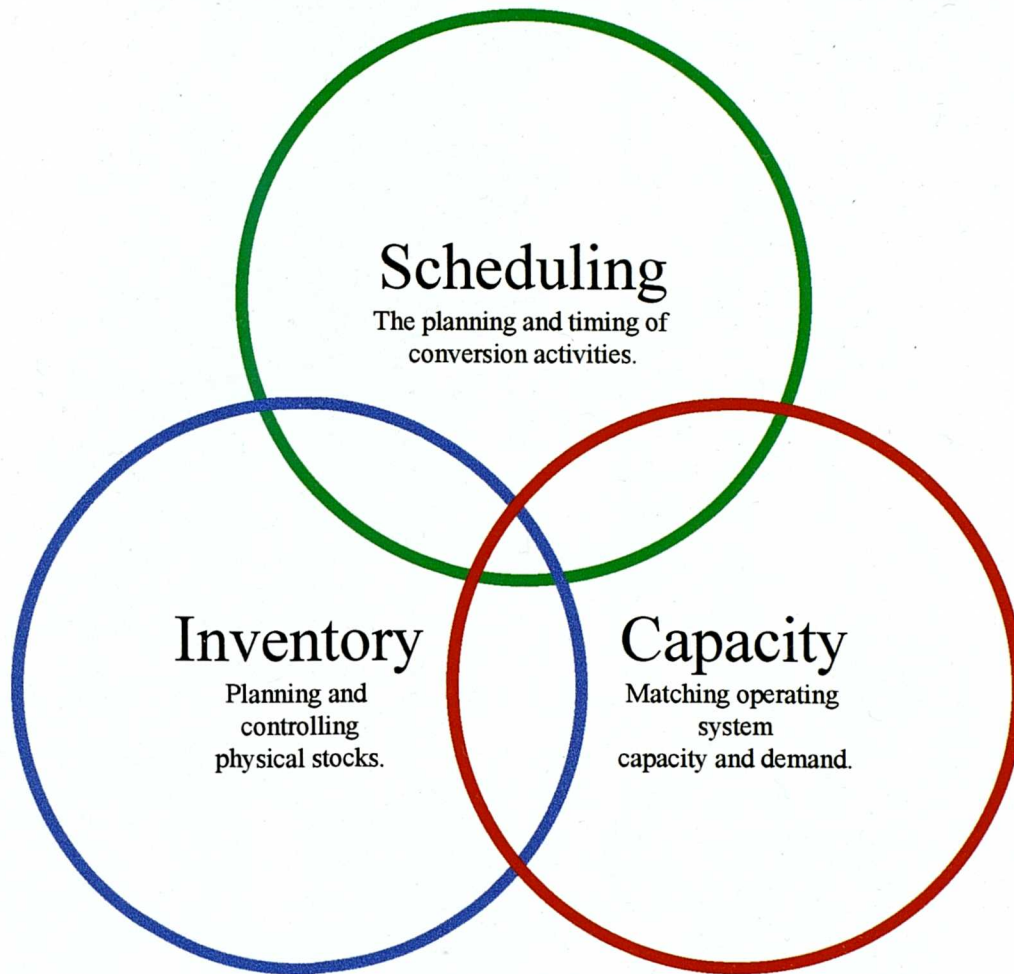


Figure 2.3 – The principal problem areas of materials logistics.

Adapted from Wild, R. (1989). "Production and Operations Management: Principles and Techniques." 4th ed. Cassell : London.

The type of problems experienced in each of these principle areas is influenced by the structure of the organisation and its supply chain. The trade-offs between each of these areas is often industry dependent. Managers in different types of organisations will use different strategies and techniques to manage the inventory, capacity and scheduling problems. The schedule reflects the needs of the customers, while inventory and capacity are managed to match the output of the system to the customers needs. However, due to the close relationship of the three areas, decisions in one area may result in additional uncertainty being generated within the system.

2.5.1.1 *Inventory Management*

Waters' [Waters, 1992] defines inventory management as:

"Inventory management consists of all the activities and procedures to ensure the right amount of each item is held in stock"

The main purpose of holding inventory is to act as a buffer between supply and demand. However, inventory may also be used strategically to give value to a product by its geographical position. Waters discusses ten reasons for holding inventory, these are:

1. To act as a buffer (decoupling) between different operations.
2. To allow for mismatches between supply and demand.
3. To allow for demands which are larger than expected, or at unexpected times.
4. To allow for delayed deliveries or deliveries that are short of items.
5. To avoid delays in passing products to customers.

6. To take advantage of price discounts on large orders.
7. To buy items that may be going out of production or are difficult to find.
8. To buy items when price is low and is expected to rise
9. To make full loads and thus reduce transport costs.
10. To maintain stable levels of operations.

The above list highlights that inventory can be used strategically, but is often used as a way to manage uncertainty. This uncertainty may be the result of problems with capacity management or poor scheduling.

The location and management of inventories has a major impact on both resource productivity and customer service. The existence of finished goods inventory may result in organisations being able to achieve high customer service levels, in terms of availability, but their existence may be costly. A focus on holding raw materials stock may also benefit customer service but productivity may be adversely affected because more resources may stand idle, while waiting for customer orders. Planning the quantity and location of inventory may be costly but is also necessary. Inventory can tie up a considerable amount of an organisation's capital, so a trade-off between the high costs and using inventory to increase flexibility, customer service levels and insulating against uncertainty in demand, needs to be constantly reviewed.

2.5.1.2 Scheduling

The schedule is responsible for delivery performance. Vollmann et al [Vollmann, Berry, & Whybark, 1992] define a schedule as:

“A plan with reference to the sequence of and time allocated for each item or operation necessary to complete each item.”

To develop an effective schedule the entire sequence of operations, time estimates for each operation, and the required resource capacities for each operation are required. Scheduling is a process, the schedule is prepared, actual performance is observed and rescheduling takes place as uncertainty becomes resolved i.e. forecast demand becomes actual customer orders. Due to the necessary forecasting of future requirements schedules are rarely 100% effective and “right”. This therefore requires some buffering in the form of inventory or flexibility in capacity.

The nature of the scheduling problem is influenced by the presence and location of inventories, which in turn are related to the customers of the system. Scheduling relates to the “timing” of the physical flow or transfer of goods, the complexity of this is clearly dependent on the number of stages that are within the system. Where stock is held in a warehouse the customer demand will be met by the scheduled output from stock, these stocks will be replenished by scheduled inputs either from other warehouses or direct from suppliers. In the absence of finished goods inventory the customer demand will be met by the scheduled output from the manufacturing function, this requires scheduled input of raw materials and scheduled deliveries from suppliers.

2.5.1.3 Capacity Management

Capacity creates flexibility that can be used to buffer against uncertainty. Chase and Aquilano [Chase & Aquilano, 1995] define capacity as:

“The amount of resource inputs available relative to output requirements at a particular time”

This definition does not differentiate between good and bad use of capacity. Chase and Aquilano also provide the U.S. government definition of capacity, this is defined as follows:

“That output attained within the normal operating schedule of shifts per day and days per week including the use of high cost inefficient systems”

This definition recognises that the amount of capacity present is linked to the schedule for a given period. A schedule involving many machine set-ups reduces the overall productive time of a machine and hence its capacity.

When designing any system the determination of capacity is a key planning and design problem, the adjustment of capacity is a major control problem impacting on both the scheduling and inventory management. Effective capacity management can improve resource productivity and customer service. Poor capacity management can result in low resource utilisation and poor customer service.

All functions within an organisations and all players in a supply chain are concerned with inventory, scheduling and capacity decisions.

2.5.2 *Purchasing*

Purchasing is critical to the effective management of material logistics. Positioned at the interface between the customer and the supplier, responsibility often falls on this function for managing the relationship between the customers and suppliers in the supply chain. Leenders et al [Leenders, Nollet, & Ellram, 1994] describe purchasing's role as the gateway to suppliers so other business functions can communicate with their counterparts within the supplier organisations. Leenders et al also comment that purchasing can often block access to suppliers and this is detrimental to effective management of the supply chain.

The purchasing strategy must address the question of how many sources should be used for each component or service and what type of relationship should be formed with each supplier. The purchasing department will not give all suppliers the same level of attention. The purchasing matrix is a useful tool to assess the supply base according to supplier risk factors that may generate uncertainty for the customer [Syson, 1992]. Table 2.1 shows the categories and the risks involved.

The matrix is dynamic and the leverage items of today may become the bottleneck or non-critical items of tomorrow. Depending on the sector within which the purchased item falls, different purchasing and inventory policies are required. The selection of the suppliers and inventory strategy employed is dictated by the position of an item on the matrix.

Two key areas that the purchasing function is actively involved in are supplier selection and the development of customer supplier relationships.

| | | | |
|---|-------------|---|--|
| Level of Risk | High | Bottle neck items: <ul style="list-style-type: none"> • Need to handle efficiently. • Focus on systems/automation. (EDI) • Use forecasts based on past demand. • Shortage of supply/high risk of non-availability • Minimum order quantities. • Political factors may influence demand e.g. Patents. • Security of inventory. | Strategic items: <ul style="list-style-type: none"> • High value items • Balance of power between buyer and seller. • Parties are dependent on each other. • High level relationship. • Development of long term relationships. • Strategic inventory |
| | Low | Non-critical Items: <ul style="list-style-type: none"> • Need to handle efficiently. • High volumes. • Wide choice of suppliers. • Focus on systems/automation. (EDI) • Use forecasts based on past demand. • Inventory optimisation. | Leverage Items: <ul style="list-style-type: none"> • Significant buying power in favourable market conditions. • Wide choice of suppliers. • Spot and long term deals |
| | | Low | High |
| Degree of influence customer has on relationship | | | |

Table 2.1 – The Purchasing Matrix

Adapted from Syson, R. (1992). "Improving Purchase Performance." Pitman : London.

2.5.2.1 ✓ *Supplier selection.*

Dickson [Dickson, 1966] identifies from the literature over fifty distinct factors presented as meaningful to consider during the vendor selection decision. This demonstrates that supplier selection is multi-objective in nature. The nature of supplier selection has resulted in decision support tools being developed [Weber & Ellram, 1993].

Traditionally supplier selection focuses on the quantifiable aspects of the purchasing decision such as cost, delivery reliability and quality. Ellram [Ellram, 1990] identifies additional factors that should be considered when selecting supply partners for effective supply chain management. Ellram categorises these factors under the headings of financial issues, organisational culture and strategy, technology and miscellaneous factors.

- Financial issues focus on the supplier's historical economic performance and stability. The organisational culture and strategy includes a number of intangible factors including a feeling of trust, the outlook and attitude of the management, strategic fit, and the compatibility across levels and functions between the supplier and buyer organisations. These factors are seen as important to the long-term future of the supply relationship.
- Technology factors are important to organisations selecting suppliers for supply partnerships where future technological capability is of importance. To assess these issues the supplier's design capability, speed of new product development and also current and future manufacturing capabilities require assessment and benchmarking.

- The miscellaneous factors include safety record of the supplier, business references and the supplier's customer base.

2.5.2.2 *Managing the customer supplier relationship.*

The Bose Corporation, manufacturer of quality audio equipment, has taken partnership sourcing a step further. To manage supplier relationships to the level required Bose recognised more people were required within their organisation, but due to budget restraints no further people could be employed in this role. This acted as a driver to develop the JIT2 concept.

The just-in-time concept was seen to eliminate inventory and bring the customer and supplier closer together on an operational basis [Greenblatt, 1994]. The JIT2 approach eliminates the buyer and the salesman from the customer/supplier relationship, thus fostering increased communication between the parties. A supplier employee who resides full time in the customer's purchasing office replaces the buyer and supplier. This "supplier in-plant" is empowered to use the customers' purchase orders and place orders on their own company. The "supplier in-plant" also does the material planning for the materials supplied by his company. The "in-plant" is also part of the production planning process so production is planned concurrently with the supplier organisation. This streamlines the supply process by removing the "planner to buyer to salesman to supplier's plant" process by making this the responsibility of one individual. This has dramatically reduced the uncertainty experienced by the supplier organisations. The benefits of this streamlining have also resulted in major business improvements for Bose. These include [Greenblatt, 1994]:

- 50% improvement relating to on time deliveries, damage and shortages.

- 6% reduction in material costs.
- 26% improvement in equipment utilisation.
- Major reductions in inventory holdings.

Amongst the authors presenting detailed discussion of the importance of supplier development and purchasing to supply chain performance are Hines [Hines, 1994], Lamming [Lamming, 1993] and Syson [Syson, 1992].

2.5.3 *Manufacturing Planning and control*

Figure 2.4 depicts a generic manufacturing planning system. The total demand for end items is collected from customer orders and also forecasts from the marketing function. A high level master production schedule is developed by viewing the current finished goods inventory files, forecasts, orders and any policy decisions which may be applied (for example, at certain times of year a policy of building up stock may be applied). To prevent unreasonable demands on manufacturing resources “rough cut capacity planning” is carried out. This focuses, for example, on possible material shortages and the purchase of additional tooling. After the “rough cut capacity planning” the Master Production Schedule should be broadly feasible.

The aim of the Master Production Schedule is to timetable the arrival of finished product into the warehouse in order to meet customer demand. Due to manufacturing constraints production may be in batches and customer demand usually fluctuates resulting in a difference between the desired production batch size and the demand quantity.

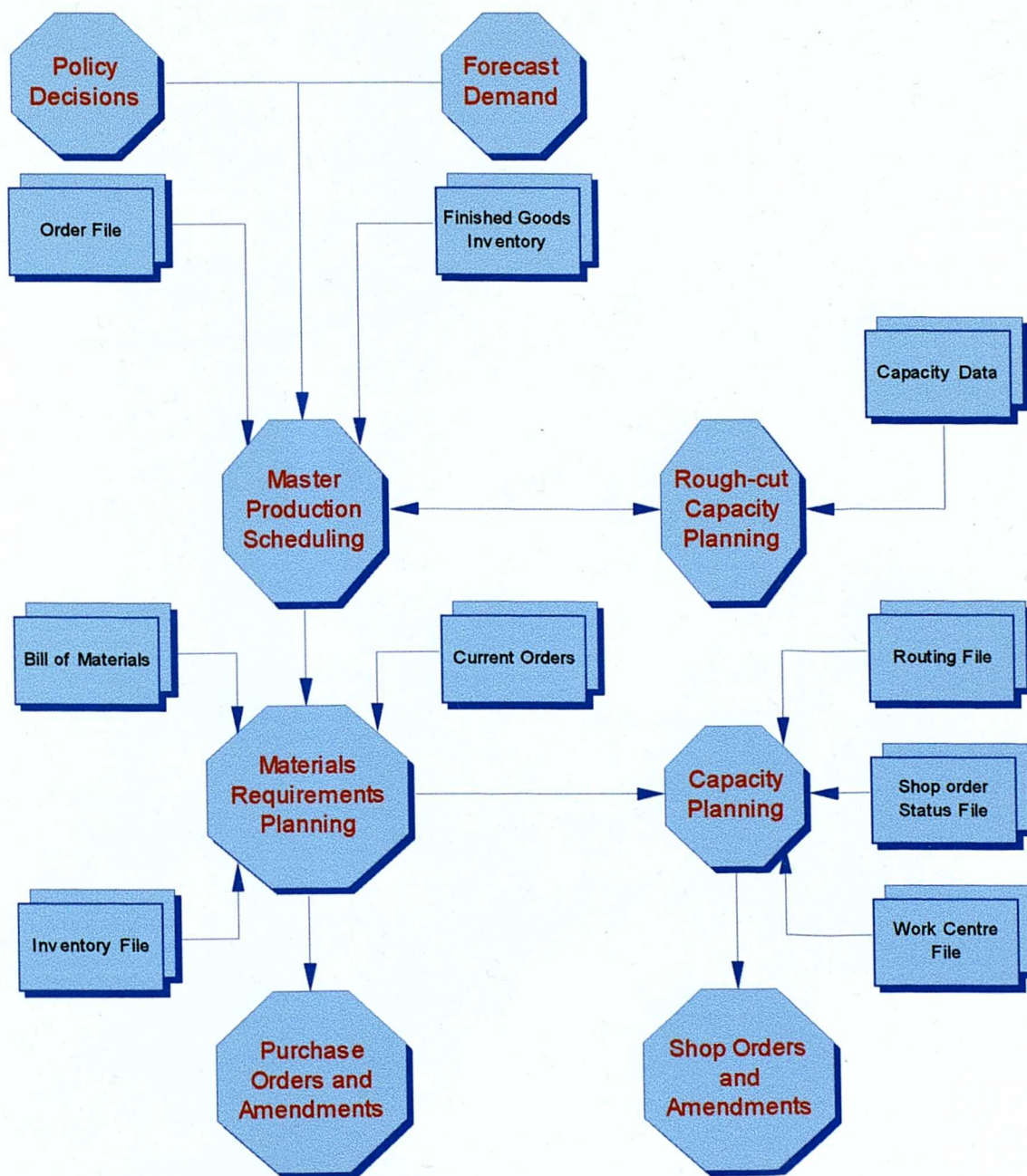


Figure 2.4 – Generic Manufacturing Planning System

Adapted from Vollmann, T.E., Berry, W.L., and Whybark, D.C. (1992). "Manufacturing Planning and Control Systems." 3rd ed. Irwin : Boston.

Once a feasible Master Production Schedule is obtained detailed capacity requirements planning, materials requirements planning and scheduling take place in order to achieve the Master Production Schedule. This procedure defines what needs to be made, what needs to be purchased and the timing of these events.

Unfortunately, due to uncertainty within the system the schedules developed may not be fulfilled exactly and hour by hour changes may take place.

It is not uncommon for the manufacturing planning systems to be run on a monthly basis due to the computer time required to do all the various calculations.

It should be emphasised that materials requirements planning (MRP), as its name suggests, is a planning tool, not a control tool. A survey of best practice in Logistics revealed that of the “leaders” in logistics only 20% professed to use MRP, while of the “laggers” 50% used MRP systems [A.T. Kearney Consultants, 1991]. Braithwaite [Braithwaite, 1996] comments that most of the “laggers” have also achieved Class A certification for the quality with which the MRP systems have been installed. Best practice in the use of MRP involves using the system for planning and then using simple materials control techniques such as “Kanban control” to manage the flow of materials through the operation. This policy was confirmed by the A.T. Kearney investigation.

For detailed discussions on Materials Requirements Planning, Kanban and hybrids of these approaches both Vollmann et al [Vollmann, Berry, & Whybark, 1992] and Wild [Wild, 1989] are texts worth referring to.

2.6 Information Requirements

The importance of effective information management can be observed by viewing the transaction statistics of the major supermarket chain Tesco. By the end of 1991 the organisation's computer system was handling the following weekly transactions [Cunningham, 1994]:

- 9 million sales transactions
- 50,000 invoices
- 13,000 depot-to-store deliveries, and
- 10,000 store replenishment orders.

These statistics demonstrate that it would be nearly impossible to handle this amount of information without effective information flows both internally and between the organisation and its many suppliers.

Bowersox [Bowersox & Closs, 1996] classifies supply chain information under two main headings; Planning and co-ordination flows and operational requirement flows. The overall relationship between these two information flows is illustrated in figure 2.5.

2.6.1 Planning and co-ordination flows

Information is vital to ensure the effective co-ordination of the supply chain. The co-ordination activity results in plans which specify the strategic objectives, capacity constraints, logistical requirements, inventory deployment, manufacturing

requirements, purchasing and procurement requirements, and finally forecasting. The key driver for these plans should be the supply chain's strategic objectives focusing on customer service but related to the financial and marketing objectives.

The capacity constraints identify limitations or bottlenecks within the supply chain organisations. The result of understanding these constraints is a schedule that can be used to achieve the strategic objectives. Logistics requirements apply to the work that the distribution facilities equipment and labour must undertake in order to implement the capacity plan. This requires information inputs from forecasting, customer orders, inventory status and marketing. Inventory deployments detail the composition and location of where inventory is held in the supply chain. The planning and co-ordination activity defines the type of inventory, where it is positioned and when it should be in a given location. The operational requirements of inventory require it to be managed on a day to day basis. Manufacturing requirements are derived from the inventory deployment and logistics requirements areas. MRP as discussed in section 2.5.3 defines what needs to be purchased, what needs to be manufactured and when. Manufacturing requirements define the day-to-day production schedule to satisfy the strategic objectives of the business. Purchasing and procurement schedule and plan the components to support the manufacturing requirements. Purchasing co-ordinates decisions regarding supplier selection and the type of relationship required with the supplier. Finally forecasting utilises historical data and current activity levels in order to predict future activity levels.

The overall purpose of the planning and co-ordination information flow is to integrate the plans and activities within the individual organisations and wherever possible across the complete supply chain.

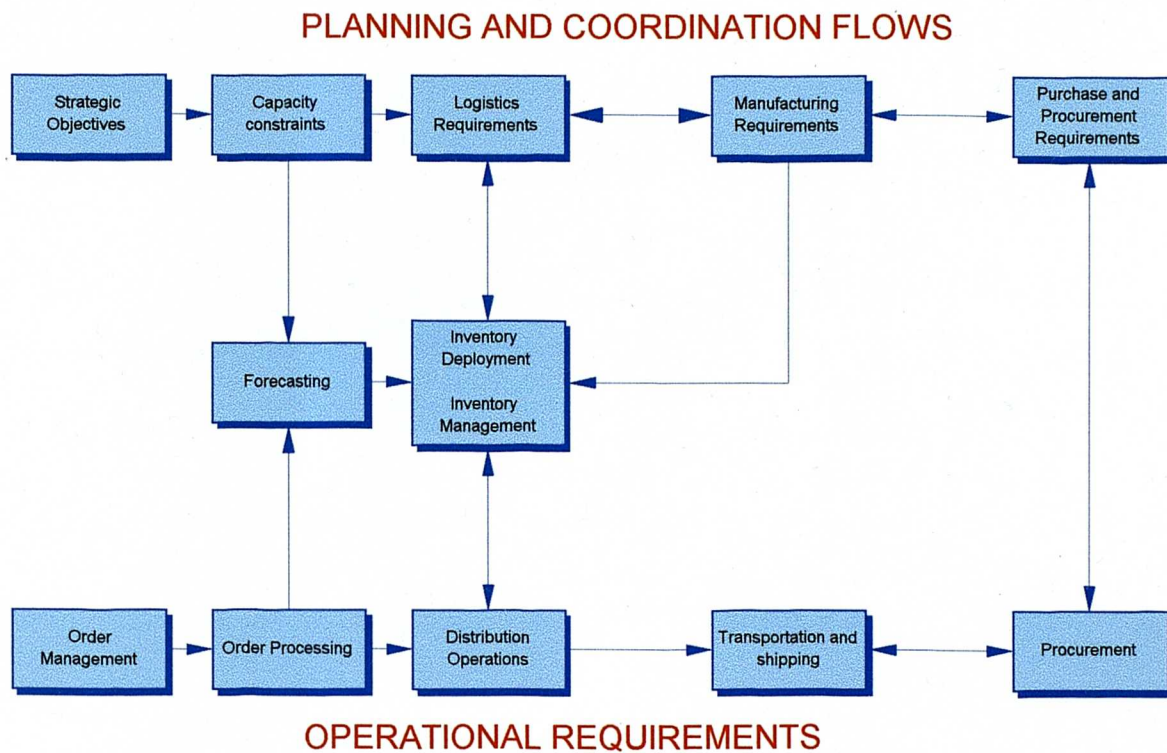


Figure 2.5 – Supply chain information requirements.

Adapted from Bowersox, D.J., and Closs, D.J. (1996). "Logistical Management." McGraw-Hill : New York.

✓ 2.6.2 *Operational requirement flows*

The second category defined by Bowersox and Closs [Bowersox & Closs, 1996] is the informational requirements for operations. Operational information enables order management, order processing, distribution operations, inventory management, transportation and procurement.

Order management refers to the transmission of resource requirement information between the supply chain members. Key to this activity is the accuracy and timeliness of the information. The transfer of information between supply chain members can be achieved by a variety of methods including phone, fax or electronic data interchange. Order processing assigns inventory to customer orders. Distribution operations are responsible for co-ordinating the information to provide the product assortments required by the customer, the key emphasis is to store and handle inventory as little as possible while still meeting the customer service requirements defined through the strategic objectives. The role of inventory management information is to ensure the various supply chain operations have adequate inventory to perform as planned. Transportation and shipping information directs the movement of inventory. Change in ownership and the movement across national boundaries also requires supporting documentation. The procurement information is necessary to complete purchase order preparation, modification and release.

Operational information's overall purpose is to provide the detailed data required for integrating the supply chain's operation on a short-term basis.

2.6.3 Electronic Data Interchange (EDI)

Palmer defines EDI as [Palmer, 1989]:

“The electronic transfer from one computer to another of computer processable data, using an agreed standard to structure the data”

The emphasis of this definition is the computer to computer communication. The data exchange should be without manual intervention, thus resulting in seamless data transfer and processing between suppliers and all echelons in the supply chain.

Emmelhainz [Emmelhainz, 1990] describes the following direct benefits of using EDI. These include:

- Increased internal and external productivity
- Improved supply chain relationships
- Improved ability to compete internationally
- Decreased operation costs.

The reduced operating costs can be attributed to a variety of issues including a reduction in clerical and labour costs, reduced inventory due to improved planning and, due to the reduction in lead-times, a reduction in pipeline inventory.

To achieve the transmission of data agreed standards for data transmission have to be achieved. This has resulted in a number of industry and country specific standards being developed. However, there is concern between users that what should be a reasonably simple exercise in order transmission is becoming increasingly complex resulting in inefficient EDI use and consequently inefficient internal IT system usage

within supply chain organisations. McGuffog [McGuffog, 1997] defines the key obstacles to cost effective EDI as the unnecessary complexity of the messages and the processes they relate to, this results in inconsistent interpretations of the data elements and messages by some EDI hub organisations. This problem is currently being addressed by the UK Confederation of EDI standards who are proposing a replacement standard "SIMPL-EDI".

2.7 Time Compression

Time is becoming more important in the value perception of customers. It is also an important cost-driver. Removing time from company processes therefore reduces cost. Time-based strategies can increase competitive advantage on both the value and cost sides of the equation.

A definition recently proposed by the Institute of Logistics states that [Canadine, 1994 p.21]: -

"Logistics is the time-related positioning of resources"

It follows that Effective Logistics Management is the process required to effect the positioning of resources (i.e. manpower, machines, facilities, materials, products, money, energy and information) in the right position in the supply chain at the right time. Logistics focuses on the total system design, integration of one process with another, system efficiency, deployment of resources and above all the effective management of time.

Research over the past ten years has indicated that it is not uncommon for the average time spent actually “adding value” within a manufacturing environment to be as little as five per cent of the total process time. In effect this means that in such a situation we waste ninety five per cent of the time [Bhattacharyya, 1995; Peters, 1991; Stalk, 1987]. For the total supply chain things are generally even worse. As little as one tenth of one percent has been found to be “adding value” time. In effect this means “time related positioning” is not achieved in such a supply chain, for over 99% of the time!

Experience indicates that focusing on the effective management of the key resources of the business can derive major benefits [Wilding & Sweeney, 1994]. The key to success involves understanding what constitutes best practice in management of these resources with respect to time, and how this can be applied, given the unique characteristics of a particular business. Henry Ford said when comparing the management of the material resource with time:

“Time waste differs from material waste in that there can be no salvage”

Time-Based systems with an emphasis on speeding up process times result in a reduction in cumulative lead-times. This results in lower inventory and thus a further reduction in response time. A Time Compression “Virtuous Circle” is produced [Wilding & Newton, 1996], as depicted in figure 2.6.

Within a manufacturing environment it is easy to focus on the actual shop floor production process. However, this is only a small part of the processes required to qualify as a manufacturing company. Customer service, marketing, purchasing etc. all

have direct and indirect inputs to the production process. The production process, as stated above, may add value for only five per cent of the time. For example, the time to schedule orders into production (up to 4 weeks in some major automotive companies) and, the time to replenish stocks all have a major impact on the effectiveness of a supply chain. These areas have also become prime focus areas for Time Compression.

Focusing on the flow of information in the supply chain often brings opportunities to improve response time dramatically and hence reduce inventory, working capital and therefore cost.

Wilding and Newton demonstrate the effectiveness of this approach with a simple example [Wilding & Newton, 1996]. In one large multi-national company, the European sales companies did not understand the needs and operation of the factories and vice versa. Simple analysis of the internal ordering and replenishment process opened communication channels and the company as a whole has benefited.

In the same organisation re-order point planning was used in each of the sales outlets. Large orders placed infrequently on the central factory often overloaded the capacity of the factory, warehouse, packing and shipping departments and caused long and unreliable lead-times. Sales outlets lost confidence in the ability of the factory to supply to quoted lead-times and relationships rapidly deteriorated. In fact the factory had sufficient capacity to meet end customer demand. It was the internal inventory planning systems that were causing the problems.

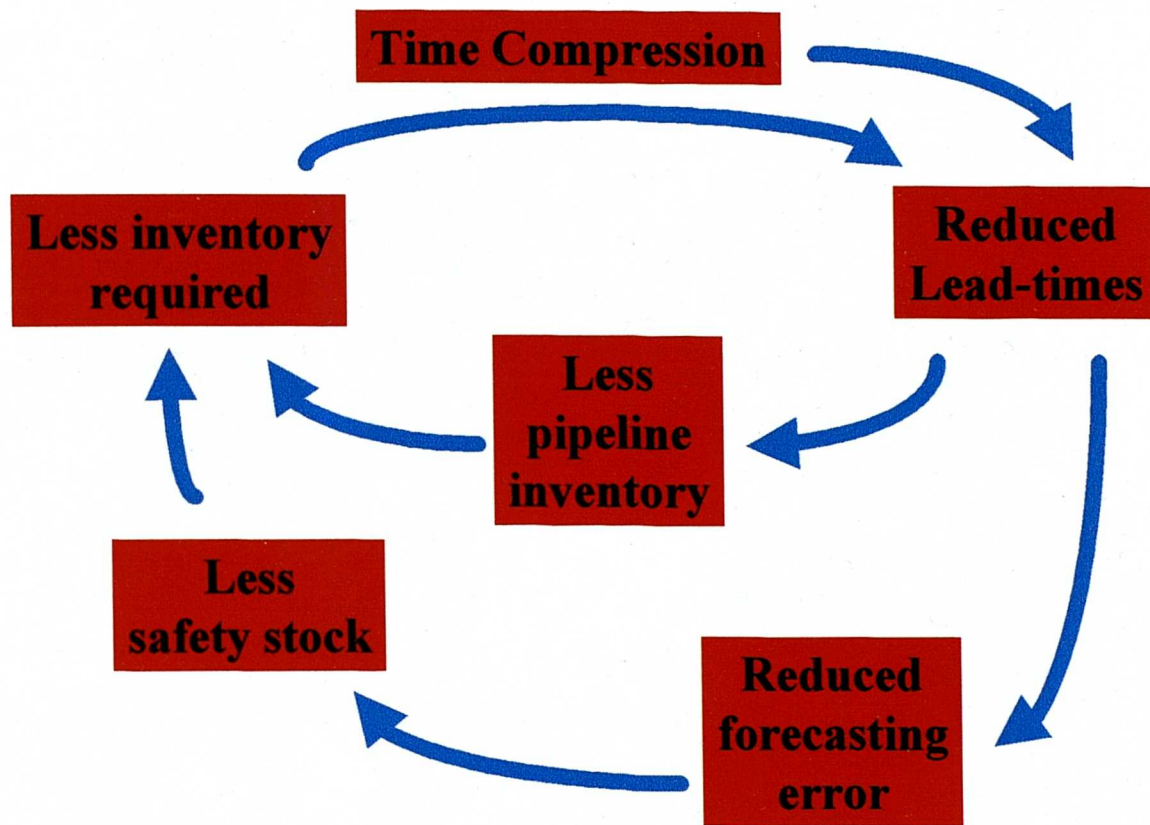


Figure 2.6 – The time-compression “virtuous circle”.

Source: Wilding, R.D. & Newton, J.M. (1996) “Enabling time-based strategy through logistics”, *Logistics Information Management*, Vol.9 No.1, pp.32-38.

After only three days data gathering and analysis of its European supply chain, using a Time Based Process Map developed on a standard spread sheet package, the team was able to reduce a key lead-time from eight weeks to under three weeks.

2.8 Quality of products and service

To achieve customer satisfaction, quality needs to be maintained in both the tangible and intangible parts of the product. Quality should be defined as conformance to the total customer requirement. Over engineering products for a particular market can be as costly to the organisation as under engineered “poor quality” items. Over engineered products may incur increased costs in design and material costs, which may result in the product being too costly for the market needs. Hines [Hines, 1994] describes how Hewlett Packard define quality. Hewlett Packard classifies quality under two main categories, quality of products and quality of sales. Each of these categories is further divided into three sub-groups. These will be briefly discussed.

2.8.1 *Service Quality*

Quality of sales is broken into two key areas relating to the service component of the product.

- “Before sales quality” is the quality of collecting information on market needs, the quality of advertising, sales literature, product sales and training. The quality of the sales activity is dependent on quality of customer seminars, ease of use of sales literature, proposal for solution to customer, distribution, installation and delivery.

-
- “After sales quality” is dependent on the quality of maintenance, repairs, parts and claim management and the delivery of replacement parts.

In many markets today the service quality may be more important to the customer than the tangible product.

2.8.2 Product Quality

Product quality is sub-divided into three main areas these are product planning, design and manufacturing.

Product planning quality depends on the analysis of market needs and the matching of product characteristics to the market needs. Design quality focuses on the marketability of the product, the product performance, reliability, serviceability, the adaptability of the product to changing market needs and the lasting value of the product. Manufacturing quality is the quality of the components, production process, inspection and packaging. Product quality is intended to satisfy the tangible needs of the customer.

For effective supply chain management all the above categories of quality need to be addressed by the organisations in the supply chain. The fashionable concept of exceeding customer expectations may be costly and gain little competitive advantage for the organisation. Similarly products that do not meet the customers' requirements are just as costly to the organisation. This further emphasises the need for working closely with customers.

2.9 Costing Systems

Costing systems used within the supply chain can have an indirect effect on the performance of the supply chain. Traditional cost accounting approaches tend to focus on historical data and merely record the cost of the product. The rather arbitrary way overhead costs are accounted for has been a concern to many. This has resulted in the development of approaches such as Activity Based Costing that can be used dynamically to predict cost and also target areas of non-value-adding activity. Yoshikawa et al [Yoshikawa et al., 1993] have produced an excellent discussion on the various approaches used to costing within industry.

Accounting cycles should be aligned across the supply chain. For example, organisations using a 4-week month can have conflicts with those using a 4-4-5 week accounting cycle because account systems may pass on a forecast for a 5-week period to another with a 4-week period. This may result in the misinterpretation of the weekly production requirements within one of the organisations resulting in excesses or shortages within the supply chain.

2.10 Conclusion to Chapter 2

This chapter has defined supply chain management and presented the drivers and requirements for this approach. The brief overview presented above sets in context the remainder of this research. The main focus of this research is the generation of uncertainty by the internal supply chain systems. In the next chapter a review of the research into this area will be presented.

Chapter 3

Amplification & Uncertainty in Supply Chains

3.1 Introduction

The lack of literature focusing specifically on amplification and uncertainty has been recognised by recent reviews of supply chain management and research [Vidal & Goetschalckx, 1997; Thomas & Griffin, 1996; Slats et al., 1995].

Vidal [Vidal & Goetschalckx, 1997] presents one of the most comprehensive reviews of modelling in supply chain management. The work identifies ten specific research opportunities, which are seen as important for the progression of the subject area. Two of the issues raised by Vidal and Goetschalckx are 1) the requirement for the explicit inclusion of stochastic features in modelling supply chains and 2) the inclusion of service level models within supply chain simulations. The research documented in this thesis goes some way to addressing the shortcomings raised by the authors.

Thomas and Griffin [Thomas & Griffin, 1996] present a detailed review of the literature relating to the co-ordination of two or more main stages in the supply chain, for example buyer-vendor, production-distribution co-ordination. The review identifies the lack of research into the network structure of supply chains. The authors argue that the models often become too large and complex to provide solutions and this emphasises the need for carefully selected approximations that will

not sacrifice the integrity of the solutions. This often allows for the study of logistical problems that would otherwise be too complex.

Slats et al [Slats et al., 1995] provides a further review of supply chain modelling techniques. The paper highlights the deficiencies of analytical models applied within the literature. These were that unrealistic assumptions are applied within the models and also that uncertainty is generally ignored.

It is interesting to note, that all the reviews to date neglect to refer to the literature and findings on supply chains resulting from the behavioural science approach. This work provides an insight into the behaviour of supply chains, which much of the “main stream” supply chain management literature does not address.

The following chapter reviews the literature relating directly to uncertainty in the supply chain.

3.2 Classification of literature

The work which forms the foundation for much of the current research is Forrester’s original “Industrial Dynamics” work [Forrester, 1961]. This directly generated two avenues of work. The first, defined by the author as the Control Theory approach, focuses on applying the principles used for example in, electrical circuits and process control, to devising ways to dampen the dynamics within the supply chain. The work of Towill [Towill, 1996] is an example of this type of methodology.

The second avenue can be defined as the Behavioural Science approach. This was developed from investigations into human decision making using a hand simulation of

Forrester's supply chain, called the "Beer game". This focuses on the rules applied by managers operating the hand simulation, and demonstrates how human decision making can generate uncertainty.

A third approach, found within the literature can be described as the Practitioner approach. This is generally, as the title infers carried out by practitioners, one thing that does tend to characterise this body of work is the use of stochastic simulation models for studying the impact of uncertainty and descriptions of case studies where methodologies to reduce uncertainty are applied.

It should be emphasised that as the subject area has evolved the boundaries between these categories have become less distinct. Authors are tending to use a number of different approaches to investigate the research problem.

The evolution of the literature within each classification can be seen to develop through a cycle of theory, methodology and then case studies. For example, within the Control theory approach literature, theory can be seen in Burns' paper dealing with amplification [Burns & Sivazlian, 1978]. A Methodology is documented by Wikner et al [Wikner, Towill, & Naim, 1991] and finally we find the application of the methodology into an industrial environment and a case study documented in a paper by Berry [Berry, Towill, & Wadsley, 1994]. This results in further refining of the methodology and then further application into industry.

The chapter will progress by describing Forrester's pioneering work and then will describe the progression of the literature through each of the main classifications, Control theory approach, Behavioural science approach and Practitioner approach.

Finally, the chapter will be summarised outlining the research questions raised by the review of the literature.

3.2 The work of Forrester

3.2.1 Industrial Dynamics

Jay Forrester of MIT carried out the first piece of work undertaken to understand demand amplification within a simple linear supply chain in the early 1960's. In his now classic text "Industrial Dynamics" [Forrester, 1961] he discusses the dynamic behaviour of a simple supply chain consisting of four echelons; a retailer, distributor, factory warehouse and factory.

Forrester recognised that for many management problems, mathematical methods fall far short of being able to find the "best" solution. Mathematical solutions generally focus on achieving "optimum" solutions. This generally is achieved by the simplification of the problem to such a degree that it is devoid of practical interest and application [Forrester, 1961 p.3]. In recognising that the total system is of key importance, industrial dynamics was developed as a method of systems analysis for management. It deals with the time-varying interactions between parts of the management system.

Addressing the misunderstanding between the theorists and practitioners Industrial Dynamics can be seen as a methodology to bridge the gap.

As Forrester states [Forrester, 1961 p.8]:

“Managing is the task of designing and controlling an industrial system. Management science, if it is to be useful, must evolve effective methods to analyse the principle interactions of the important components of a company and its external environment”

Even over 30 years later management academics need to make ideas accessible and emphasise practical application of ideas. Practitioners and managers also need to gain the courage to step out of traditional comfort zones and recognise lessons learnt by theorists. In supply chain management this has never been so true, still many of the lessons learnt by Forrester are not being addressed in supply chain design, and organisations continue to make the same errors made by organisations in the past.

3.2.2 Information Feed-back Systems

The most important foundation of industrial dynamics (sometimes referred to as management dynamics or systems dynamics) is the concept of servo-mechanics (or information feedback systems). An information feedback system as defined by Forrester as [Forrester, 1961 p.14]:

“ An information-feedback system exists when the environment leads to a decision that results in action which affects the environment and thereby influences future decisions”

The process is continuous and a new result lead to new decisions which keep the system in continuous motion. Forrester identifies three key characteristics of Information-feedback systems to which they owe their behaviour these are:

- Structure

- Delays
- Amplification

The structure shows how the parts relate to each other. For example the high level structure of the simple supply chain. Delays always exist in the availability of information and the making of decisions. Amplification usually exists in information-feedback systems, especially those involving decision policies frequently used within industrial and social systems. Amplification manifests itself when an action is more forceful than that implied by information inputs and decision rules. All effects combine to determine the behaviour of such systems. Forrester also noticed that this behaviour can be anything but well behaved [Forrester, 1961 p.15]:

“In fact, a complex information-feedback system designed by happenstance or in accordance with what may be intuitively obvious will usually be unstable and ineffective.”

Forrester’s work focused on two main issues, gaining a better understanding of decision making processes and heuristic rules, and an experimental approach to give an insight into general systems behaviour.

Forrester applied his methodology to a variety of industrial and non-industrial situations including such diverse areas as Church growth and the impact of social structure on research costs [Forrester, 1975].

3.2.3 *The simple Forrester supply chain*

To maintain simplicity Forrester focused on a limited sub-system of the entire network. His model dealt with the structure and policies within a multi-stage distribution system (or supply chain). His main focus was to address the questions of:

- How does the system create amplification?
- What changes in policies affect oscillations?
- How will the system cope with changes in customer sales?

The information required to create the model focuses on organisational structure, delays in decisions and actions and policy on orders and inventories. Three principle components to orders were focused on:

- Orders to replace goods sold.
- Orders to adjust inventories upward or downward as the level of business activity changes.
- Orders to fill supply pipelines with in-process orders and shipments.

Forrester's model did not include any complex forecasting activity, he used a conservative approach and presumed that sales would continue at their present level [Forrester, 1961 p.23].

Orders were passed down the chain as follows:

Each echelon in the chain receives a sales order and then after a sales analysis and purchasing delay, orders are placed on the next higher level of the system. This order

placed on the supplier includes items to replace those items just ordered by the company's customer. A proportion of order accounts for items in process (for example; orders in mail, goods in transit, orders at supplier). This is necessarily proportional to the average level of business activity and to the length of time required to fill an order. If not ordered explicitly for the purpose of the "pipeline" they occur by default during inventory adjustment. After sufficient time for averaging out short term sales fluctuations by exponential smoothing a gradual upward or downward adjustment is made in the inventories as the rate of sales increases or decreases.

The above model can be simulated by groups of people around a board game, however for consistency and ease of use Forrester used a computer programmed with a bespoke programming language called DYNAMO. The board game simulation was later developed as a management exercise called the "beer game" which is still used to teach managers the requirements for systems thinking [Senge, 1993].

3.2.4 Forrester's experimental approach and results.

Forrester tested his model using a number of different scenarios. The experiments and key results are detailed as follows

3.2.4.1 Step input

A 10% increase in retail sales was introduced to the system. Due to accounting, purchasing and mailing delays the increase in the next level's orders (i.e. the distributors) lags the retail sales by one month, when it reaches the 10% level the orders continue to increase to a peak of 18% above the original orders. Forrester explains this effect is due to new orders being added for two key reasons.

- to increase inventories somewhat
- to raise the level of orders and goods in transit in the supply pipeline by 10% corresponding to the 10% increase in retail sales.

These inventory and pipeline increments occur as transient or non-repeating additions to the order rate and when they have been satisfied the orders should drop back to the enduring 10% increase.

At the next echelon in the model, the factory warehouse, responds to an increase of 18% in orders, it subsequently adjusts its inventory and fills the associated supply pipeline. A peak of 34% occurs 14 weeks after the 10% blip in retail sales. The same effect occurs at the factory. 21 weeks after the retailer received the initial increase in orders, a 45% increase in output occurs. It is also important to note that these effects can now occur in reverse. As the retailers satisfy their inventory requirements they decrease their orders. This results in excess inventory in the supply pipeline, which now has to be removed. This results in further swings at all echelons in the chain and the factory output drops to 3% of the original output. This drop occurs approximately ten months after the original blip in retail sales [Forrester, 1961 p.25].

This classical response to the step increase is often referred to as the “Forrester Effect”.

3.2.4.2 Periodic variations in retail sales (Oscillations of 10% above and below original)

In practice it is rare to find sales demand increasing in one distinct step. Often the variations oscillate. To simulate this Forrester used a sine curve to model periodic sales fluctuations. The periodic disturbances became accentuated as they passed down the

chain resulting in inventory variations of +62% and -45% of the original level at the factory [Forrester, 1961 p.26].

3.2.4.3 *Random Retail sales*

Recognising that the even periodic demand is a simplification of real demand data seen in practice, Forrester used sales data generated by random noise. Forrester noted that even if there is no average or periodic change in demand the system had the tendency to convert the random events into oscillations with peaks occurring some eight to nine months apart. Forrester deduced that [Forrester, 1961]:

“ The system, by virtue of its policies, organisation and delays, tends to amplify those retail sales changes to which the system is sensitive. Conversely, other frequencies of disturbance will be suppressed.”

3.2.4.4 *Limiting factory capacity to 20% above original*

The model up until now presumed infinite capacity at the factory. In the next experiment the capacity was limited to 20% above the original undisturbed sales level. A 10% step increase was input into the sales as described above. The result of this was an increase in unfilled orders to 345% above the normal level and a backlog of 6 weeks production, this reverses to drop to 79% below normal level. If viewed in the short term (say 9 months) this could result in managers contemplating an expansion of facilities to increase capacity.

3.2.4.5 *Faster order handling*

Forrester recognised that a major cause of the amplification effect was the result of the time-delays in the system. Forrester reduced these and improvement was witnessed. However Forrester comments [Forrester, 1961]:

“Speeding the flow from previously used information sources is often not the best way to improve operations; entirely different bases for reaching decisions, using different and already available information will often produce greater improvement at lower cost” (e.g. Orders placed directly on the production warehouse.)

3.2.4.6 *Eliminating Distributor level*

Forrester noted that re-engineering the supply chain can achieve far greater benefits, this is becoming a major focus of organisations in the 1990's (see for example [Van Ackere, Larson, & Morecroft, 1993]). The re-engineering of the supply chain was explored by the elimination of the distributor level in the model which resulted in a production overshoot of 26% compared with 45% overshoot when the distributor level was included in the supply chain.

3.2.4.7 *Changing inventory policy.*

The policy used in the model specifies an inventory correction based on sales exponentially smoothed over the previous 8 weeks. Forrester altered this and looked at the effect of changing the time over which the data was smoothed. This was varied between 4 and 26 weeks. The more gradual the inventory correction the more stable the model was seen to be. Forrester observes that:

“many sales forecasting methods tend to accelerate the inventory reactions to change in sales levels. Such forecasting will therefore tend to make operation of the system less stable.”

3.2.4.8 *Impact of advertising*

Forrester also enhanced the model to replicate the effects of advertising. It was noted that a demand pattern was created with an approximately two-year period. Forrester concluded that advertising is a possible cause of long cyclic disturbances. He suggested other initiatives that may have similar effect including consumer credit, sales forecasting methods and price discounting.

3.2.5 *Summary*

One of the key outputs of Forrester's work is a practical demonstration of how various types of business policy create disturbances which are often blamed on conditions outside the system. Random, meaningless sales fluctuations can be converted by the system into annual or seasonal production cycles thus sub-optimising the use of capacity and other key resources [Forrester, 1961 p.22].

Forrester's work as stated earlier branched off to look at a variety of other industrial and social systems. However in subsequent years authors have continued to investigate supply chain issues.

3.4 Control Engineering Approach

Burns [Burns & Sivazlian, 1978] continued to investigate the amplification effect. One question that was left unanswered is "is demand amplification totally unavoidable or necessarily undesirable". Burns used servomechanism theory to look at inventory control within the supply chain, which had been used up until then solely for inventory control of an individual supplier. Burns work is very theoretical and mathematical in content. He

found that the agents for demand amplification were the result of inventory policies and time delays as well as the system itself. The creation of “false orders” due to the over reaction of the system was followed by a new sequence of “negative orders”. He noted that if the chain is driven with pure noise and some frequency components of the noise were close to the natural frequency of the system, then a cyclic output was produced. This results from the natural frequency being selectively amplified as it passes through each echelon. The period of the oscillations can approximate to 12 months. Stalk and Hout [Stalk & Hout, 1990] discussed how this can be misinterpreted by managers as a seasonal variation that may result in further amplification by managers introducing advertising campaigns to try to level the variation. Burns concluded that the inventory adjustment necessitated by variation in the order pattern produced wide swings in orders, and that this source of amplification is “legitimate and unavoidable”. However the “false order” effect severely aggravates the amplification effect. Burns devised a new inventory policy to remove the effect and subsequently damp the system.

3.4.1 The IOBICS approach

Some of the most recent work being carried out on demand amplification has been undertaken by Towill and his colleagues. Towill uses a combination of simulation and other analytical techniques based on control engineering in the design of Inventory and Order Based Production Control Systems [IOBPCS]. The first publications on this approach by Towill date back to the early 1980s. Two key approaches to demand amplification have been taken. The first uses linear control theory to analyse single or multi-loop systems. Generally this approach focuses on optimising the individual parts of the chain and subsequently hoping that the addition of these will result in a global

optimum. The other approach used by Towill is a development of Industrial dynamics. Towill uses the continuous time modelling technique developed by Forrester. The main focus of the early work [Towill, 1982] was the design of systems that can recover from shock demands to protect production systems, thus protecting the production process from random variations in consumption. This is probably the main reason for trying to smooth dynamics and a fact that seems to be forgotten in much recent work on demand amplification. Towill [Towill, 1982] found an optimum solution for the model tested, he concluded that if time adjustment of inventory, production delay and demand averaging time are all equal the dynamics of the system are greatly reduced. This in practice is difficult to achieve due to variations in the system. Towill's control theory approach was further developed in 1984 [Towill, 1984]. An analogy between the PID (Proportional, Integral and Derivative) control system and decision making within the IOBPCS system is given. The approach results in a model where all parameters are specifically defined with no random elements present. In reality random variations in the system are present. Sensitivity analyses has to be carried out to establish how variations in the key variables impact on the system. Towill defines six states that the system can take, defining three as stable and three as unstable. If the system has a sudden shock imposed the states are as follows:

- Stable s shaped response
- Stable under-damped response
- Stable but initial negative response
- Unstable exponential response

- Unstable oscillatory response with ever increasing magnitude.
- Unstable limit cycling response.

To this list one can now add some of the more recently documented non-linear dynamic system responses such as Chaotic response. It should be noted that the simulations undertaken by Towill are run for about 40 weeks, a relatively short period of time, so many of the more recently documented non-linear dynamic responses would not be apparent.

Towill's work was aimed at gaining cause and effect rules which can give direction for change [Towill, 1988]. Towill and Edghill [Edghill, Towill, & Jones, 1987] proposed that buffering shipping processes with stock would reduce the dynamic behaviour. However systems which automatically adjust inventory targets to buffer the system resulted in increased amplification and excess inventory being held. Edghill [Edghill, Olsmats, & Towill, 1988] carried out a sensitivity analysis on a modified "Forrester" supply chain and concluded that one of the key causes of amplification was variability in production output against the schedule.

3.4.1 Methods of reducing amplification

Towill's team in the last few years has summed up their findings on how to reduce amplification. Wikner [Wikner, Towill, & Naim, 1991] Proposed five key approaches:

- Tuning Decision rules of the model.
- ✓ • Reducing Time Delays.
- Removing echelons from the chain.

-
- Improving each echelon's decision rules.
 - Integrating information flow and dividing orders into "Real" and "Cover" categories.

This final rule involved the recommendation that orders sent to suppliers should have two columns of "real" and "cover". In practice, this would be considered impractical in most environments, as differentiating between these order categories is nearly impossible.

Towill further developed Wikner's ideas [Towill, 1991] advocating the reduction of time delays and the removal of echelons from the chain. It was recognised that the period of the amplification cycle exaggerated the problem. A two-year cycle for example would result in heavy investment in unnecessary capacity. Towill concluded that five main factors impacted on amplification:

- Perceived demand - forecast
- Disturbances
- Transmission Lags - in material and information
- Decision Rules used for inventory
- Uncertainty associated with perceived demand, quality of information and the values of transmission lags.

He went on to discuss the issue of the strategic positioning of stocks and how Wikners approach would impact on the above. The main conclusion was that reduction in time delays had the most significant benefit.

Towill [Towill, 1992] indicated a turning point in his work, in this paper he attempted to make the issues accessible to industry and provided a simple framework based on Wikners work for addressing dynamic behaviour. Five approaches in order of effectiveness were discussed:

- Removal of distributor layer in model
- Integration of Information flow
- ✓ • Reduction of time delays
- Improvement of pipeline inventory policy
- Tuning existing ordering parameters

This approach was further summarised by attacking cycle times and the promotion of collaboration and the free exchange of information within the supply chain. He subsequently went on to apply this approach to various industries including the health care environment [Towill, Naim, & Wikner, 1992].

3.4.3 Applications within Industry

Showing how the current supply chain strategic approach of “Partnership Sourcing” could improve dynamic behaviour Towill further developed these concepts [Towill & Naim, 1993]. Partnership sourcing can be defined as “a commitment by customers and suppliers regardless of size to long term relationships, based on clear mutually agreed objectives to strive for world class capability and competitiveness”. The five approaches were further refined, resulting in a more accessible and easier to apply list of actions:

- Fine tune existing ordering rules
- ✓ • Reduce cycle times
- Removal of distribution layer
- Include goods in supply pipeline in ordering rule
- Integrating information flow throughout the supply chain.

The author demonstrated how partnership sourcing could be used to achieve the above approaches and using the Forrester model, the benefits to be gained.

Evans [Evans, Naim, & Towill, 1993] took the five actions listed above and documented the impact of Electronic Data Interchange on achieving them. The main impacts were on the reduction of mailing, clerical and order filling delays. Through industrial cases studied in the paper Evans discussed the benefits of EDI quoting a 73% reduction in costs and a 50% reduction in lead times.

Berry [Berry, Towill, & Wadsley, 1994] further developed these issues focusing on a real electronic components supply chain. The supply chain was modelled and verified using data collected over the past ten years. The dynamic behaviour of the chain was greatly reduced from an amplification factor per echelon of 4:1 to 1.35:1 by the implementation of JIT, Logistics integration and time-based management techniques. Simulations were run for relatively short periods of time, (approximately 40 weeks).

More recently Towill [Towill & Del Vecchio, 1994] has demonstrated the use of filter theory and the application of expert systems can be used in optimising the stock holding of

the Forrester model. However this is somewhat academic and its application in real supply chains at this point in time is debatable.

Towill [Towill, 1994] presents a review of Burbidge and Forrester's work and how over the past 30 years managers still have not learnt basic principles. Both Burbidge and Forrester urge practitioners to "keep it simple" in manufacturing systems. The paper further advocates the removal of time for better dynamic behaviour.

A good review of Towill's approach to modelling was presented in a series of articles published in 1993 by the Institute of Mechanical Engineers [Towill, 1993a; Towill, 1993b].

3.5 Behavioural science approach

Researchers investigating human decision making behaviour have undertaken the most recent research into the complex dynamics of supply chains. The work carried out has been based on data collected, over a period of 30 years, from players of the "Beer Game" hand simulation of the original Forrester Supply Chain. John Sterman, one of Forrester's colleagues from MIT was the first to analyse the rules used by players and start building simulations based on the heuristics used by them [Sterman, 1989a; Sterman, 1989b]. The focus of the work has been to investigate the decision-making behaviour of teams rather than individuals. It approaches this by coupling economics with psychology by emphasis on the behaviour of the total system.

3.5.1 *The Beer Game*

The Beer Game is a role playing simulation based on the Forrester model. It was developed by MIT and has been used for over 30 years. Thousands have played the game, throughout the world participants have ranged from undergraduate students to senior directors of top organisations.

The MIT version of the game is played on a board that portrays the simple Forrester supply chain model consisting of four sectors: a retailer, wholesaler, distributor and factory. One person manages each sector. A deck of cards represents customer demand. Each week the retailer takes the top card from the deck, the retailer then ships the required number of units out of their inventory. The retailer subsequently orders beer from the next sector, the wholesaler who ships beer on request and places orders on the distributor. This procedure passes down the chain until the factory finally has orders placed on it.

At each stage shipping and order receiving delays are built in. These simulate the time required to receive, process, ship and consequently deliver the orders. The delays have a crucial impact on the dynamics of the system.

The participant's objective is to minimise total costs during the game. Within the MIT version of the game inventory holding costs of \$0.5 /case/week and stockout costs, the cost of having a backlog of orders, are \$1.0 /case/week.

The decision made by the participants is simply how many orders have to be placed. Participants aim to keep inventory as low as possible while avoiding backlogs. Inventory must be ordered and the delivery lead-time is potentially variable as it

depends on whether there is adequate upstream inventory to satisfy the order immediately.

The game is run with three to eight teams of four participants. Participants are randomly assigned the roles of retailer, wholesaler, distributor and factory. Each participant is asked to place \$1 into a kitty to be waged against the other teams. Though this is seen as a trivial reward it emphasises the goal of minimum team costs and tends to have a powerful motivational effect.

Each participant goes through the following steps during each time period:

- 1) Receive inventory and advance shipping delay.
- 2) Fill orders, retailer takes the top card from customer order deck.
- 3) Record inventory or order backlog on record sheet
- 4) Advance order slips, any order slips in the "Orders placed box" are moved to the "Incoming orders box."
- 5) Place orders, each participant decides what to order and places an order slip face down in the "Orders placed box."

The game is started in equilibrium. Each pile of inventory contains 12 cases of beer, the initial throughput is 4 cases per week and customer demand remains at 4 cases per week. The first four weeks of the game are used to allow the participants to familiarise themselves with the procedures. Demand remains constant for the first four weeks with each player only ordering four cases per week. At the start of week four players are allowed to order any non-negative quantity of beer they wish. At the

start of week five a step increase in demand to 8 cases per week occurs. The participants are then required to react to this.

The participants are told the game will run for 50 weeks but play is stopped in week 36 this avoids any horizon effects. The game generally last 90 minutes and is followed by a debriefing session.

3.5.2 Information availability within the “Beer Game”

The availability of global information about the supply chain is limited during the game. Participants have very good local information from their record sheets. However, they are directed not to communicate during the game.

The participants do not know the customer demand. The Retailer is the only player to discover the true customer demand. The other participants learn what their customer orders are but only after a delay of one week.

The players, however, do sit together and some cross talk is unavoidable, also the inventory levels at all echelons in the supply chain are clearly visible to the participants and this information may be utilised by the players. It is interesting to note that this is generally more information than a real company would have about inventory levels throughout the supply chain.

The information limitations result in participants being unable to jointly plan a strategy. However, the global goal of minimising costs is known, this results, as in real life, participants addressing the problem of “global optimisation” by dividing it into sub-goals and assigning these to different areas within the organisation or system.

3.5.3 Observations from the "Beer Game"

In supply chain terms the model is very simple but Sterman points out that mathematically it is complex as the system would result in a 23rd order non-linear differential equation to describe its behaviour. This means the calculation for optimal behaviour is presently a non-trivial exercise. A benchmark model has been created using computer simulation to act as a comparison for results.

It has been found by this technique that the average team generally creates costs for the system 10 times that of the benchmark. The individual echelons generally exceed the benchmark by a similar amount.

During the game a number of key types of behaviour are witnessed:

- 1) Oscillations - large amplitude fluctuations in inventory and orders are witnessed.
- 2) Amplification - The amplitude and variance of the orders increase steadily from the customer to the retailer and onto the factory. The average peak of factory orders is 32 cases, an amplification of 700%!
- 3) Phase Lag - The order rate tends to peak later as one moves from retailer to factory. Customer orders increase from 4 to 8 in week five but the retail orders peak in at approximately week 16. These phase lags are caused by decision making and order delays through the supply chain.

3.5.3.1 The behaviour of teams

Sterman argues that research into the decision-making behaviour is comprehensive, however the decision making behaviour of teams in management science and economics is not consistent with individual decision making. Sterman demonstrates

that a company's decision to increase production can feed back through the market to influence price, profits and demand. This in turn may produce shortages of labour and materials. Competitors may subsequently respond to these factors and thus influence future production decisions.

The results showed that participants generally try to anchor the stocks at the initial level. Most subjects fail to take account of the supply line inventory. Generally only 34% of supply line inventory is taken into account. Individual managers do not ignore the goods they have on order, the problem is aggregation of the orders.

Participants become frustrated, reporting feelings of helplessness. They subsequently blame the cause of the dynamics on external events such as customer demand pattern. When asked how to improve the performance many ask for better forecasts of customer demand. The key to improved performance is dependent on the policies individuals use to manage the system.

3.5.3.2 The decision rules used

The decision making process at the centre of the work is the stock management problem. This is a common decision making task which can be applied to all disciplines of management and science. Regulation of stock takes the following form, a manager seeks to maintain a quantity at a particular level, stock can not be influenced directly but only by changes in the inflow and outflow rate. Examples of this problem can be found in the regulation of a domestic shower temperature, the manipulation of money supply to stimulate the economy and avoid inflation and even the regulation of one's drinking of alcohol to maintain "happy drunkenness" without over doing it or getting a hangover!

The inflow rate needs to compensate for losses and usage to counteract disturbances that push the stock away from the desired level. Often lags in time are present between the change in stock and the realisation of that change by the decision-maker. These lags impact on the manager's actions. Within the supply chain a manager regulates the stock focusing on three key areas:

- 1) Replacement of expected losses from stock, i.e. orders.
- 2) Reducing the discrepancy between the desired and actual stock, for example the target of one week's cover.
- 3) Maintaining an adequate supply line of unfilled orders. for example raw materials orders placed to cover the supplier lead-time.

3.5.4 *The simulation of Beer Game Heuristics*

A key outcome of Sterman's research was that although the system was being operated in a far from optimal way, the participants operation exhibited significant similarities between players and teams. This suggested to Sterman that all players, to determine the orders, were using some form of similar heuristic rule. This he was successful in simulating.

Sterman [Sterman, 1989a] used results collected over 4 years involving over 192 participants and 48 trials.

The decision rules address the following criteria:

As demand increases then the orders increase and vice versa. There is a lag due to the time it takes decision makers to form a view of the extent of the permanence of the change in demand.

Each sector sets a target level of inventory. Orders are raised or reduced to compensate for this.

Each sector keeps track of orders pending in upstream supply line, but as yet, not delivered. If the inventory in the supply line gets bigger then normal orders are reduced. However, if inventory in the supply line is deemed to be too small, orders are increased.

The equations used in the simulation are explained as follows:

During the experiment the Stock is the sum of the Participant's Stock, Supply line inventory, sum of orders in the mailing delays and the backlog of orders at the participant's supplier.

$$O_t = \max\{0, IO_t\}$$

The loss rate is the rate at which the participant receives orders. (Participants "lose" stock from their buffer at the rate at which orders arrive.)

$$\text{Expected losses} = L^*, \text{Desired stock} = S^*, \text{Desired supply line stock} = SL^*$$

Therefore

$$\text{Order } O_t = \text{Max} (0, L^* + AS_t + ASL_t)$$

Where L^{\wedge} equals the expected losses (forecast), AS_t equals the adjustment for internal inventory discrepancy, ASL_t equals the adjustment made to the target supply line inventory

$$L^{\wedge}_t = \theta R_{t-1} + (1-\theta)L_{t-1} \quad 0 \leq \theta \leq 1$$

Where R equals the order-receiving rate and θ defines how fast expectations are updated. If θ equals 1, then the forecast is updated weekly and is equal to the amount delivered in the previous week. This form of equation is familiar to that used for simple exponential smoothing.

$$AS_t = \alpha_s [S^* - S_t] \quad (\text{i.e. Stock adjustment} = \alpha (\text{desired stock} - \text{actual stock}))$$

α_s characterises how fast the inventory gets updated in case of a discrepancy between the desired and actual inventory. If α_s equals 1, an intention to remove the discrepancy in one week is expressed. If α_s equals 0.25, an intention to remove the discrepancy in four weeks is expressed.

Similarly;

$$ASL_t = \alpha_{SL} [SL^* - SL_t] \quad (\text{Supply line stock adjustment})$$

If S^* and SL^* are constant then $\beta = \alpha_{SL}/\alpha_s$

$$\text{and } S' = S^* + \beta SL^*$$

$$\text{then } O_t = \text{Max} [0, L^{\wedge}_t + \alpha_s(S' - S_t - \beta SL_t + \epsilon)]$$

β can be interpreted as the fraction of units ordered but not yet received that has been taken into account when a new order is placed by the participants on their supplier. If

β is equal to 1 then participants fully recognise all supply line inventory. If β is equal to 0 no supply line inventory is recognised by the participants.

ε is an additive disturbance term, the disturbance used in this experiment was Gaussian white noise.

The experiments performed by Sterman were used mainly to show it was possible to model individual and team processes. The Beer Game has become a key investigative tool for this area of management science and psychology.

Sterman [Sterman, 1987] developed a further computer game/model based on the beer game. This focused on the running of a simple economy. Participants were given complete and perfect information regarding the structure of the economy, values of all variables and past history of the system. However, the majority of the participants still managed to generate significant and costly oscillations.

The problem was once again a stock management problem. Participants were required to invest in capital plant and equipment to satisfy demand. New orders were received from the Capital and Goods sectors, production is calculated and newly produced capital is sent to each sector. Depreciation is calculated and finally the participant makes one decision on how much capital to order.

From this work Sterman concluded three points:

- 1) Participants have misperceptions about the time delays.
- 2) Participants have misperceptions about the feedback from the decision to the environment.

- 3) If the time frame for the dynamics is short learning can be expected to dampen instability over time. People who have fast feedback on decisions and make the decision regularly learn how to stabilise the situation.

3.5.5 Decision making in a simple inventory management task

Diehl and Sterman [Diehl & Sterman, 1993] further investigated the impact of time delays and feedback using a simple one-person inventory management task. Participants were responsible for reviewing inventory levels, sales and production costs and then made a decision of how much to change the production level in response to a stochastic demand. Time delays and the effects of feedback were varied from experiment to experiment. The subject's performance was measured against two benchmarks, optimal behaviour and the behaviour of a "take no action" rule.

It was found that costs were four times greater than optimal despite financial incentives, training and repeated playing of the game. The participants were outperformed by the "take no action" rule and it was concluded that attempts to control proved counterproductive. In easy conditions i.e. no time delays or feedback, subjects dramatically outperformed the "take no action" rule. Analysis revealed three types of participant behaviour:

- Attention to inventory only - participants respond only to the inventory discrepancy.
- Attention to inventory and change in inventory - participants respond to rate of change of inventory as well as current stock.

- Attention given to inventory and “expected” change of inventory - the supply line is partially accounted for.

It was also found that as the complexity of the environment increased, participants tended to revert to simple rules which tended to neglect the effects of time delays and feedback, this led to further degradation of performance. The participants were found to be insufficiently adaptive despite perfect knowledge of the system’s structure and parameters. The need to “control” seemed to override the ability of the participants to learn. Diehl concludes that the heuristics used to control complex tasks are dynamically deficient and result in sub-optimised performance. Computer simulation is again recommended as a management tool, which avoids human misperceptions about the system.

Sterman [Sterman, 1994] observes:

“.....decision makers often continue to intervene to correct apparent discrepancies between desired and actual state of the system even after corrective actions have been taken to restore the system to equilibrium, this leads to overshoot and oscillations”

In the same paper Sterman concludes that simulation is the only way to test management system models. Misperceptions about the environment are always present and these are the greatest inhibitors to improved supply chain performance. Sterman [Sterman, 1994] cites the example of a team of managers asked to reduce the supply lead-time. Initially they were asked to draw a schematic of where time was spent in the system (see Figure 3.1). After further investigation the actual lead times were obtained. The proportions of these did not relate in any way to the perceived

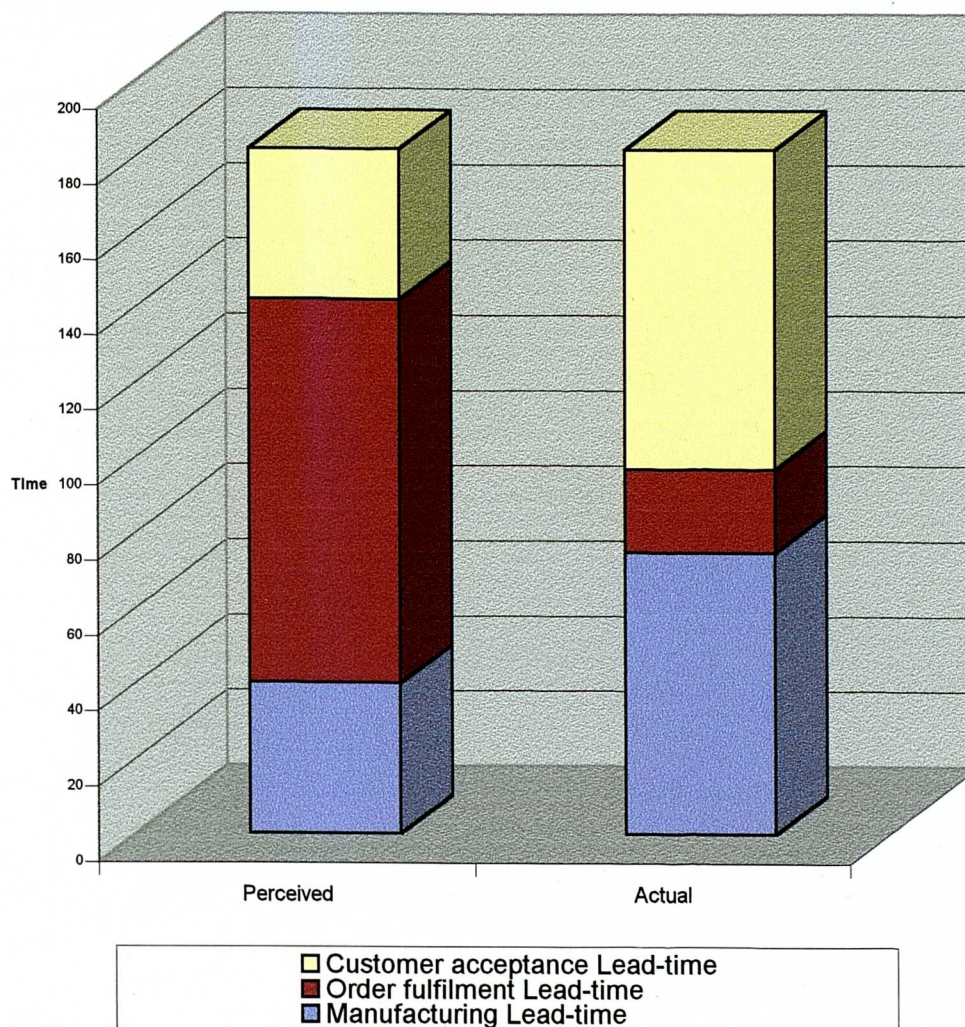


Figure 3.1 – Management misperceptions on supply chain lead-times.

Adapted from Sterman, J.D. (1994). "Learning in and about complex systems." System Dynamics Review Vol. 10, Issue 2-3, pp.291-330. (Note: The managers were responsible for the order fulfilment area)

values. It is interesting to note that the team was made up of members who had responsibility for order fulfilment, this area was given priority in their mental models of the system and the vendors and customers were seen as insignificant.

The issue of misperception within the environment has been further emphasised by the work of Lomi et al [Lomi, Larsen, & Ginsberg, 1994]. They conclude the following:

“A disquieting conclusion that emerges from the present research is that stable preferences, lack of structural change and lack of time constraints are not sufficient to ensure that behaviour will ever approach that that would be chosen rationally on the basis of perfect knowledge”

They pointed out that incremental trial and error learning is ineffective in comparison to getting managers involved in the development of models of any systems.

The above investigations would seem to indicate that some uncertainty can result from manager misperceptions about the environment within which they work. This can result in inappropriate decisions being made that aggravate the dynamics of the system.

3.5.6 Behavioural Science approach to amplification

Using these models an insight into “Business Process Re-engineering” within the supply chain has been gained [Van Ackere, Larson, & Morecroft, 1993]. The paper explores the impact of various BPR techniques on a modified Forrester model. The impact of four key approaches was analysed. The approaches in order of impact are as follows

-
- All parties have access to customer demand data.
 - No intermediaries between factory and retailer (c.f. removal of distributor layer)
 - The factory has access to customer demand data
 - The removal of all ordering delays

Lee et al [Lee, Padmanabhan, & Whang, 1997a; Lee, Padmanabhan, & Whang, 1997b] develop this theme in a discussion of the “bullwhip” effect occurring in supply chains. The Bullwhip effect is the term used by Procter and Gamble to describe the amplification and demand distortion that occurs within the supply chain. The paper argues, in contrast to Sterman [Sterman, 1989a] that amplification and uncertainty is generated by rational behaviour rather than misperceptions as discussed by Sterman. The authors refer to four causes of the bullwhip effect.

- Demand Forecast Updating - the Forrester effect, due to increasing safety stock and stock in the pipeline.
- Order Batching - customers tend to order goods at certain times during the week, for example Monday morning. Organisations running Materials Requirements Planning or Distribution Requirements Planning to generate purchase orders do so at the end of the month. These periodic batching of processes result in surges in demand at certain points in time.
- Price fluctuations - the impact of promotion results in forward buying, this occurs particularly in the grocery industries. For example, Tesco supermarkets recently reduced the price of baked beans to 3 pence a tin. This resulted in customers buying large quantities of the product, however it is unlikely that the price will result in

increased consumption of the product. As a result the customer's consumption pattern does not reflect the buying pattern. This results in bigger variations in demand patterns.

- Rationing and shortage gaming - when product demand exceeds supply organisations often ration sales to retail customers. This results in end customers placing multiple orders with different retailers hoping this will result in more chance of the product being received within a given lead-time. This of course results in excess demands for products and the manufacturing organisation increasing capacity to satisfy all the apparent orders.

These sources of uncertainty are very much analogous to Forrester's original investigation of uncertainty generation (See section 3.2.4). However, Lee et al have taken these concepts and used examples of relevance to today's market conditions.

The authors [Lee, Padmanabhan, & Whang, 1997a] propose a number of actions to deal with the above causes of amplification and uncertainty. These include:

- The use of EDI and point of sale data, including discounts for customers on products to encourage information sharing.
- The use of every day low price (EDLC) strategies.
- Allocation of product to retailers based on historical past sales.

The research documented above tends to clarify Towill's finding. However the approach has focused on human decision making behaviour rather than the control systems approach. The "beer game" is seen to be a microcosm of how real organisations function and demonstrates how human decision making behaviour can give rise to dynamic effects. It also raises the argument that the control systems developed are based on human

decision making processes and if these create counter intuitive behaviour then the control system developed and subsequently automated is unlikely to be better. The control system only carries out the logic established by the manager.

The behavioural science approach has been further developed investigating the generation of non-linear dynamic behaviour generated by human decision making, this will be explored further in Chapter 4.

3.6 Practitioner approach

The practitioner approach to amplification and uncertainty has resulted from organisations recognising the need to manage and plan for uncertainty within their operations. This has provided additional insights into the sources of uncertainty. The technique generally used within the investigations is the use of stochastic simulations to investigate the impact of random events within the supply chains.

3.6.1 *Houlihan*

John Houlihan focused on demand amplification in International Supply Chains [Houlihan, 1987]. In contrast to many other investigations Houlihan presents a practitioner view of the causes of amplification. Houlihan was responsible for supply chain management in a large American organisation, and he took the lessons of Forrester and developed a methodology for gaining improvements in real supply chains. He classified the sources of demand amplification into two groups, internal and external causes. The external causes include the business cycle, time delays, planning distortions and inventory movements. As a result of economic swings companies generally increase their vulnerability by inducing

unreal business cycles and even further amplify them by local protective policies. The internal cause was summed up in the flywheel effect (see Figure 3.2). This cycle occurs as follows, an upswing in demand produces a shortage, local protection of the department or function results in an over order, this then impacts on the internal forecast and results in a surge in the new forecast, unreliable delivery results in further over compensation. Houlihan documents how this effect is prevalent in cross-functional systems and is more apparent in international supply chains. The work also demonstrated how functional objectives create conflicts that result in further amplification and sub-optimisation. This was developed further and “action points” for purchasing directors for the management of supply chains was developed [Houlihan, 1988]. These include improved analysis methods, taking an active role in corporate decisions and upgrading the status and pay of purchasing staff. It can be seen that these points tend to focus on the interface between customer and supplier. This is more akin to “supplier management” than “supply chain management” [Davis, 1993]. This traditionally comes under the control of purchasing.

3.6.2 Davis

As can be seen from the majority of work the issue of Uncertainty is not inherent in the simulation used to date. Davis [Davis, 1993] discusses the application of simulation in re-engineering Hewlett Packard’s supply chain. Hewlett Packard have developed a

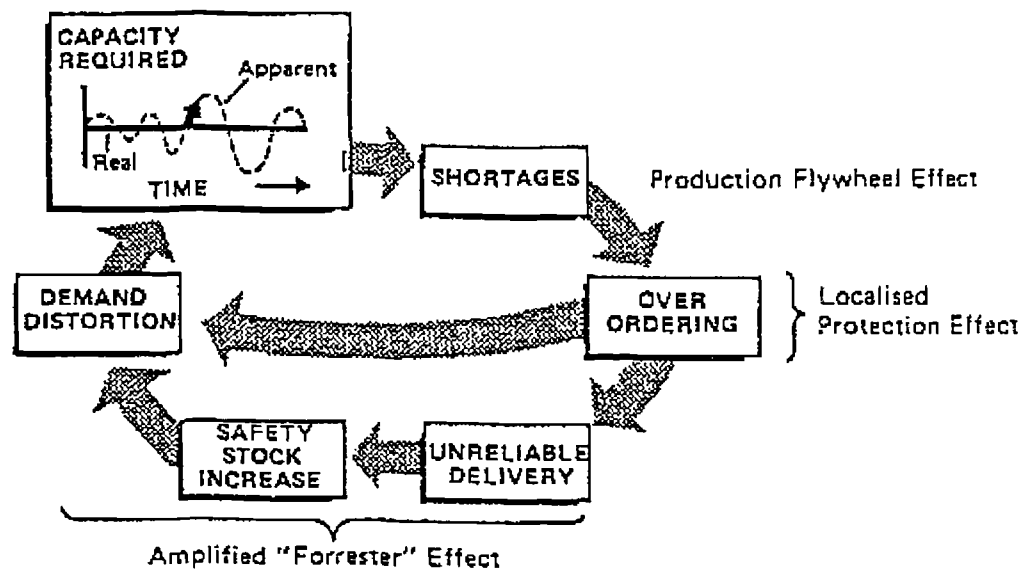


Figure 3.2 – The Flywheel Effect.

Source: Houlihan, J.B. (1987). "International Supply Chain Management." *International Journal of Physical Distribution and Material Management* Vol. 17, Issue 2, pp.51-66.

framework for addressing uncertainty that impacts on supply chain performance. The key areas of uncertainty addressed fall within three categories, supplier, manufacturing and customer.

Supplier performance is a factor of uncertainty in lead-time, due to materials arriving late, delayed delivery, machine breakdown etc. HP measures supplier “on-time” performance, average lateness and the degree of lateness using standard deviations.

Manufacturer key performance measures are frequency of down time, repair time and variation in repair time (i.e. the standard deviation). Customer measures are average demand and variability and forecast accuracy.

Davis also proposes the “Uncertainty cycle” (see Figure 3.3). Uncertainty propagates through the supply network, analogous to demand amplification. The propagation of mathematical uncertainties is complicated and the subsequent calculation of how much inventory to hold to buffer the uncertainty is seen as a key question by Davis. Inventory is often seen as the company’s insurance against future demand. Davis demonstrates that a reduction of inventory of 50% is possible across the supply chain. An analysis of inventory shows that 40% is “natural” stock or that which is there because of review periods, WIP, pipeline etc. The remainder is there to buffer against process variance, supply variance and demand variance.

Key stages in HP’s supply chain methodology are:

- Benchmark current performance.
- Control uncertainty by understanding it.
- Plan changes by use of models and simulation.

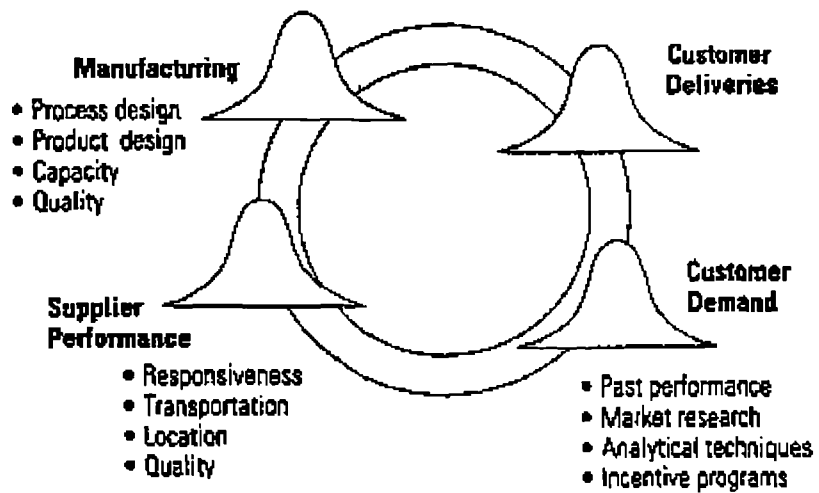


Figure 3.3 – The Uncertainty Cycle.

Source: Davis, T. (1993). "Effective Supply Chain Management." Sloan Management Review , Issue Summer, pp.35-46.

HP also have experience of the added benefit when implementing the methodology of improved team work and co-operation, increased customer focus and improved supplier relationships. HP now integrate design of products and supply chain engineering, as it is recognised that they have major impacts on each other.

3.6.3 Further observations on amplification.

The “Demand Amplification Project” undertaken at the University of Cardiff has shown that modern world class supply chains are still plagued by amplification [Jones, 1997]. The work was motivated by the observation that Forrester’s work has been discussed and applied for some 40 years. It was presumed that organisations have had considerable time to design demand amplification out of their key supply chain business processes.

The project tested whether demand amplification existed within the present United Kingdom, fast-moving-consumer-goods (FMCG) industry. The organisations and supply chains investigated were without exception characterised by outstanding performance, continuous improvement and commercial success [Jones, 1997]. The findings identified that demand amplification, despite all efforts, is still a major business issue resulting in a reduction in supply chain performance.

Tom McGuffog of the organisation Nestle also highlights the frustration experienced by companies in addressing demand amplification [McGuffog, 1997]. McGuffog attributes the complex dynamics experienced to “institutionalised” or “random” effects. Institutionalised effects are caused by the way the business or departments operate, for example, the timing of data processing, decision taking, capacity of

factories and its cycle of meetings. Random effects are attributed to mistakes, holidays, sickness and breakdowns etc.

McGuffog observes that the effect of all these factors results in delays, excess inventory, waste, write-off of products and excess capacity. The implementation of complex statistical forecasting systems does not substantially assist in the interpretation of the order data as no underlying pattern is present that is susceptible to statistical analysis [McGuffog, 1997].

3.7 Conclusion of Chapter 3

It can be seen from the above review that the issue of uncertainty and in particular internally generated uncertainty has received little attention in recent years. This conclusion is supported by the findings of recent literature reviews on logistics and supply chain modelling [Slats et al., 1995; Thomas & Griffin, 1996; Vidal & Goetschalckx, 1997].

The main focus of research has been the reduction of the Forrester amplification effect within linear supply chains. Only in the most recent published research are details of further causes of amplification and uncertainty being referred to [Lee, Padmanabhan, & Whang, 1997a]. This still does not explain the complexity of the dynamics experienced by industry.

Little investigative research has considered sources of uncertainty within supply networks and the subsequent interactions that may generate uncertainty between suppliers in a supply network. This conclusion is also supported by Thomas et al [Thomas & Griffin, 1996].

The review also demonstrates that generally uncertainty is accepted as something that will always be present and cannot be removed. This argument is valid in part, as random events will never be totally eliminated. However, this view results in the causes of uncertainty receiving little attention. Researchers and managers subsequently become focused on developing methods to alleviate the “symptoms” of uncertainty rather than focusing on the removal of the “causes” of uncertainty.

The survey also reveals that little work has been undertaken focusing on the quantification of the dynamics and the proportion generated internally against that generated by external events. A further question that has not been addressed is whether the internal dynamics generate uncertainty through a chaotic mechanism.

In summary the research questions raised so far are as follows:

- Is a significant amount of uncertainty generated by the internal processes?
- How is uncertainty generated by internal processes and are there other sources of internal uncertainty apart from amplification present?
- Can these effects be quantified for a given system?
- Does deterministic chaos contribute to the uncertainty within the supply chain?

The final question requires a further review and this will be addressed in the next two chapters.

Chapter 4

Non-linear Dynamics and Chaos

4.1 Introduction

Chaos theory, often known as complexity science or non-linear dynamics, uses established mathematical techniques with the help of computer simulation to explore the nature of complex systems (natural, economic, physical etc.) which up to now have been seen as resistant to analysis [Van de Vliet, 1994].

“Chaotic” is an unfortunate term to use to describe such systems. This has resulted in confusion and the misapplication of the term. As discussed in Section 1.6.1 the term chaos is used with a variety of meanings within literature. Its use can be assigned broadly to 3 areas.

- Chaos describing unpredictability and randomness.
- Chaos as a metaphor for small actions generating large changes in systems.
- Chaos describing random behaviour generated by law {deterministic chaos}.

When viewing, in particular, the literature on chaos within management systems these three uses of the term can be taken separately. This will be discussed and developed as a classification for the application of chaos theory in Section 4.7.

Chaos is deterministic, generated by fixed rules that in themselves involve no element of chance {hence the term deterministic chaos}. In theory, therefore, the system is predictable, but in practice the non-linear effects of many causes make the system less predictable. The system is also extremely sensitive to the initial conditions, so an infinitesimal change to a system variable's initial condition may result in a completely different final condition or response.

This presents us with a good news / bad news scenario. The good news is that apparently random behaviour may be more predictable than was first thought, so information collected in the past, and subsequently filed as being too complicated, may now be explained in terms of simple rules. The bad news is that due to the nature of the system there are fundamental limits to the horizon and accuracy of prediction. Past patterns of system behaviour are never repeated exactly but may reoccur within certain limits. For example the weather, a true chaotic system, has limits to the forecast horizon. Even if every variable was known exactly the theoretical maximum forecast is 2 to 3 weeks [Stewart, 1989 p.286].

This chapter will give an overview of the history of chaos and then characterise and define the main properties of chaotic systems. Finally a review of the application of chaos theory to areas relevant to this thesis will be presented.

4.2 The History of Chaos

It is generally agreed that the term "chaos" was first used to describe the type of behaviour discussed above in a paper written by Li and Yorke [Li & Yorke, 1975]. However, the phenomena which Li and Yorke describe had been a source of interest

to scientists for many years. In this section a brief history of chaos theory is presented. More detailed histories and explanations of the development of chaos theory can found in Stewart [1989] and Gleick [1987]. However this section gives an overview of the development of the theory. This will act as a foundation on which chaos can be characterised and defined.

4.2.1 Newton and Laplace: Laws and determinism.

In 1686 Sir Isaac Newton published “Mathematical Principles of Natural Philosophy”. The main message of this text is that “Nature has laws, and these laws can be identified”. The revolution in thinking generated by Newton led to the vision that the universe functions in a “clockwork” predictable way. If all the laws are known then anything can be predicted indefinitely into the future. The laws were represented as mathematical equations with no element of chance. If all the variables are defined and the starting conditions known then the system is predictable.

The French mathematician Pierre Simon de Laplace further developed this concept. Laplace proposed that the laws of nature imply strict determinism and complete predictability, however because of errors in observations the introduction of probabilistic theory is necessary. In 1776 Laplace in his book “Philosophical Essays on Probabilities” states (see [Stewart, 1989 pp.7-11] and [Crutchfield et al., 1986]):

“The present state of the system of nature is evidently a consequence of what it was in the proceeding moment, and if we conceive of an intelligence which at a given instant comprehends all the relations of the entities of this universe, it could state the respective positions, motions and general affects of all the entities at any time in the past or future”

Laplace went on to propose that the movement of the greatest bodies of the universe and the lightest atoms could be modelled using a single law. This philosophy of total predictability is often referred to as “Laplacian determinism”.

4.2.2 Poincare: the first sight of chaos.

This concept of determinism was held until the early 20th century. Henri Poincare was one of the first mathematicians to question the deterministic nature of systems, it can be argued that this mathematician was the first to recognise the existence of what we define as deterministic chaos. Poincare studied the motion of two body systems, and found it to be periodic. However, Poincare started to study in detail the motion of three body systems [Stewart, 1989 pp.57-73]. In 1890 he published a memoir “On the problem of three bodies and the equations of dynamics”. Poincare developed differential equations to describe the motion of three bodies and discovered the solutions were periodic in appearance, however the motion did not conform to what was expected and would not converge towards a set pattern of motion. This he presumed was due to errors in his analysis and would be corrected with additional work. However, thirteen years later, in 1903, Poincare stated [Crutchfield et al., 1986]:

“A very small cause which escapes our notice determines a considerable effect that we can not fail to see, and then we say the effect is due to chance. If we knew exactly the laws of nature and the situation of the universe at the initial moment, we could predict exactly that situation of that same universe at a succeeding moment. But even if it were the case that the natural laws had no longer any secret for us, we could only know the initial situation approximately. If it may happen that small differences in the initial conditions produce very great differences in final phenomena. A small error in the former will produce an enormous error in the latter. Prediction becomes impossible, and we have the fortuitous phenomenon.”

Poincare recognised that some systems were sensitive to the initial conditions and small errors may be amplified to dramatically alter the final state of the system. It was traditionally believed that a small error would remain small and would result in a final measurement with the same error.

4.2.3 Lorenz: unpredictability in weather systems.

Edward Lorenz a U.S. mathematician who became involved in weather prediction during the war was the person who first started to investigate the consequences of chaos. Lorenz's research focused on the forecasting of weather systems. He pioneered the use of computers for forecasting. Lorenz had created a number of equations that modelled the weather with good accuracy. He observed that the equations generated patterns and this he hoped to use for more accurate forecasting. Lorenz then discovered chaos purely by accident. In the winter of 1961 Lorenz

decided to examine one particular time series of data in more detail. Instead of starting the run at the beginning, to save time he copied the numbers from the midpoint of the previous run. The simulation progressed and he noticed that the data from the two runs diverged rapidly bearing no resemblance to each other. On further investigation he realised the numbers that were input were to three decimal places but the original figures in the computer's memory were to six decimal places. This error was found to be exponentially amplified. Lorenz found that he was able to predict the next peak in a graph if the previous peak was known accurately but the prediction of any other peaks into the future was impossible with any accuracy due to the error amplification. Short term forecasts were possible, but long-term forecasts were nearly impossible [Peitgen, Jurgens, & Saupe, 1992 p.657]. Lorenz recognised that the equations being used were not behaving in the traditional way that mathematicians would expect.

For non-linear dynamic systems the assumption of one-to-one, cause and effect relationships implicit in most human logic does not hold. For chaotic systems, a tiny change in conditions may result in an enormous change in system output, whereas a substantial change in conditions may be absorbed without significant effect to the system's output.

Lorenz developed his now famous analogy, "the Butterfly effect".

4.2.4 The butterfly effect

The sensitivity to initial conditions that Lorenz identified in his weather system equations led him to conclude that tiny changes in conditions over time will become dramatically amplified and in some situations have dramatic consequences. There are

many versions of the Butterfly effect but they all have the same theme and consequence.

The flapping of a single wing of a butterfly generates a tiny change in the state of the atmosphere. Over a period of time, the atmosphere diverges from what it originally would have done. So in say a month's time a tornado that was not originally going to happen occurs causing much devastation. In summary, the flap of a butterfly's wing may result in a tornado in another part of the world.

This analogy caught the imagination of scientists and the general public alike. This it can be argued was the birth of chaos theory as we know it today.

4.3 Environments prone to chaos

Mathematicians have discovered that non-linear feedback systems are particularly prone to chaos. Information is fed back thus impacting on the outcome in the next period of time [Stacey, 1993a p.146].

An information feedback system can be defined as follows [Forrester, 1961 p.14]:

“ An information-feedback system exists when the environment leads to a decision that results in action which affects the environment and thereby influences future decisions”

The process is continuous and new results lead to new decisions which keep the system in continuous motion.

There are two main types of feedback system; negative and positive. A negative feedback system controls or damps in order to maintain stability, while a positive

feedback system amplifies escalating small changes leading to predictable equilibrium behaviour which is unstable in nature [Distefano, Stubberud, & Williams, 1976]; [Stacey, 1993a p.150].

Systems can exhibit three main types of behaviour; stable, periodic and chaotic.

Stable behaviour - After some initial oscillation the system reaches a steady state condition where all variables have a constant final value, e.g. a ball dropped on the ground will bounce a few times and then eventually become stationary.

Periodic behaviour - After some initial oscillation, the system settles down to repeating a certain oscillation or pattern precisely over and over again. The period of the pattern may be of less than one or up to many thousand units of time in length, e.g. the voltage of an ac generator or the seasonal variation in a product's demand.

Chaotic behaviour - For a system to be chaotic the conditions outlined in section 1.6.1 must be satisfied. These will be discussed further in section 4.4.3.

Mathematicians have characterised further types of non-linear dynamic behaviour including “quasi-periodic” which has characteristics of periodic and chaotic behaviour, and “hyper-chaotic” which has all the features of chaotic behaviour in addition to more complicated properties. Differentiation between these more advanced types of behaviour is often difficult so the term chaos is often used as an umbrella for these types of dynamics.

Any non-linear feedback system can operate in a negative feedback loop to produce stable equilibrium or it can be driven by positive feedback to generate explosively unstable behaviour. It can also operate in a region where it alternates between

positive and negative feedback, producing behaviour that is both stable and unstable, thus creating chaos.

All logistics and supply chain management systems are made up of a series of feedback control loops. This is the way the majority of business systems operate. This was recognised in 1958 by Jay Forrester. In his landmark paper “Industrial Dynamics - a major breakthrough for decision makers” [Forrester, 1958] he states;

“Systems of information feedback control are fundamental to all life and human endeavour, from the slow pace of biological evolution to the launching of the latest satellite. A feedback control system exists whenever the environment causes a decision which in turn affects the original environment”

Within logistics and supply chain management a large proportion of the feedback loops are non-linear.

For example, the availability of inventory affects the shipment rate from a warehouse. When inventory is near the desired level, shipment rate can equal order rate but as inventory reduces the shipment rate can become halted or checked by the amount of available inventory. This in turn leads to the issue of “service level”.

The relationship between service level and cost to an organisation is depicted as a steeply rising curve. This results from the high costs of carrying additional safety stock to cover those times of unexpectedly high demand.

It is therefore possible that the systems of control developed for managing the supply chain under certain circumstances exhibit chaotic behaviour.

4.4 Characteristics and Definitions of chaotic systems

In this section an overview of the characteristics and definitions of deterministic chaos are presented. It is important in this work to define chaos with some precision, if chaos is not defined it cannot be measured and observed with clarity. It will be seen in Chapter 5 that there is still not one single test to prove the existence of chaos but a toolkit is required which includes tools and techniques that can characterise and show the existence of the key characteristics of a chaotic system. By defining these key characteristics it is therefore possible for the researcher to select the appropriate analytical tools.

4.4.1 *Characteristics of chaotic systems*

4.4.1.1 *Deterministic Behaviour.*

A system is deterministic if its evolution in time is always completely determined by its current state and past history [Thompson & Stewart, 1986 p.188]. Deterministic behaviour requires that definite rules with no random terms govern the dynamics. For a given starting condition, X_0 it should in principle be possible to calculate all future values of X_t .

4.4.1.2 *Bounded Behaviour.*

Dynamics can be said to be bounded if the data stays within a finite range and does not approach infinity as time increases. However, to test for bounded stability, one would in theory, need to wait until time is equal to infinity. A related concept for assessing boundedness is that of “stationarity” [Kaplan & Glass, 1995]. A time series can be described as stationary when it displays “similar behaviour” throughout its

duration. “Similar behaviour” is defined if the mean and standard deviation remain the same throughout the time series.

4.4.1.3 Aperiodic behaviour.

Aperiodic behaviour is characterised by irregular oscillations that neither exponentially grow nor decay nor move to steady state [Kaplan & Glass, 1995 p.11]. These oscillations never repeat the same state twice. It is a behaviour that is neither periodic nor stochastic [Abarbanel, 1996]. A related concept to aperiodic behaviour is that of quasiperiodic behaviour. In this type of behaviour two points that are initially close will remain close over time. This is a complex form of periodic behaviour. Distinguishing between aperiodic and quasiperiodic behaviour can be difficult unless infinite lengths of time series data are analysed. In practice the use of computer simulations with finite precision may result in the same value being returned to, however the presence of very long quasiperiodic cycles or aperiodic dynamics in data is partial evidence of chaos [Kaplan & Glass, 1995 p.27].

Variety of domains of behaviour.

Chaotic systems typically can exhibit other domains of behaviour that may include stable convergent behaviour, oscillating periodic behaviour, and unstable behaviour [Gordon & Greenspan, 1994]. A system may be operating in a stable manner but when a parameter is changed periodic or chaotic behaviour may be witnessed. Also, it is also not uncommon for chaotic systems to spontaneously switch between different modes of behaviour as the system evolves with time. Systems have been observed that will produce aperiodic behaviour for a long period of time and then spontaneously “lock” on to a stable periodic solution [Mosekilde, Larsen, & Sterman,

1991]. It is therefore possible for “Islands of stability” to be present in between areas of chaotic behaviour. This characteristic has been harnessed for some chaotic systems, by changing a parameter so that the chaotic system can be controlled to produce more regular behaviour. The research question raised by this characteristic is that if supply chains are found to be chaotic, changing key parameters within systems may result in stable behaviour.

4.4.1.4 *Sensitivity to Initial conditions*

The characteristic of sensitivity is a central concept of chaos theory. However it should be emphasised that sensitivity does not automatically imply chaos [Peitgen, Jurgens, & Saupe, 1992 p.512]. This misunderstanding is prevalent in much of the management literature and is linked to the popularisation of the “butterfly effect”.

There are many sensitive systems that do not behave chaotically. A simple example of this is the equation:

$$X_{t+1} = CX_t, \text{ where } C \text{ is a parameter much greater than } 1.$$

Any small error is magnified by a factor of C during each iteration. This system is sensitive to initial conditions but in no way can be defined as chaotic. The error will remain proportionally identical as the system is iterated

Sensitivity to initial conditions within chaotic systems is more distinct. Given a small deviation in initial conditions, this small difference or error becomes amplified until it is the same order of magnitude as the correct value. The amplitude of the error is magnified exponentially until there is no means of differentiating the actual signal from the signal generated by the error. This results in two systems with starting conditions

varied by a fraction of one percent producing outcomes over time that are totally different. The error propagation of the system results in the system being inherently unpredictable and therefore long term forecasting of such systems is generally impossible. This error propagation can be quantified by the use of Lyapunov Exponents (see Section 5.6).

The sensitivity to initial conditions also results in dramatic changes occurring unexpectedly. Stable behaviour can be followed by rapid change or a system behaving in a seemingly random manner may change to a stable form of behaviour without any warning.

4.4.1.5 *Patterns in systems.*

Despite the generation of apparently random data, chaotic systems produce patterns in the data. These patterns never repeat exactly but have characteristic properties. An example of this is a snowflake. The snowflake is generated by deterministic relationships within the environment but tiny changes become amplified. This results in every snowflake being different, but when observed it clearly belongs to the category of snow flakes. The patterns generated by systems are referred to as “attractors”.

Attractors

An attractor can be defined as [Abarbanel, 1996 p.199]:

“The set of points in phase space visited by the solution to an evolution equation long after (initial) transients have died out”

Attractors are geometric forms that characterise the long-term behaviour of a system in phase space [Crutchfield, 1986]. Systems have a stable state, the state to which all initial conditions tend to gravitate, this state serves as an attractor. In classical systems, if the system gravitates towards a single point it is said to have a point attractor, if it gravitates towards a stable cyclic response it has a periodic attractor, if the attractor results from a combination of 2 or more periods the system can be defined as a quasi-periodic attractor. The term “strange attractor” is used to describe the shape of the chaotic patterns generated. These strange attractors are a classic feature of chaotic systems [Banerjee, 1993]. Figure 4.1 shows the “Strange attractor” for the Lorenz system of equations.

To understand the nature of chaotic attractors one needs to understand a simple stretching and folding operation. The exponential divergence is a local feature, attractors have finite size, so orbits on the attractor cannot diverge indefinitely. This means the attractor must fold over onto itself. The orbits however by diverging and following increasingly different paths must eventually pass close to each other. This results in a shuffling process being undertaken on the chaotic attractor, akin to a dealer shuffling a deck of cards. The randomness of the chaotic orbits is the result of this shuffling process [Crutchfield et al., 1986]. The stretching and folding process can create patterns that reveal more detail as they are increasingly magnified, these are referred to as fractals.

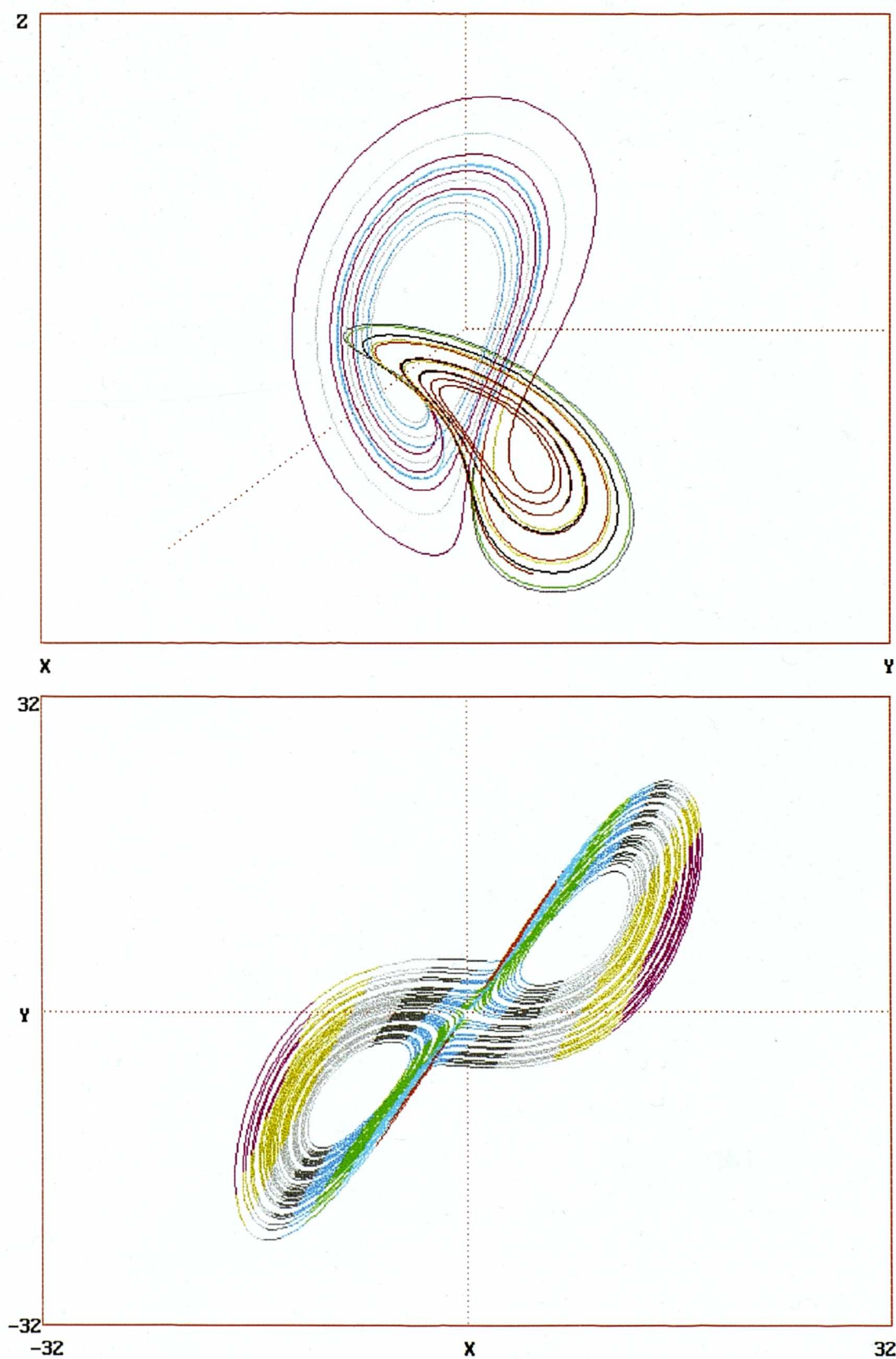


Figure 4.1 – Views of the Lorenz attractor.

The top picture shows the attractor in 3 dimensions. The bottom picture shows it in 2D with different colours for different values of the z dimension. Note the 3 dimensional trajectory of the attractor never crosses itself.

{Produced by author using "Chaos Demonstrations Version 2" by Sprott and Rowlands}

Fractals

A classical example of such patterns is the Mandelbrot set. Due to its appearance of a man made of spheres it is sometimes called the “apple man” or “gingerbread man”. It is mathematically described as the connected set of points within the complex plane where:

$$|Z_n| \text{ with } Z_n = Z_{n-1}^2 + c \text{ and } Z_0 = (0,0)$$

stays bounded as n increases to infinity, i.e. the stable solutions of the equation. As stated in Section 4.4.1.2 to check that the system is bounded a time series of infinite points is required but in practice a maximum number of iterations is required. Stable solutions in the graph are plotted in black. The boarder between the stability and instability is of key interest. The Mandelbrot set is described as one of the most mathematically complex objects ever “seen”, and yet it arises from one of the simplest equations [Sprott & Rowlands, 1995]. One feature of the Mandelbrot set is the way it retains its highly complicated structure, if viewed with increasing levels of magnification. Figures 4.2, 4.3, and 4.4 demonstrate this property. The Figures were generated by Uwe Kruger, Universitat Karlsruhe (TH). Iterating the equation for up to 65,000 times generates the colours. Depending on the stability of the system a different colour is assigned. Magnifications of 10^{13} were used in this stunning piece of work.

The figures demonstrate a number of key features. Self-similarity is witnessed in that as the edge is magnified tiny replica “gingerbread men” are seen hidden in the pattern. This also demonstrates the concept of fractals.

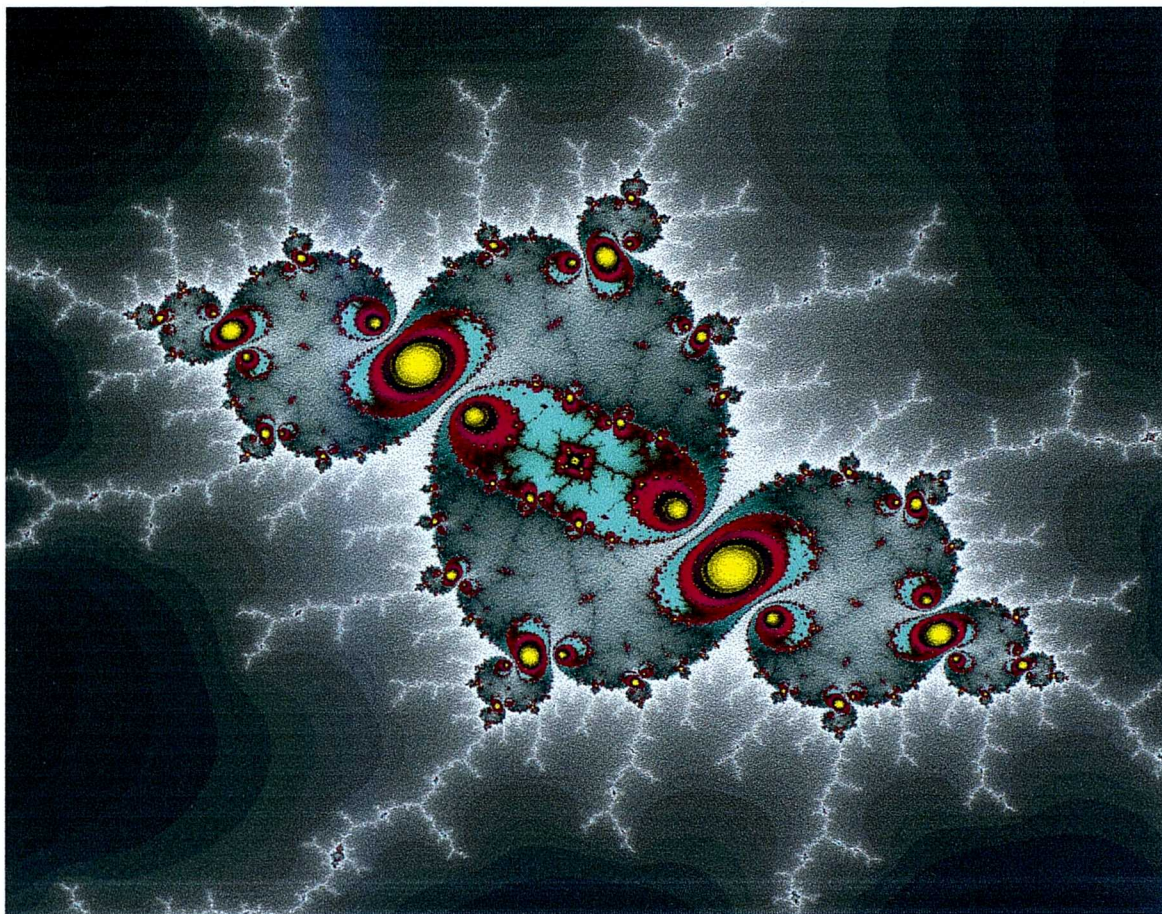


Figure 4.2 – The Mandelbrot set $\{1\}$.

Sometimes called the "apple man" or "gingerbread man". Source Uwe Kruger, Universitat Karlsruhe (TH).

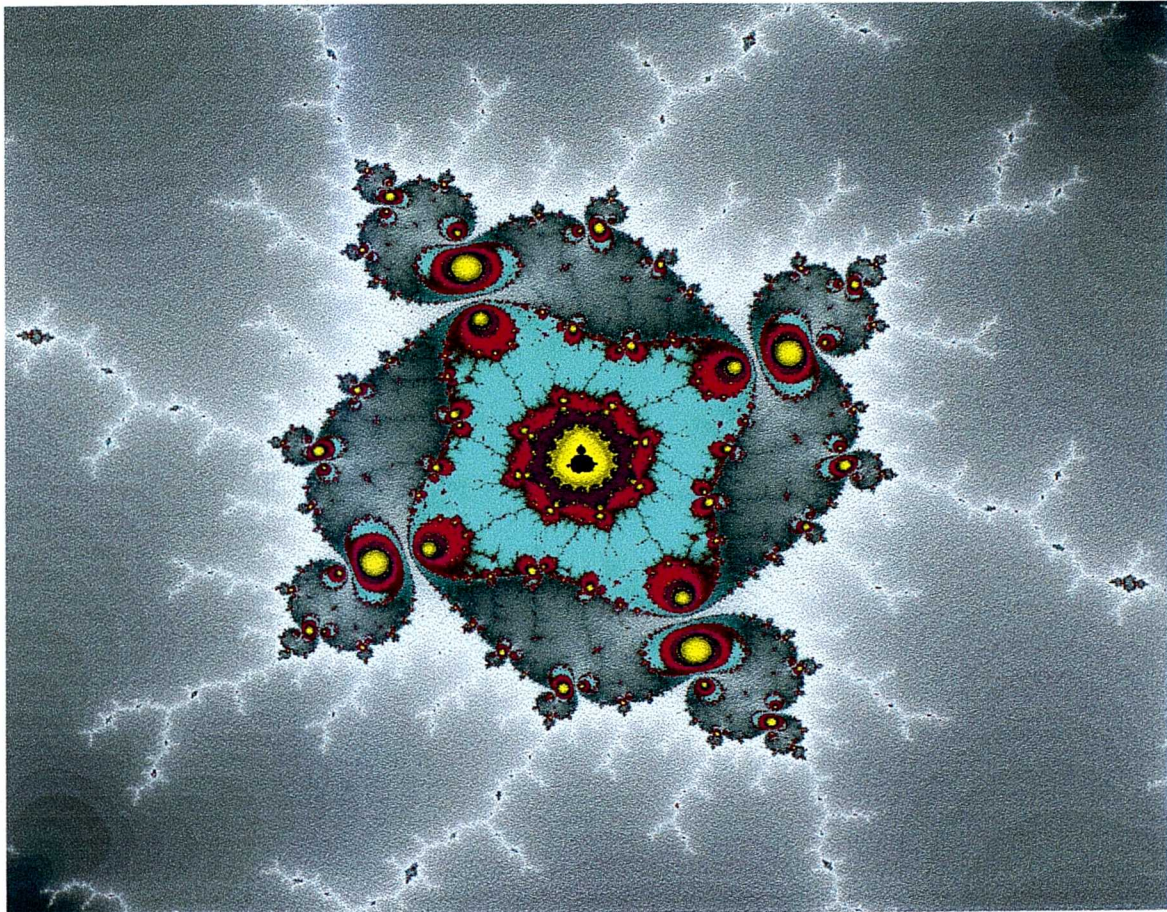


Figure 4.3 – The Mandelbrot set $\{2\}$.

The centre of Figure 4.2 magnified. Note the little “gingerbread man” in the centre of this picture. Source Uwe Kruger, Universitat Karlsruhe (TH).

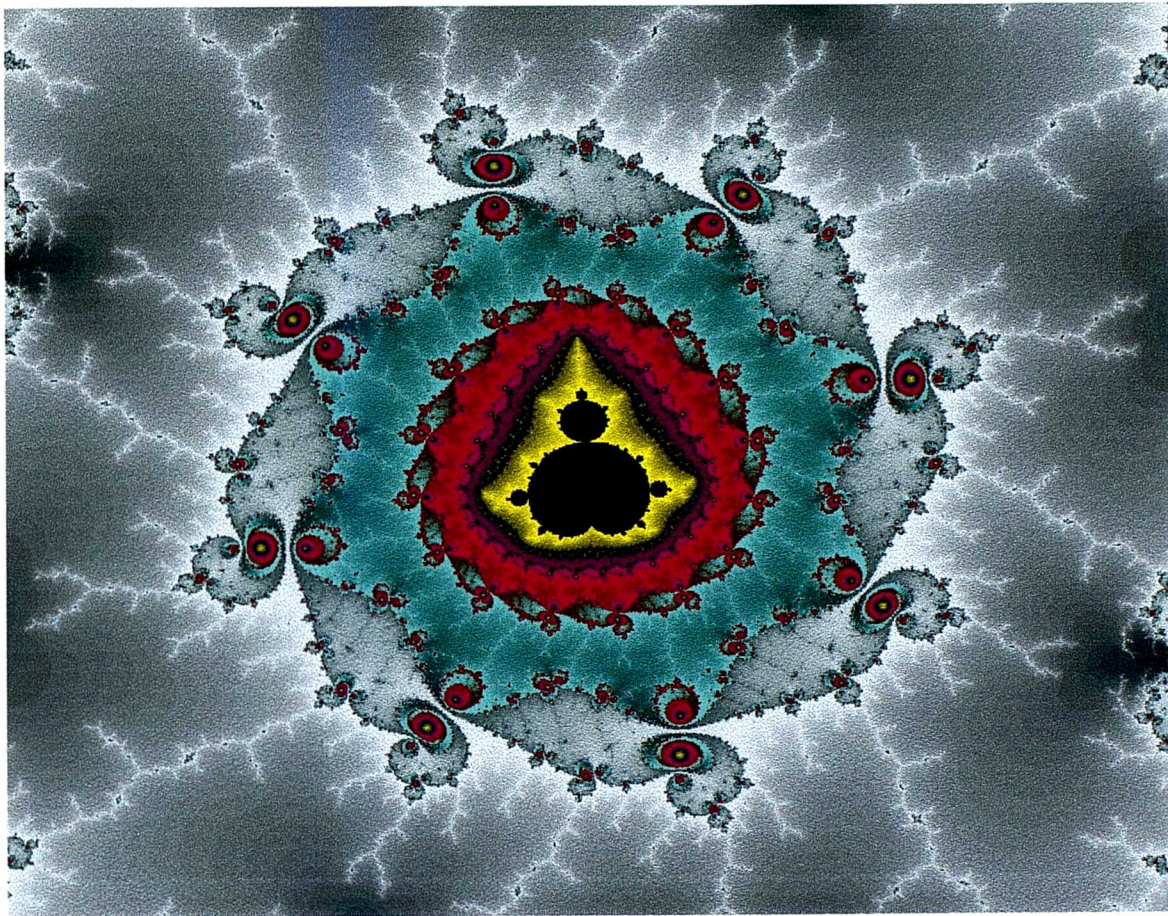


Figure 4.4 – The Mandelbrot set $\{3\}$.

The centre of Figure 4.3 magnified. The little “gingerbread man” magnified. Source Uwe Kruger, Universitat Karlsruhe (TH).

Another key feature is that the border between stability and instability is not defined. In the border region the system is intricate and vague. Stability and instability are intertwined.

We cannot predict exactly the behaviour of chaotic systems, but by understanding the patterns generated some degree of prediction is possible. Chaos generates endless individual variety, which is recognisably similar. As systems evolve with time recognisable patterns are generated. This property enables analysts to make some predictions about the system. One can predict the qualitative nature of the patterns generated and the quantitative limits within which the pattern will move [Stacey, 1993a].

4.4.1.7 Chaos invalidates the reductionist view.

One consequence of chaotic systems is that in general the reductionist view becomes invalid. The reductionist view argues that a complex system or problem can be reduced into simple forms for the purpose of analysis [Parker, 1994]. It is then believed that the analysis of the individual parts gives an accurate insight into the working of the whole system. This methodology of reductionism is also often applied to improvement within industrial systems. The optimisation of the individual units, for example manufacturing, purchasing, and distribution, is believed to result in the optimisation of the global system. Goldratt [Goldratt and Cox, 1984] demonstrated that in manufacturing environments this is often not the case. One of the rules for manufacturing developed by Goldratt and Cox state:

“The sum of the local optimums is not equal to the global optimum”

Chaos theory states that a small change to an individual unit within a system may result in dramatic effects on the global system. These effects may not in all cases be beneficial to the operation of the global system.

4.4.1.8 *Chaos undermines computer accuracy.*

Even simple equations can behave chaotically and these can have a dramatic effect on perceived computer accuracy. To demonstrate this phenomena a simple example will be described.

The example demonstrates chaos by iterating a simple equation using a standard spreadsheet package. The simple equation to be iterated is as follows:

$$X_t = KX_{t-1}^2 - 1$$

This simple equation for certain values of K is chaotic. The use of spreadsheets to demonstrate chaos enables an accessible method to demonstrate the nature of such systems [Durkin & Nevils, 1994].

When K is 1 then a stable periodic orbit occurs, the system is attracted to a cycle of 0, -1, 0, -1 {see figure 4.5}. The equation is relatively stable up until K = 1.5 producing periodic behaviour or quasi-periodic behaviour. At K = 1.5 chaos occurs and the dynamics become increasingly complicated as K increases {see figure 4.6}. However, at K = 1.74 the system behaves chaotically but at K = 1.76 stable behaviour occurs {see figure 4.7}. This stable behaviour continues until K = 1.81 and then chaotic behaviour reoccurs. Therefore an “island of stability” is present between K = 1.76 to 1.80.

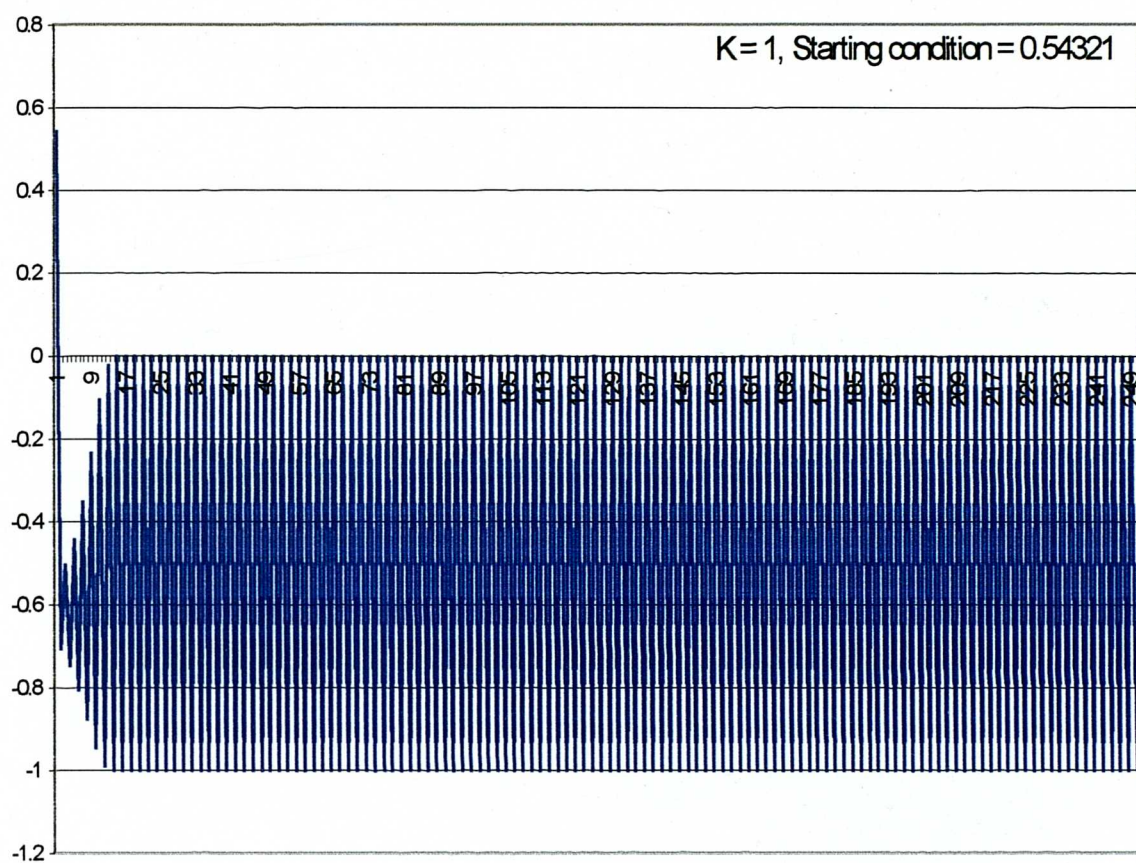


Figure 4.5 – Graph for the iteration of the equation $X_t = KX_{t-1}^2 - 1$ for $K = 1$.

Periodic Behaviour.

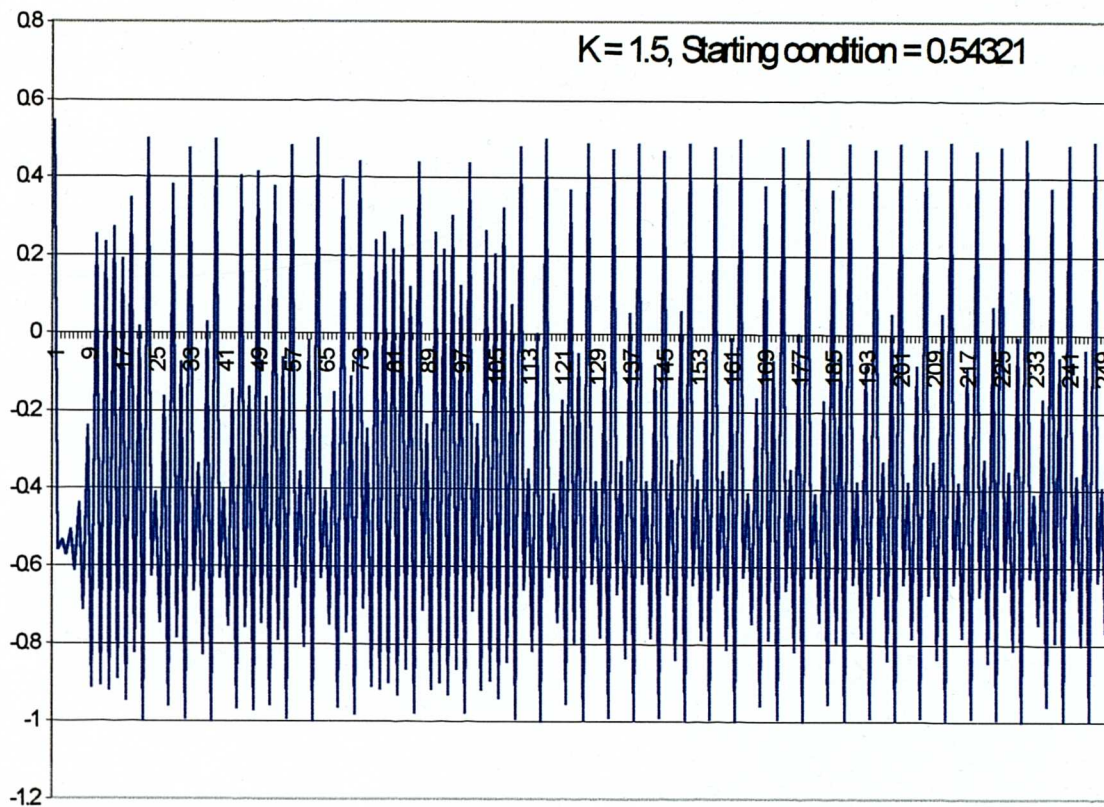


Figure 4.6 – Graph for the iteration of the equation $X_t = KX_{t-1}^2 - 1$ for $K = 1.5$

Chaotic Behaviour.

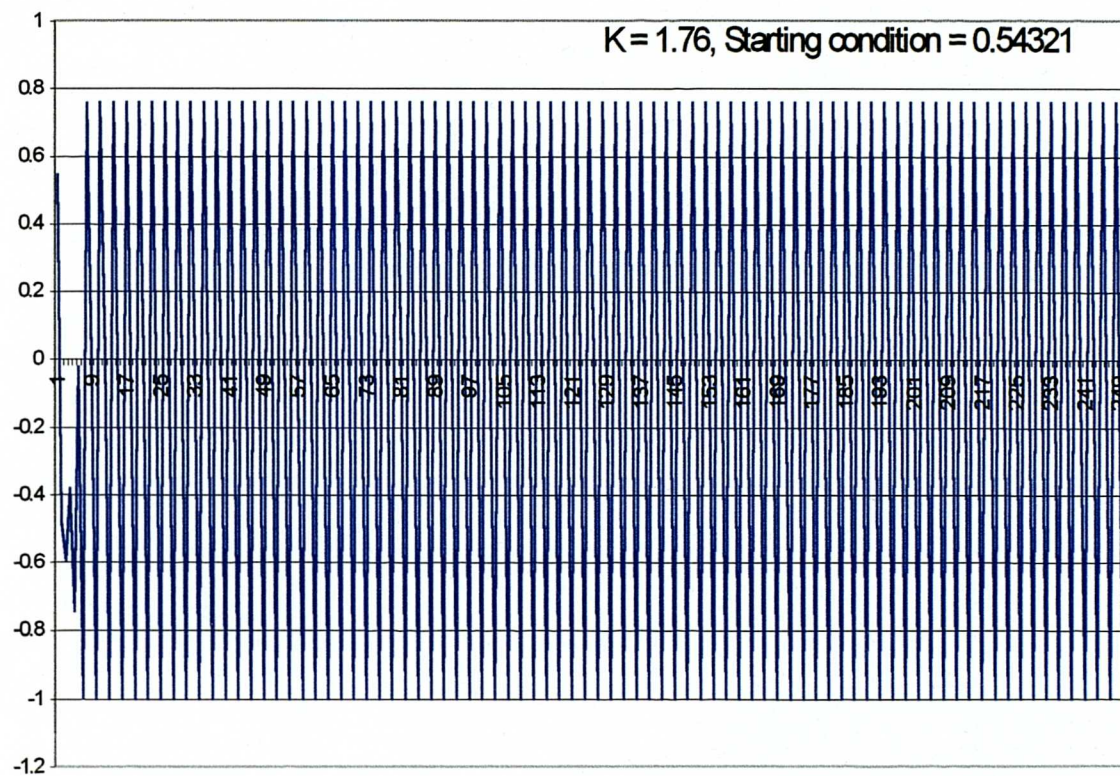


Figure 4.7 – Graph for the iteration of the equation $X_t = KX_{t-1}^2 - 1$ for $K = 1.76$.

Periodic Behaviour.

| Number of Iterations | IBM 486 using Excel Spread sheet | | PSION 3a using Psion Spread sheet | |
|----------------------|----------------------------------|-------------------|-----------------------------------|-------------------|
| Start Value | 0.54321 | 0.543210000000001 | 0.54321 | 0.543210000000001 |
| 5 | 0.890035 | 0.890035 | 0.890035 | 0.890035 |
| 10 | -0.84727 | -0.84727 | -0.84727 | -0.84727 |
| 20 | -0.07355 | -0.07355 | -0.07355 | -0.07355 |
| 40 | 0.625099 | 0.614856 | 0.62497 | 0.614805 |
| 60 | 0.455086 | -0.97999 | -0.4463 | -0.30702 |
| 80 | -0.9822 | -0.098716 | 0.306851 | -0.80001 |
| 100 | 0.05050847 | 0.0349483 | 0.322846 | -0.58814 |

(Below - Graph demonstrating how as the number of iterations increase Excel and Psion values diverge. Starting condition 0.54321)

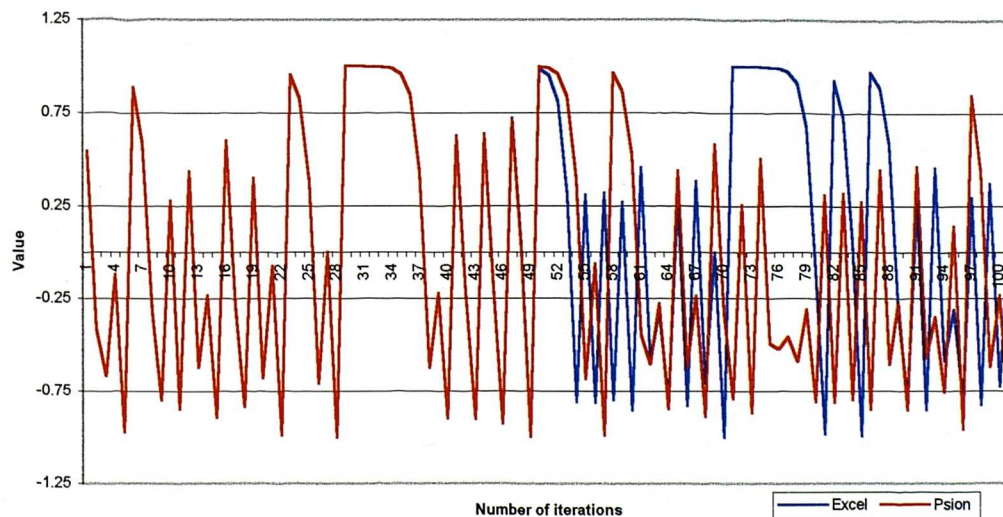


Table 4.1 – The Iteration of $X_t = 2X_{t-1}^2 - 1$ using Excel and Psion, Using the same start conditions and a small error introduced.

Note as number of iterations increase the values start to diverge, demonstrating sensitivity to software and hardware and also the initial conditions.

Table 4.1 shows the iteration of this equation when $K = 2$ (producing chaotic behaviour) on two different spreadsheet and hardware platforms and two starting conditions differing by a tiny amount. It can be seen that after twenty iterations the results start to diverge rapidly. If K is greater than 2 the equation becomes unstable and the solution approaches infinity.

This raises a fundamental issue about the impact of chaos on computer systems. An identical program run on two different makes of computer, or different standard software packages doing the same calculations can produce significantly different results [Stewart, 1989 p.21].

Peitgen [Peitgen, Jurgens, & Saupe, 1992 p.40] further emphasises this point by stating:

“More and more massive computations are being performed now using black box software packages developed by sometimes very well known and distinguished centers. These packages, therefore, seem to be very trustworthy, and indeed they are. But this does not exclude the fact that the finest software sometimes produces total garbage, and it is an art in itself to understand and predict when and why this happens. ...More decisions in the development of science and technology, but also in economy and politics are based on large-scale computations and simulations. Unfortunately, we can not take for granted that an honest error propagation analysis has been carried out to evaluate the results.”

This raises a number of issues about the nature of uncertainty within supply chains. Increasingly complex analysis and control systems are being produced to aid the management of the supply chain. In theory, uncertainty within the supply chain could be caused by the algorithms being used operating under conditions that generate chaos.

The example detailed above demonstrates a number of key properties;

- “Islands of stability” within a chaotic system.
- Sensitivity to initial conditions.
- The variety of types of behaviour exhibited by an equation with the same fundamental structure.

4.4.2 Definitions of Chaos

4.4.2.1 Stewart

Ian Stewart describes the discussion to define chaos at the Royal Society in 1986. He highlights the difficulty in gaining agreement for a precise definition [Stewart, 1989].

The definition finally accepted is as follows:

“Stochastic behaviour occurring in a deterministic system”

This presents a paradox on which Stewart offers further explanation. Deterministic behaviour is ruled by exact unbreakable law. Stochastic behaviour is lawless and irregular, governed by chance. Stewart sums up the above definition and proposes:

“Chaos is lawless behaviour governed entirely by law!”

This raises the issue that for a system to be chaotic it must be governed by fixed rules and laws and therefore can be said to be deterministic.

4.4.2.2 *Thompson and Stewart*

Thompson and Stewart [Thompson & Stewart, 1986 p.197] propose what they describe as a “positive” and a “negative” definition for chaos. The negative definition being:

“Recurrent behaviour that is not in equilibrium”

However chaotic motion has aspects that are random in nature. The randomness results from extreme sensitivity to initial conditions. Chaos is also exhibited by surprisingly simple systems. Thompson’s second “positive” definition is as follows:

“Chaos is recurrent motion in simple systems or low dimensional behaviour that has some random aspect as well as a certain order”

The definition above could generate some misunderstanding as it proposes that a random aspect is present. This could be mis-interpreted to mean a random variable is present which for a chaotic system is not the case. However the definition does emphasise that simple systems can exhibit such behaviour.

4.4.2.3 *Stacey*

Ralph Stacey eloquently defines chaos as follows [Stacey, 1993a p.228]:

“Chaos is, in one sense, an inherently random pattern of behaviour generated by fixed inputs into deterministic (that is fixed) rules (relationships), taking the form of nonlinear feedback loops. Although the specific path followed by the behaviour so generated is random and hence unpredictable in the long term, it always has underlying pattern to it, a “hidden pattern”, a global pattern or rhythm. That pattern is self-similarity, that is a constant degree of variation, consistent variability, regular irregularity, or more precisely, a constant fractal dimension. Chaos is therefore order (a pattern) within disorder (random behaviour).

This definition can be seen to emphasis the patterns generated by chaotic systems.

4.4.2.4 Abarbanel

Abarbanel [Abarbanel, 1996] gives a more detailed definition of chaos:

“Chaos is the deterministic evolution of a nonlinear system which is between regular behaviour and stochastic behaviour or “noise”. This motion of nonlinear systems is slightly predictable, nonperiodic, and specific orbits change exponentially rapidly in responses to changes in initial conditions or orbit perturbations”

This definition emphasises a key characteristic of chaos, the sensitivity to initial conditions that chaotic systems exhibit. Abarbanel also proposes the following definition:

“Chaos is irregular in time and slightly predicable, chaos has structure in phase space”

This emphasises that prediction of such systems is possible, but within a given horizon, and that data from such systems, unlike random systems, exhibit observable patterns.

4.4.2.5 *Kaplan and Glass*

Kaplan and Glass [Kaplan & Glass, 1995] provide a concise definition of chaos:

“Chaos is defined to be aperiodic bounded dynamics in a deterministic system with sensitive dependence on initial conditions”

Aperiodic, bounded, deterministic and sensitivity on initial conditions can be summarised as follows:

Aperiodic means that the same state is never repeated twice.

Bounded means that on successive iterations the state stays within a finite range and does not approach plus or minus infinity.

Deterministic means that there is a definite rule with no random terms governing the dynamics.

Sensitivity to initial conditions means that two points that are initially close will drift apart as time proceeds.

This definition includes all the key characteristics of chaotic systems. However, it could be argued that it omits the issue that patterns are present in the data. Many random number generators used in, for example, simulation packages use deterministic equations to generate pseudo-random number streams (for example see [AT&T Istel, 1995]). The data produced by such pseudo random number generators

show no discernible patterns over long time periods (many millions of points). This is an advanced form of chaos and has been defined as hyperchaotic behaviour.

4.4.3 Summary

The definition used in this thesis is adapted from that proposed by Kaplan and Glass [Kaplan & Glass, 1995 p.27] and Abarbanel [Abarbanel, 1996 p.15]. This definition includes all the major defining characteristic of chaos raised by the above discussion. In Chapter 5 the thesis will discuss how each of the various characteristics included in the definition can be identified, and where possible measured, from a time series of data. These tests will be combined in a methodology of analysis used for time series data generated by the simulation model. The definition used is as follows:

Chaos is defined as aperiodic, bounded dynamics in a deterministic system with sensitivity dependence on initial conditions, and has structure in phase space.

In addition to the terms defined on page 129, structure in phase space is defined as follows:

Structure in Phase Space. Multidimensional vectors describe nonlinear systems. The space in which these vectors lie is called phase space (or state space). The dimension of phase space is an integer [Abarbanel, 1996]. Chaotic systems display discernible patterns when viewed.

4.7 Applications into various environments.

As has been discussed, chaos theory, and its associated concepts, are new areas of mathematics that have been developed in order to extract hidden regularities from apparently random data.

Chaos theory has been applied to a variety of disciplines. In the following section, an overview is presented of the application of chaos theory to industry. The review will then develop a classification for the application of chaos theory to management. The section will then proceed to focus on the literature which, is of particular relevance to uncertainty generation within the supply chain.

4.7.1 General applications of chaos theory to industry.

The diversity of applications of chaos theory is ever increasing. The following examples demonstrate this diversity of the research into chaotic systems over the past few years.

a) Mixing and Turbulence.

The application of chaos theory in industry is becoming increasingly wide spread. An early application was the modelling and data analysis of turbulence and mixing processes [Aubry et al., 1988; Aref, 1994]. Mixing is important in applications involving heating. MacKay [MacKay, 1993] cites the application of chaos to ensuring uniform heating of plasma in nuclear fusion reactors. The Japanese company Goldstar have designed a chaotic washing machine which improves the cleaning over conventional methods [Paisley, 1993]. Mixing is of key importance in combustion

technology to improve heat output and efficiency. Chaos is proving beneficial in this application [Borghi, 1988].

b) Robotics

Applying chaos theory to robotics is proving useful. By designing chaos into the control of robot servos, the robot can learn from its environment and recognise the onset of random behaviour [MacKay, 1993].

c) Communications

Chaos is also finding applications in communications, the optimisation of telephone exchanges [Erramilli & Forsy, 1991] and also the transmission of digital signals [Uzunoglu & White, 1985]. New methods of data compression using chaos theory and fractal science have been developed and are being used by British Telecom and GEC [Waite & Beaumont, 1990].

d) Marine Structures

Thompson has used chaos theory in the investigation of the motion of ships moorings and also at sea. This is of importance for the improved design of marine structures [Thompson & Bokaian, 1992].

e) Chemical engineering

Data analysis methods developed for the analysis of chaotic behaviour have been applied to bulk chemical reactions (see for example [Scott, 1991]).

f) Medicine

The Nuffield Orthopaedic Centre at Oxford has undertaken work with the Mathematics Institute, University of Warwick. This work has applied chaos-theoretic

data analysis to detect incipient failure in artificial hip joints [Stewart, 1996]. Garfinkel et al [Garfinkel et al., 1992] have applied chaotic control methods to a prototype “intelligent heart pacemaker”.

i) Financial Sector

The financial sector has applied the theory mainly to forecasting and prediction. It is believed that stock market prices follow simple rules that, if found, can aid prediction and subsequently benefit dealers [Weiss, 1992]. It has been argued that chaos theorists get improved results for banks in comparison to theorists applying random data techniques [Shipman, 1993]. Shell (UK) has commissioned a report from the University of Warwick on commodity market forecasting [Lane & Hayes, 1989]. Further project work for “blue chip” clients is also being carried out at the “Financial Options Research Centre” at the University of Warwick on chaos related financial data analysis, unfortunately this is confidential in nature, but this example does reinforce the interest exhibited in this area by industry.

Deterministic chaos has also been identified in business cycles and the economic long wave (see for example [Brock & Sayers, 1988; Rasmussen, Mosekilde, & Sterman, 1985; Lorenz, 1987; Mosekilde et al., 1992; Sterman, 1989c]).

j) Quality Assurance

Stewart has developed a quality assurance methodology using chaos theory for application to the spring manufacturing industry. This has proved particularly successful in reducing wastage by testing spring wire suitability before the manufacture of the actual spring. [Stewart & Muldoon, 1994].

| | |
|---|---|
| DISORDER METAPHORIC “RANDOM, UNPREDICTABLE” | DETERMINISTIC METAPHORIC “AMPLIFICATION, (BUTTERFLY EFFECT)” |
| DETERMINISTIC QUALITATIVE “THEORETICAL APPLICATION” | DETERMINISTIC QUANTITATIVE “MATHEMATICAL ANALYSIS AND APPLICATION” |

Figure 4.8 – Classification of management literature discussing “Chaos”.

4.7.2 Classification of use of chaos in management.

As discussed in Section 1.6.1 the term chaos is currently much used within the management literature. The literature can be classified into four categories (see figure 4.8), as follows:

a) Disorder metaphoric

The Collins English dictionary describes chaos as meaning “complete disorder and confusion”. The term chaos has been used in this context within the management literature to describe the seemingly random disorder of customer demands for products as described by Womack and Jones [Womack & Jones, 1996 p.81] and by Tom Peters [Peters, 1988] in his book “Thriving on chaos” to describe disorganised yet responsive business structures that rapidly adapt and gain competitive advantage.

b) Deterministic metaphoric

Chaos is also used as a metaphor to describe how a small change can be amplified to have a large effect on the system. This has resulted from the popularisation of the “butterfly effect”. Authors (for example [Jones & Towill, 1996; Womack & Jones, 1996 p.87]) describing amplification within the supply chain have used the term “chaos” in this context. Chaos is used to describe amplification without support or analysis that the term is applicable in this context. The term “metaphoric” can be used to describe these circumstances because “chaos” is used as an analogy which is “imaginatively but not literally applicable” [Oxford Concise Dictionary].

c) Deterministic Qualitative

The body of literature which can be defined under this heading is characterised by detailed review of the nature of deterministic chaos systems, and the development of a theoretical framework based on the concepts of chaos theory that can be applied to a particular management issue or environment. Examples of this type of research include Stacey [Stacey, 1993a]; [Stacey, 1993b] addressing the issue of strategic management. Parker [Parker, 1994] discusses the implication of chaos theory to the management of change within organisations. Cartwright [Cartwright, 1991] discusses the implications of chaos theory to town planning.

This literature, through the use of qualitative examples and case studies has challenged traditional “cause and effect” thinking within management. It is argued that using chaos theory as a model provides a means for individuals and organisations to create and share understanding and has resulted in improved management procedures [Lissack, 1997].

d) Deterministic Quantitative

The characteristic of this body of research is the application of new non-linear quantitative analytical techniques to gain greater understanding of management systems. This work is either based on the analysis of actual data, for example stock market indices or data generated by mathematical models or simulations of real or hypothetical management environments. Examples of works that fall under this classification are the analysis of chaos in a model of duopolistic competition [Whitby, Parker, & Tobias, 1996], and the work by Mosekilde et al [Mosekilde, Larsen, & Sterman, 1991] investigating chaos generated under certain conditions within the Beer Game.

It should be emphasised that some overlap has occurred in some works between the last two classifications. For example, Levy [Levy, 1994] discussed the application of chaos theory in a “qualitative” way to strategic management and uses a spreadsheet simulation of a simple supply chain to demonstrate the amplification and arguably “sensitivity to initial conditions” in a “quantitative” way. Levy uses this model very effectively to aid his discussion of management within chaotic systems. However, the paper does not discuss any methodology for analysis of chaos and the author’s conclusion that chaos is present would seem to be based on limited qualitative observations. It is therefore unclear if the model is behaving in a chaotic manner.

4.8 Review of work with relevance to uncertainty in supply chains.

The two main areas of literature focusing on chaos in industry which are of relevance to this thesis are general “qualitative” discussions and investigations into management within uncertain chaotic environments, and investigations into generation of chaos through decision making processes in the “Beer Game”. These areas of literature raise further research questions, which will be discussed at the end of this section.

4.8.1 Management within chaotic environments. (Qualitative Deterministic)

The recognition that management systems are complex structures composed of non-linear feedback loops has led analysts to use chaos theory as a framework within which to view the strategic management processes. Traditional linear “cause and effect” relationships have been found to be insufficient for effective planning within a

number of management environments. Stacey [Stacey, 1993b] challenges the conventional view that an organisation's success is dependent on operating in states of stability and consensus. Stacey argues that this "rational" approach to strategic management concentrates on a static analysis of competitive position. This is outdated and the organisation should be viewed as a dynamic system. By understanding the dynamic processes within an organisation managers can adapt strategic management processes to generate success. Stacey concludes that the non-linear feedback loop structure is prone to chaotic behaviour and therefore innovative strategies are required for success.

Stacey proposes a number of consequences of operating within a chaotic environment to which managers need to adapt.

As the long-term future is unknowable, long term forecasts cannot be made. Recognisable patterns can be witnessed in management systems and it is these that need to be understood, these can then be used to guide decisions, as relationships within the patterns are identified. Traditional corporate and strategic planning will not achieve the objective intended because long-term prediction is virtually impossible.

In these circumstances the concept of contingency loses its meaning. Contingency postulates a linear relationship between "cause and effect". Tiny changes can generate large effects and successful organisations need to be both mechanistic and organic at the same time. They need to manage predictable short term futures but also adapt quickly to the long term unknowable future. This results in actions not being driven by pictures of the future but by the beliefs and the intrinsic merits of a task.

Stacey concludes that the issues raised above emphasise the need for successful organisations to be in a constant state of learning. Such organisations create their environments and futures. McMaster [McMaster, 1996 p.193-205] also emphasises this issue arguing that organisations require unpredictability and chaos to create an environment in which learning can take place. If everything was predictable and controlled organisations would not develop, they would have no need to generate new structures and patterns of behaviour.

Parker [Parker, 1994] suggests that for creative change management within organisations, the system needs to be held at the frontier between instability and stability (i.e. chaos). Stable management environments fail as they do not evolve or adapt, while total instability leads to confusion and eventual breakdown.

These concepts have been developed further by Parker and Stacey [Parker & Stacey, 1994], who highlighted further implications of non-linear thinking on management and economics. They conclude that chaos theory provides a new departure point for the study of economics and organisations. The authors propose a number of policy recommendations. These include:

- Longer-term economic future is inherently unknowable, therefore policy should emphasise the conditions to allow for adaptability and change.
- To be innovative a system must operate at the chaos frontier. This is supported by research into the physical sciences. It is argued that chaos permits true choice in economic systems.
- Enterprise drives change; chaos theory in drawing attention to adaptability and change, it supports the need for entrepreneurial adaptation.

- Chaos theory may explain the uncertainty experienced in economics. Slight errors in demand management may be highly magnified. Government intervention into markets may add uncertainty.
- Any system that attempts long-term planning will eventually breakdown. Policy should be focused on creating systems that are capable of self-organised evolution.
- Chaos theory suggests that the economic system is best understood when organisations and economies evolve along complex time trajectories. Policies that reduce the economy's ability to adapt should be questioned as they will reduce the economy's flexibility and hence its ability to adapt.

Levy [Levy, 1994] proposes chaos theory as a useful theoretical framework for understanding the dynamic evolution of industry and the complex interactions between industrial players. Levy demonstrates his theory with the aid of a simple spread sheet simulation of the real international supply chain of California Computer Technology (CCT). The simple simulation depicts the interactions between a manufacture of computers, its suppliers and market.

The CCT supply chain simulation shows how small disruptions to the supply chain interact to make the chain highly volatile imposing significant costs on the organisation. (This can be viewed as a specific example of the “Forrester effect”, as little quantitative analysis for chaos is discussed in the paper.) Levy argues that by understanding the macro-economic environment as complex dynamic system possible managerial approaches that lower the cost of operating the supply chain can be identified. He observes that tiny variations in inventory and demand are magnified every time the system oscillates.

Levy suggests a number of key implications for management within a chaotic system.

- Long term planning is very difficult. Small disturbances are multiplied over time and because of the non-linear relationships the system is very sensitive to initial conditions. The payoff of investing in more complex and accurate models of forecasting may be small. However, rather than placing large amounts of resource on forecasting, resource should be allocated to planning where a number of scenarios should be planned for.
- Industries do not reach stable equilibrium.
- Dramatic change can occur unexpectedly. Small external changes can occur causing unexpectedly large changes in demand and inventory.
- Short-term forecasts and prediction of patterns can be made. Fluctuations will occur between certain tolerance bands. Chaotic systems trace repetitive patterns that may yield useful information. Fractal patterns may be present.

Levy concludes that the industrial system must be viewed as a whole, and the reductionist view is invalid. The two most important dimensions to this system are uncertainty and the time relationships. The timelags in communication, production and distribution create an environment where a disruption in one element generates a sequence of changes in other parts of the system. Levy observed that if the standard deviation of the variation in demand falls below a certain level the demand instability does not have a significant impact on the system and chaos tends to be less likely. Levy advocates lean production techniques, which may reduce the variation in this serial supply chain model. However, the research outlined within this thesis may

suggest that an organisation independently implementing lean techniques within the supply network may incur additional costs for itself due to parallel interactions.

It can be seen from the discussion above that chaos can be seen as an opportunity for creativity, and accepted as a given issue over which one has little control. This then leads to the requirements for new management strategies.

Gordon and Greenspan [Gordon & Greenspan, 1994] proposes a different methodology for management in chaotic systems. Gordon identifies approaches which emphasise the avoidance of chaos within management systems. The methods proposed are summarised as follows:

- Slowing things down - increase the time interval between actions on the system, this was found by Gordon to move the system towards stability.
- Exposing the system to a shock - this Gordon argues can force the system into a state of stability. However this crude method of control is difficult as the timing and size of shock must be judged accurately. Therefore it may not always result in a desirable outcome.
- Changing the attractor - in order to use this approach the dynamics of the system must be understood. The system is then changed to alter the attractor generated to one which is more stable.
- Reduce feedback - understand the variables and parameters that have some control over the system, and determine the values to reduce the feedback. (For example, in simple exponential smoothing the smoothing constant can be reduced.)

- Break the feedback loop - use policies that decouple components in the system.

Gordon argues that this will never produce optimal solutions but will render the system stable and non-chaotic.

4.8.2 Chaos in human decision making - the stock management problem. (Quantitative Deterministic).

4.8.2.1 Non-linear Dynamics in the Beer Supply Chain.

In Section 3.5 a discussion of the understanding gained about demand amplification from the use of models developed from a behavioural science perspective was presented. This work progressed into an investigation into non-linear dynamic behaviour experienced within decision making in the “Beer Game”. This body of research provides the greatest insight of any research to date into the generation of uncertainty, through chaos, within a theoretical supply chain model.

The model developed by Sterman [Sterman, 1989a] was concurrently used to investigate the non-linear dynamics within the Beer Game. Erik Mosekilde [Mosekilde & Larsen, 1988] investigated whether chaos could result from the decision making policies within the system. Using the simulation developed by Sterman (see section 3.5.4), the authors developed a systems dynamics model. It was recognised by the authors that generally simulations were run over a short period of time, say 60 weeks. This time period is less than the fundamental period of the system and therefore will not reveal the existence of complex modes of behaviour within the system. Very few policies were investigated within the simulations and up until Sterman [Sterman, 1989a] no attempt had been made to analyse which order policies participants of the Beer Game actually used.

Mosekilde and Larsen [Mosekilde & Larsen, 1988] modified Sterman's equations slightly by removing the gaussian noise and introducing a smoothing constant. The three parameters, which were mapped were:

- AT, the time constant associated with the adjustment of inventories to the desired level, this was generally equal to 5 weeks.
- B, the fraction of unfilled orders accounted for by the ordering policy.
- D, the fraction of anticipated shipments taken into account.

(B and D equate to α_s and β in the Sterman's example presented in Section 3.5.4). B characterises how fast the inventory gets updated in case of a discrepancy between the desired and actual inventory. D can be interpreted as the fraction of units ordered but not yet received that has been taken into account when a new order is placed by the participants on their supplier.

The authors used a technique of "bombing" the parameter space, i.e. randomly selecting a value for B and D and running the simulation accordingly, this cuts down the number of simulations required and is a valid approach to searching for types of behaviour present. (This is analogous to activity sampling in industrial engineering [Whitmore, 1975]). The results showed that Stable, Periodic and Chaotic behaviour in inventory and order fluctuations does exist within certain regions of the model. It was found that the regions where chaos exists are easily accessible to managers operating in the real world and therefore one could presume these types of behaviour do occur in real industrial and management environments.

Generally fast inventory adjustments introduce instability i.e. when α_s (or B) is greater than 0.3. Below this figure stable solutions appear [Lomi, Larsen, & Ginsberg, 1994].

Mosekilde, Larson and Sterman [Mosekilde, Larsen, & Sterman, 1991] produced a detailed discussion of chaos in human decision making. They produced results that provided direct experimental evidence that chaos can be produced by the decision-making behaviour of real people in simple managerial systems. The system used was once again Sterman's model based on the Beer Game supply chain. The investigation was extensive and 40,000 simulations were completed to cover the parameter space. The authors discovered that 23% of participants used decision rules that operated the system in a region of parameter space producing chaotic behaviour, the remainder of the participants producing stable or periodic behaviour. An example of the analysis of parameter space is shown in figure 4.9. By inspection, fingers of stable behaviour penetrate deep into regions of unstable behaviour. Crossing these fingers are further fingers of periodic behaviour for which internally generated oscillations "lock" onto the discrete time period of the model. In some regions stable behaviour is surrounded by chaotic solutions on all sides.

One key issue discussed in the paper is the cost implications of operating in the chaotic region. It was shown that when the model produced stable solutions significantly lower costs were achieved. When the model produced a chaotic solution costs could be up to 500 times higher than when operating in a stable manner. It was also shown that the higher the target inventory the smaller the regions of chaotic behaviour and conversely the lower the inventory the greater the regions of chaotic behaviour. For the system investigated costs were independent of α_s (the rate at which inventory discrepancies are eliminated), for stable solutions. This implies that

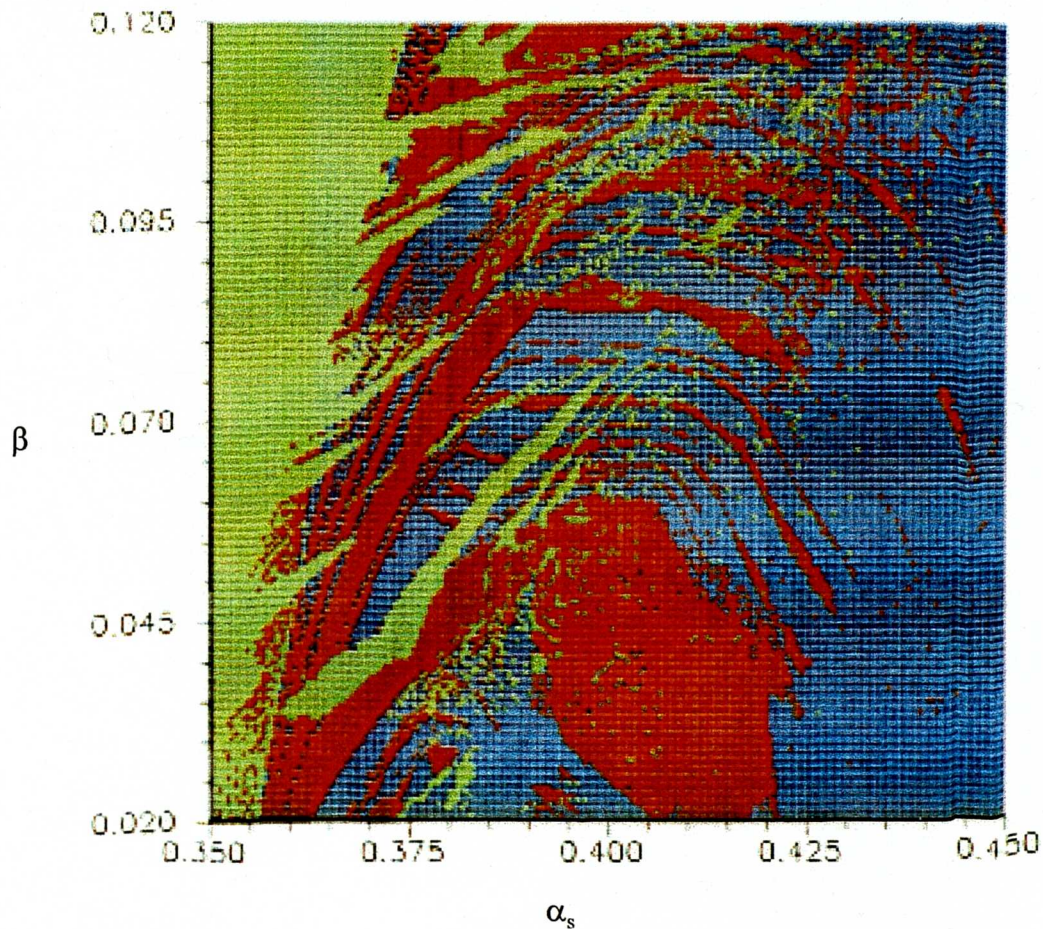


Figure 4.9 – Complex behaviour resulting from “Beer game” decision making.

Where β is the fraction of unfilled orders accounted for by the ordering policy and α_s is the fraction of anticipated shipments taken into account.

Green = stable, Blue = chaotic, Red = periodic. Note in certain regions a stable solution is surrounded by chaotic solutions on all sides.

Source: Mosekilde, E., Larsen, E., and Sterman, J.D. (1991). "Coping with complexity: deterministic chaos in human decision making behaviour." Beyond Belief: randomness, prediction and explanation in science. Editors J. L. Casti, and A. Karlqvist CRC Press .

the final equilibrium state attained by the supply chain after all initial transients have died out is independent of the rate at which inventory discrepancies are eliminated. The authors demonstrated that the more complex forms of chaos were observed when low target inventories, little consideration of supply line inventory and the rapid correction of discrepancies between desired and target inventories were applied. This reflects an aggressive stock adjustment policy with low desired inventory and the tendency to neglect supply line adjustments. The authors commented that more research at this time was required on the impact of random disturbances on the system stating:

“It is obvious that such random blows severely reduce the predictability of these systems. But does the existence of stochastic shock swamp the uncertainty caused by chaos?.....further investigation is required to answer this question for different systems.”

It is recognised that the slightest changes in ordering policy or initial conditions can produce dramatically different behaviour.

The cost associated with operating in the unstable region were also discussed by Larsen, Morecroft and Mosekilde [Larsen, Morecroft, & Mosekilde, 1989]. Here a cost verses inventory curve was plotted. (See figure 4.10). The curve demonstrated that when managers were over ambitious in setting low target inventory levels chaos is more likely to occur and generally costs are likely to rise. This argument is witnessed in practical industrial environments, driving inventory down to low levels results in distress due to stockouts, rapid and erratic reordering and poor customer

service levels. It can be demonstrated for the majority of production environments that one unit too little inventory is far more costly than one unit too much inventory.

Meikle [Meikle, 1995] when investigating the scheduling of jobbing shops also demonstrated this effect. When calculating optimum inventory level for job shop operation the curve produced was identical in form to that in figure 4.10.

The paper's [Larsen, Morecroft, & Mosekilde, 1989] key conclusion is that well defined and rational order policies can create a wide variety of complex behaviour. This behaviour can in certain circumstances result in unpredictably high costs. It is also recognised by the authors that "navigating" the low cost parameter space to achieve minimum costs is virtually impossible by trial and error and suggestions are made for decision heuristics that avoid the high cost, unstable solutions. These include the recommendation of global information so factories are aware of the customers' demand, the shortening of the supply chain by removing say the wholesaler or distributor, and "locking" the two sectors in the middle of the chain together, so they only reorder the exact amount of inventory they have sold.

The above work was advanced further by Thomsen et al [Thomsen, Mosekilde, & Sterman, 1991; Thomsen, Mosekilde, & Sterman, 1992]. They showed using the "Beer Game" model that decision making in this environment could lead to chaos, hyperchaotic and higher-order hyperchaotic dynamics. Hyperchaotic and higher-order hyperchaotic solutions are distinguished by the presence of two or more positive Lyapunov exponent values. The Lyapunov exponent measures the local rate of expansion of state space. This is negative for systems with stable equilibrium and positive for chaotic systems. (This will be discussed in detail in Section 5.6).

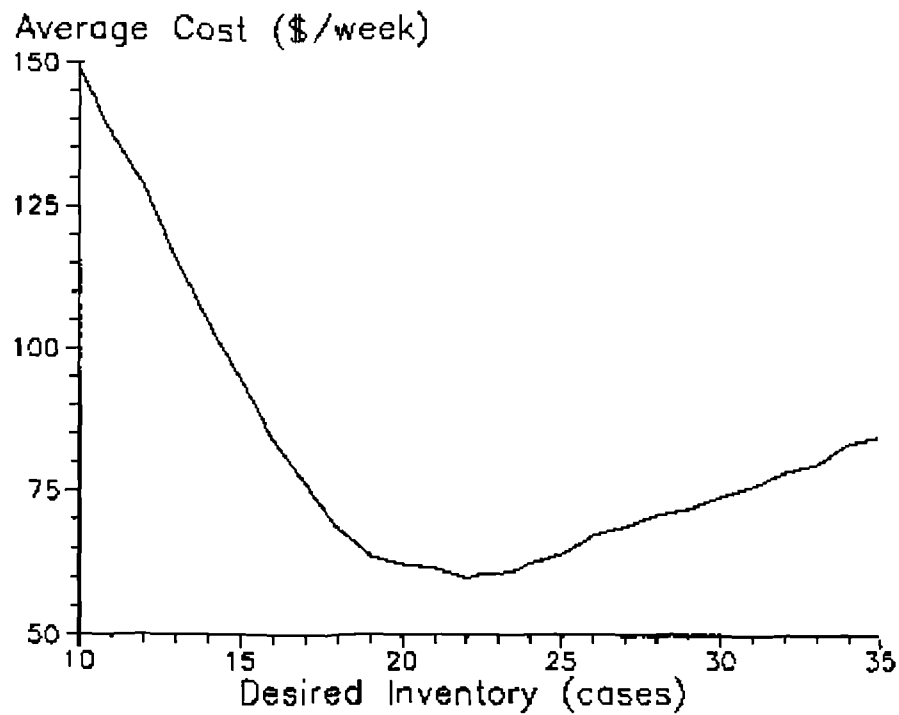


Figure 4.10 – Cost vs. Inventory Curve.

Produced from "Beer Game" experiments. Low desired inventory resulted in chaotic behaviour and increased costs.

Source: Larsen, E., Morecroft, J.D.W., and Mosekilde, E. (1989). "Complex behaviour in a production distribution model." Presented at TIMS XXIX, Osaka, Japan. 23-26th July 1989.

The authors also demonstrated that the system exhibited an interesting form of intermittency, switching randomly between hyperchaotic solutions. Thomsen ran his simulation over 100,000 weeks (equating to nearly 2000 years!) to detect much of this behaviour. It is questionable therefore if these higher forms of behaviour have any major impact in the short term.

The conclusions of this work argue that economic and managerial systems rarely operate near to equilibrium. The recognition that apparently random behaviour can be produced by simple, fully deterministic structures must influence the way we distinguish between classifiable internal processes and random external events. Unrecognisable phenomena occurring within the system, which are attributed external causes because of lack of understanding may be internally generated. For example, in the Beer Game all participants except the retailers attribute the enormous demand variations directly to the customer order rate.

4.8.2.2 *Chaos in a “parallel” stock management problem.*

A further example of how chaos can take place in management systems is documented by Rasmussen and Mosekilde [Rasmussen & Mosekilde, 1988]. The paper demonstrated how period doubling bifurcations and chaotic behaviour could be internally generated in a production company where resources are shared between marketing and production. A simple model was constructed where a company was assumed to allocate resources between production and marketing in accordance with shifts in inventory and/or backlog in orders. When orders are small resources are moved from production to marketing to increase sales thus resulting in a decrease in output from production. When a backlog in orders is large resources are focused on

the production activities and removed from the marketing function. As the company approaches maximum capacity the company experiences decreasing productivity as additional resources are applied to production i.e. a non-linear function is present.

The delays in allocation create the potential for oscillating behaviour. Subsequently if reallocation of resources is rapid enough self-sustained oscillations take place and the system becomes destabilised. To complete the model feedback between inventory/backlog and customer defection rate is incorporated. If finished products inventory is low, delivery lead time may be unacceptable to the customers. This causes the simple oscillations to become unstable. Through a cascade of period doubling and bifurcation's the system creates chaotic oscillations. The authors used Poincare sections, return maps and calculated the highest Lyapunov exponent. These techniques were used to test for the degree of chaos in the oscillations. (A discussion of these analysis tools will be undertaken in Chapter 5.)

4.9 Conclusion to Chapter 4.

This Chapter has discussed the history of chaos theory and described the environments that are prone to chaos. It can be seen that supply chains consist of non-linear feedback loops and therefore the possibility of some uncertainty being attributed to deterministic chaos is a possibility.

This raises the first key question:

- Is uncertainty generated by deterministic chaos within real supply chains?

The chapter has also discussed the characteristics of chaotic systems and defined what deterministic chaos is. The chapter has then proceeded to give an overview of the diverse applications of chaos theory within industry.

The application of the term chaos within management literature has also been discussed and classified. The discussion has then proceeded to focus on literature that is of relevance to this thesis and has discussed the application of chaos theory to strategic management and also the quantitative analysis of chaos within human decision making behaviour in the “Beer Game” supply chain.

The quantitative investigations into the “Beer Game” supply chain and related resource allocation problems in management yield some useful insights into the behaviour of supply chains. The recognition that aggressive stock management rules can generate uncertainty in the form of chaos is an observation that is practically recognised by industry.

The investigations do leave some questions unanswered. In the work to date, the investigations have focused on the human decision making behaviour in a theoretical supply chain. This decision making involves misperceptions about the amount of inventory in the supply line and the number of orders placed. The participants tend to forget or misjudge what has been ordered. In practise, computerised stock and order management systems are used which do not suffer from misperceptions and can account for all orders and inventory available. This raises the question: that “If an automated stock and order management system is used with no misperceptions about its environment can the non-linear nature of the system generate uncertainty within the supply chain by a deterministic chaos route?”

The work to date also does not address the amplification of chaos within a supply chain. Much of the previous research has focused on the analysis of inventory dynamics in the final upstream echelon in the supply chain, if chaos is generated is it continually amplified as the orders are passed up the supply chain in a manner analogous to demand amplification?

Once again, a linear supply chain has been used in the “Beer Game” investigations, so network effects have not been considered. However, Rasmussen and Mosekilde [Rasmussen & Mosekilde, 1988] have determined that parallel relationships can result in chaos under certain circumstances. This requires further investigation to see if supply networks are more or less chaotic than linear supply chains.

If chaos is generated within the supply chain is this the overriding mechanism for the generation of uncertainty and does the chaotic nature of the system override the stochastic shocks?

A final important question that is raised is if some of the uncertainty generated within supply chains can be attributed to deterministic chaos, can “islands of stability” be identified for certain parameter settings and can these be utilised in stabilising or reducing uncertainty?

If the system is found to be chaotic then the qualitative chaos theory management approach would also be appropriate and recommendations for managing within such supply chains can be made.

The next Chapter describes the relevant analysis techniques for non-linear systems. The methodology used to identify whether measured data from a system is stable or chaotic will also be described.

Chapter 5

Methodology to detect and quantify chaos.

5.1 Introduction

In this chapter an explanation of the methodology for detecting and quantifying deterministic chaos within measured data is discussed. The aim of this chapter is to present an overview of key tools and techniques for analysis and devise a robust methodology that is accessible to practitioners and can be used in supply chain research. The chapter then discusses the use of Lyapunov exponents and how these can be used to determine the average predictability horizon of a chaotic system. This can then be used as a method of quantifying the amount of uncertainty from chaos within a system.

When detecting chaos within measured data one is looking for the key characteristics of the definition of chaos developed in the last chapter i.e.:

Chaos is defined as aperiodic, bounded dynamics in a deterministic system with sensitivity dependence on initial conditions, and has structure in phase space.

In this chapter a methodology will be discussed that will identify the existence of the key characteristics of a chaotic system from measured data.

5.2 The use of the null hypothesis.

As outlined in the previous chapter proving definitively the existence of chaos from observed data would require an infinite amount of data. This therefore requires a stochastic technique that will make use of an appropriate null hypothesis. This procedure means that one does not set out to prove the existence of chaos but to reject some other null hypothesis that implies chaos is not present. The procedure of hypothesis testing is widely used in statistical analysis and a similar approach can be used for determining whether chaos is present in data.

Kanji [Kanji, 1993] describes a five step method for hypothesis testing. The steps are as follows:

1. Formulate a practical problem in terms of hypotheses.
2. Calculate a discriminating statistic, T .
3. Identify the critical region in that if T falls, leads us to reject the hypothesis.
4. Decide the size of the critical region.
5. Identify how close the value T falls with respect to the boundaries of the critical region.

For the analysis of chaotic systems the following paragraphs will describe the hypothesis, discriminating statistic and how the statistic used identifies the critical region. However due to the nature of such systems further analysis techniques are used to provide further evidence for the existence of chaos.

5.2.1 Identifying the appropriate hypothesis.

For the analysis of data from an unknown system the null hypothesis used may be as follows:

“The data are random data i.e. the same as white noise.”

This hypothesis suggests a test, in that if any relationship can be found between successive measurements the hypothesis is proved null.

This first hypothesis is somewhat simplistic for the analysis of most chaotic systems because proving a relationship between points in measured data does not guarantee the existence of chaos. Kaplan and Glass [Kaplan & Glass, 1995 p.342] suggest a more appropriate null hypothesis this states:

“The dynamics are linear with Gaussian white noise random inputs.”

Kaplan and Glass refer to this hypothesis as the “Linear-dynamics null hypothesis”. This hypothesis is inconsistent with the possibility of chaos because, as discussed in chapter 4, linear dynamics cannot produce chaos. Therefore if a set of data is chaotic one should be able to reject the above hypothesis.

Within the investigation undertaken in this thesis the model used for the generation of the data is deterministic i.e. no random inputs are present. It is unlikely that any noise within the data is significant so the relevance of this hypothesis is suspect, but still worth investigating just in case there are significant unexplained random inputs, for example from computer noise. To further develop this null hypothesis it is important in this study to show that within the data collected there is no evidence of periodicity i.e. the data is not periodic or quasiperiodic within the time frame the data is viewed.

Therefore, the null hypothesis used in this work is as follows:

*“The dynamics are linear with Gaussian white noise random inputs,
or the dynamics are linear exhibiting periodic behaviour.”*

5.2.2 Selection of the discriminating statistic.

To demonstrate that any data is inconsistent with the null hypothesis a discriminating statistic needs to be selected. This quantity can be calculated for the measured data and also for a set of data that is known to be consistent with the null hypothesis. There are many discriminating statistics that can potentially be used in the analysis of chaotic systems however one of the most robust and commonly used is the Lyapunov exponent [Abarbanel, 1996; Kaplan & Glass, 1995; Peitgen, Jurgens, & Saupe, 1992; Sprott & Rowlands, 1995]. This quantifies sensitivity to initial conditions and can also differentiate between random, periodic and stable behaviour [Sprott & Rowlands, 1995].

To test to see if the measured data is consistent with the null hypothesis, the discriminating statistic is calculated. Then a range of values for the discriminating statistic is calculated for a time series that is consistent with the null hypothesis. If the value of the discriminating statistic calculated for the measured data falls outside the range of values calculated for data consistent with the null hypothesis then the data is inconsistent with the null hypothesis and is probably chaotic.

“Surrogate data” is the method used for the generation of data consistent with the null hypothesis. The technique involves performing a Fourier transformation on the measured data, the phase of each Fourier component is set to a random value between

0 and 2π , and then an inverse Fourier transformation is undertaken. This technique removes any deterministic relationships within the data but preserves the power spectrum and correlation function [Kaplan & Glass, 1995 pp.343-344; Sprott & Rowlands, 1995]. It therefore generates data consistent with the null hypothesis.

Once again, by calculating the discriminating statistic for the surrogate data sets one can generate a range of values for data consistent with the null hypothesis. Then by seeing if the discriminating statistic for the measured data falls within this range further evidence is provided of whether the measured data is consistent with the null hypothesis.

5.3 Nonlinear Data Analysis.

The analysis of non-linear data series involves two key stages [Kaplan & Glass, 1995 p.303; Abarbanel, 1996 p.11]. These steps must be undertaken in order to gain robust values for most discriminating statistics. The first stage uses measured data to reconstruct the dynamics of the system. The second stage involves the characterisation of the reconstructed dynamics and the calculation of any discriminating statistics. For the data to be characterised as chaotic it must be shown that the data is deterministic, bounded, aperiodic and displays sensitivity to initial conditions. The data also needs to display structure in phase space. A system is deterministic when future events are causally set by past events. This is a key feature of any deterministic simulation model [Pidd, 1984 p.18] and was the approach used for the experimentation referred to in this thesis. Ensuring the data are bounded, aperiodic and sensitive to initial conditions can be quantified by using a number of

standard techniques. Standard statistical techniques can be used for checking that the data is bounded. The calculation of Lyapunov exponents is a key technique for characterising chaotic behaviour and quantifying sensitivity to initial conditions; this also detects periodic behaviour. The above issues will be discussed further in the following paragraphs.

5.4 Reconstruction of the Phase Space.

The methods used for the reconstruction of the phase space fall into two categories, geometric and algorithm based. For effective analysis techniques from both categories need to be used.

a) Geometric Techniques.

The use of return maps to display the relationship between successive measurements is fundamental to the analysis of data from non-linear systems [Kaplan & Glass, 1995 p.303]. The principle is simple, the variable is measured at time T and plotted against the same variable at $T-1$. The plot then demonstrates graphically the relationship between a variable and the previous value of that variable. Random data plotted in this way produces a mass of points with no definable structure indicating no relationship between one point and the next. Plots of T verses $T-n$, where n is any positive integer, can also be produced. With chaotic data as n increases any discernible structure in the plot becomes lost and eventually resembles a plot for random data. These plots are sometimes referred to by other names including return plots, first-return plot and Poincare return map. One benefit of these plots is that they enable information about the overall attractor to be gained. The use of measured data

results in a sampling activity being undertaken on the attractor at regular intervals. The return map therefore depicts a cross section of the attractor, which enables the non-linear analyst to see the attractor's structure [Gleick, 1987 p.143]. Figure 5.1 depicts how this takes place.

Plotting one variable against a related variable at time T can also produce information about the system. This gives a visual representation of any relationship between the variables. Within the supply chain simulation one is able to plot the inventory at one echelon against that in another location in the supply chain. By doing this the relationship between these inventory levels can be visualised. If a chaotic relationship is present a new line will be drawn for each oscillation never repeating the previous path. After a sufficient time the lines will cover the whole space producing a dark indistinguishable shaded image [Larsen, Morecroft, & Mosekilde, 1989]. The system can be seen to be aperiodic; the same state is never repeated. A periodic solution will always produce a closed curve, the curves can be simple circles or more complex swirls, however the system will trace the same path during each period. Figure 5.2 shows phase plots demonstrating the types of behaviour outlined above.

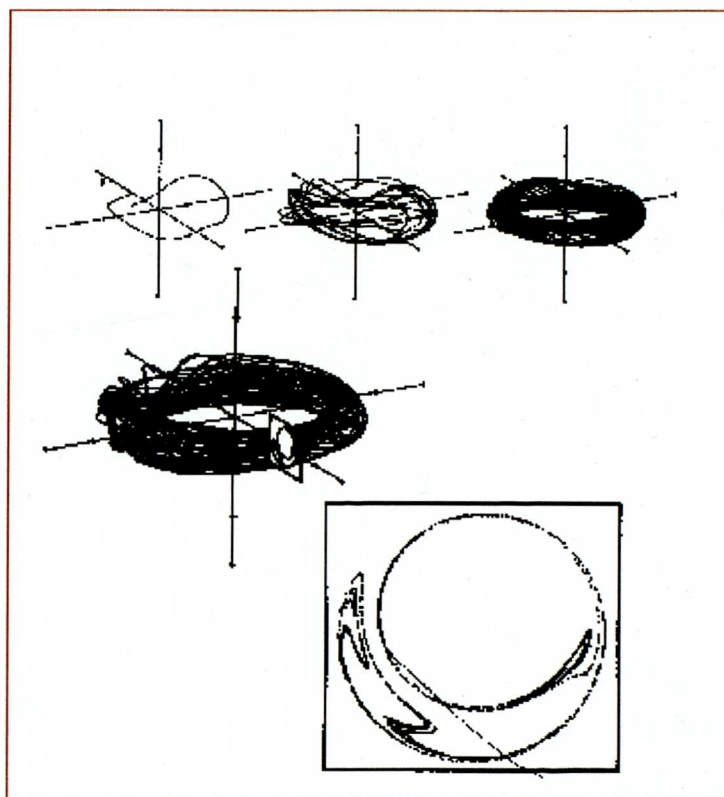


Figure 5.1 – Return Map depicting the cross-section of the attractor.

Source: Gleick, J. (1987). "Chaos, Making a new science". Viking : New York.

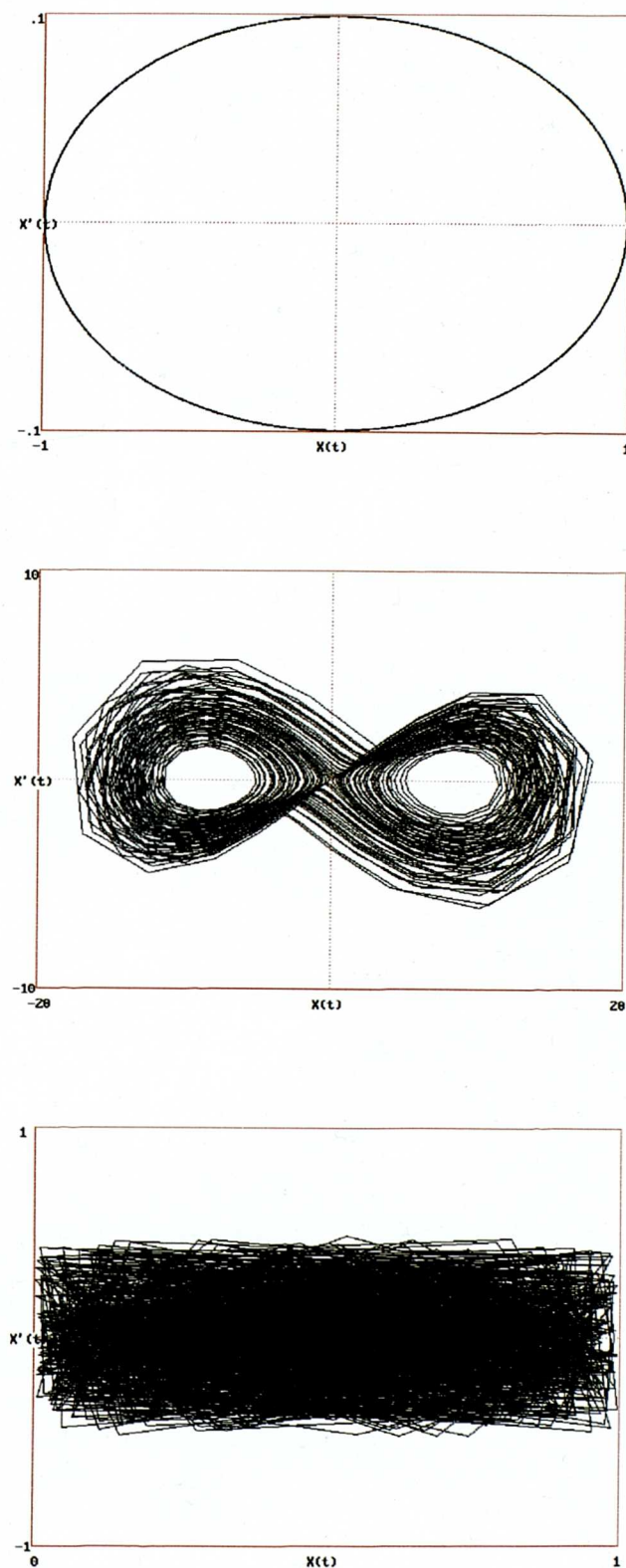


Figure 5.2 – Phase Plots showing Periodic (Top), Chaotic (Middle) and Random (Bottom) behaviour.

b) Algorithms Based Techniques.

Algorithm based techniques are required to gain specific values to enable reconstruction and subsequent determination of discriminating statistics. In the following paragraphs the essential techniques used for reconstruction will be discussed.

5.4.1 Embedding a time series

Essential to gaining robust values of most discriminating statistics is ensuring that the time series is “embedded”. Embedding is the process of finding a space in which the dynamics are smooth and no overlaps or intersections occur within the orbits of the attractor.

For chaos to be present the system must have at least three variables present [Kaplan & Glass, 1995 p.308]. This means that two-dimensional dynamics in phase space are unable to represent chaotic behaviour. However, the dynamics can be reconstructed in a three dimensional space by plotting points as a three-dimensional co-ordinate. For example:

$$\{D_t, D_{t-h}, D_{t-2h}\}$$

Where h is called the embedding lag.

More generally, we can embed a time series in a multi-dimensional space by plotting n co-ordinates,

$$\{D_t, D_{t-h}, D_{t-2h}, \dots, D_{t-(n-1)h}\}$$

n is the embedding dimension of the time series.

This technique of representing measured data as a sequence of points in n -dimensional space is referred to as “time-lag embedding”. It is an important technique in non-linear dynamic analysis and is supported by a geometric theorem attributed to Takens and Mane [Takens, 1981; Mane, 1981]. A key issue in non-linear analysis is using the appropriate value of n to unfold the attractor.

5.4.2 Takens' Embedding Theorem

The embedding theorem states that if one is able to observe a single quantity or variable from some dynamical system, then the geometric structure of the dynamics of the attractor can be “unfolded” from this set of scalar measurements [Abarbanel, 1996]. This means that the reconstructed dynamics of a system from observed data is geometrically similar to the original attractor for both continuous-time and discrete time systems [Kaplan & Glass, 1995].

So if there exists a dynamical system $X(t) \rightarrow X(n+1)$ where $X(t)$ phase space is multidimensional, the theorem says that if we observe a single quantity $Y(n)$ generated by this system then the sequential order of points $Y(n) \rightarrow Y(n+1)$ follows the unknown dynamics of $X(t) \rightarrow X(n+1)$. Therefore the behaviour of the actual system is reflected in that of any observed data from that system.

The importance of embedding can be visualised as follows. One can imagine that if, for example, data from a 3 dimensional system is represented in two dimensions the data needs to be “squashed” into this two dimensional space. The data will overlap in places and it will be difficult to clearly define the orbits the system is travelling because intersection of an orbit with itself may occur. If however a system is

represented in a higher dimension than required the intersections of an orbit with itself will be undone. A two-dimensional system depicted in three dimensions ensures that the smoothness and uniqueness of the orbits within the attractor are preserved. Embedding the time series enables the data to be “unfolded” thus revealing all the information about that system.

Takens [Takens, 1981] proved that if the original attractor has a dimension of D then an embedding dimension of $n = 2D+1$ will be sufficient to reconstruct and “unfold” the attractor. The importance of this theorem will be seen in the next section as the correlation dimension and capacity dimension approximate to the dimension D .

5.4.3 The Correlation Dimension.

The calculation of the correlation dimension of a time series is of particular importance as it can be used to estimate the embedding dimension required for further analysis of discriminating statistics. The correlation dimension gives an indication of the complexity of the system under investigation and if sufficient data is available can be used as a discriminating statistic in the analysis of measured data [Kaplan & Glass, 1995].

The correlation dimension is calculated by selecting each point in the time series and constructing a hyper-dimensional sphere of embedding dimension n and radius r around this point. The fraction of points within the time series that fall within this sphere is then calculated for various values of r [Sprott & Rowlands, 1995].

What is significant is how the fraction changes with increasing r . For periodic data the curve is flat because as r increases a small number of additional points fall into the

sphere. For random data the slope is steep because as r is increased more and more points fall within the sphere, for chaotic systems a gentle slope is observed [Kaplan & Glass, 1995 p.315]. By plotting the log (fraction of points within the sphere) against log (radius of the sphere) the correlation dimension is the slope of this graph. A correlation dimension of greater than 5 indicates essentially random data [Sprott & Rowlands, 1995].

One problem in the analysis of time series is that one needs to know the embedding dimension to “unfold” the attractor but one needs to know the embedding dimension before the attractor can be unfolded! This conflict presents a problem for the analyst.

However, Grassberger and Procaccia [Grassberger & Procaccia, 1983] observed that if one calculates the correlation dimension for increasing values of embedding dimension eventually the graph will plateau when an adequate embedding dimension is reached as the data becomes unfolded. This then obeys the embedding theorem in that the embedding dimension adequate to unfold the attractor is $n = 2D+1$ where D is the correlation dimension. In time series analysis this can be used to estimate the required embedding dimension for analysis.

Calculating the Capacity Dimension, which uses multidimensional cubes instead of spheres, is a similar technique, this should be approximately the same as the correlation dimension. It is obtained by a similar procedure to the correlation dimension, a plot of the embedding dimension against the capacity dimension should plateau when an adequate embedding dimension is used [Sprott & Rowlands, 1995]. This technique can be used to clarify results obtained by the use of the correlation dimension. However many data points are required to get an adequate

approximation. The correlation dimension is more robust as less data is required to gain good approximations [Sprott & Rowlands, 1995].

Within the literature there is much discussion about how to undertake the above calculations and the amount of data required to gain accurate values for the correlation and capacity dimension [Abarbanel, 1996 p.73; Sprott & Rowlands, 1995]. The calculations have also been found to be very susceptible to noise. For example, one rule of thumb states that an accurate estimate of the correlation dimension can be achieved by using a minimum of $10^{2+0.4d}$ data points [Tsonis, 1992]. In practise, for most systems, such a large number of data points may be difficult to obtain.

5.4.3 False nearest neighbours.

The large quantities of data required for accurate calculation of correlation dimensions have lead to the development of more robust methods to calculate the embedding dimension. One such technique developed by Abarbanel [Abarbanel, 1996] calculates the percentage of false nearest neighbours against the embedding dimension.

A false nearest neighbour can be defined as a point that has arrived near another point on the attractor because the attractor is being viewed in a dimension too low to completely unfold the data [Abarbanel, 1996 p.260].

This is analogous to viewing a length of string. Imagine the string is made up of many points or spheres joined together. The true nearest neighbours would be points on the string next to each other. If the string is now rolled into a ball a false nearest

neighbour would be points in the ball that are next to each other but not consecutive points in the string. When the string is “unfolded” these false nearest neighbours will drop to zero.

The benefits of this approach is that it requires less data to gain a value of the embedding dimension and is less sensitive to noise [Abarbanel, 1996 pp.40-43]

5.4.4 Summary.

The above techniques all enable an accurate value of the embedding dimension to be calculated if sufficient data is present. However, when characterising chaos some discriminating statistics provide an excellent approximation if, as outlined in the embedding theorem, a higher than required embedding dimension is used. In the analysis undertaken in this thesis all three techniques were applied {correlation dimension, capacity dimension and false nearest neighbours} as this reduced any ambiguity generated by the nature of the data. For example, it was sometimes found that clear plateaux were not witnessed on the correlation dimension against embedding dimension graph, the results from the calculations of capacity dimensions and false nearest neighbours were used to clarify the minimum embedding dimension required to calculate the discriminating statistic used. Selecting an appropriate embedding dimension for a finite amount of data is not an exact science and so a conservative approach was used in its selection for subsequent analysis.

5.5 Characterising Chaos.

To measure the key characteristics of a chaotic system a number of values can be used. The last section discussed how the correlation dimension is a measure of the complexity of the attractor. In this section the focus will be on one of the most important attributes of a chaotic system, its sensitivity to initial conditions. This can be measured and quantified by the use of Lyapunov exponents. The Lyapunov exponent can also be used as the discriminating statistic to test the null hypothesis outlined in Section 5.2.

5.6 The use of Lyapunov Exponents.

5.6.1 *Sensitivity to initial conditions.*

The Lyapunov exponent is a measure of the exponential growth rate of the system. If a chaotic system is iterated the original starting number $\{N\}$ grows. This can be described as follows:

$$N_t = N_0 + \delta N 2^{\lambda t}$$

Where N_t is the number at time t , δN is the accuracy with which N can be specified and λ is the Lyapunov exponent.

This can be rearranged as follows:

$$\lambda = \frac{1}{t} \log_2 \left[\frac{N_t - N_0}{\delta N} \right]$$

Lyapunov exponents have proved to be one of the most useful diagnostic tools for detecting chaos [Peitgen, Jurgens, & Saupe, 1992]. The exponent measures the average exponential rate of divergence or convergence of nearby orbits in phase space [Wolf et al., 1985]. In more practical terms the exponent is a measurement of sensitivity to initial conditions. For example, imagine two identical copies of an equation. They are identical except that their initial conditions can be made to vary. If one variable is set as X_0 and the other as Y_0 , the variables are very close together differing by, say, 1×10^{-6} . If the system is chaotic as the equations are iterated from the two initial times of X_0 and Y_0 , the value of X_i and Y_i start to move apart, initially the difference will continue to be small but as time progresses the difference increases until X_i and Y_i show no correlation to each other, yet the dynamics of both are described by identical equations. The “stretching apart” of the distance between initially nearby points is one way to characterise the strength of this sensitivity dependence [Kaplan & Glass, 1995]. Sensitivity to initial conditions implies that an arbitrarily small interval between initial values will be enlarged significantly by iteration. The maximum Lyapunov exponent can be described as the maximal average factor by which an error is amplified within a system [Peitgen, Jurgens, & Saupe, 1992 p.715]. Sano & Sawada [Sano & Sawada, 1985] propose that the Lyapunov exponent is the key to characterising chaotic behaviour. Once the Lyapunov exponent has been calculated other key description parameters can be estimated.

The determination of Lyapunov exponents is an important problem in the analysis of possibly chaotic systems since Lyapunov exponents qualitatively determine not only the sensitivity dependence on initial conditions but they also give a quantitative measure of the average rate of separation of nearby trajectories on an attractor [Stoop & Meier, 1988].

The Lyapunov exponent has proved to be an effective discriminating statistic for the null hypothesis outlined in section 5.2. A system can be defined as chaotic if at least one positive Lyapunov exponent is present. If the maximum exponent is negative the system is stable or periodic. If the value is zero the system is stable or periodic but may be close to bifurcation, i.e. the system is marginally stable [Peitgen, Jurgens, & Saupe, 1992; Wolf et al., 1985]. In general there are as many exponents as there are dynamic equations [Sprott & Rowlands, 1995].

5.6.2 Information Dissipation

Shaw [Shaw, 1981] describes how the exponent can be viewed as a measure of how information is created or destroyed within a system. If the Lyapunov exponent is negative then the system has the ability to “absorb” information, i.e. if the system is subjected to a small change in conditions this information is not communicated into the future. For example, a small change in inventory within the supply chain will not alter the dynamics of the system very far into the future. The information about this small change in conditions is therefore absorbed and seen as of no consequence in describing the system into the future. Despite shocks to the system, it remains stable and easily predictable, the shock is absorbed and has no consequence to future behaviour.

When the Lyapunov exponent equals zero the small change in conditions will remain present indefinitely and will be important in describing the future behaviour of the system. The information is therefore never lost to the system, the system is stable and predictable indefinitely into the future. If the system is to be predicted into the future the magnitude of the shock needs to be taken into account but the system is still stable and is predictable into the future. Within the supply chain environment this would be analogous to a customer increasing demand, if the increase in demand is known then prediction of inventory can be predicted into the future.

If the exponent is greater than zero the small change in conditions will become magnified and distorted. Therefore information becomes lost over time and it would be necessary to take a new set of measurements to describe the system. For example, if one is to describe a system such as a lottery ball dispenser that creates random numbers, its behaviour can only be described by observing each number in turn. Each number will be new to us and only by having the series of each number produced by the dispenser can its behaviour be described adequately. Each number will be independent of the previous number so the information contained in the previous number is lost when a new number is selected. If the system has a positive Lyapunov exponent prediction may still be possible in the short term. The exponent can be used to give an indication how stable the system is and over what period of time a small error is magnified to a level that makes distinguishing it from the original signal impossible. If, for example, a supply chain was operated in such a way that perfect information was available and every shock or change in demand could be known the inventory or demand could only be predicted for a given period of time into the future because small unobserved errors would become magnified exponentially over time.

5.6.3 Predictability Horizon.

The magnitude of the exponent gives a reflection of the time scale over which the dynamics of the system are predictable, so the exponent can be used to approximate the average prediction horizon of a system [Wolf et al., 1985; Shaw, 1981]. After this prediction horizon has been reached the future dynamics of the system become unforecastable. This occurs because any cause and effect relationship between current data and previous data becomes increasingly blurred and is eventually lost. For a discrete system the Lyapunov exponents are measured in bits/iterations so in the model described here, this will be bits/day (where bits = binary digits).

If the Lyapunov exponent is known, an approximation of how far ahead the future behaviour is predictable can be made. This can be calculated by dividing the relative accuracy with which the two nearby points are specified by the Lyapunov Exponent [Wolf et al., 1985].

For example, if the system has a positive exponent of 0.75 and an initial point is specified with an accuracy of 1×10^6 or 20 bits (To describe 1×10^6 in binary code 20 bits are required i.e. $11110100001001000000 = 1 \times 10^6$), then future behaviour would be unpredictable after 26 iterations ($20/0.75$). After this time the small initial uncertainty will cover the whole attractor requiring a new measurement of the system to describe its behaviour.

If the inventory within a warehouse can be specified with an accuracy of 1×10^3 i.e. 1000 ± 1 units of inventory then this equates to an accuracy 1111101000 (10 bits), and the inventory control system behaves chaotically with a Lyapunov exponent of 0.15 bits/iteration. Then time until accuracy can only be specified with accuracy of 1

bit or 1 unit of inventory is $10/0.15 = 67$ days. After this period of time the exponential increase in the error renders any methods of prediction invalid.

5.6.4 Calculation of Lyapunov exponents from a time series.

Determining the Lyapunov exponents for a mathematical model is a reasonably accurate and well-established procedure. However a key objective in this study has been to measure the exponent from time series data generated by a simulation. Wolf [Wolf et al., 1985] developed one of the first algorithms for the calculation of non-negative Lyapunov exponents from a finite amount of time series data. The algorithm approximates the maximum non-negative exponent for any time series data. In some systems all Lyapunov exponents can be deduced from the knowledge of the largest one [Peitgen, Jurgens, & Saupe, 1992 p.720].

Other algorithms have been developed by Sano & Sawada [Sano & Sawada, 1985] and Eckmann et al [Eckmann et al., 1986] and these are seen as the current state of art for the analysis of several Lyapunov exponents from a time series and offer some advantages over the algorithm described in [Wolf et al., 1985] for certain types of analysis [Peitgen, Jurgens, & Saupe, 1992 p.751].

The Lyapunov exponent calculation using Wolf's algorithm is restricted to non-negative exponents and is only able to calculate the largest. The ease of calculation from finite amounts of time-series data and the accuracy of the estimation of the non-negative exponents offset these limitations. Negative exponents can also be calculated by this method, however the accuracy of these is somewhat suspect.

The algorithm monitors the long-term growth rate of a small volume element in the attractor. To determine the stability of a dynamic system the fate of a small perturbation (change) of a trajectory is investigated by averaging the exponential growth or decay rates. A full description of the algorithm complete with FORTRAN programme can be seen in Wolf et al, 1985 [Wolf et al., 1985].

5.6.4.1 Procedure for the analysis of Lyapunov exponents from a time series

The procedure used to calculate the maximum average Lyapunov exponent from measured data can be summarised as follows [Wolf et al., 1985; Wolf, 1986]. Wolf observed that a small error could be simulated by identifying two close neighbouring points on a attractor, but on different orbits and monitoring the growth of the vector between them.

1. Reconstruct the attractor using the embedding theorem.
2. Identify an initial point and locate a neighbouring point on an orbit of the attractor close to the initial point. Calculate the distance between these points {Defined as length $L(t_0)$ }. This distance is analogous to the small error δN in the original equation.
3. Follow the evolution of these points as they pass through the attractor. At time t_1 the initial length will have grown to $L^1(t_1)$. {Analogous to $N_t - N_0$ }.
4. Identify new initial data point close to orbit of original initial data point and repeat the above procedure.
5. Repeat steps 1 to 4 until data is exhausted.

6. Calculate Lyapunov exponent by averaging exponential growth as follows:

$$\lambda = \frac{1}{t} \sum_{j=1}^m \log_2 \left[\frac{L^1(t_{j+1})}{L(t_j)} \right]$$

Where m is the number of replacement elements and t is the time between replacements. Figure 5.3 shows diagrammatically the nature of the above procedure.

The attractor is reconstructed using the embedding theorem described in Section 5.4.1. It can be shown that the Lyapunov exponents of the reconstructed attractor are the same as the original continuous attractor [Wolf, 1986]. Selection of the embedding dimension is of important when using the algorithm. If it is set too low a dramatic over estimate of the exponent may occur, if the dimension is set too high and noise is present in the data the algorithm becomes more susceptible to this noise [Wolf et al., 1985]. When using the algorithm the analyst specifies the relative accuracy of the data, below which noise is expected to be dominant [Sprott & Rowlands, 1995].

The algorithm is not accurate for estimating negative Lyapunov exponents. This is because when a point is chosen close to the initial point and the points are converging, the time over which the length element between these points can be followed is short [Wolf et al., 1985]. However, the algorithm will provide qualitative evidence that the maximum exponent is negative indicating stable or periodic behaviour.

The length of time step $\{t\}$ between replacements also needs consideration. If the time step is too large the trajectories get far apart and the exponential divergence of the orbits is lost, if the time step is too short the calculation becomes very slow and

information about the phase space becomes lost [Sprott & Rowlands, 1995; Wolf et al., 1985].

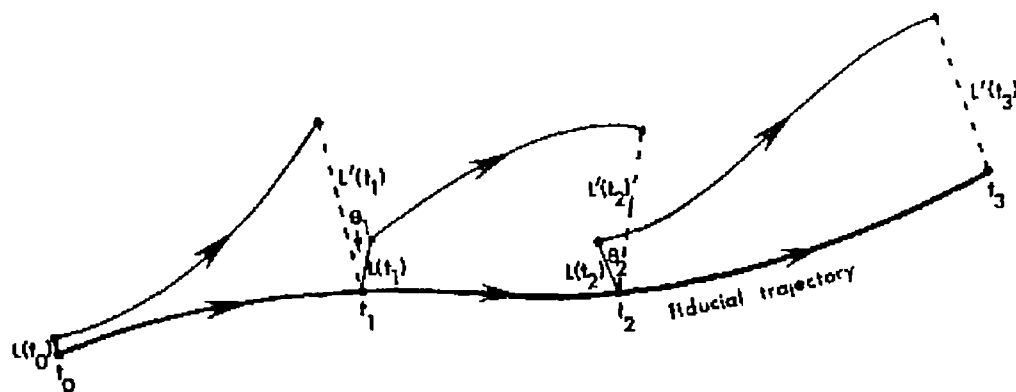


Figure 5.3 – Procedure for the analysis of Lyapunov exponents from a time series.

Source: Wolf, A. (1986). "Quantifying chaos with Lyapunov exponents." *Chaos*. Editor A. V. Holden, pp.273-90. Manchester University Press: Manchester, U.K.

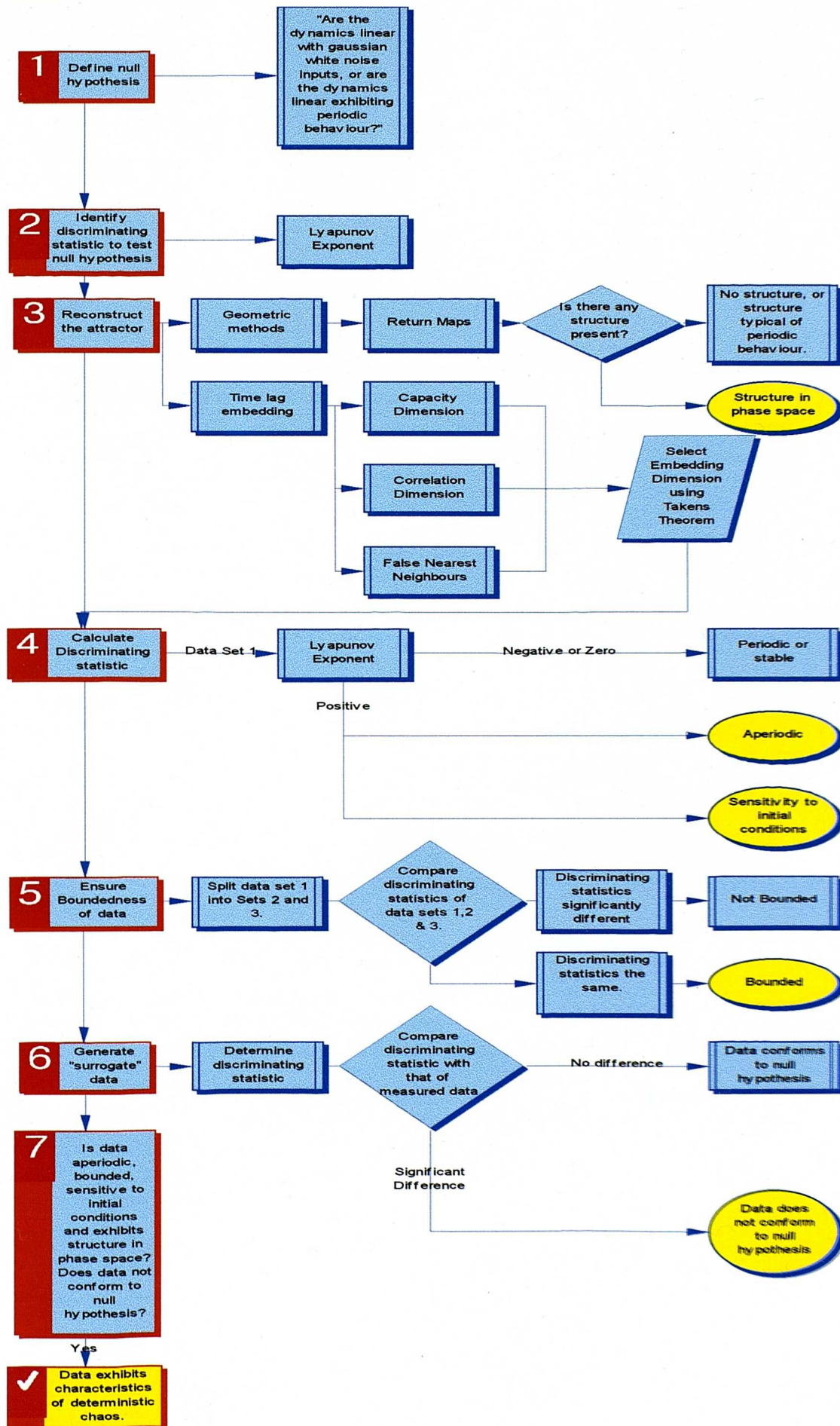


Figure 5.4 – Diagram to show non-linear analysis methodology.

5.7 Summary of analysis methodology used in thesis.

The analysis methodology developed for the research documented in this thesis is depicted in Figure 5.4. Each step in the methodology will now be discussed.

Step 1 - Define the null hypothesis

The measured data analysed will be from a deterministic simulation model this will be described in Chapter 6. The use of a deterministic simulation ensures that no uncertainty is present from external sources. The same input should result in the same output and after any initial transient behaviour the system should define a stable or periodic attractor, unless the system generates deterministic chaos. It should therefore be possible to use the null hypothesis stating:

“The measured data stabilise to a periodic or fixed point attractor?”

However, a cautious approach was taken in the research and the possibility of unattributed “computer noise” becoming a major influence on the results is also to be investigated. This resulted in the following null hypothesis:

*“The dynamics are linear with Gaussian white noise random inputs,
or the dynamics are linear exhibiting periodic behaviour.”*

Step 2 - Identify discriminating statistic to test the null hypothesis.

The discriminating statistic to be used is the Lyapunov exponent, this enables a clear measure of “sensitivity to initial conditions” to be made which can be used for the calculation of average prediction horizons. The average prediction horizon can then

be used to quantify the uncertainty generated within the system. The magnitude of the exponent also differentiates between aperiodic data and stable or periodic data.

Step 3 - Reconstruct the attractor

To reconstruct the attractor to which the measured data proceeds both geometric and algorithm based approaches were used.

The measured data from the simulation required the initial transients to be removed so the steady state data was used for reconstruction. Plotting the measured data against time and noting on the graph where any fluctuations settled down achieved this. This generally occurred after between 200 and 700 time periods. A conservative approach was used and the first 1000 data points were discarded. A further check on the data to ensure no initial transients are present was the test for boundedness outlined in step 5 of the methodology.

Return maps were then produced, this gave a view of the overall structure of the attractor. This made it possible to distinguish between random, periodic and possible chaotic behaviour.

The time series was then reconstructed using time lag embedding techniques. This was done to obtain an accurate embedding dimension that could then be used to obtain the discriminating statistic. Three techniques were used, enabling cross-checking and promoting confidence in the embedding dimension figure. The capacity and correlation dimension were calculated and also plotted against embedding dimensions. Using the Takens embedding theorem values of embedding dimension were also calculated from the capacity and correlation dimensions. Percentage false nearest neighbours against embedding dimension graphs were also used to obtain

values for embedding dimensions. Using these three techniques a robust approximation of the embedding dimension could be obtained despite only finite amounts of measured data being available.

Step 4 - Calculate the discriminating statistic.

Once the embedding dimension has been calculated the Lyapunov exponent can be calculated for the measured data. This gives a measure of sensitivity to initial conditions and also distinguishes between aperiodic, stable or periodic data.

Step 5 - Ensure “boundedness” of data.

Dynamics can be said to be bounded if the data stays within a finite range and does not approach infinity as time increases. However, to test for bounded stability, one would in theory, need to wait until time is equal to infinity. A related concept for assessing boundedness is that of “stationarity” [Kaplan & Glass, 1995 p.314]. A time series can be described as stationary when it displays “similar behaviour” throughout its duration. “Similar behaviour” is defined if the mean and standard deviation remain the same throughout the time series. Ensuring that the mean and standard deviation in one third of the time series is equal to that in the remaining two thirds can assess this. (One could use quarters or tenths if so desired.)

An alternative approach, which is more applicable to analysis of chaotic data, is splitting the measured data into two {for convenience these will be called data sets 2 and 3. Data set 1 is the original data with initial transients removed} and calculating the discriminating statistics for these data sets. If these values are of the same magnitude as each other and also data set 1 then one can be confident that the data is bounded.

If the data was found not to be bounded an investigation of whether all the initial transients had been removed from the initial data was carried out.

Step 6 - Generate and analyse “surrogate” data.

The surrogate data was created using the method outlined in Section 5.2.1. This data has all the deterministic relationships removed. The discriminating statistic was then calculated for the surrogate data and compared with the figure for data set 1. If these are of the same magnitude it indicates the data generated conforms to the null hypothesis.

Step 7 - Review evidence from steps 1 - 6.

By reviewing the evidence obtained from steps 1 to 6 it is possible to demonstrate whether the data fails to adhere to the null hypothesis and thus exhibits the properties of deterministic chaos i.e.:

Chaos is defined as aperiodic, bounded dynamics in a deterministic system with sensitivity dependence on initial conditions, and has structure in phase space.

If the systems investigated are shown to exhibit chaotic behaviour this will provide evidence that uncertainty within the supply chain may result from the internal processes used to control the system.

5.8 Conclusion to Chapter 5

In this chapter a robust methodology for the detection of chaos has been presented. This methodology can be applied to the detection of chaos from simulated supply chains. A description of the deterministic simulation and the simulation methodology

used to address the research questions outlined in Chapter 4 will take place in Chapter 6.

Chapter 6

Investigation into the generation of supply chain uncertainty by deterministic chaos.

6.1 Introduction.

In section 4.9 the research questions raised by literature on chaos and supply chains were outlined. The previous chapter (chapter 5) developed a methodology for the analysis of data series to detect and quantify the presence of chaos. In this chapter the methodology will be applied to data generated from a number of simulated supply chains in order to investigate the research questions raised in section 4.9.

The chapter proceeds by describing in detail the simulation methodology used for the investigations. A description of the validation process used to ensure that the simulation models reflect the reality of industrial supply chains is undertaken, this includes a brief review of the literature in this area. The use of the tool used for analysis of the data is described and its use is validated.

The chapter then proceeds to describe the investigations developed to address the research questions. The results of these investigations are then presented and discussed briefly. A more detailed discussion of the findings will be undertaken in chapter 8, within the context of the literature.

6.2 Description of supply chain simulation methodology.

The simulation approach used to investigate the non-linear dynamic behaviour of supply chains was a development of that created by Mike Wilson [Wilson, 1993; Wilson, 1994a; Wilson, 1994b], Director of Logistics Simulation Ltd, Poynton, Cheshire. This software and approach to the simulation was chosen as it is used commercially as a training and strategic development tool by a number of blue chip companies including ICI, Black & Decker and Blood Products Ltd [Wilson, 1994a]. It has been tested widely amongst industry and is shown to mimic with good accuracy the characteristics of actual supply chains. It offers a high degree of functionality, which means complex supply chain structures can be created very quickly. Its modular construction also reflects well the reality of warehousing and inventory control used in a large number of supply chains. The original software package was further modified under the guidance of the author to create further functionality that was required to enhance the investigation into non-linear dynamic behaviour. The data used for analysis was the time series output of the inventory level within warehouses in the supply chain.

The main advantages over other simulation approaches of using Wilson's [Wilson, 1993] modular approach are as follows:

- A modular program is easier to re-configure e.g. adding and/or removing echelons, suppliers, customers etc.
- Modular programs are quicker to debug and the verification of the internal operations are simpler, resulting in improved emulation of reality.

- The modules can be integrated into other applications if this is desired.
- Other parties can write modules that can be easily integrated.
- Different programming languages are appropriate for different modules. For example the “Tactical Simulation Model” uses Visual Basic for the operator interface, C++ for speed, and FoxPro for large data handling.

The “Tactical Simulation Model” used has been developed to model the supply chain and gain greater understanding of the interactions between the individual elements. The basis of the model is that each element within the supply chain is represented by an independent modular program capable of emulating the actual activities of the supply chain. The package focuses on the front end of the supply chain and the interactions between customers, warehouses and suppliers. The model has no restrictions on supply chain structure. For example, warehouses can place orders on other warehouses, and if desired customers can buy direct from suppliers. There is also no limitation to the number of levels within the chain or the modules at that level. This emulates reality well as a number of regional warehouses may place orders on national warehouse, and for example the warehouses of large retailers place orders on the warehouses of large suppliers and so on down the supply chain.

The warehouse is the major module within the simulation, it can emulate a number of typical reordering policies. These include Re-order level method, Periodic Review Method and Automatic Re-order, which forecasts demand, calculates the optimum inventory cover level and places an order to account for expected demand for a given period i.e. a variable quantity variable re-order period system.

The “Tactical Simulation Model” can monitor inventory levels on a daily basis at all points of the chain. It also monitors the chain’s ability to satisfy end customer demand. The simulation is therefore capable of modelling a complex chain and the role of inventory within the chain.

6.2.1 Programme Environment.

The program modules run in Microsoft Windows. The main advantage of using Windows is the built in communications protocol Dynamic Data Exchange (DDE), which simplifies the process of writing the modules and also enables easy communication between the modules. A further advantage is there are many applications that support DDE and so it was possible to utilise these in specific modules. The Windows environment for example supports many different languages including Visual Basic, Pascal and C++. Database languages including FoxPro can be used. This is particularly suitable for database intensive applications such as scheduling. The Windows DDE uses a client server relationship, in which the client initiates the conversation and when it is established, transactions can take place.

The DDE environment enables each module to communicate information to other blocks in the supply chain. Information regarding orders and stock movements to and from each element within the chain is easily achieved.

The supply chain is configured using a set of individual modules including supplier modules, warehouse modules and customer modules. Each module emulates an individual company, site or customer. The modules communicate with other participating modules within the simulation by transactions. A transaction, analogous

to orders and delivery notes, are sent between modules. The information included in each transaction is as follows:

- The transaction type i.e. Order or Product.
- The product code.
- The quantity.
- The name of the sending module.
- The name of the receiving module.
- The order reference.

6.2.2 Two phase time keeping.

A key approach used within the model is two phase time keeping. A time period is split into two parts: A processing phase where the input buffers are analysed and any required responses are put into a holding buffer. A transmission phase, where all the transactions in the holding buffer are passed to the destination module for processing in the next time period.

The reason for using two phase time keeping is to ensure all the modules in the simulation remain synchronised. Without this feature one module may finish processing and send information to another module in mid-operation to be processed at the same time. The order with which modules do their processing is uncertain, and this may cause unknown response times to transactions. The two-phase procedure maintains uniformity and ensures all modules are operating at the correct time. This

procedure does however prevent more than one type of transaction being acted upon in the same time slice. In all “Tactical Simulation Models” a further module is required called the “Master Module”. This acts as a timekeeper controlling the two phase procedure and only increments the calendar when all modules have acknowledged that their daily processing is complete.

In practise the two-phase procedure reflects warehouse practice well. A large engineering warehouse generally operates on two shifts a receiving and updating shift and a dispatch and ordering shift.

The following example describes how two-phase time keeping within the model functions if the time period is in days:

Day 1 Phase 0 - Customer orders are placed in customer order buffer

Day 1 Phase 1 - Order sent to supplier’s order input buffer.

Day 2 Phase 0 - Order is processed by supplier and Product sent to delivery buffer.

Day 2 Phase 1 - Product sent to customer.

Day 3 Phase 0 - Customer receives Product and updates statistics.

Therefore if the customer places an order on Day 1 it is received on Day 3 giving a two-day lead-time.

The simulation also allows for the supplier lead-time to be varied. If the lead-time is set to 5, a lag of 5 days is introduced. So instead of product being dispatched on Day 2 Phase 1 it will be dispatched Day 7 Phase 1 resulting in the customer receiving the

product on Day 8 Phase 0. {An effective 7 day lead time including mailing and delivery delays.}

6.2.3 Simulation operation.

Each module within the supply chain being simulated runs a daily procedure. The following simple example using one product and a three module supply chain was discussed by Wilson [Wilson, 1994b]. See Figure 6.1.

The basic dialogue within and between the modules could be as follows:

Customer

Am I going to place an order today? If so, how many items am I going to order and how long will it be until I next place an order?

Have I received any deliveries from my supplying warehouse?

If so up date the statistics.

Warehouse

Have I received any deliveries? If so, amend available stock.

Add any orders received today.

Have I enough products to satisfy my oldest order? If so, despatch products and update stock records.

Have I reached my re-order point? If so, place an order on supplier for re-order quantity.

Supplier

Have I received any orders? If so, despatch the required products.

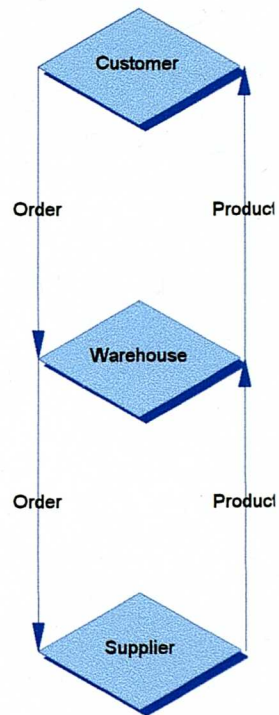


Figure 6.1 – Simple warehouse supply chain.

6.3 Detailed description of simulation module operation.

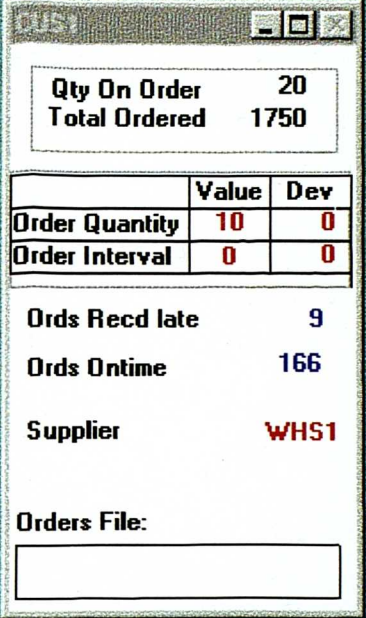
The following sections describe the operation of the simulation model developed by Wilson [Wilson, 1993; Wilson, 1994b];[Logistics Simulation Ltd., 1995] and the modifications introduced as a result of collaborations with the author during this research.

6.3.1 Customer Module.

The Customer module is what drives the supply chain, it represents the end demand in the chain. The key role of this module is to place orders on the warehouse and monitor the warehouse delivery performance in meeting these orders. See figure 6.2 and 6.3.

Each day, the Customer module generates orders for the warehouse. The name of the warehouse supplying the customer is given by the “Supplier” reference. The user can change this.

The number of orders and the quantity on order are controlled by the parameters Order Quantity and Order Interval. The value and the deviation can be set for these parameters. The module uses random number generation to produce orders that have an average value equal to the Order Quantity but will vary in value according to the deviation. For example if the Order Quantity equals 10 and the Standard Deviation equals 4, the module will generate orders that have an average of 10 but will vary according to a Normal distribution. The distribution is truncated to avoid negative values.



The image shows a simulation customer interface window titled "CUS1". It displays various order and performance metrics. At the top, it shows "Qty On Order" as 20 and "Total Ordered" as 1750. Below this is a table with three columns: an unlabeled column, "Value", and "Dev". The table contains two rows: "Order Quantity" with a value of 10 and a deviation of 0, and "Order Interval" with a value of 0 and a deviation of 0. Further down, it shows "Ords Recd late" as 9 and "Ords Ontime" as 166. The "Supplier" is listed as "WHS1". At the bottom, there is a label "Orders File:" followed by an empty text box.

| | |
|---------------|------|
| Qty On Order | 20 |
| Total Ordered | 1750 |

| | Value | Dev |
|----------------|-------|-----|
| Order Quantity | 10 | 0 |
| Order Interval | 0 | 0 |

Ords Recd late 9
Ords Ontime 166
Supplier WHS1

Orders File:

Figure 6.2 – Simulation customer interface.

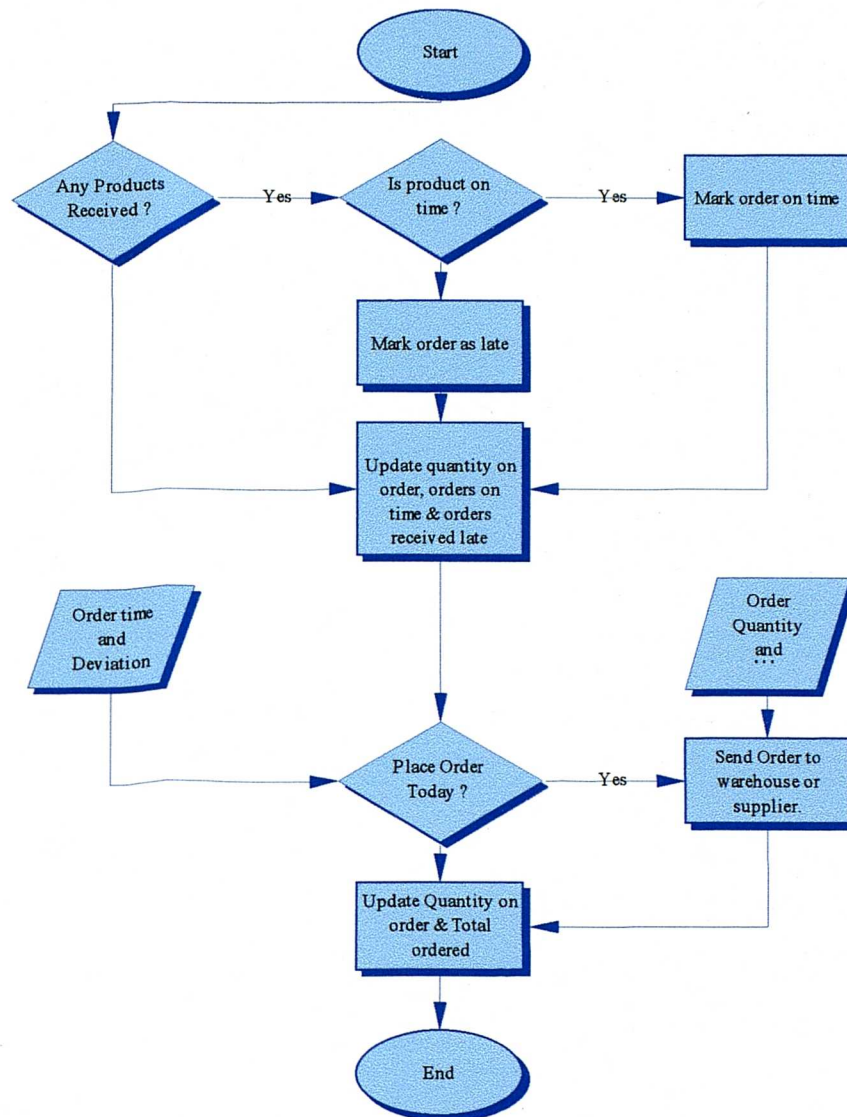


Figure 6.3 – Flow diagram of customer Module.

The frequency with which the orders are generated is driven by the Order Interval parameters. The value and deviation can be set in a similar way to the Order Quantity parameters. An Order Interval equal to zero will generate daily orders, an interval of one every other day etc.

It should be noted that the deviations were not used in the majority of the experiments as it was undesirable to have the system being driven with stochastic (random) data.

Each time the module generates an order it gives it an order reference. The module receives stock from the warehouse to satisfy the orders. Each receipt is matched against the original order reference placed. If the receipt is within 1 day of order placement it is considered to be on time, if it arrives outside this time frame it is deemed to be late.

The module also has the facility for down loading order files in a comma separated format (*.csv) from other applications, for example Microsoft Excel. This enables the use of actual demand data, orders following classical sine curves, step increases in orders etc. The file name and location is simply typed in this box in the standard DOS form. E.g. a:\tactical\sin1.csv.

6.3.2 Warehouse Module.

The warehouse module receives product from its suppliers and satisfies orders from its customers. The warehouse also places stock replenishment orders on its supplier. The supplier could be another warehouse or a supplier module. As in most supply chains the warehouse could receive stock from a warehouse further up the supply

chain and its customer could be a warehouse further down the supply chain. The name of the warehouse's supplier is denoted by the Supplier reference.

The warehouse has three main activities, these are order processing, receiving stock and the stock replenishment activity. These will be addressed in turn.

6.3.2.1 Warehouse Order processing.

The warehouse receives an order in the form of a transaction, the warehouse checks its stock to see if it can satisfy the order. If it can it will send the product to the customer in the form of a transaction. The warehouse will reduce its "quantity on hand" figure by the quantity of this order. If the warehouse does not have stock to meet the order, the order will stay on file at the warehouse as a Back Order until sufficient product is available to satisfy the order.

6.3.2.2 Warehouse receiving stock.

The warehouse places orders on its supplier and subsequently receives product in the form of a transaction. Each transaction includes information on the product, quantity and the order reference. The warehouse uses the order reference to calculate the time elapsed since the order was placed to calculate the supplier lead-time i.e. the time it took for the supplier to satisfy the order. The module calculates and displays the supplier lead-time and deviation of lead-time in weeks.

On receiving product the warehouse updates the quantity on hand figure. The transaction details are checked so that the product received can be matched against the appropriate order generated by the warehouse. The module cancels this from the orders placed file and updates the quantity on order.

The warehouse then proceeds to check the Orders placed file to see if it has enough products to satisfy any more customer orders on the list. If the warehouse can satisfy an order it will send product to its customer and update the quantity on hand and backorder figures. The warehouse continues to examine the Customer order file until all orders are satisfied or the quantity on hand is insufficient to meet the next order on the list.

Figure 6.4 depicts the process chart for the Warehouse order processing and stock reception systems.

6.3.2.3 *Warehouse Stock Replenishment System.*

The warehouse generates its own orders, which are placed on suppliers for stock replenishment. The “Tactical Simulation Model” has three main options that the user can choose to calculate how much should be ordered from the supplier and when the order should be placed. The three methods are Reorder level, Auto Reorder and Periodic Review. Each will be discussed in turn.

a) Reorder level System

This replenishment method will generate an order on the supplier whenever the quantity on hand falls below a pre-set figure, the Reorder point. The quantity ordered is pre-set by the Reorder quantity. Traditionally the order quantity may be calculated using, for example the economic order quantity equation. {see [Waters, 1992 pp.31-74]}. The user can specify both the order quantity and reorder point. For example if the Reorder point is set to 50 and the reorder quantity 150 the system will place an order of 150 on its supplier if the quantity on hand is less than 50. {See Figure 6.5 for flow diagram.}

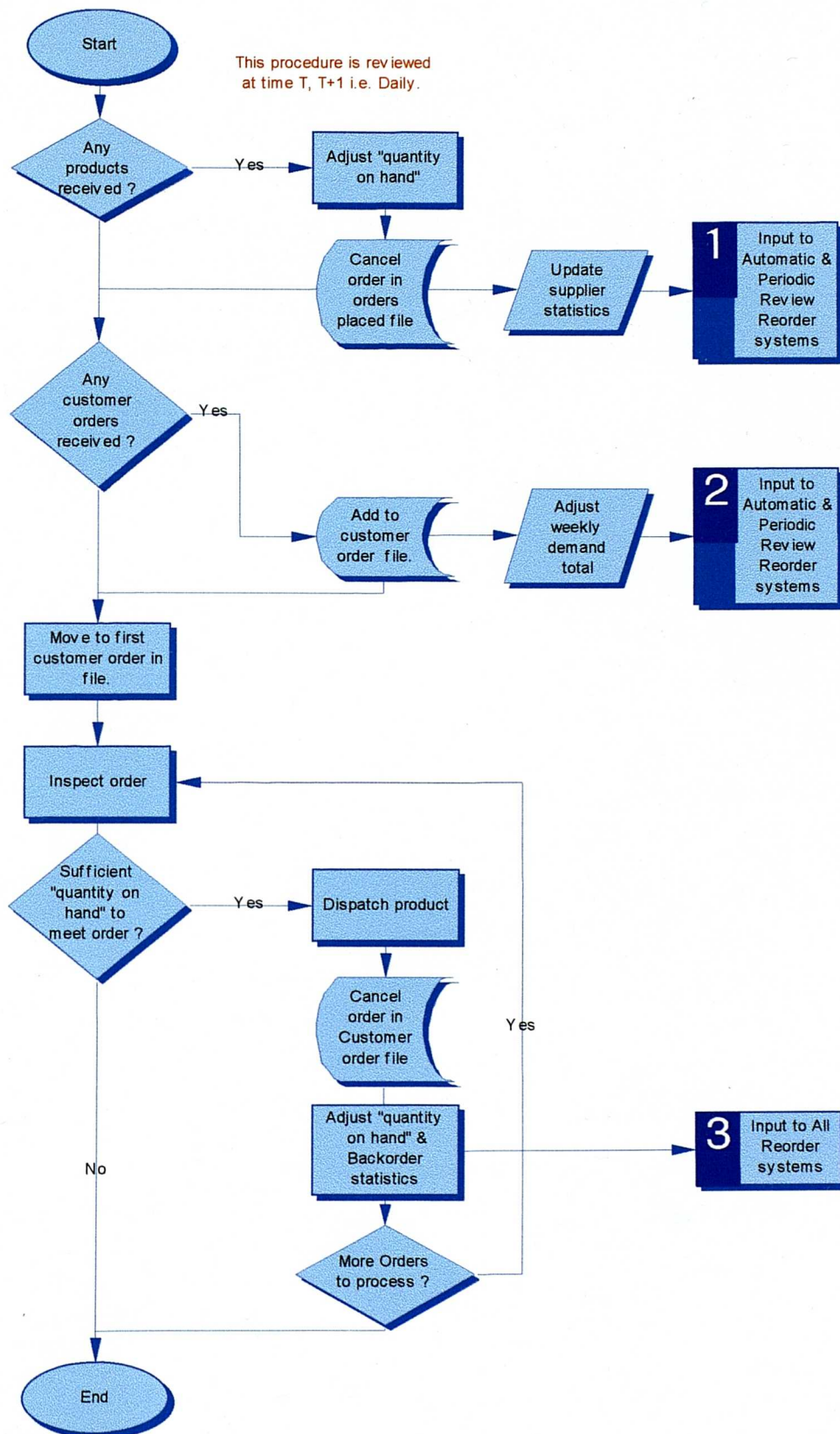


Figure 6.4 – Flowchart of Warehouse module process.

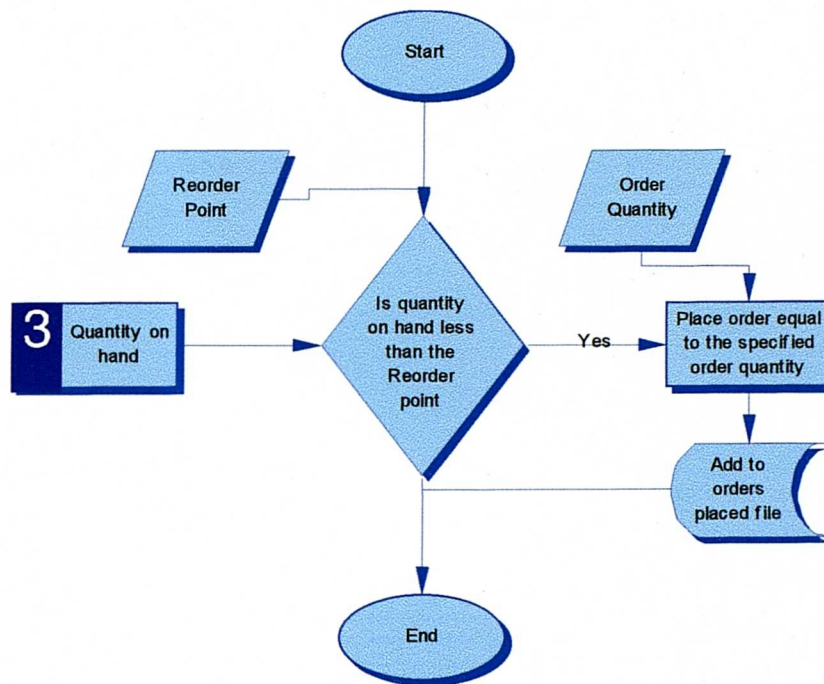


Figure 6.5 – Flow diagram of warehouse re-order point system.

b) Automatic Reorder

This method also generates an order when the quantity on hand falls below a certain level, in this method the reorder point is called the “Cover” level. The cover level is calculated based on the rate of customer orders that the warehouse has to satisfy and the lead-time within which its supplier is going to deliver i.e. the supplier lead-time. To calculate the cover level required the warehouse calculates a forecast. The forecast is a prediction of the number of products that it will have to send to its customer in one week. It is calculated by taking the actual demand that the warehouse has received since the simulation started to run and using this to make a prediction of what the demand will be in the coming week. It should be noted that the model uses a Simple Exponential Smoothing equation which results in the more recent data being given the most weight. This results in a high emphasis being given to the most recent data, but the emphasis declines exponentially with the age of the data.

The warehouse then uses its forecast to check to see if it has enough stock to last until the next time it can expect to receive product from its supplier, this is dependent on the supplier lead-time. The system also ensures that a safety stock is maintain; set at the number of weeks of cover required. The system also considers pipeline stocks by asking the following question: -

Is the “Quantity on hand + Quantity on Order - Quantity on Backorder ≤ 0 ” if the answer is yes then place additional order.

The system uses well-established and commonly used techniques that are still advocated by industry (see for example [Silver & Peterson, 1985; Waters, 1992; Bowersox & Closs, 1996]).

The Forecast, Cover and Order quantity calculations are as follows:

The forecasting system is based on Simple Exponential Smoothing, the mathematical formula to calculate the forecast is as follows [Waters, 1992] [Silver & Peterson, 1985 pp. 105-107; Logistics Simulation Ltd., 1995]: -

$$F_{t+1} = F_t + \alpha \{D_t - F_t\}$$

Where α is the exponential smoothing constant, F_t = Forecast made last week for this week, D_t = Demand for week ending today.

The system then calculates the Forecast Error, i.e. its ability to forecast accurately.

The figure calculated is the Mean Absolute Deviation (MAD) [Waters, 1992; Silver & Peterson, 1985; Logistics Simulation Ltd., 1995]. This is calculated as follows:

$$M_{t+1} = (1 - \alpha) \times M_t + \alpha \times \|D_t - F_t\|$$

Where M_t = Mean Absolute Deviation calculated last week.

The Cover is calculated using the above formulae and the supplier lead-time and deviation. The calculation is as follows:

$$C_{t+1} = F_{t+1} \times LT + \beta \{ \sqrt{LT} \times M_{t+1} + \sqrt{F_{t+1}} \times LTD \}$$

Where C_{t+1} = cover required for next week, β = a constant to determine the Service Level.

The quantity the warehouse orders from its supplier is simply calculated as follows:

$$O_{t+1} = W \times F_{t+1}$$

Where O_t = Order Quantity, W = number of weeks cover required.

It can be seen that the system is using various statistical methods to predict the forecast error and subsequently reduce the number of orders that cannot be satisfied from stock. Figure 6.6 shows the flow diagram for this system.

c) *Periodic Review System*

The periodic review method places an order for stock replenishment at a pre-set time interval called the Review Period. The day within the review period when orders are placed is also specified and is referred to as the order day. When the system reaches the order day the warehouse places an order for enough products to last until the next time the order is to be placed. The system also takes into account the supplier lead-time to ensure additional product is available to cover this time period. The system uses a forecasting system to predict customer demand identical to the Automatic Reorder System described above. The order quantity is calculated using the following equation:

$$O_t = LT \times F_t + F_t \chi + \{\beta \sqrt{\chi} \times M_t\} - QOH - QOR - QBO$$

Where χ = Interval before next order, QOH = Quantity on hand, QOR = Quantity on order, QBO = Back order quantity.

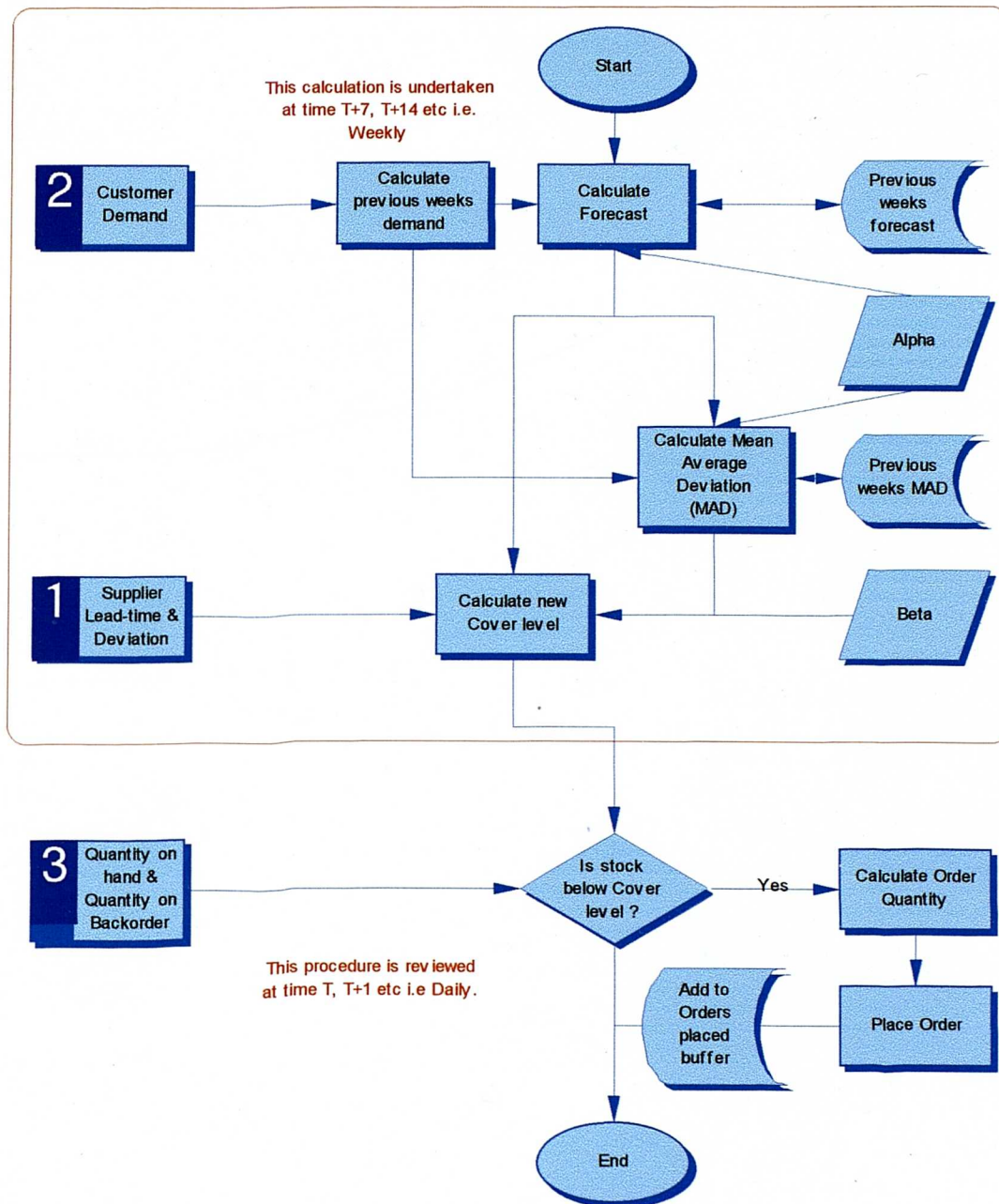


Figure 6.6 – Flow diagram of warehouse automatic reordering system.

The system is attempting to predict the amount of error and the number of orders it will be unable to satisfy from stock. Figure 6.7 shows the flow diagram of the periodic review system.

6.3.2.4 The warehouse during run time.

Figure 6.8 shows the warehouse block form as the simulation is being run. The warehouse offers three buttons for the selection of the Reorder systems as described above. The user can alter items in Red and only the parameters needed for each method are on display as the system is running.

During run time the warehouse form displays a graph at the bottom. The graph shows the quantity on hand minus the quantity on back order verses time. The graph is updated by clicking once with the left mouse button, can be enlarged by clicking twice on the left button. This data can be transferred in tabular format to the Windows clipboard by clicking once on the right mouse button. In clipboard format the data can be transferred into spreadsheets and other analyses packages.

6.3.3 The Supplier Module.

The supplier receives orders for product from warehouses and/or direct from customers, after a given lead-time sends products to satisfy this order. In the model used the supplier has no capacity constraints. The lead-time and lead-time deviation are pre-set by the user. The lead-time deviation can be used to emulate any unpredictability of the supplier in satisfying the order in the given lead-time. The lead-time deviation is similar to that used in the customer module and randomly generates the time to release orders according to a Normal distribution. The total

number dispatched is updated with each transaction. The Logistics setting is a facility used by Logistics Simulation Ltd to pass the customer demand directly to other echelons in the supply chain. This was unused throughout the simulation work carried out by the author. Figures 6.9 and 6.10 depict the supplier module form and operation flowchart for the supplier module.

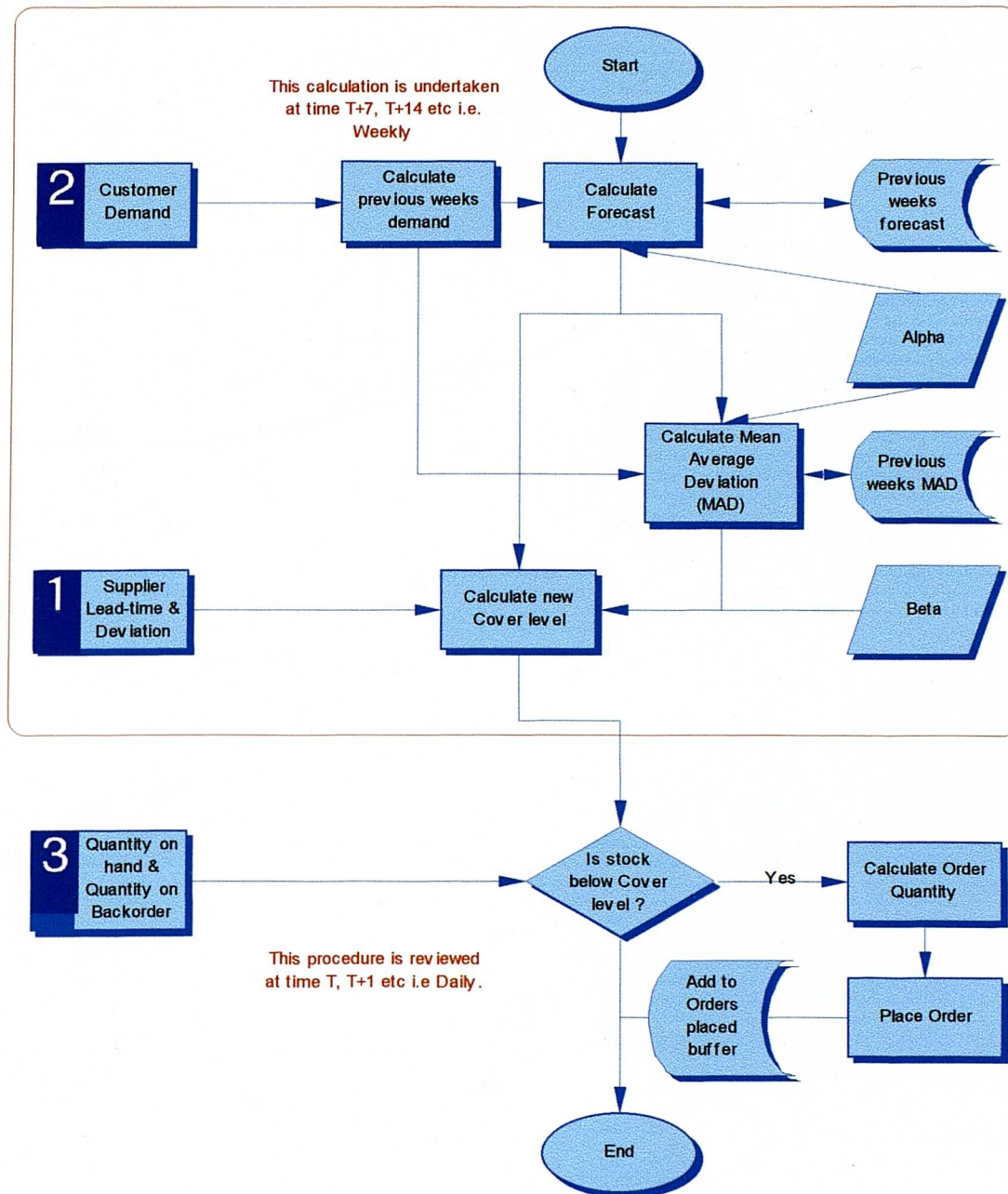


Figure 6.7 – Flow diagram of warehouse periodic review reorder system.

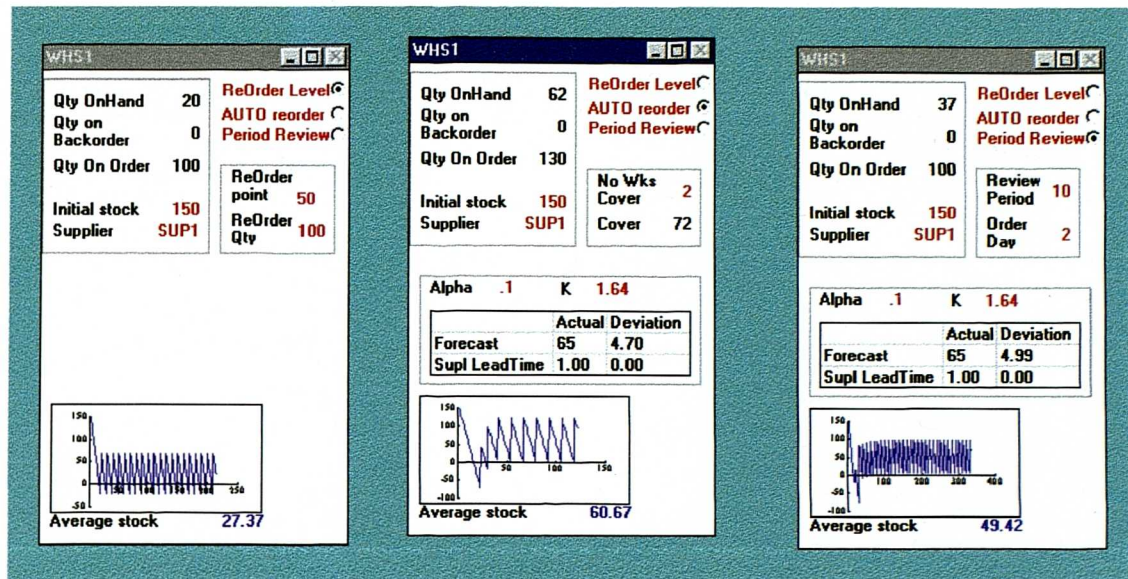


Figure 6.8 – Simulation warehouse interfaces.

Tactical Warehouse module interface for a) Re-order point system b) Automatic Re-order and c) Periodic Review. (From left to right) The user can modify parameters displayed in Red. The Blue data can be moved to Windows clipboard for further analysis.

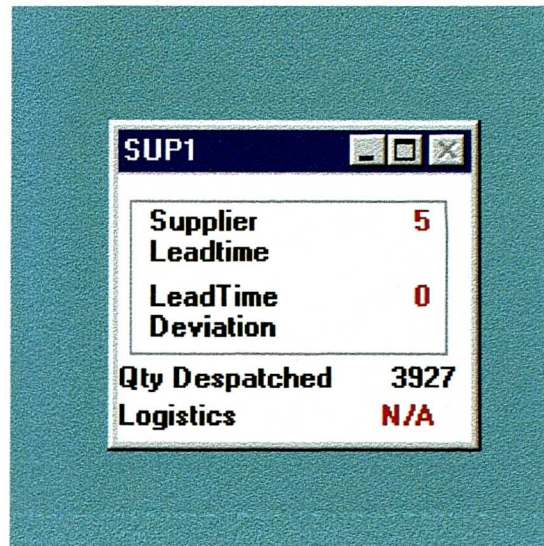


Figure 6.9 – Simulation supplier interface.

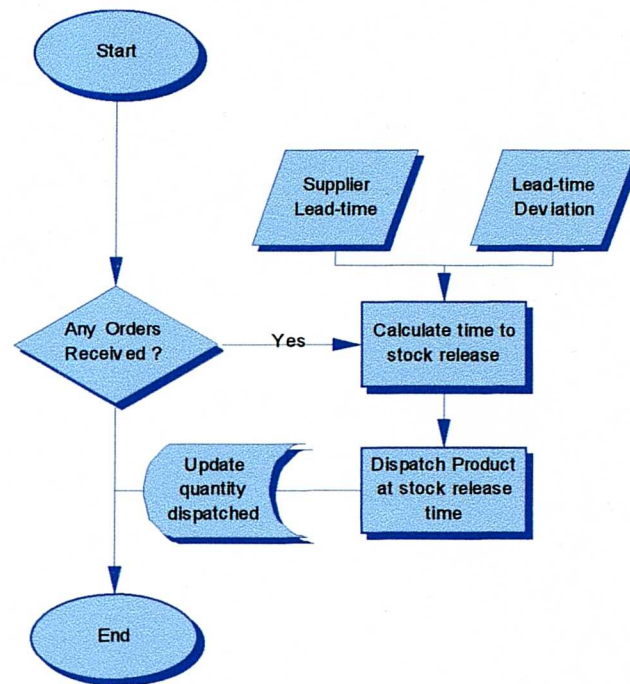


Figure 6.10 – Flow diagram of supplier module.

6.4 Validation of model.

Before a simulation model can be used with confidence the simulation must be validated. The process of simulation validation has been described by Schlesinger [Schlesinger, 1974] as:

“The process of substantiating that the model within its domain of applicability is sufficiently accurate for the intended application.”

Oakshott [Oakshott, Greasley, & Smith, 1997] emphasises that it is practically impossible to make any simulation agree perfectly but it should be “adequate” for the intended purpose.

A survey of the literature generally supports a three-stage validation process. Carson [Carson, 1986] identifies these stages as verification, validation and credibility. These are distinguished as follows:

- Verification is the responsibility of the programmer to ensure the simulation performs in a way in which the programmer intended.
- Validation is the responsibility of the simulation user {domain expert} and the programmer to guarantee that the simulation is a true representation of environment being simulated. Validation focuses on ensuring the simulation is sufficiently accurate to test different conditions.
- Credibility of the simulation requires the acceptance of the simulation user {domain expert} that the simulation is valid and can be used as an investigative tool to aid decision making.

The above definitions imply that the definition of credibility is a higher level of user acceptance than is generally generated by validation.

Naylor and Finger [Naylor & Finger, 1967] propose a three-stage approach, which has been further developed in recent years by Law and Kelton [Law & Kelton, 1991].

The three phases are defined as:

- Face Validity – this is a high level verification that ensures that the model seems to be producing reasonable results.
- Testing of the assumptions – this involves the changing of parameters to check the model performs as expected under different conditions, (analogous to Carson’s validation phase).
- Statistical comparisons between real system and the simulation output - this phase involves determining the simulation model’s true characteristics in comparison with the actual system simulated. This should be continued until acceptable confidence limits can be obtained for the results.

Law and Kelton [Law & Kelton, 1991] raise a number of reservations on the use of statistical tests on simulation data. The main concerns are as follows:

- The data is generally non-stationary – the majority of simulations are run over a relatively short time period {under 100 time units} and the data collected from the real system is generally based on small samples. Statistical results generally presume that the data is independent of time.

- Autocorrelation – the measurements taken from a simulation and data collected from the real system for the purposes of validation are almost certainly autocorrelated.

Both these effects however can be minimised by using long simulation runs to produce large samples [Oakshott, Greasley, & Smith, 1997].

The verification process generally involves the testing and checking of the computer code to ensure that it truly represents the assumptions and data accurately. Carson, Law and Kelton [Carson, 1986; Law & Kelton, 1991] suggest the following techniques:

1. Structured programming techniques.
2. Program testing under a variety of input parameters to check for extreme reactions.
3. Collection and display of statistics in order to expose possible sources of error
4. An “outsider” should read the code and check the logic, this overcomes problems where a programmer becomes so involved that they are unable to see the correctness of the logic.
5. “Trace” the simulation by printing out event lists, statistics and variables which can then be checked to verify the model’s reaction to certain conditions.
6. Run the model under simplified assumptions, for which the model’s true characteristics can be known or calculated.

Grinsted [Grinsted, 1990] further develops the above list by adding two techniques that exploit the visual interactive nature of most modern simulation packages:

7. A few extremely long runs to check for unusual cases, rare bugs, or unusual or catastrophic combinations of conditions.
8. Careful observations of key events should be undertaken on screen, stepping through each event in turn. This is an animated equivalent to the trace method, but should not be seen as a replacement.

The author would also propose the following techniques that have proved beneficial in the verification of simulations used in this thesis.

9. Run stochastic simulations in a deterministic mode to check logic – the noise generated by random number sampling can hide programming errors.
10. If random number generators are used in different parts of a simulation, correlate outputs from the number streams as this identifies if the random number streams are independent. It is also important to check that the random number streams are bounded, this can be checked by producing a cumulative sum graph of the output and running the simulation for say 10,000 time periods. (This methodology identified some spurious random number streams in the Witness simulation package used in the next chapter.)

6.4.1 Validation of warehouse supply chain simulation

One of the main reasons for the choice of the “Tactical” simulation model used in this work is that it had undergone extensive verification and validation. It has also been

proved “credible” by its use in a variety of practical industrial applications. However, some modifications to the original package were required to ensure the functionality needed for non-linear dynamic analysis. These modifications required further extensive verification and validation to be undertaken by the author and the programmers at Logistics Simulation Ltd. The procedures outlined above were therefore reapplied.

Grinsted [Grinsted, 1990] observes that the process of validation is poorly treated in the literature. Where consideration has been given it relies predominantly on the use of historical data collected from the actual environment being simulated [Oakshott, Greasley, & Smith, 1997; Law & Kelton, 1991]. Although the Tactical Simulation has been used to model actual supply chains, the layout of some of the supply chains used in this thesis, though based on systems generally found in industry, were not based on specific cases. This therefore required a further stage in the validation process involving getting a team of “experts” to validate the model [Oakshott, Greasley, & Smith, 1997]. The methodology used for this is that developed by the Simulation Group within the Warwick Manufacturing Group [Grinsted, 1990]. The supply chains to be analysed were created and the output verified as “sensible” or “not sensible” by a team of experienced engineers and practitioners. The outputs are then subsequently assigned to the categories “acceptable” or “of concern” or “unacceptable”. Any outputs resulting in classifications “of concern” or “unacceptable” were thoroughly investigated and modifications to the simulations were made if necessary. Any modification resulted in the full ten-step validation process being reapplied and also a further review by the panel of experts.

6.5 Validation of data analysis software.

The software package selected for the dynamic analysis of the measured data was “Chaos Analyser - The Professional Version. (Version 2) 1995” by J.C. Sprott and G. Rowlands. This is one of the few commercially available analysis packages for the analysis of chaotic data and brings together a selection of analysis tools in one package. There are many chaos analysis tools available via the Internet, however there is little evidence of independent validation of these tools. The American Institute of Physics and the American Physical Society have both extensively validated the “Chaos Analyser” package used in this thesis [Sprott & Rowlands, 1995].

The software has also been independently validated and has received very favourable reviews from the mathematics community {See for example [Casti, 1996; Scheeline, 1995; Risley, 1997]}. The package was co-written by Professor George Rowlands, a colleague based in the Department of Physics at the University of Warwick, and this enabled readily available technical support during the early stages of the research.

The main weakness of the package is the graphics output, which is of low resolution. However this was not detrimental to the analysis results achieved.

To check any sensitivity to hardware platform and the operating systems the author did further validations of the package. The package runs in DOS, but the author also validated the use of the package with Windows 3.1 and Windows 95. The validation involved using the standard sample data sets provided with the package, undertaking the analysis and comparing the results with those published in the user guide and other sources {for example [Wolf, 1986]}. It was found that the package was insensitive to the hardware platforms and operating systems used to run it.

6.6 Investigation Methodology.

The methodology used was developed to address the four questions raised in Section 4.9. A number of different supply chain structures were created using the “Tactical Simulation model” described in Section 6.3. The automatic reorder system described in section 6.3.2.3 was used. The data series of apparent inventory (quantity on hand minus the quantity on back order verses time) from each warehouse in the supply chains was analysed. This was found to give a good reflection of the attractor present within the warehouse and consequently the nature of the order patterns generated by the system.

Each customer, warehouse and supplier was set up with any variables set to values that would reflect those used commonly in industry. These were set to the following values unless stated otherwise in the investigation descriptions.

Customer modules

- Order interval = 0 (Equating to an order placed each day)
- Order quantity and order interval deviation = 0 (No random variation present)

Warehouse Modules

- Warehouse Initial Stock = 150
- Exponential Smoothing Constant $\{\alpha\} = 0.1$
- Service level Constant $\{\beta\} = 1.64$ (equating to a service level of 95%.)
- Number of weeks cover required $\{W\} = 2$ weeks.

Supplier Module

- Supplier lead-time = 7 days (from warehouse placing an order to goods being received by the warehouse.)
- Order Interval deviation = 0 (No random variation present)

Pilot investigations indicated the possibility that the results, in certain situations, were sensitive to customer demand. Three demand levels were therefore selected to drive the simulations. These were a daily demand of 10, 25 and 40 units.

For each change in supply chain structure and/or change in variable the validation procedure described in Section 6.4 was applied.

The simulations were run to time period 3000 (this limitation was due to the size of the windows clipboard and also the length of time required for each simulation run.)

The removal of the initial transients and dividing the data into data sets to test for “boundedness” was carried out in a standard Windows text editor (for example, Notepad, Wordpad or Word). A small Windows based programme was also written to convert the data series into a comma-separated format, which was a preferred format for the chaos analysis package.

The average prediction horizon was calculated as described in section 5.6.3 presuming an initial accuracy of 1 in 10,000 (i.e. 14 bits).

The time taken to undertake a simulation run and prepare and analyse one data series was approximately 1 hour. This equates to one data point in a graph.

6.7 Description of Investigations.

6.7.1 Investigation 1 – Is chaos generated within a real supply chain with no misperceptions about orders or inventory?

The supply chain structure used to investigate this research question is depicted in Figure 6.11. It consists of a customer, two warehouses and a supplier.

The simulation was run for the three demand levels described above (i.e. 10, 25 and 40 units).

The data series from each warehouse was analysed using the Methodology for detecting chaos described in Chapter 5.

An additional experiment to depict the sensitivity to initial conditions was also performed. This involves changing the initial stock level from 150 to 151 and viewing the divergence of the resulting data series. A similar experiment comparing the data series for constant demand with demand with a small random input was also performed.

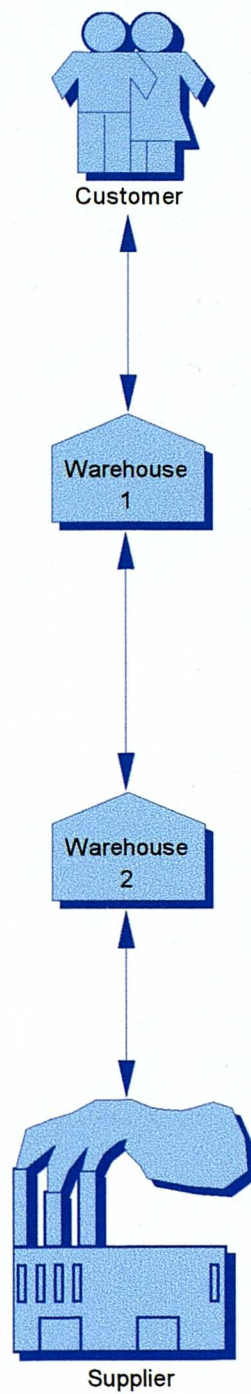


Figure 6.11 – Investigation 1: Supply chain structure.

6.7.2 Investigation 2 – Impact on degree of chaos by increasing supply chain complexity through increasing the number of echelons.

The supply chain structures used in this investigation are depicted in Figure 6.12 . The number of warehouse echelons in the supply chain was increased to a maximum of five.

The data from each warehouse was analysed using the methodology described in chapter 5. However the main emphasis of the investigation is to quantify how the increasing complexity of the supply chain resulting from increasing the number of echelons impacts on the degree of chaos, and so steps 3 to 5 were therefore used. This is measured by the Lyapunov Exponent value that was then used to calculate the Average Prediction Horizon of the data from each warehouse. The relationship between the data series of each warehouse was also investigated in order to identify any linear relationships or relationship patterns between the data series.

6.7.3 Investigation 3 – Impact on degree of chaos by increasing supply chain complexity through increasing the number of customer channels.

The supply chain structures used for this investigation are shown in Figure 6.13 . Similar to investigation 2 where the number of echelons are increased, investigation 3 increases the complexity by increasing the number of channels in the supply chain.

The data analysed was from warehouses 1 and 2 in the supply chains described above. The data was analysed in the same manner in which the data for investigation 2 was analysed.

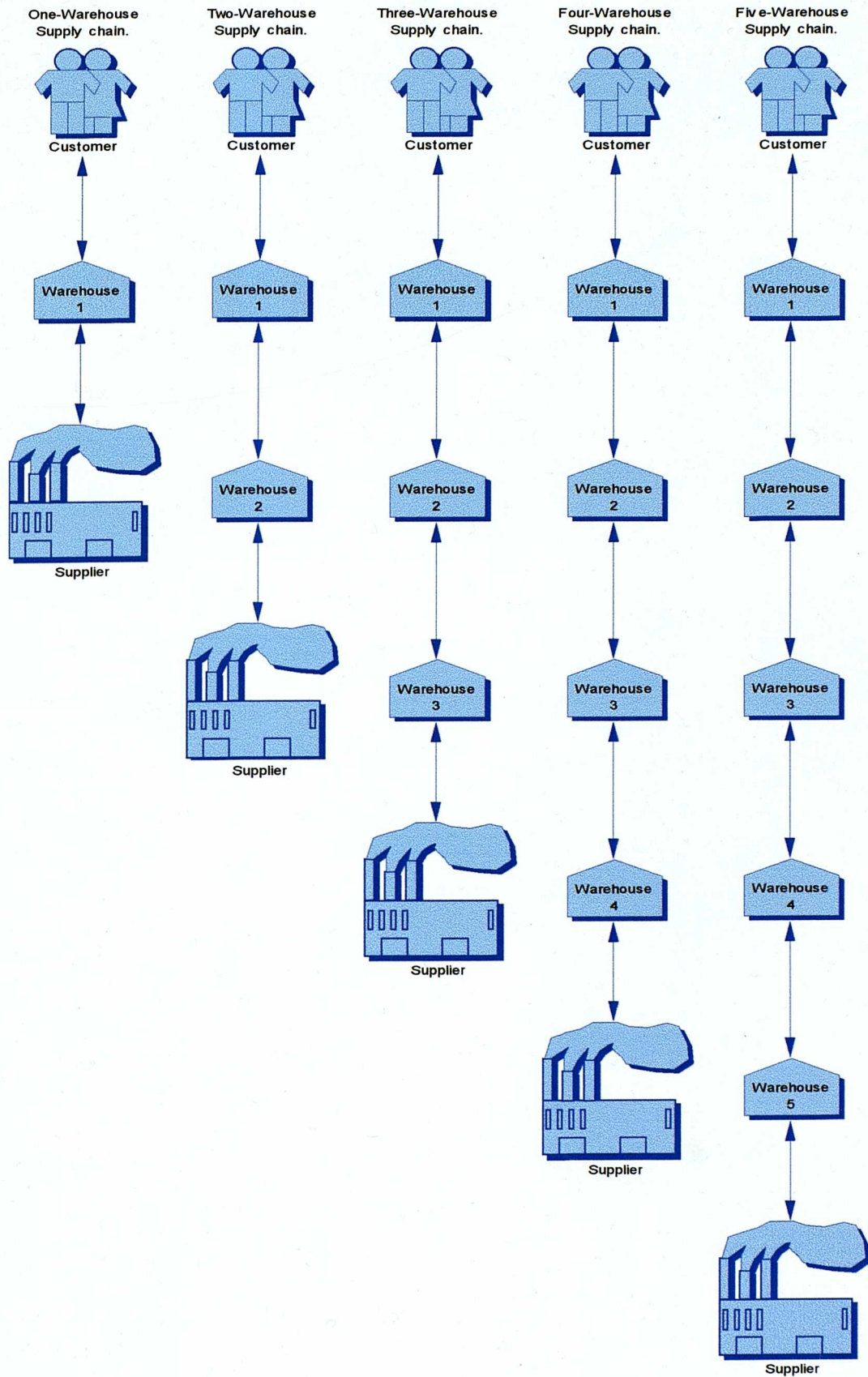


Figure 6.12 – Investigation 2: Supply chain structures.

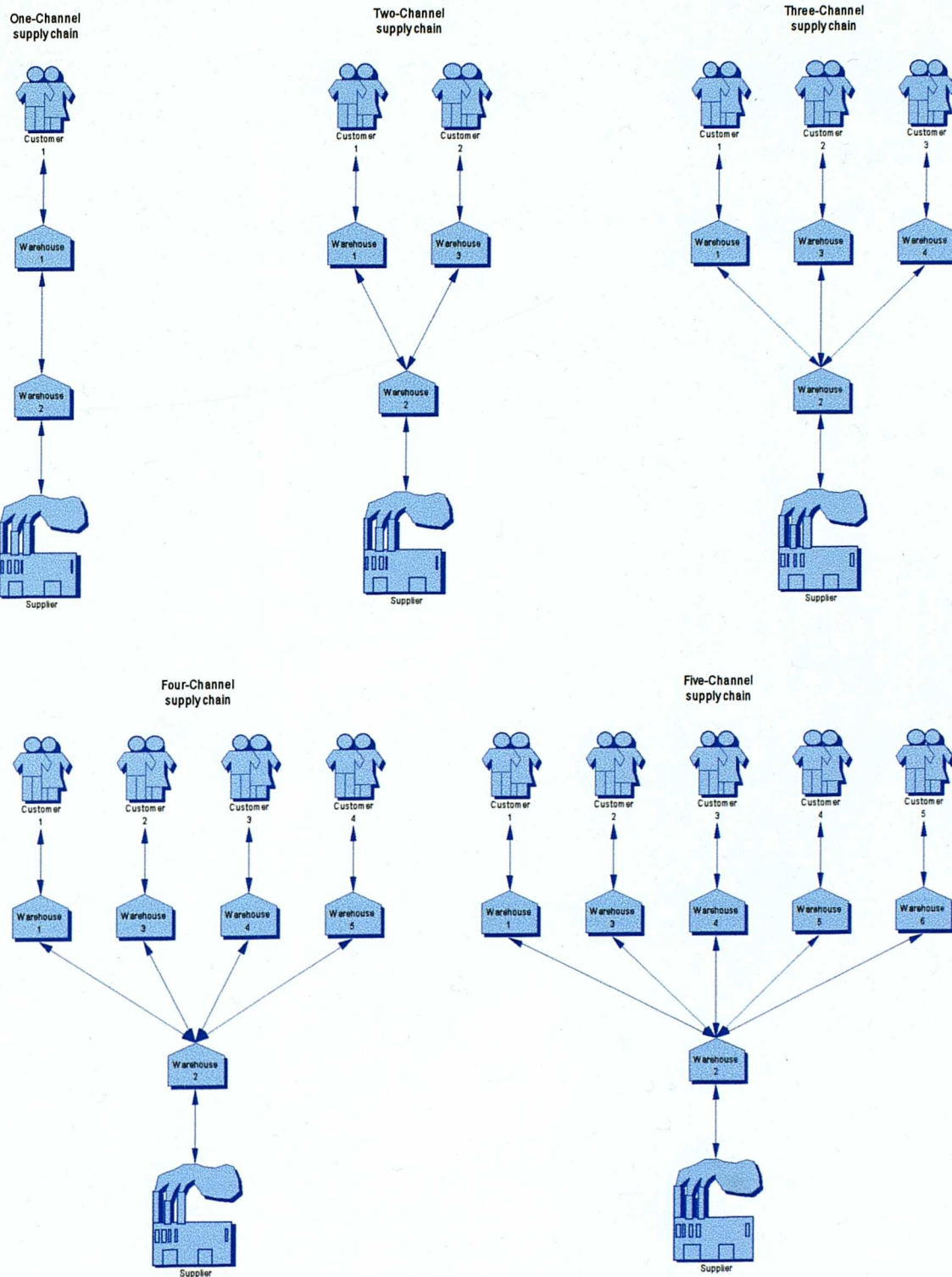


Figure 6.13 – Investigation 3: Supply chain structures.

6.7.4 Investigation 4 – Identification of “Islands of stability”.

This investigation involved using two supply chain structures as depicted in figure 6.14 .

It was identified in the early stages of this investigation that the “Islands of stability” are highly system dependant and moved if variables were changed.

Using a one-warehouse supply chain (figure 6.14a) the demand was varied to identify “Islands of stability” defined as where the average prediction horizon is greater than 1000 days.

This was also undertaken for a two-warehouse supply chain (figure 6.14b). The supplier lead-time was also altered to identify any sensitivity to this parameter.

The one warehouse supply chain was also used to investigate the impact of a change in the “service level” constant for the warehouse.

6.8 Analysis of Results.

6.8.1 Introduction

The full implications of the findings outlined in this chapter will be discussed within the context of the literature in Chapter 8. However, the following sections will present the findings of the investigations outlined in section 6.7. To aid the reader, notes have been added to some of the figures to draw attention to key issues and other points of interest that occur in the data. (The results are presented in tabular form in Appendix 1).

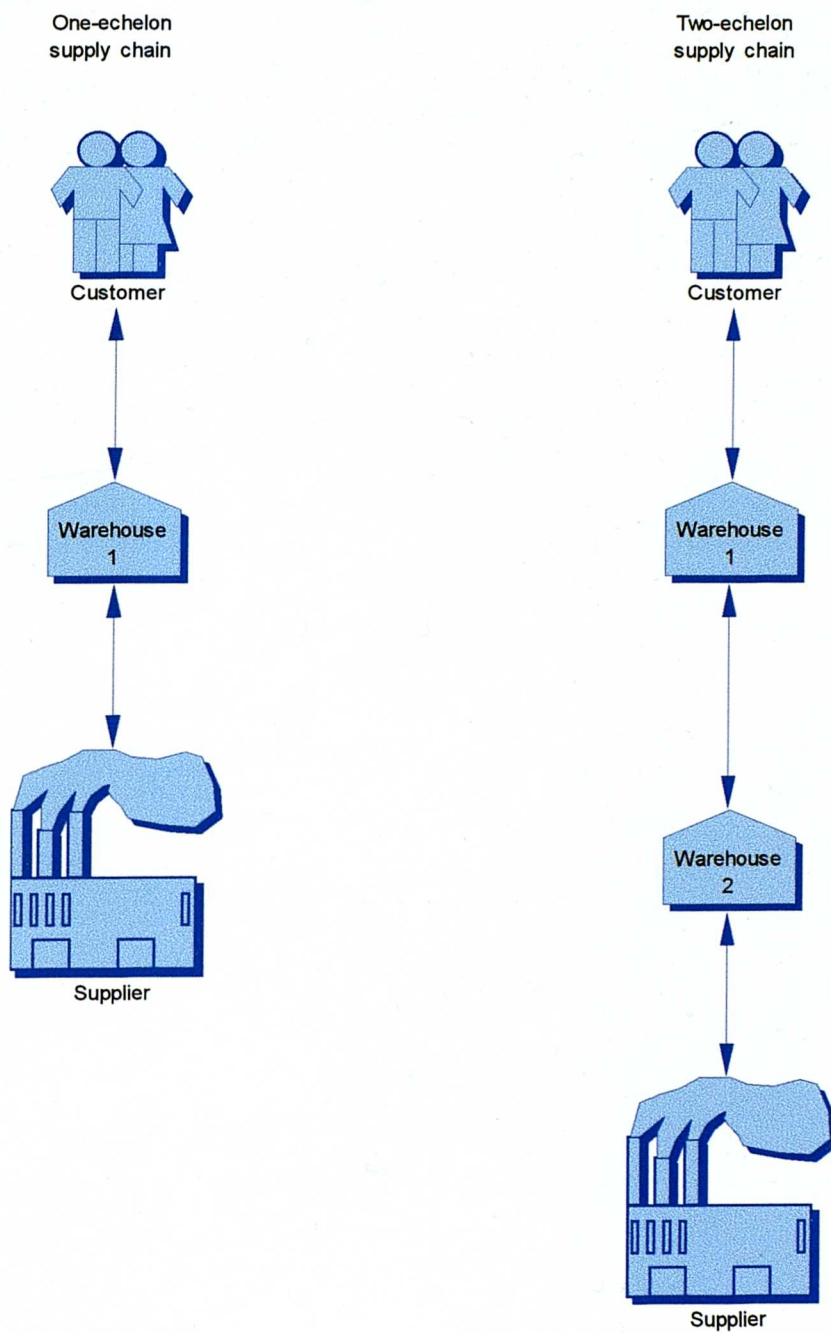


Figure 6.14 – Investigation 4: Supply chain structures.

6.8.2 Results of Investigation 1 – Is chaos generated within a real supply chain with no misperceptions about orders or inventory?

a) Warehouse 1

Figures 6.15, 6.16 and 6.17 show sample data series of 250 days generated within warehouse 1 for daily demand levels of 10, 25 and 40 respectively. By a simple visual comparison it would appear that for a daily demand of 10 produces near periodic behaviour occurs. A daily demand of 25 produces a more complex quasi-periodic behaviour that seems to repeat every six peaks on the graph. A daily demand of 40 produces quasi-periodic behaviour repeating every 4 peaks on the graph.

Figures 6.18, 6.19 and 6.20 show the attractors for this data generated by plotting time t against $t-1$, for daily demand of 10, 25 and 40. This gives some confirmation of the tentative conclusions drawn above. Figure 6.18 depicts a closed loop characteristic of periodic behaviour. Figures 6.19 and 6.20 show attractors characteristic of quasi-periodic behaviour.

Figures 6.21, 6.22 and 6.23 show the return maps of the data for daily demand of 10, 25 and 40 respectively. Figure 6.21 shows that the system “cuts” through the map at only two distinct points, this is indicative of periodic behaviour. Figures 6.22 and 6.23 show that the attractor “cuts” through the map on a limited number of distinct points indicating quasi-periodic behaviour.

Table 6.1 shows the Lyapunov Exponents calculated for the data series from warehouse 1. For a daily demand of 10 and 25 a small positive exponent was calculated indicating a small degree of sensitivity to initial conditions within the data. However for the daily demand of 40 the Lyapunov exponent indicates stable

predictable behaviour. Table 6.1 also shows the Lyapunov exponents for data sets 2 and 3, the small difference between the set 1, set 2 and set 3 exponents indicate that the data is bounded. The Lyapunov exponents calculated for the Surrogate data are significantly different indicating that the warehouse data analysed does not conform to the null hypothesis.

In summary, the data from warehouse 1 shows structure in phase space which would indicate near periodic or quasi periodic behaviour. The Lyapunov exponents indicate a small degree of sensitivity to initial conditions for demand levels 10 and 25 and no sensitivity to initial conditions for a daily demand of 40. The data analysed is bounded and the analysis of the surrogate data refutes the null hypothesis. In conclusion the data from warehouse one demonstrates a very small degree of chaos for daily demand of 10 and 25 however this would in practice be insignificant. For a daily demand of 40 the evidence indicates no chaos is present and the data is quasi-periodic.

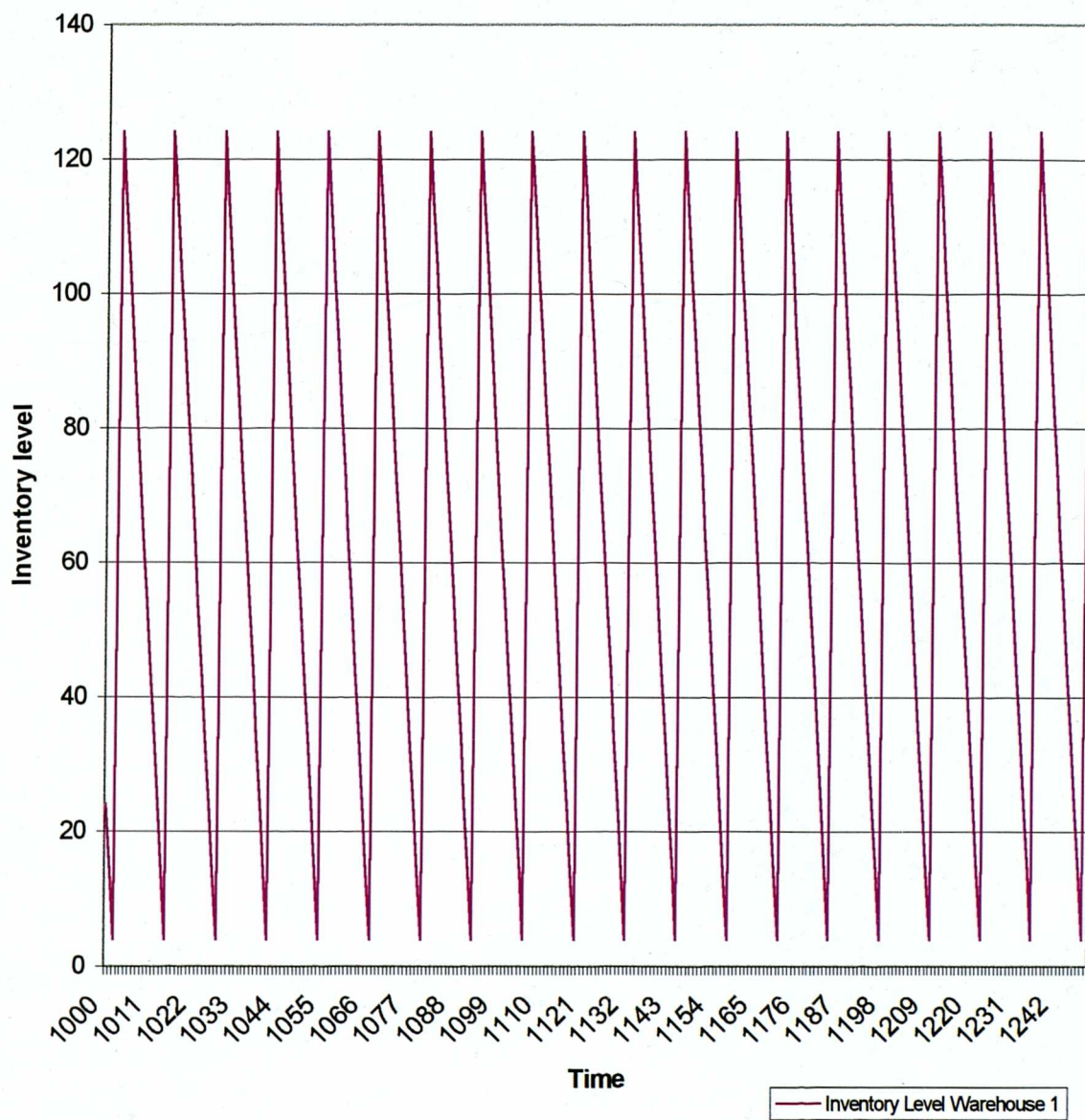


Figure 6.15 – Sample data series Warehouse 1, Demand = 10.

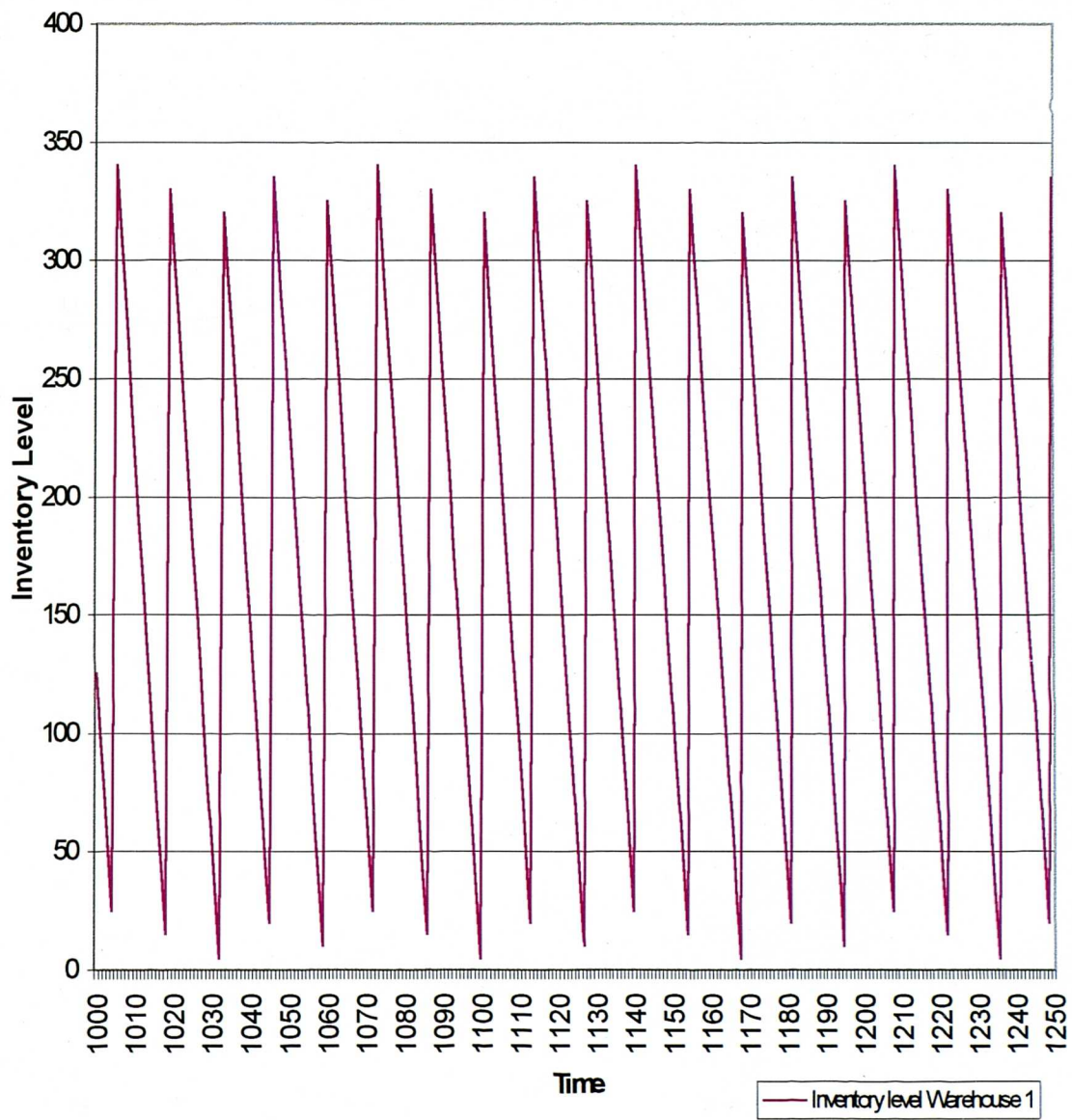


Figure 6.16 – Sample data series Warehouse 1, Demand = 25.

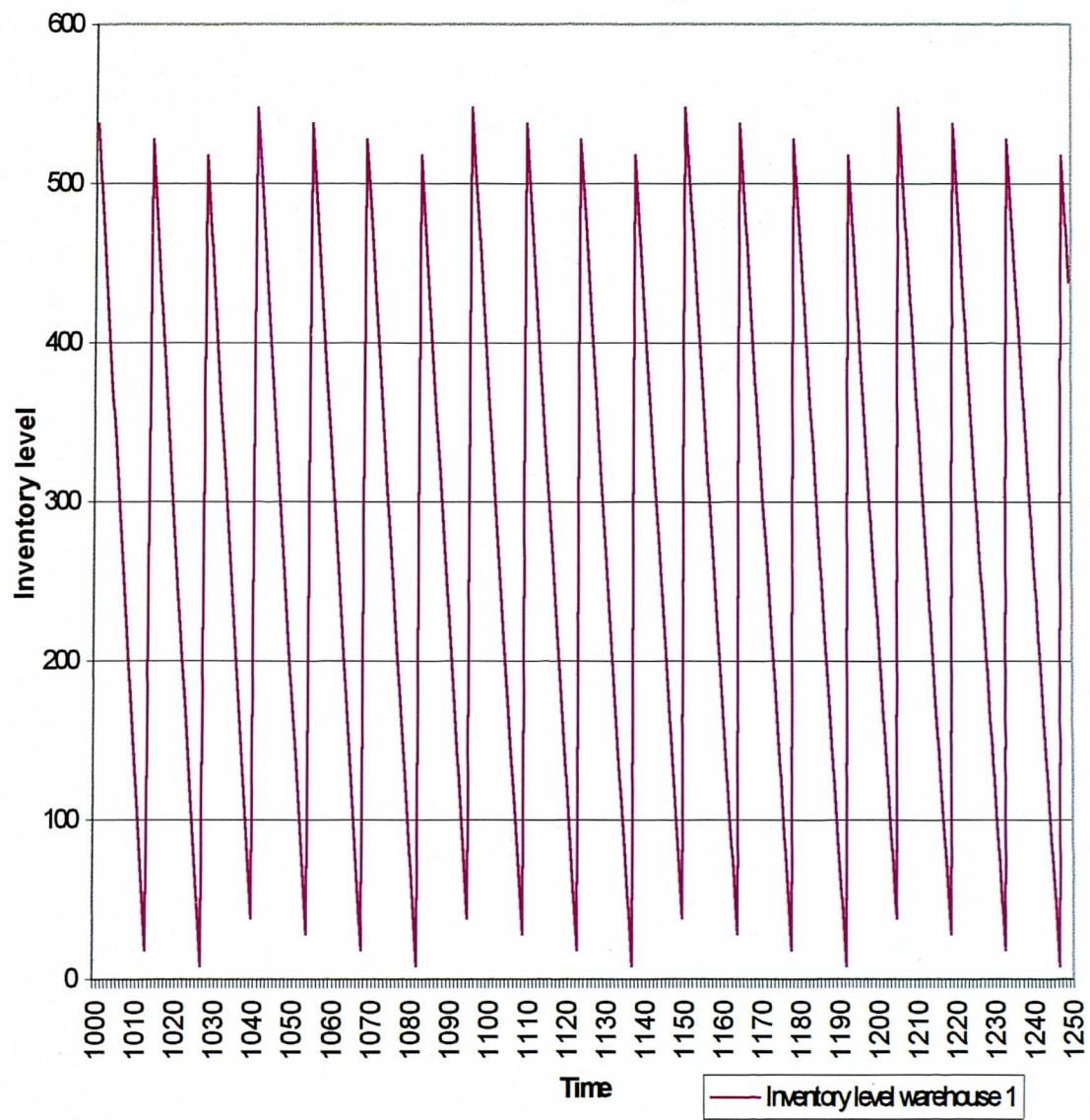


Figure 6.17 – Sample data series Warehouse 1, Demand = 40.

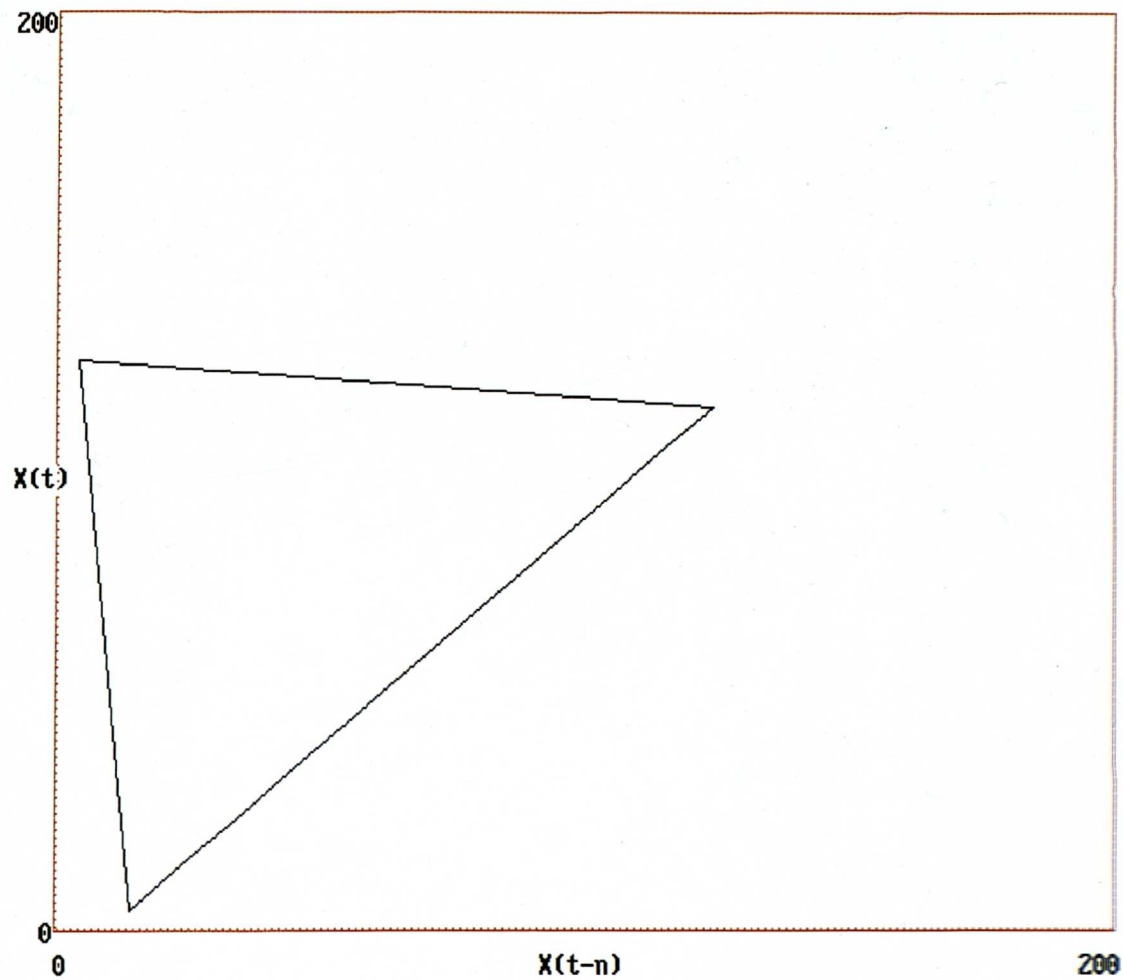


Figure 6.18 – Warehouse 1 attractor, Demand = 10.

Graph shows Inventory at time (t) against Inventory at time ($t-n$) where (n) is equal to 1. Customer demand is equal to 10 units per day.

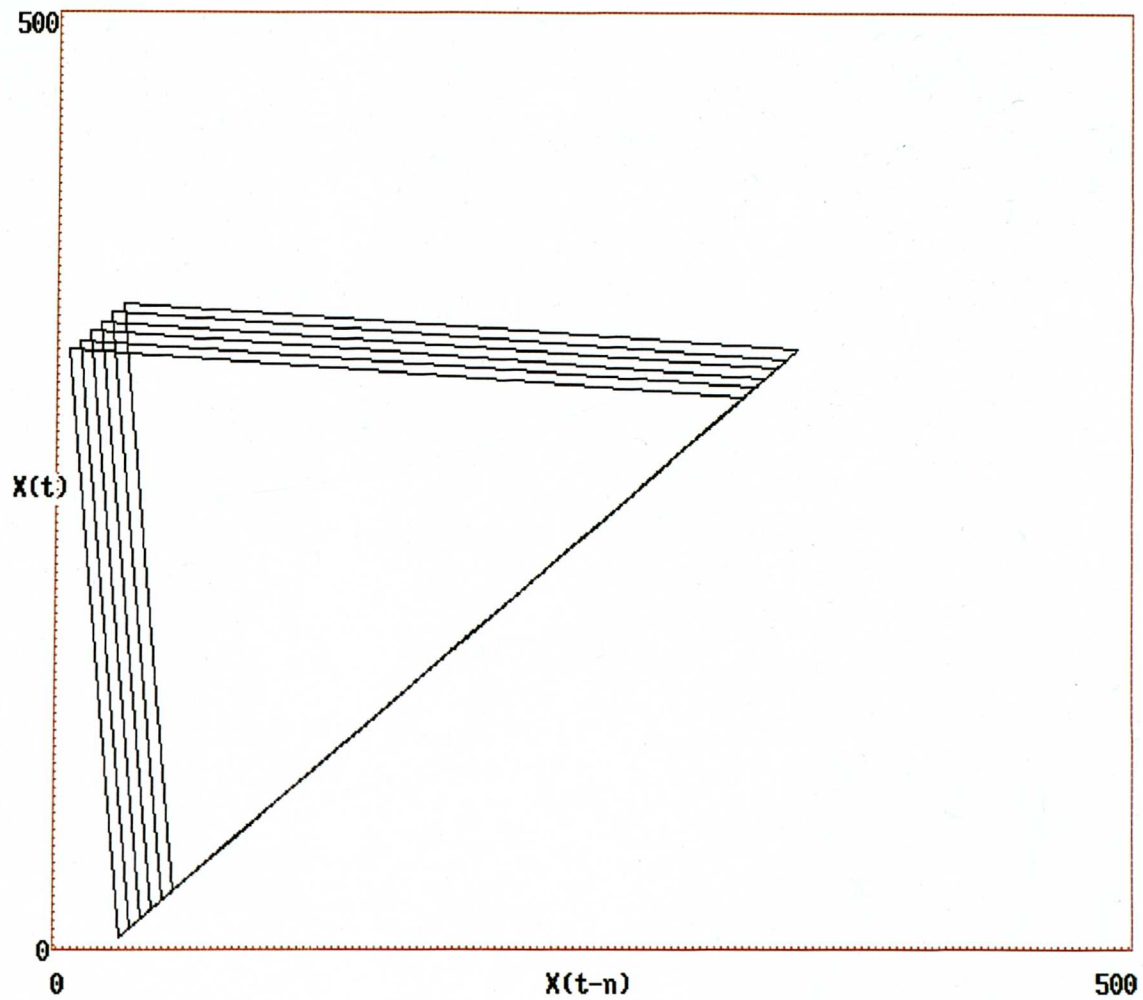


Figure 6.19 – Warehouse 1 attractor, Demand = 25.

Graph shows Inventory at time (t) against Inventory at time $(t-1)$ where (n) is equal to 1. Customer demand is equal to 25 units per day.

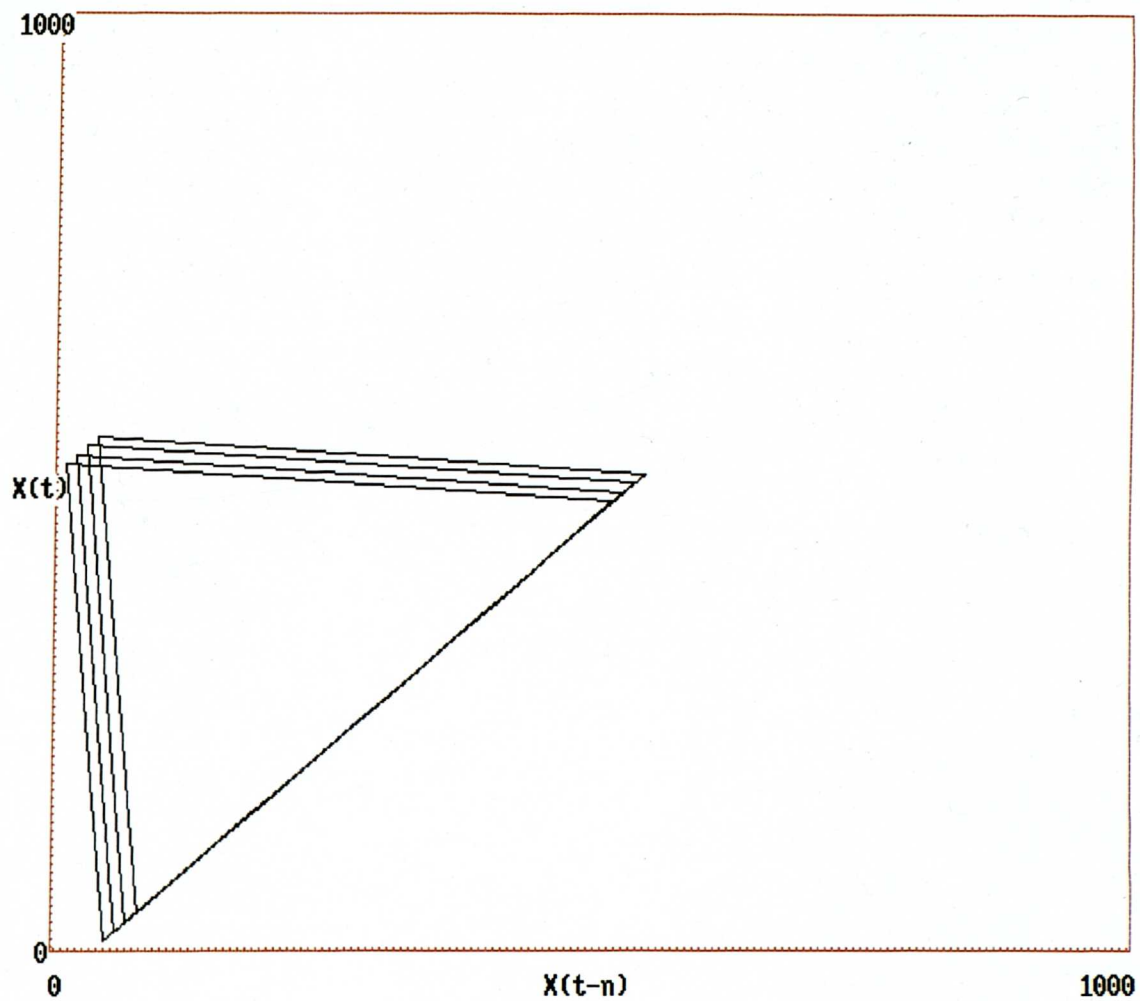


Figure 6.20 – Warehouse 1 attractor, Demand = 40.

Graph shows Inventory at time (t) against Inventory at time (t-n) where (n) is equal to 1. Customer demand is equal to 40 units per day.

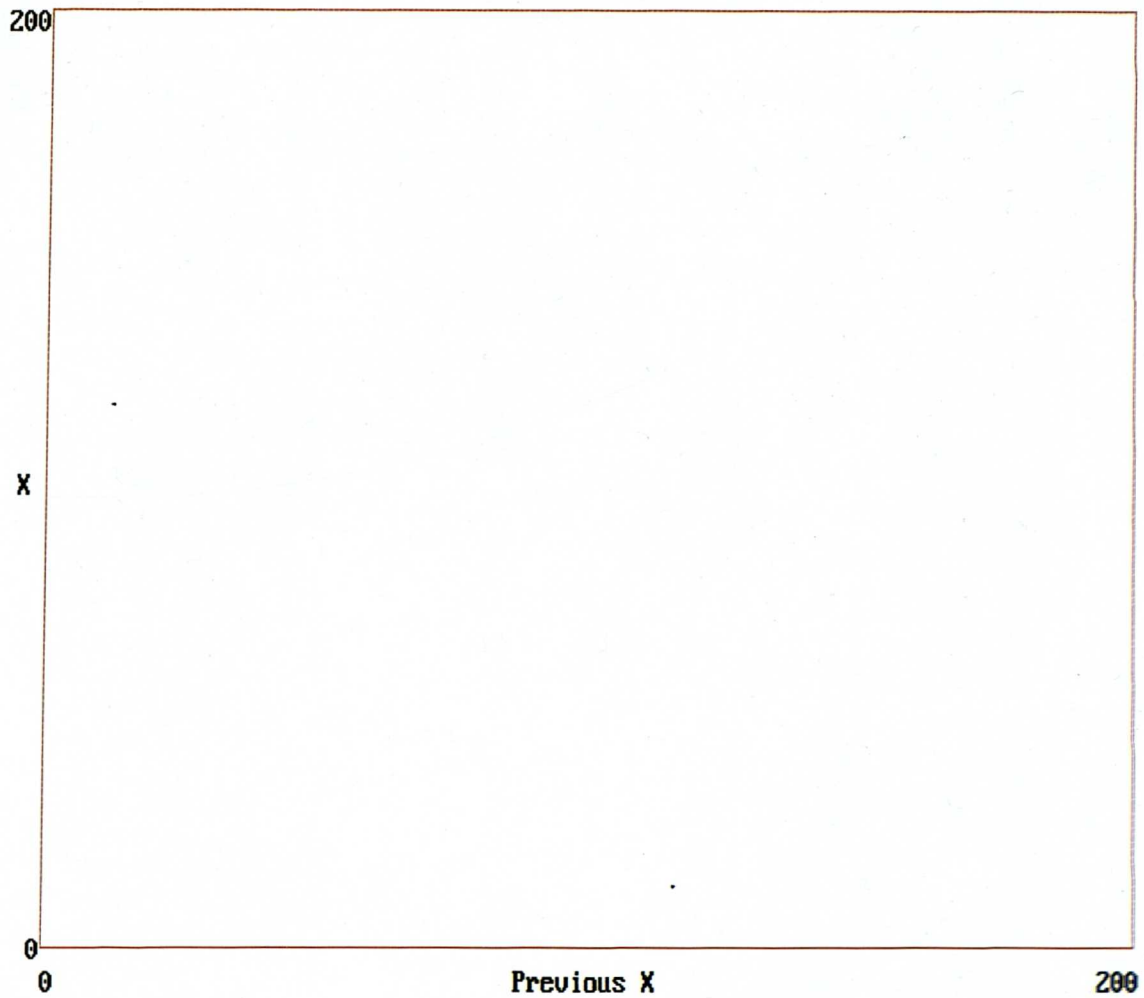


Figure 6.21 – Return Map Warehouse 1, Demand = 10.

Graph shows a "slice" through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 10 units per day. The map indicates that the data is following a fixed path, thus generating a two tightly clustered points on the map.

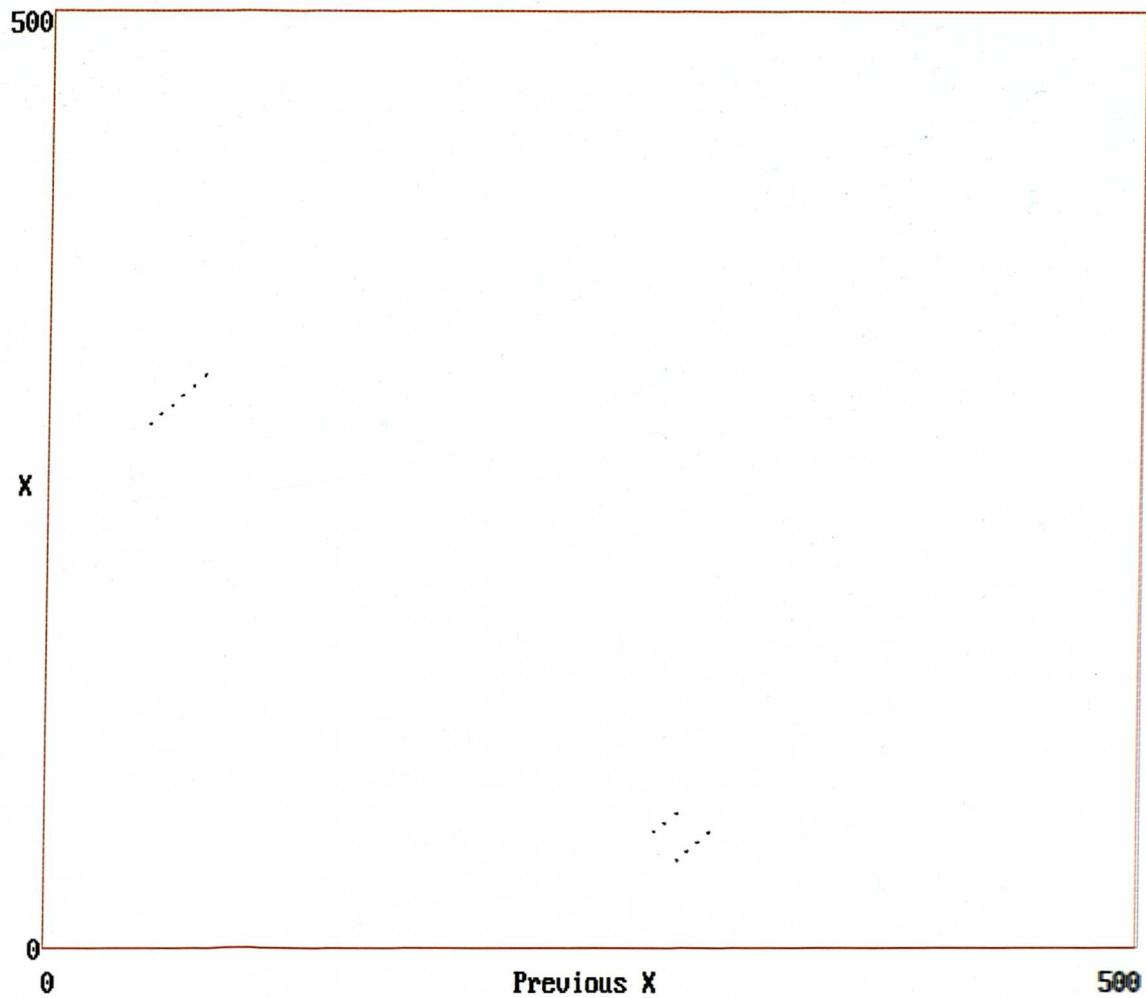


Figure 6.22 – Return Map Warehouse 1, Demand = 25.

Graph shows a “slice” through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 25 units per day. The map indicates that the data follows a number of trajectories this may indicate quasi-periodic behaviour.

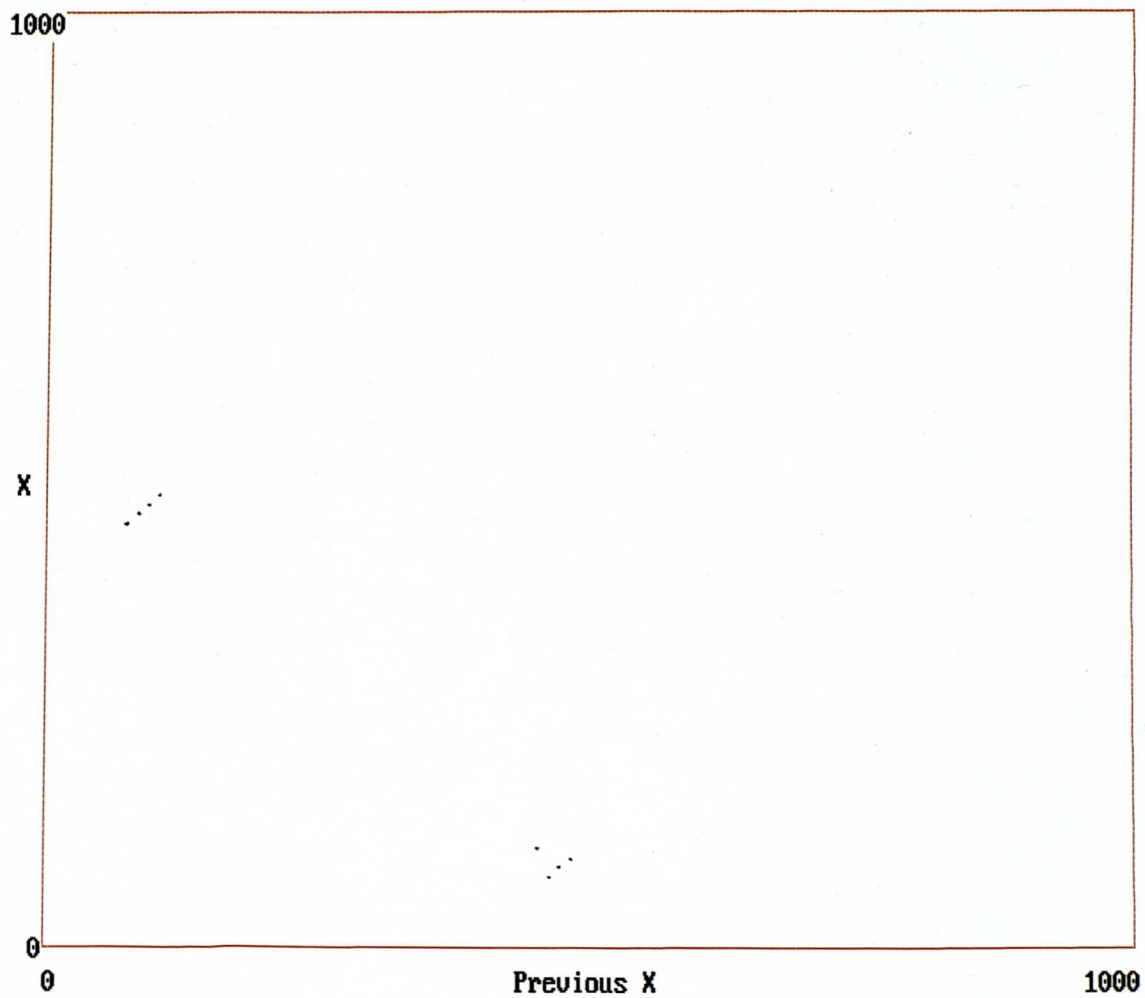


Figure 6.23 – Return Map Warehouse 1, Demand = 40.

Graph shows a “slice” through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 40 units per day. The map indicates that the data is follows a number of trajectories this may indicate quassi-periodic behaviour.

| FOR WAREHOUSE 1 | DEMAND = 10 | | DEMAND = 25 | | DEMAND = 40 | |
|--------------------------------|-------------------|----------------------|-------------------|----------------|-------------------|----------------|
| Data analysed | Lyapunov Exponent | Difference to set 1. | Lyapunov Exponent | Diff. to set 1 | Lyapunov Exponent | Diff. to set 1 |
| Set 1 – Edited | 0.142 | | 0.071 | | 0 | |
| Set 2 – check for boundedness. | 0.141 | 0.001 | 0.066 | 0.005 | 0.015 | -0.015 |
| Set 3 – check for boundedness. | 0.145 | -0.003 | 0.077 | -0.006 | 0 | 0.000 |
| Surrogate data | 0.659 | -0.517 | 0.731 | -0.660 | 0.745 | -0.745 |
| | | | | | | |

Table 6.1 – Investigation One - Lyapunov Exponents for Warehouse 1 Inventory Data.

Table shows Lyapunov exponent values for the Inventory Data within Warehouse 1. Data set 1 is the edited warehouse inventory data with the initial conditions edited out. Set 2 and Set 3 are generated by splitting Set 1 into two halves (Set 2 and Set 3). The Lyapunov exponent values for the 3 data sets are not significantly different, thus indicating that the data is reasonably bounded. The surrogate data is generated from data set 1, the Lyapunov exponents for the surrogate data can be seen to be significantly different to the values calculated for the original data set (Set 1). This indicates that the original data (set 1) does not readily conform to the null hypothesis.

b) Warehouse 2

Figure 6.24, 6.25 and 6.26 show sample data of 250 data series from warehouse 2 for daily demand of 10, 25 and 40 respectively. Unlike warehouse 1 (see figures 6.15, 6.16 and 6.17) no obvious periodic or quasi-periodic behaviour is present within the time frame for which the data is viewed. The sharp peaks witnessed for demand equal to 25 and 40 occur because the system readjusts the cover level and these are followed by times of seeming stability.

Figure 6.27, 6.28 and 6.29 show the attractors for warehouse 2 generated for daily demand levels of 10, 25 and 40 respectively. These can be seen to be complex in nature, it should be emphasised that the “square spiral” witnessed in figure 6.27 is built up in a random fashion. Figure 6.28 and 6.29 shows two characteristic areas in the plot. The warehouse switches between these modes of attraction. It is interesting that this occurs at the higher demand levels as this may indicate the demand “driving” the system into different orbits of attraction. These figures would seem to indicate either long period complex quasi-periodic behaviour or chaos.

Figure 6.30, 6.31 and 6.32 show the return maps for daily demand equal to 10, 25 and 40. These slices through the attractor show a large number of “cuts” passing through the map and a distinctive structure which is characteristic of chaos. Figures 6.31 and 6.32 show an interesting region to the left of the maps where the points seem to fold. Again this type of structure is characteristic of chaotic systems.

The Lyapunov exponent values in Table 6.2 are all positive for warehouse 2 indicating sensitivity to initial conditions. The Lyapunov exponent values for sets 2 and 3 show the system to be bounded. The surrogate data generated from the data series

produced Lyapunov exponent values significantly different from the original data series indicating the data does not readily conform to the null hypothesis.

In summary, the data from warehouse 2 displays structure in phase space that is characteristic of a chaotic system or very long (greater than 2000 days) period quasi-periodic behaviour. Positive Lyapunov exponent values, for all levels of demand, also provides evidence of sensitivity to initial conditions. The data is bounded and analysis of surrogate data dispels the null hypothesis. In conclusion the data series for warehouse 2 in all cases would seem to be chaotic.

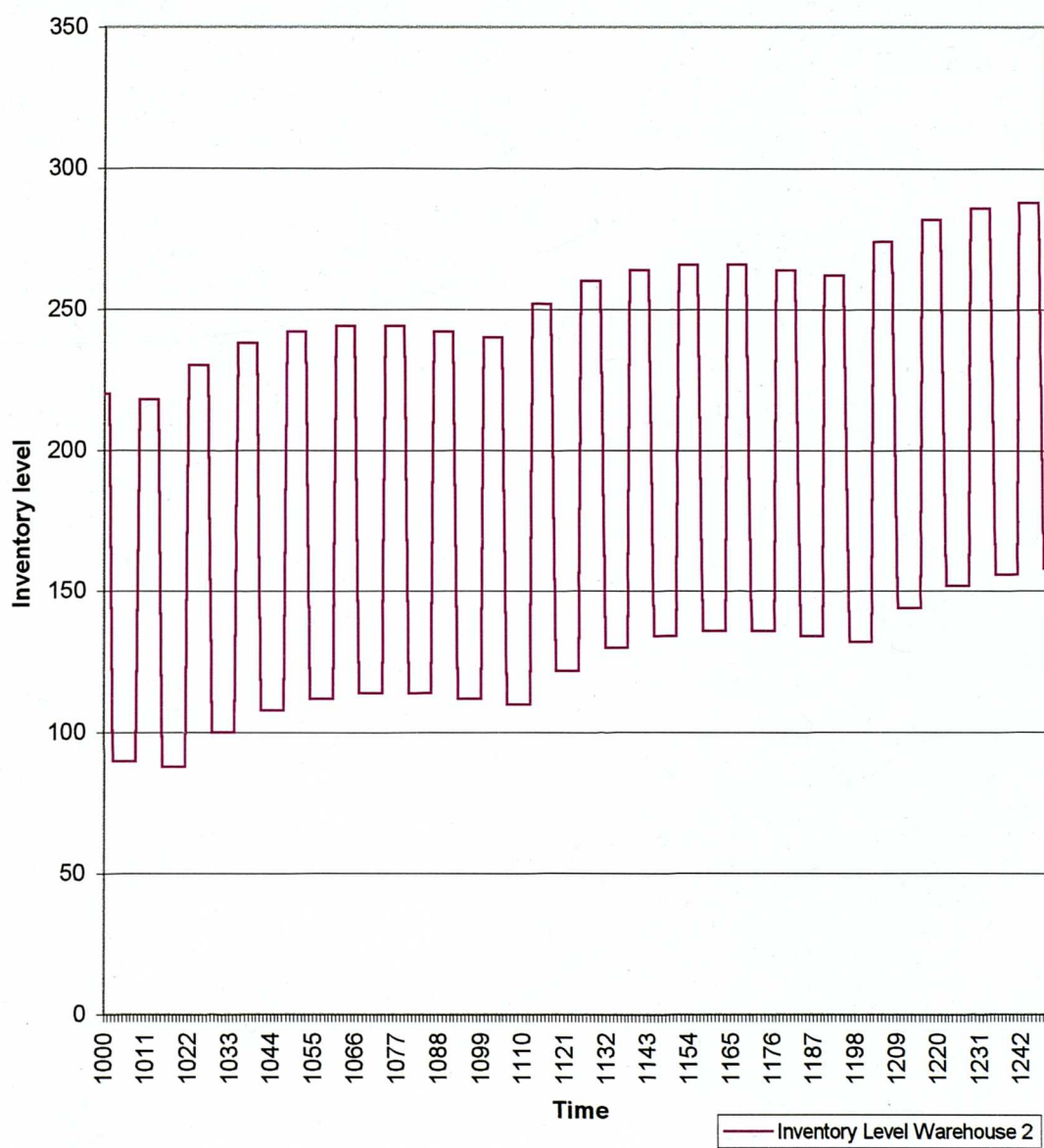


Figure 6.24 – Sample data series Warehouse 2, Demand = 10.

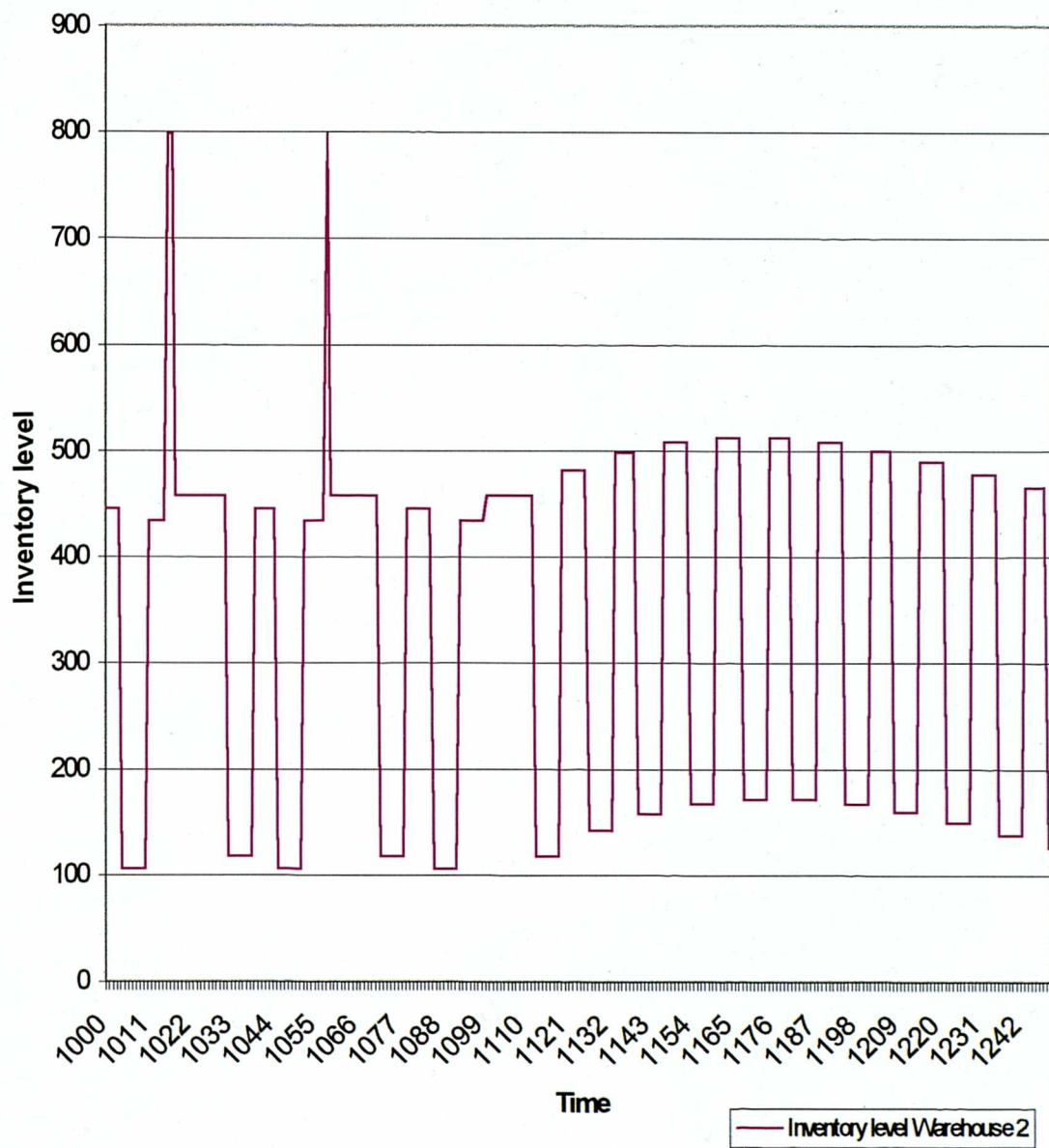


Figure 6.25 – Sample data series Warehouse 2, Demand = 25.

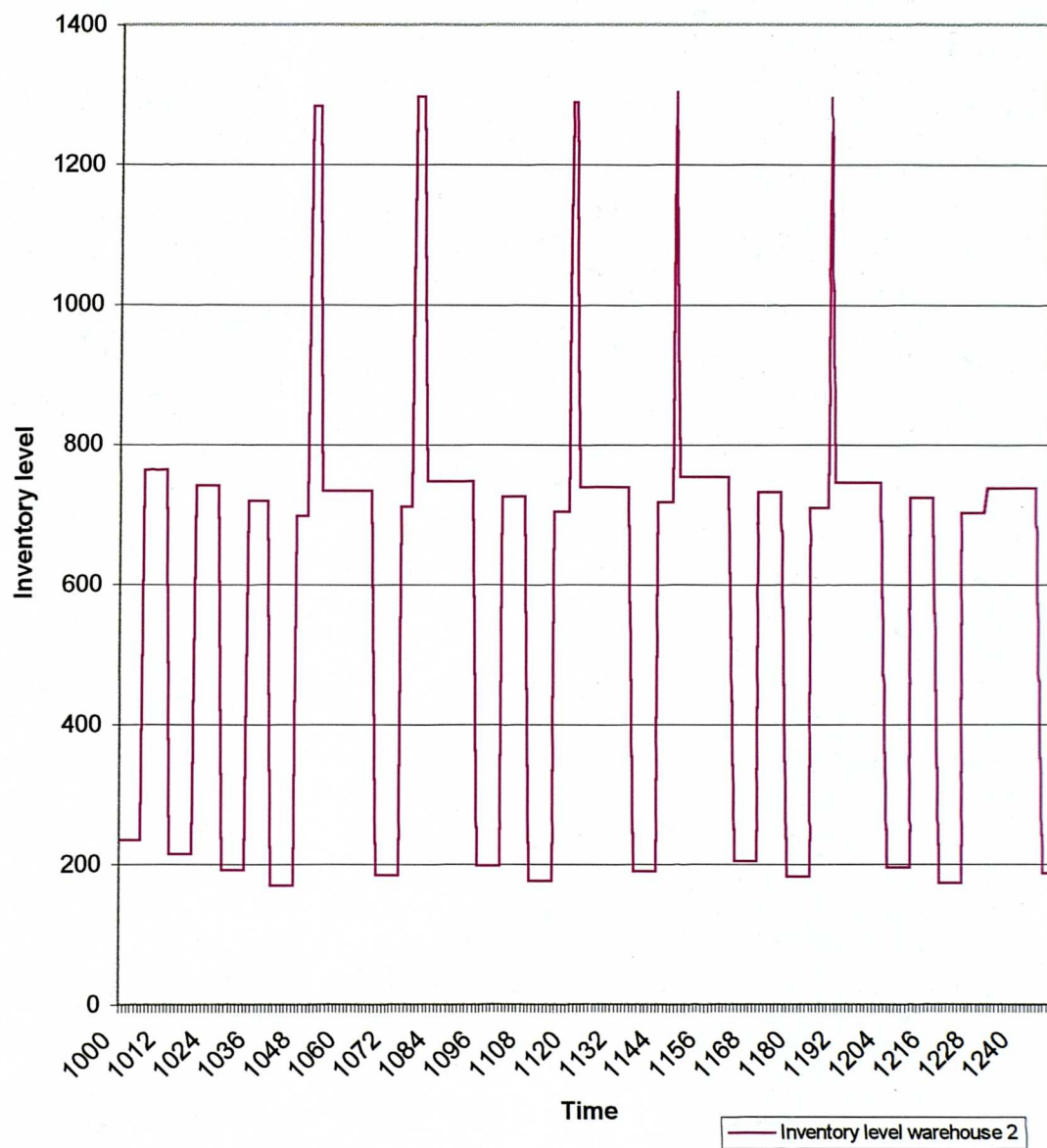


Figure 6.26 – Sample data series Warehouse 2, Demand = 40.

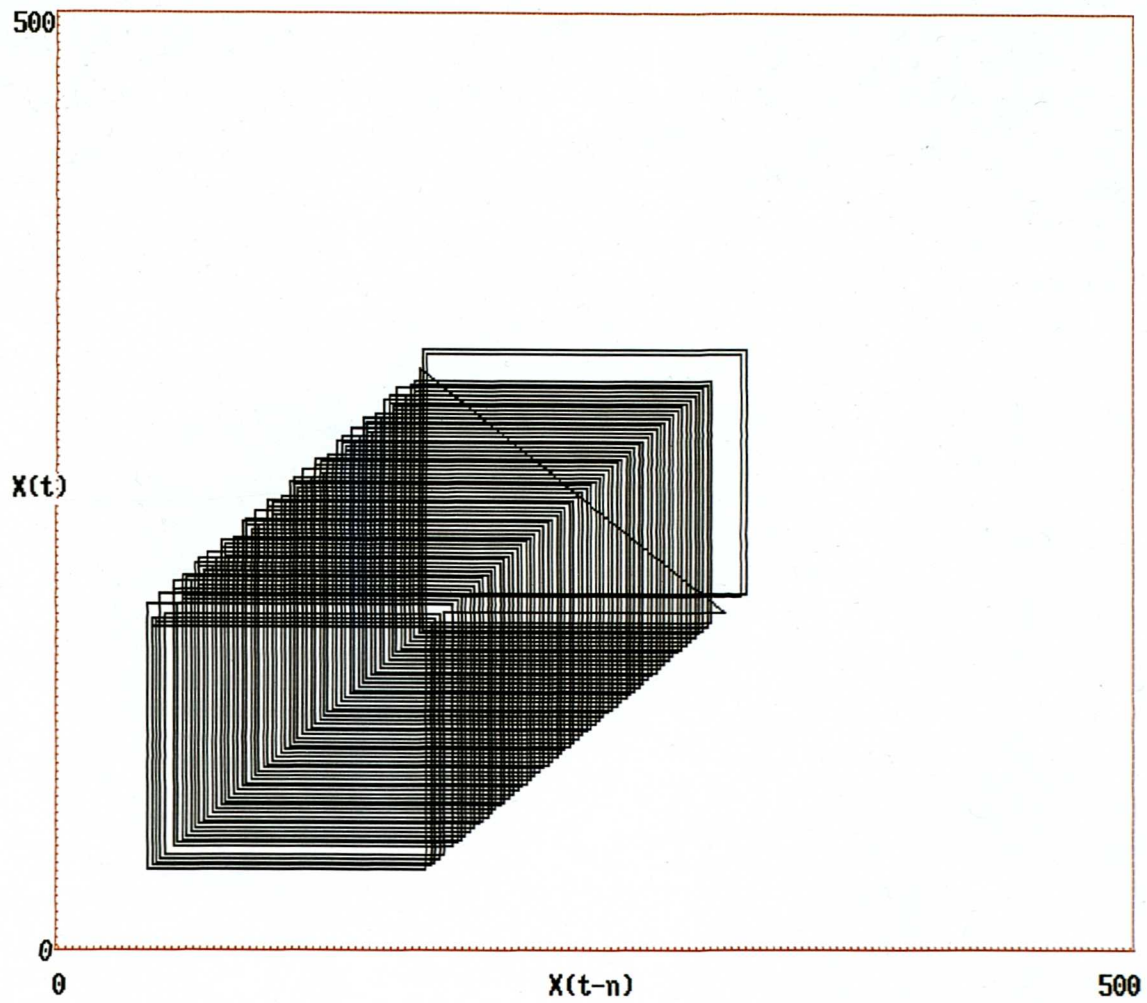


Figure 6.27 – Warehouse 2 attractor, Demand = 10.

Graph shows Inventory at time (t) against Inventory at time (t-n) where (n) is equal to 1. Customer demand is equal to 10 units per day.

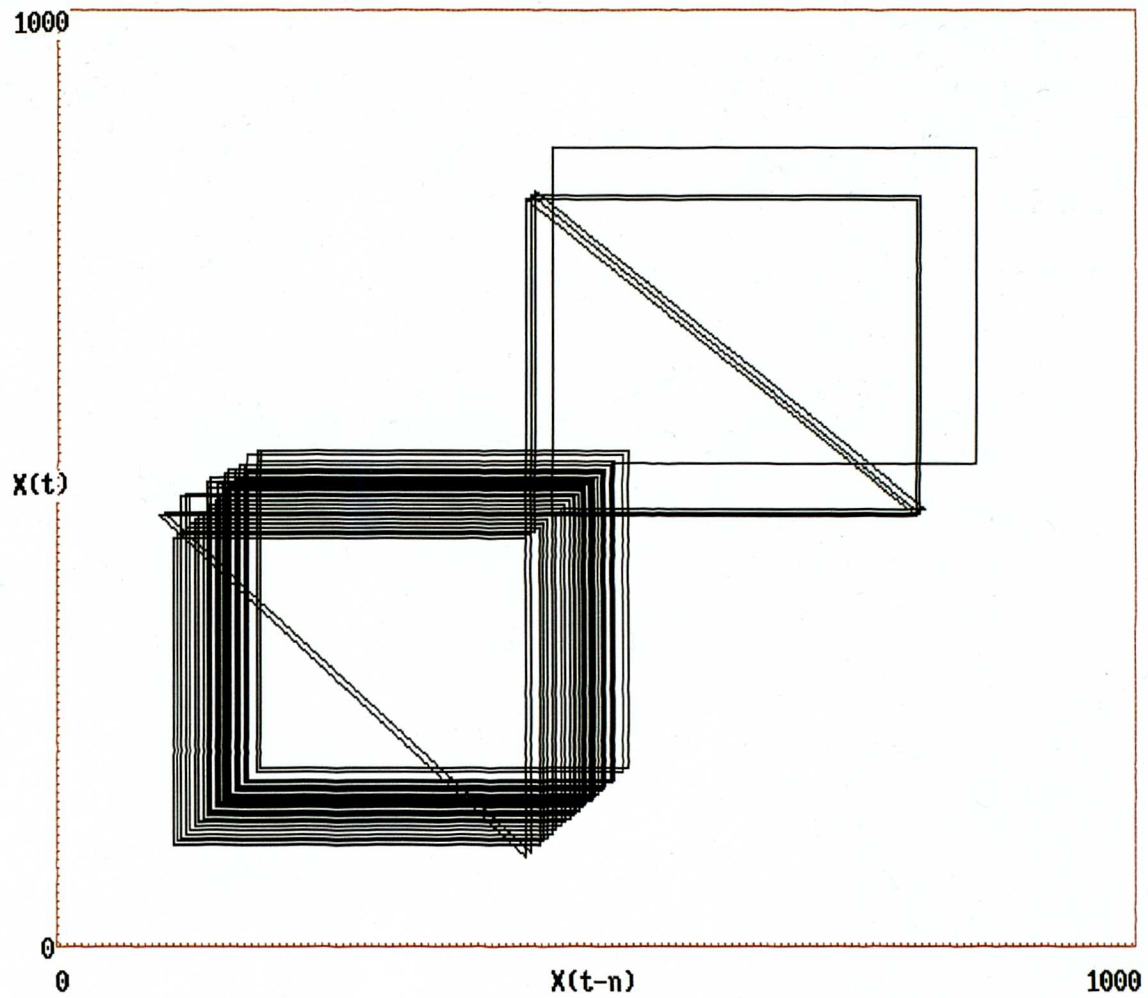


Figure 6.28 – Warehouse 2 attractor, Demand = 25.

Graph shows Inventory at time (t) against Inventory at time (t-n) where (n) is equal to 1. Customer demand is equal to 25 units per day.

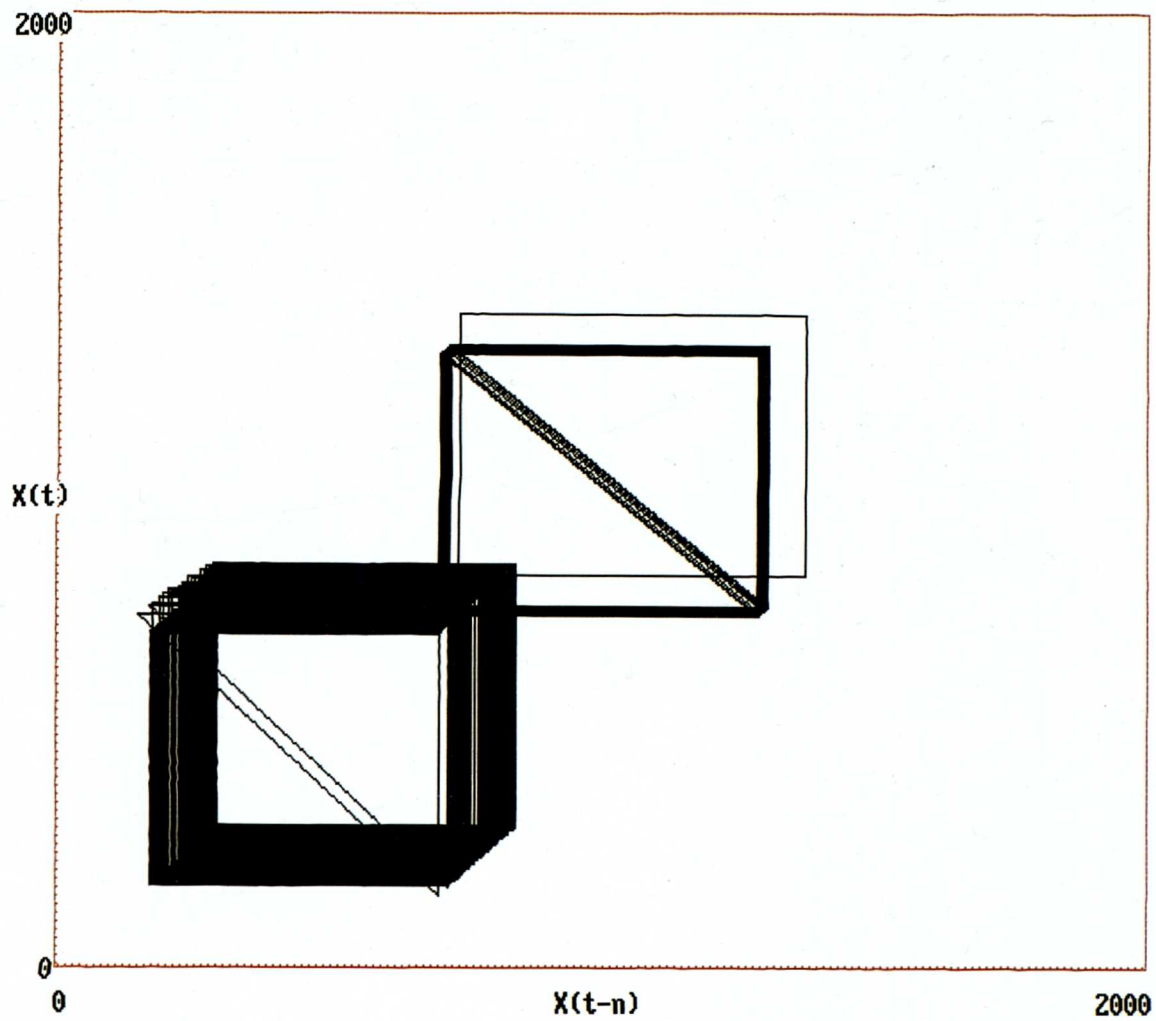


Figure 6.29 – Warehouse 2 attractor, Demand = 40.

Graph shows Inventory at time (t) against Inventory at time (t-n) where (n) is equal to 1. Customer demand is equal to 40 units per day.

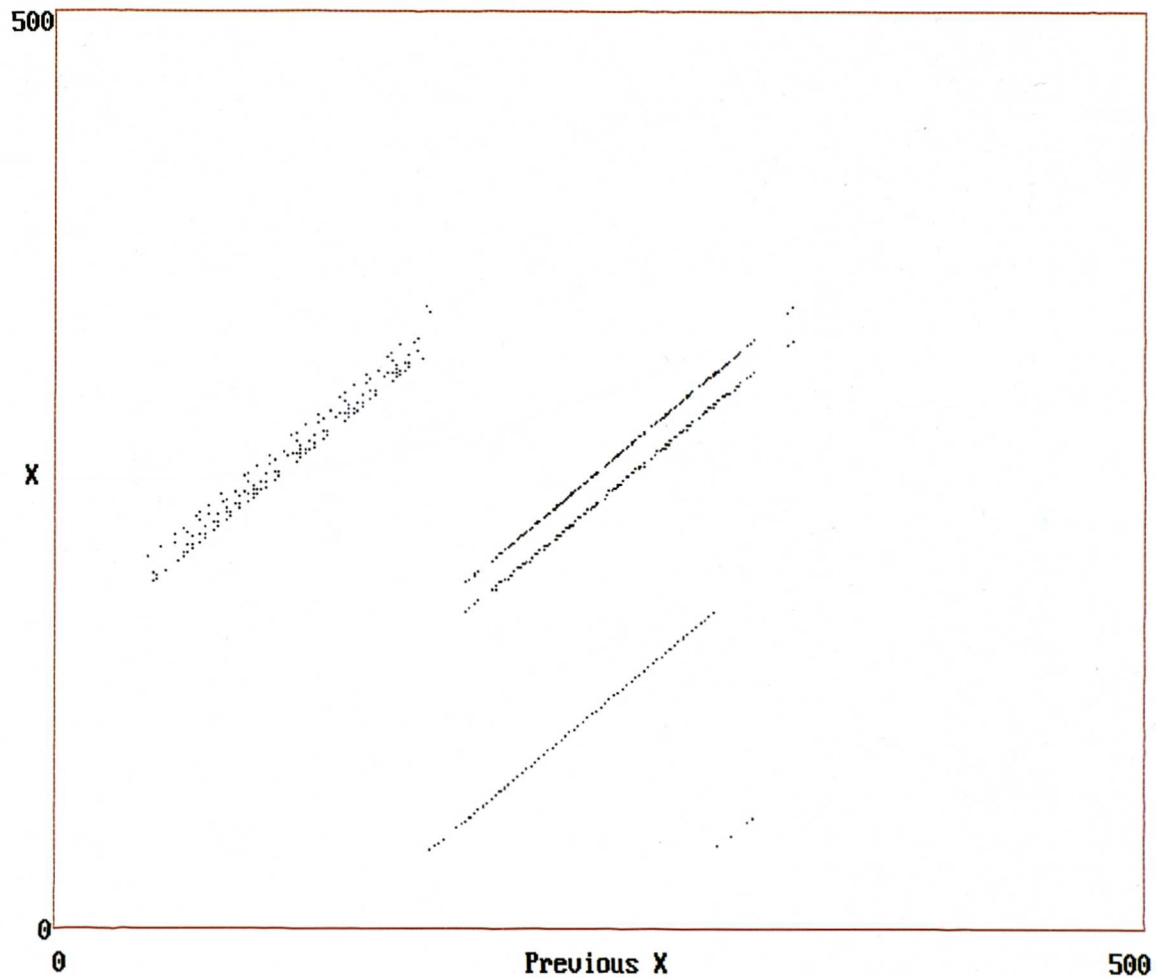


Figure 6.30 – Return Map Warehouse 2, Demand = 10.

Graph shows a “slice” through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 10 units per day. The structure and large number of trajectories passing through the map indicates chaos.

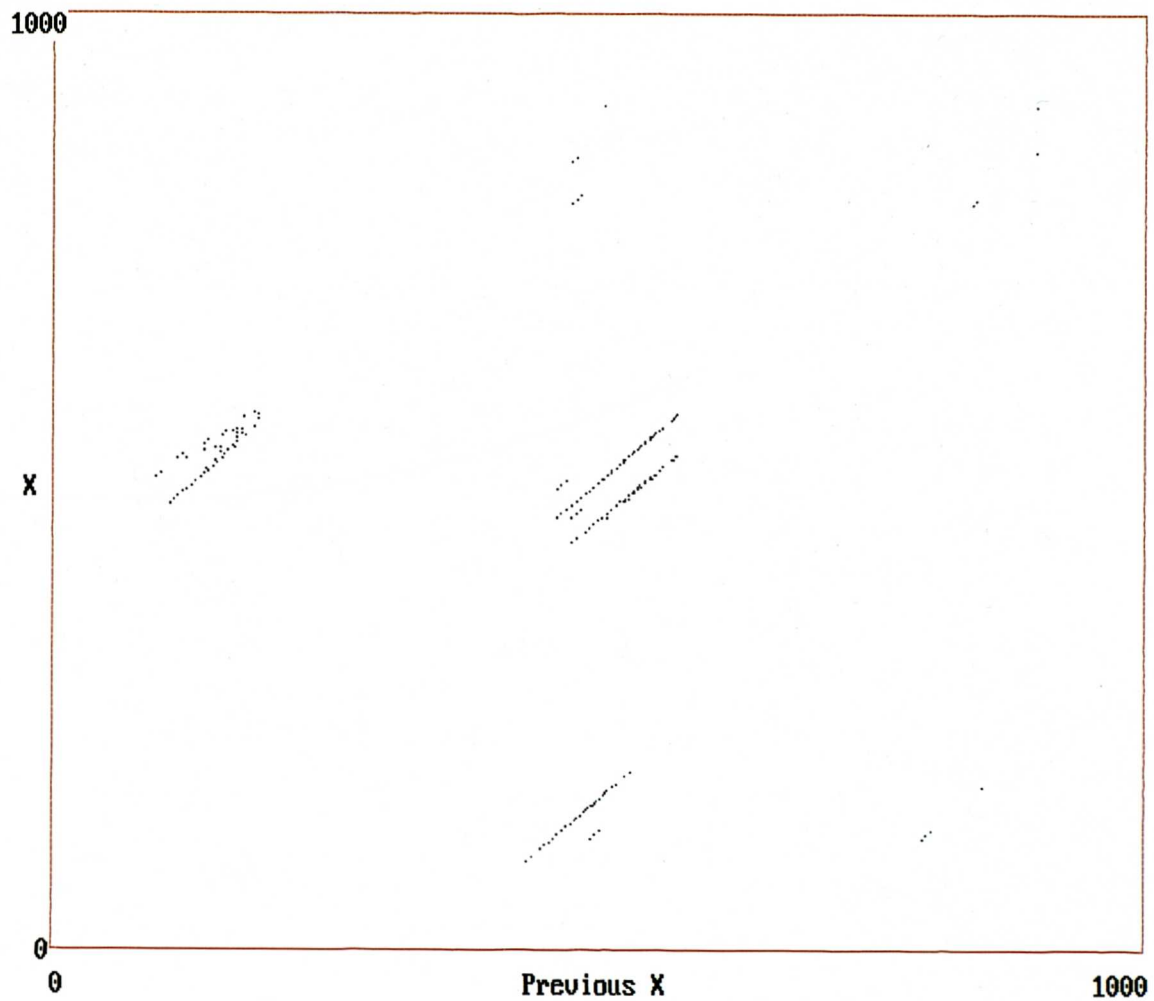


Figure 6.31 – Return Map Warehouse 2, Demand = 25.

Graph shows a “slice” through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 25 units per day. The structure and large number of trajectories passing through the map indicates chaos. Note also a characteristic folding of the data on the left of the diagram,

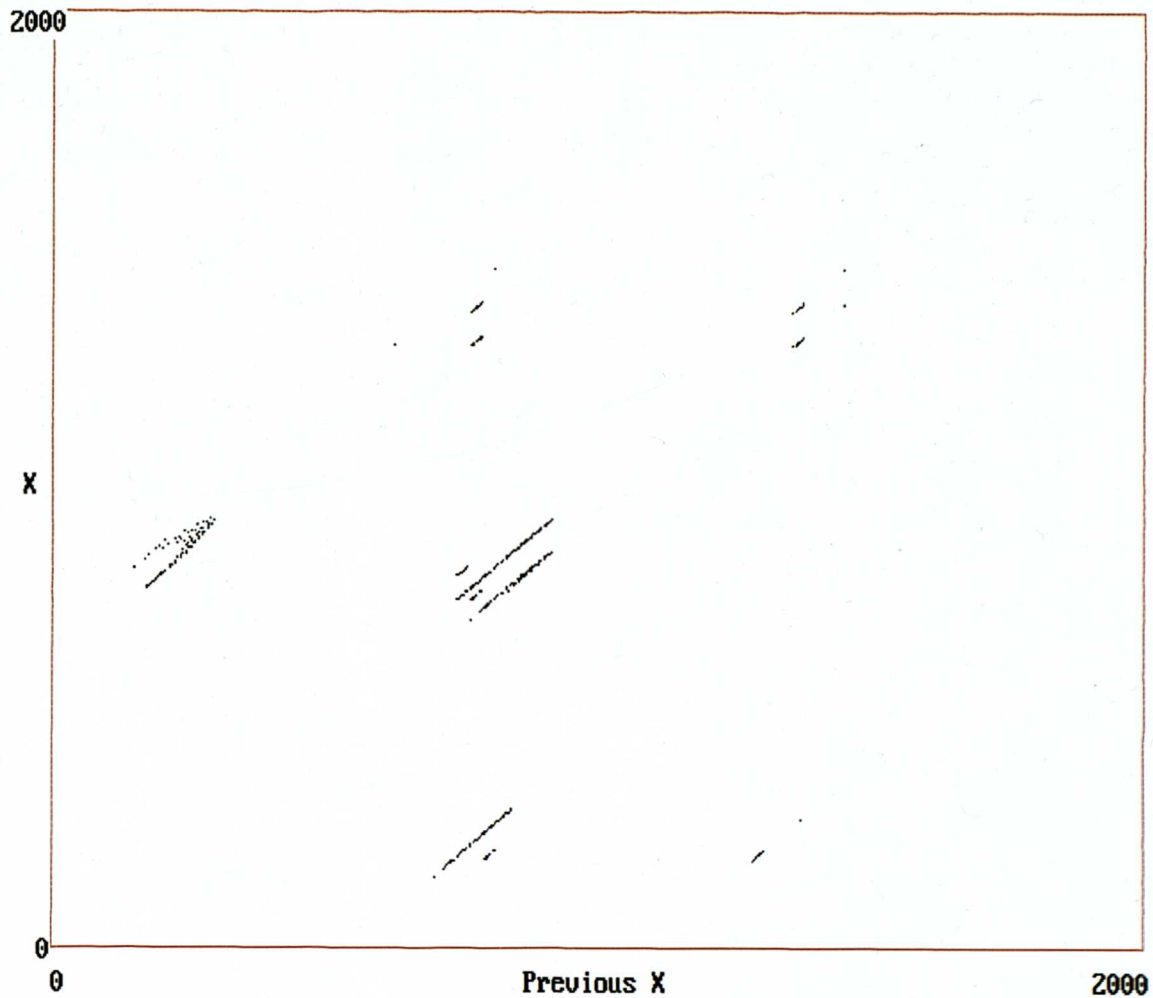


Figure 6.32 – Return Map Warehouse 2, Demand = 40.

Graph shows a "slice" through the attractor generated by plotting Inventory value (x) plotted against previous inventory. Customer demand is equal to 40 units per day. The structure and large number of trajectories passing through the map indicates chaos. Note also a characteristic folding of the data on the left of the diagram,

| FOR WAREHOUSE 2 | DEMAND = 10 | | DEMAND = 25 | | DEMAND = 40 | |
|--------------------------------|-------------------|---------------------|-------------------|----------------|-------------------|----------------|
| Data analysed | Lyapunov Exponent | Difference to set 1 | Lyapunov Exponent | Diff. to set 1 | Lyapunov Exponent | Diff. to set 1 |
| Set 1 – Edited | 0.145 | | 0.407 | | 0.477 | |
| Set 2 – check for boundedness. | 0.162 | -0.017 | 0.389 | 0.018 | 0.421 | 0.056 |
| Set 3 – check for boundedness. | 0.122 | 0.023 | 0.423 | -0.016 | 0.503 | -0.026 |
| Surrogate data | 0.217 | -0.171 | 0.207 | 0.200 | 0.260 | 0.217 |
| | | | | | | |

Table 6.2 – Investigation One - Lyapunov Exponents for Warehouse 2 Inventory Data.

Table shows Lyapunov exponent values for the Inventory Data within Warehouse 2. Data set 1 is the edited warehouse inventory data with the initial conditions edited out. Set 2 and Set 3 are generated by splitting Set 1 into two halves (Set 2 and Set 3). The Lyapunov exponent values for the 3 data sets are not significantly different, thus indicating that the data is reasonably bounded. The surrogate data is generated from data set 1, the Lyapunov exponents for the surrogate data can be seen to be significantly different to the values calculated for the original data set (Set 1). This indicates that the original data (set 1) does not readily conform to the null hypothesis.

c) Relationship between warehouse 1 and 2 inventory

Figures 6.33, 6.34 and 6.35 show the relationship between the inventory in warehouse 1 and 2 for daily demand of 10, 25 and 40 respectively. These were plotted from a small part of the time series. It is of interest that a characteristic pattern is present which never repeats exactly. It is also of interest that the spikes of inventory occurring in warehouse 2 which force the system into a different orbit of attraction tend to occur when the inventory in warehouse 1 is below a certain level (for example, in figure 6.34 they occur when the inventory in warehouse one is below 100 units). The pattern and relationship could possibly be used for prediction between certain limits.

d) Demonstration of sensitivity to initial conditions.

Figure 6.36 demonstrates the effect of sensitivity to initial conditions within warehouse 2. This is a somewhat crude experiment; but it gives a useful insight into the dynamics. It can be seen that slightly differing initial stock levels over time results in the graphs diverging. In the case where a small random input is placed over the initial demand the random input seems to temporarily stabilise the dynamics. However after a certain period a series of chaotic spikes can be observed.

e) Conclusion

In conclusion, the results described above provide direct evidence that deterministic chaos can be generated in a real automated warehouse supply chain where no misperceptions about demand or its environment are present. The non-linear nature of the system would, under conditions not uncommon in the real world, readily generate chaotic behaviour. This behaviour results in uncertainty within the supply chain limiting the prediction horizon of the supply chain.

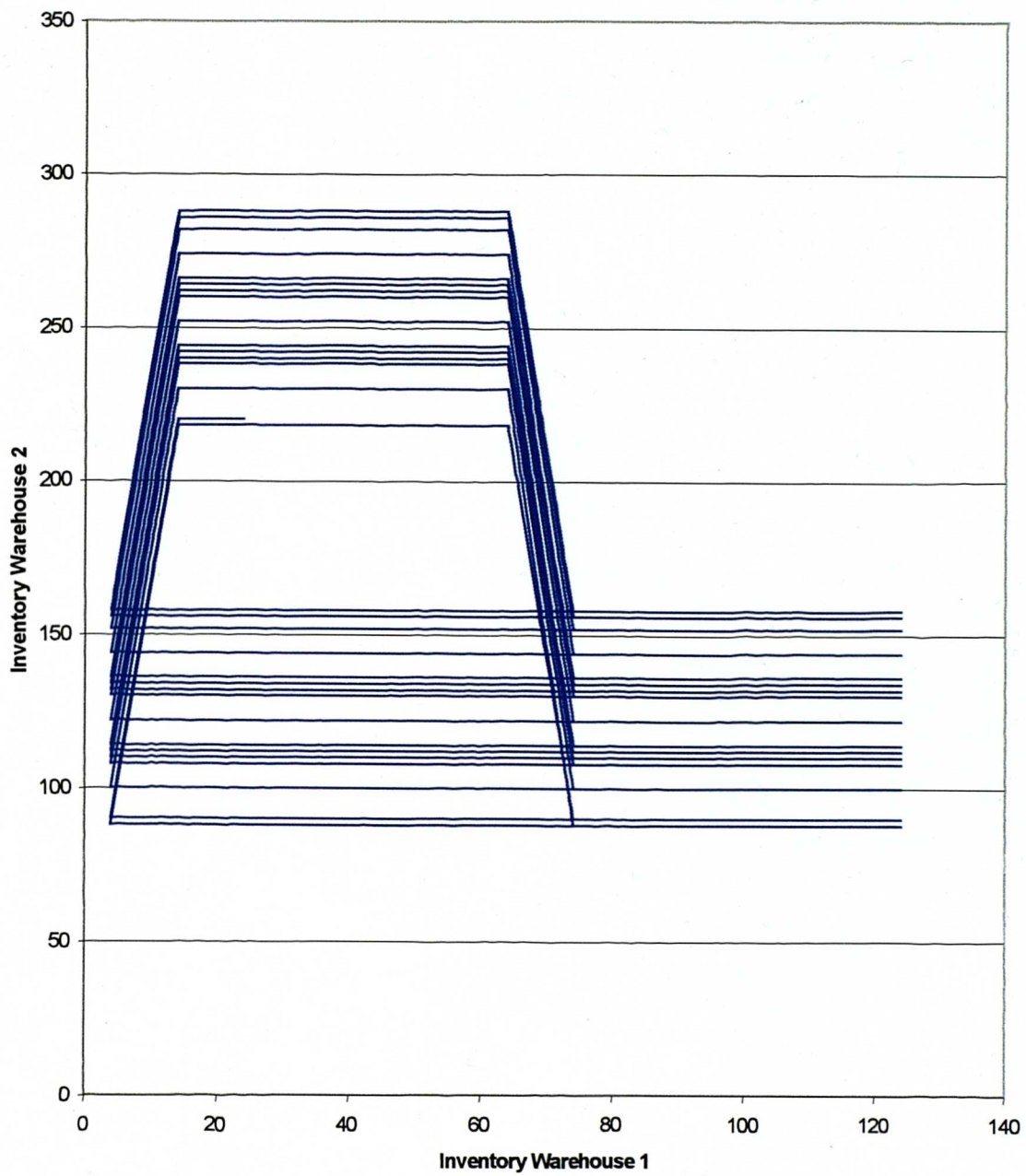


Figure 6.33 – Relationship between Warehouse 1 inventory level and Warehouse 2 inventory level, Demand = 10.

Graph shows relationship between warehouse inventory levels for 250 time periods (1000-1250). Note repeating pattern however pattern never repeats exact values thus covering the phase space.

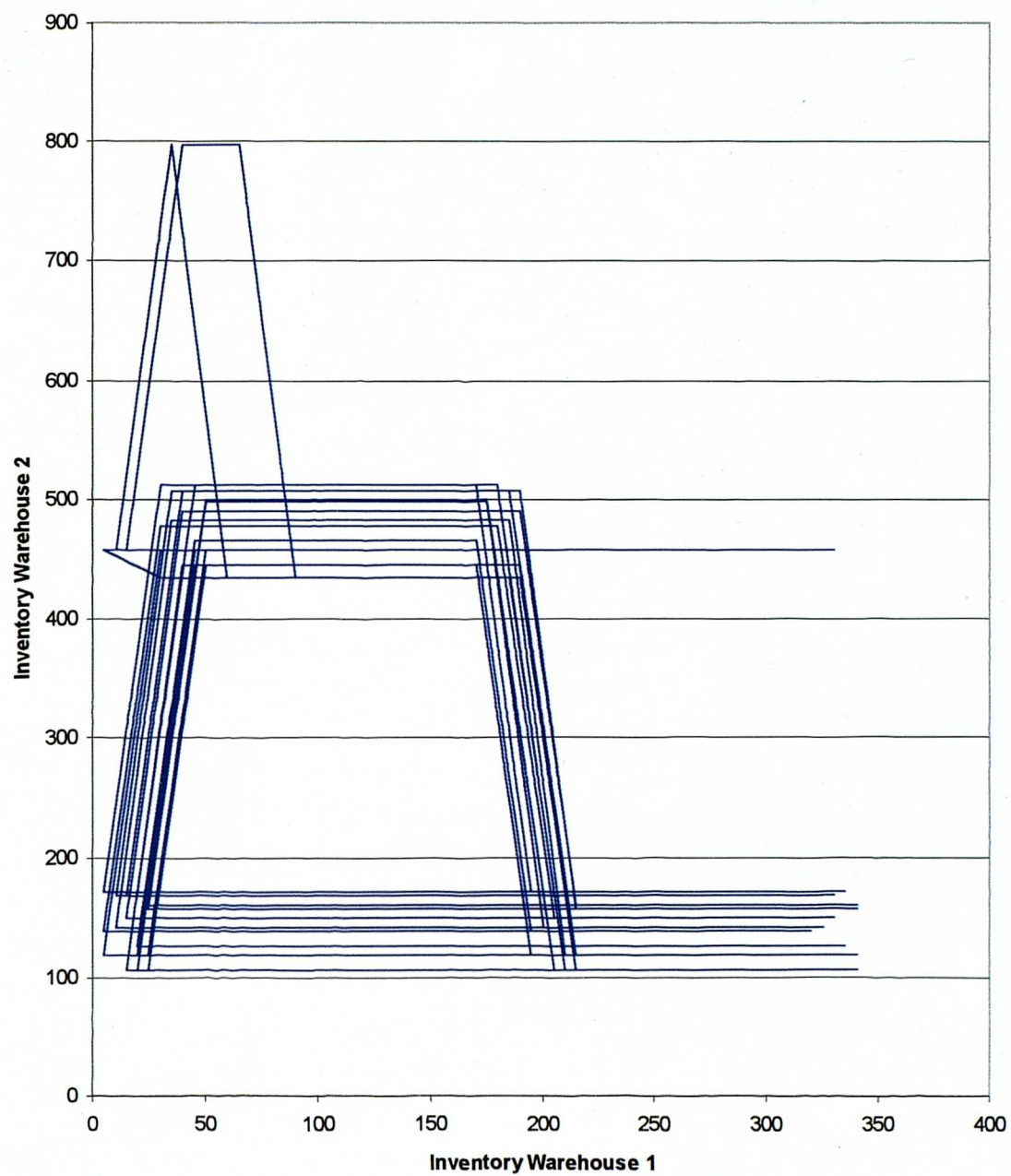


Figure 6.34 – Relationship between Warehouse 1 inventory level and Warehouse 2 inventory level, Demand = 25.

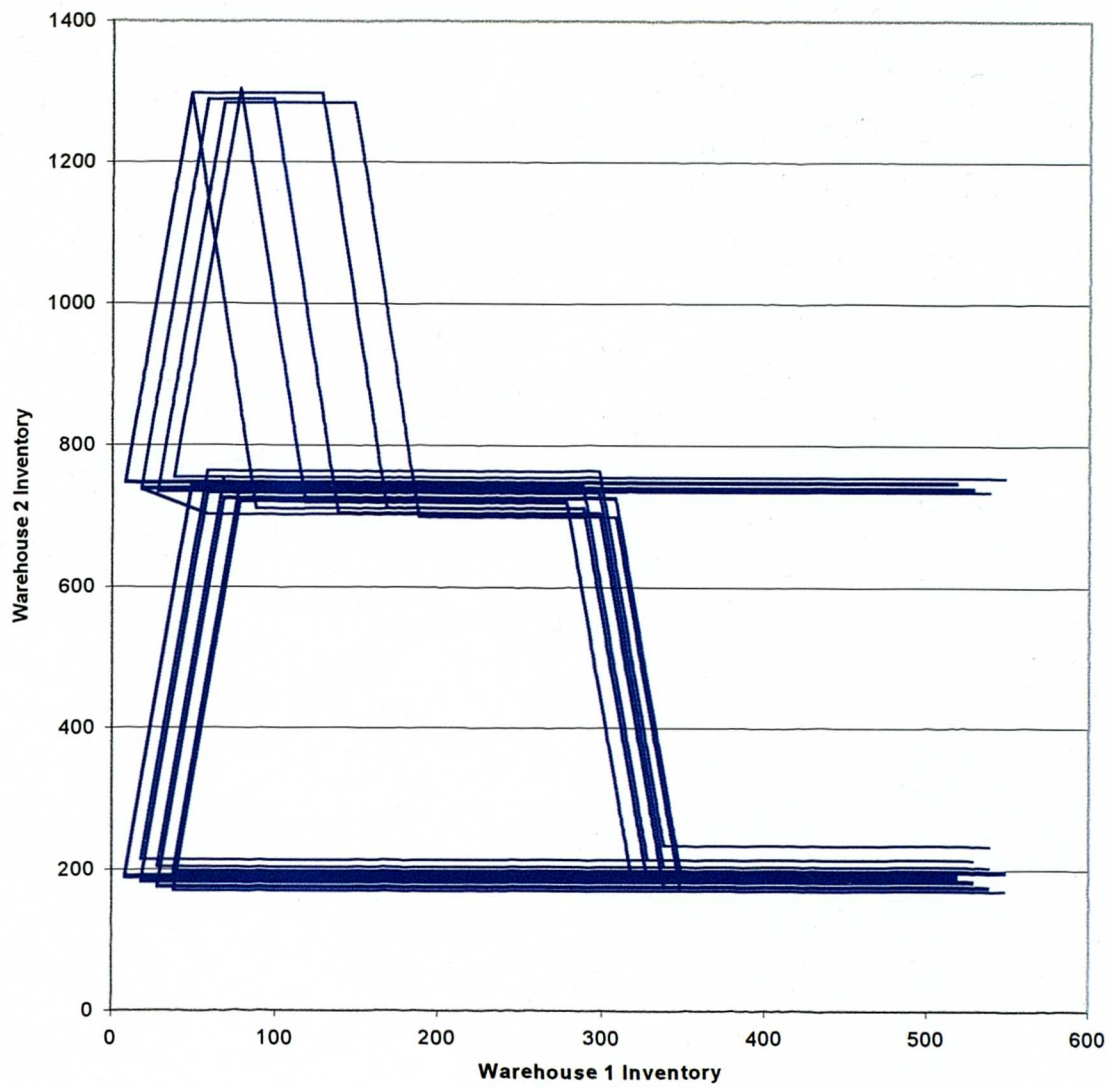


Figure 6.35 – Relationship between Warehouse 1 inventory level and Warehouse 2 inventory level, Demand = 40.

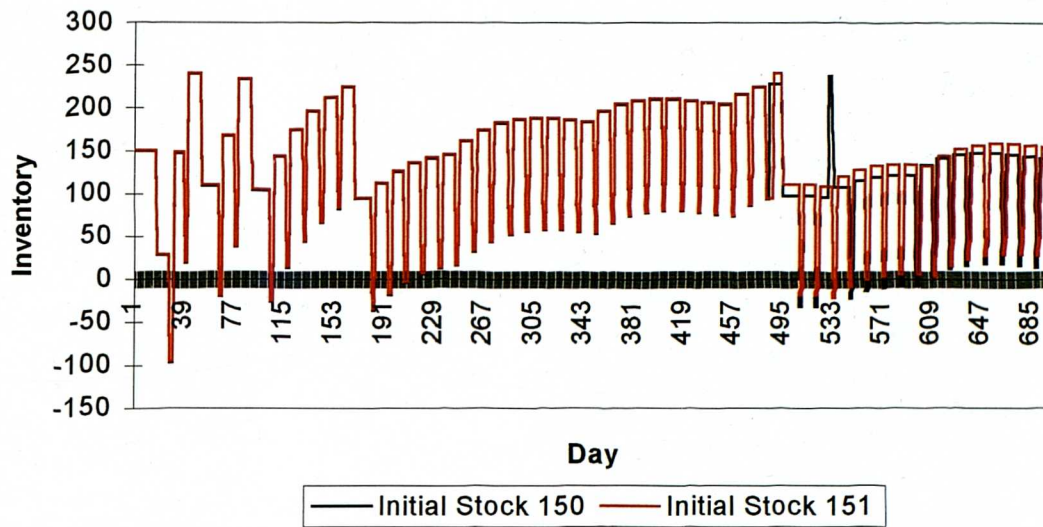


Figure 6.36a – Inventory in Warehouse 2 for slightly different initial stock levels.

Note the divergence of the data series at Day 457 and “Chaotic spike” at approximately Day 533.

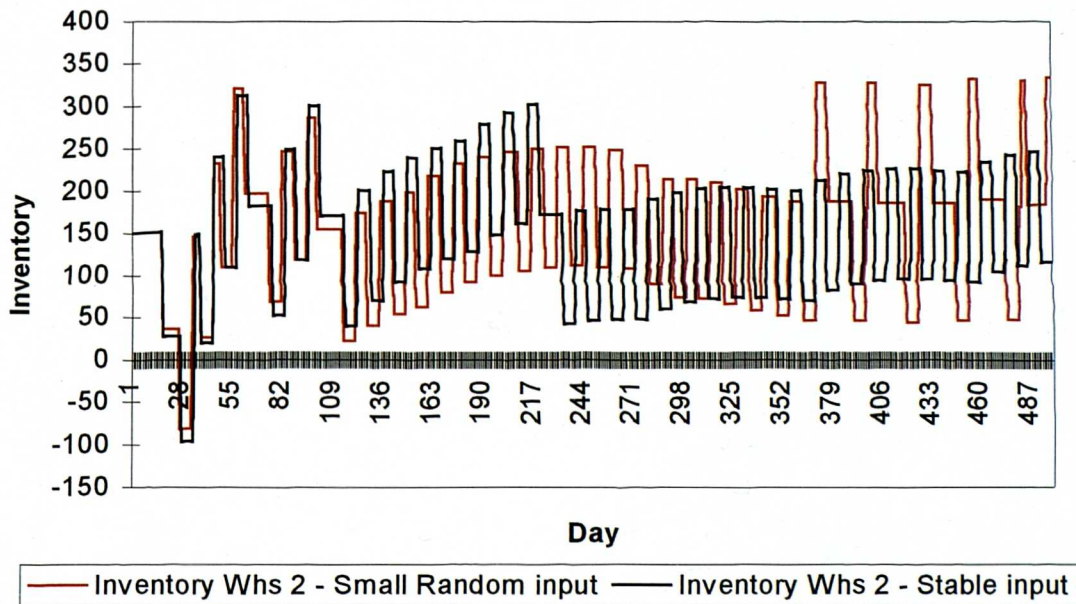


Figure 6.36b – Inventory in warehouse 2 for same starting conditions but using stable demand and demand with small random input.

Note that data series with small random input seems to stabilise between Day 136 and 179. This is then followed by a series of “chaotic spikes”.

Figure 6.36 – Demonstrations of sensitivity to initial conditions within Warehouse 2.

6.8.3 Results of Investigation 2 – Impact on degree of chaos by increasing supply chain complexity through increasing the number of echelons.

a) Amplification of chaos in a five-warehouse supply chain.

Figure 6.37 shows the Average Prediction Horizon plotted against the echelon in a 5 warehouse supply chain for daily demand levels of 10, 25 and 40 units. It can be seen that as one proceeds from the customer up the supply chain the prediction horizon of the data reduces as the degree of chaos in each echelon increases. However, this increase is not indefinite, the prediction horizon plateaus at warehouse 2 or 3. In contrast, investigations into demand amplification indicate this form of uncertainty increases with each echelon of the supply chain. The fact that the degree of chaos is not continually increasing with each echelon tends to support what we find in the real industrial environment, as even a raw material producer can make effective forecasts in the short term. If chaos increased indefinitely then raw material producers would be unable to make any worthwhile forecasts.

Figure 6.38 depicts the average prediction horizon for supply chains with 1 to 5 warehouse echelons and daily demand of 10, 25 and 40. This graph reinforces the findings made in Figure 6.37 but the large data sample demonstrates the consistency of the observed effect and the plateau.

In both figure 6.37 and 6.38 the final warehouse in each supply chain is not plotted because “end effects” occurs within the supply chains due to the “perfect” supplier used at the end of the chain.

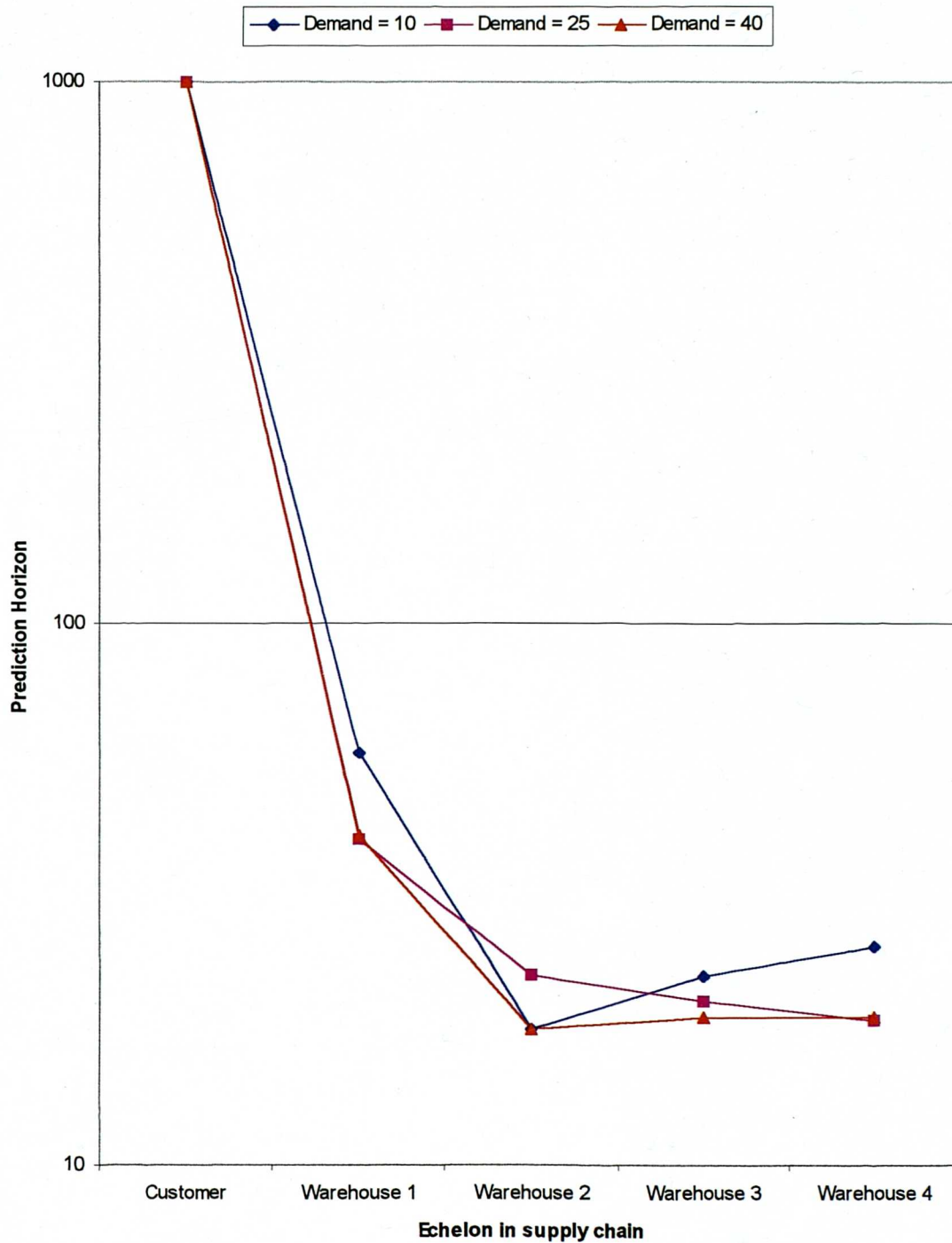


Figure 6.37 – Average Prediction Horizon against echelon in supply chain.

Graph shows average prediction horizon against echelon for 5-warehouse supply chain. The prediction horizon is seen to plateau as the number of echelons increases indicating that chaos is not indefinitely amplified as it passed down the supply chain.

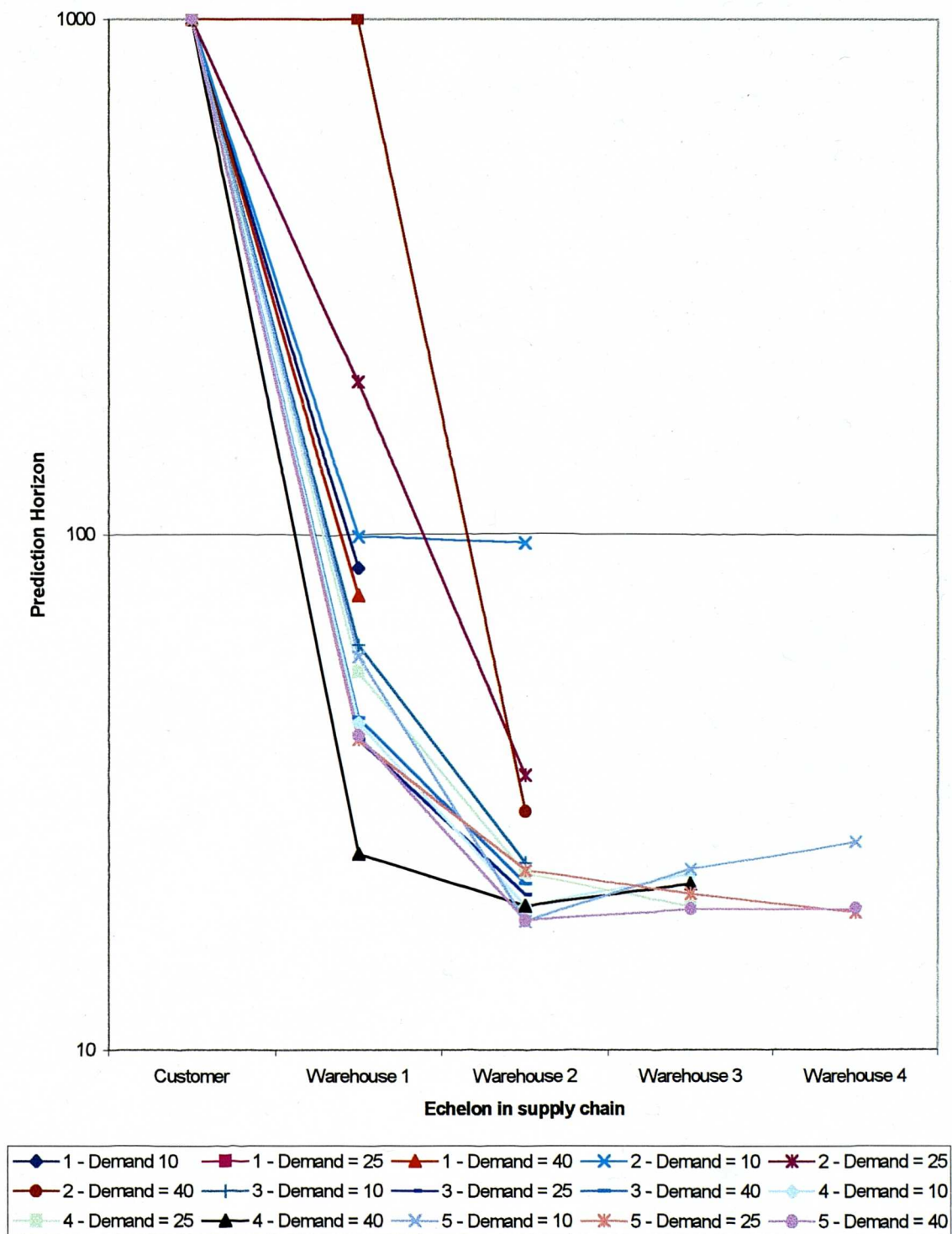


Figure 6.38 – Average Prediction Horizon against echelon in supply chain.

Graph shows average prediction horizon against echelon for supply chains with 1 to 5 warehouses and demand of 10, 25 and 40. The prediction horizon is seen to plateau as the number of echelons increases indicating that chaos is not indefinitely amplified as it passed down the supply chain.

b) Impact of increasing supply chain complexity on individual echelons in the supply chain

Figure 6.39 demonstrates the impact of having an increasing number of upstream echelons on warehouse 1. Warehouse 1 directly supplies the customer and therefore sees the constant demand. Mis-supply and shortages that may occur in the other upstream warehouses therefore affect its data series. As the number of echelons in the supply chain is increased the prediction horizon in warehouse 1 can be seen to exhibit a downward trend. This indicates that the degree of chaos in warehouse 1 increases as the number of echelons in the chain increases, this results in a reduced prediction horizon for its data series.

Figures 6.40, 6.41 and 6.42 show the prediction horizon for each warehouse in the supply chain as the number of echelons are increased for daily demand of 10, 25 and 40. These graphs reinforce the observations made from Figure 6.39 but also show that as the number of echelons in the supply chain increases all echelons experience a downward trend in prediction horizon and hence an increase in the degree of chaos present. (This would seem to indicate that supply chain reengineering where echelons are removed could reduce the amount of chaos for all echelons in the supply chain).

c) The Relationship between the data series of the echelons.

Figures 6.43, 6.44, 6.45, and 6.46 show the relationship between the inventory level in warehouse 1 and warehouse 2, 3, 4 and 5 respectively. Each figure shows a distinctive pattern that never repeats precisely, this is typical of a chaotic system. Figure 6.47 is the same as Figure 6.46, however all 2000 data points have been plotted to demonstrate how overtime the pattern starts to fill up the phase space.

d) Conclusion

In conclusion, investigation 2 has demonstrated that chaos within the supply chain is not amplified indefinitely but tends to plateau after passing through a number of echelons. This is in contrast to demand amplification that progressively increases with each echelon in the supply chain. Increasing the number of echelons in the supply chain results in a reduced prediction horizon for all warehouse echelons i.e. as the length of the supply chain increases (and hence its complexity) all players in the chain are affected by an increased degree of chaos and thus uncertainty. Distinctive patterns can be witnessed within the relationships between inventory between warehouse 1 and the subsequent echelons, and this may be utilised for short-term forecasting.

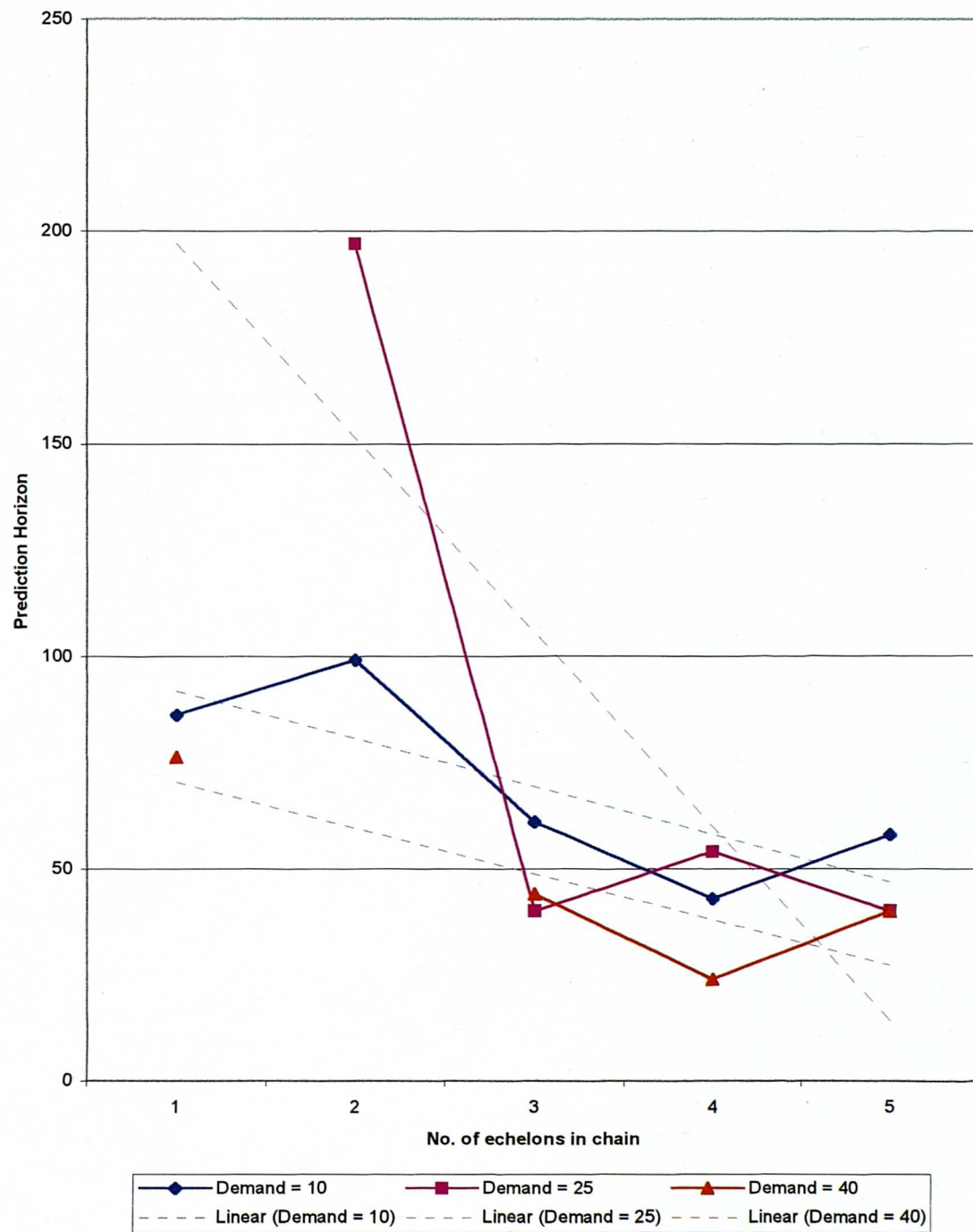


Figure 6.39 – Prediction Horizon against number of echelons in supply chain for Warehouse 1.

Graph shows average prediction horizon against number of warehouse echelons for Warehouse 1, the warehouse closest to the customer. As the length of the chain increases it can be seen that a downward trend in the prediction horizon occurs. (2 data points indicating an infinite prediction horizon have been edited to show underlying trends these are Echelon 2/Demand = 40 and Echelon 1/Demand = 25)

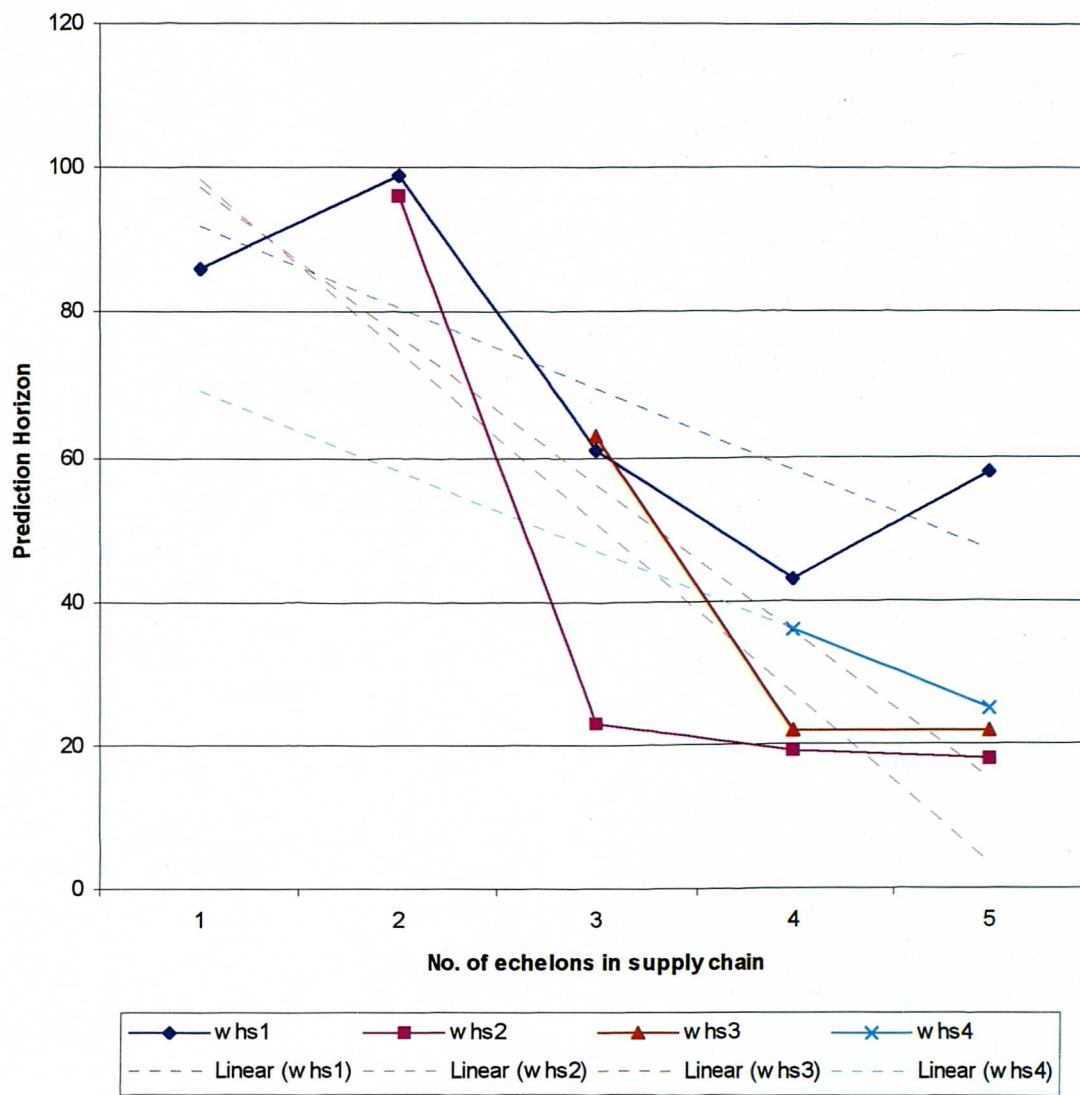


Figure 6.40 – Prediction horizon against number of echelons in supply chain for each warehouse. Demand = 10.

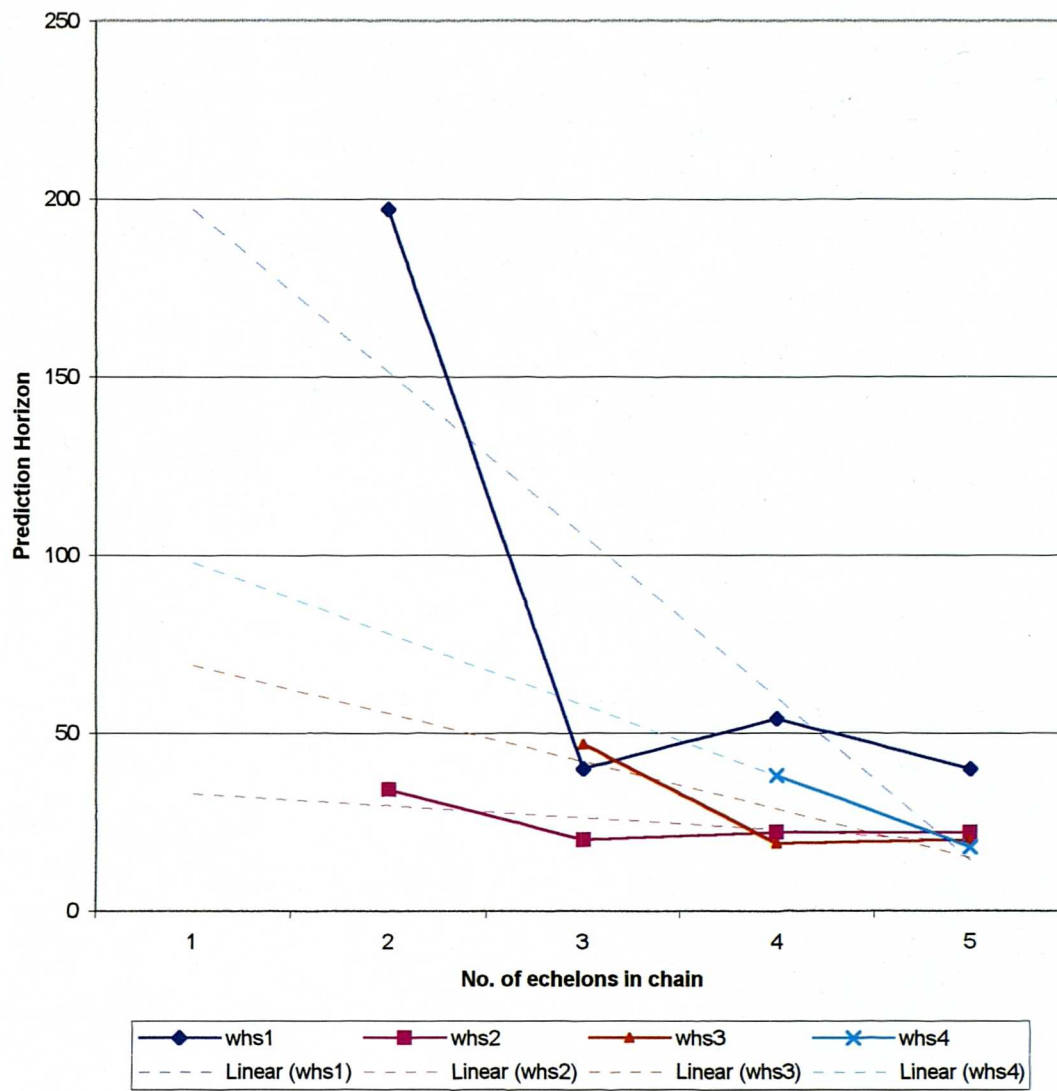


Figure 6.41 – Prediction horizon against number of echelons in supply chain for each warehouse. Demand = 25.

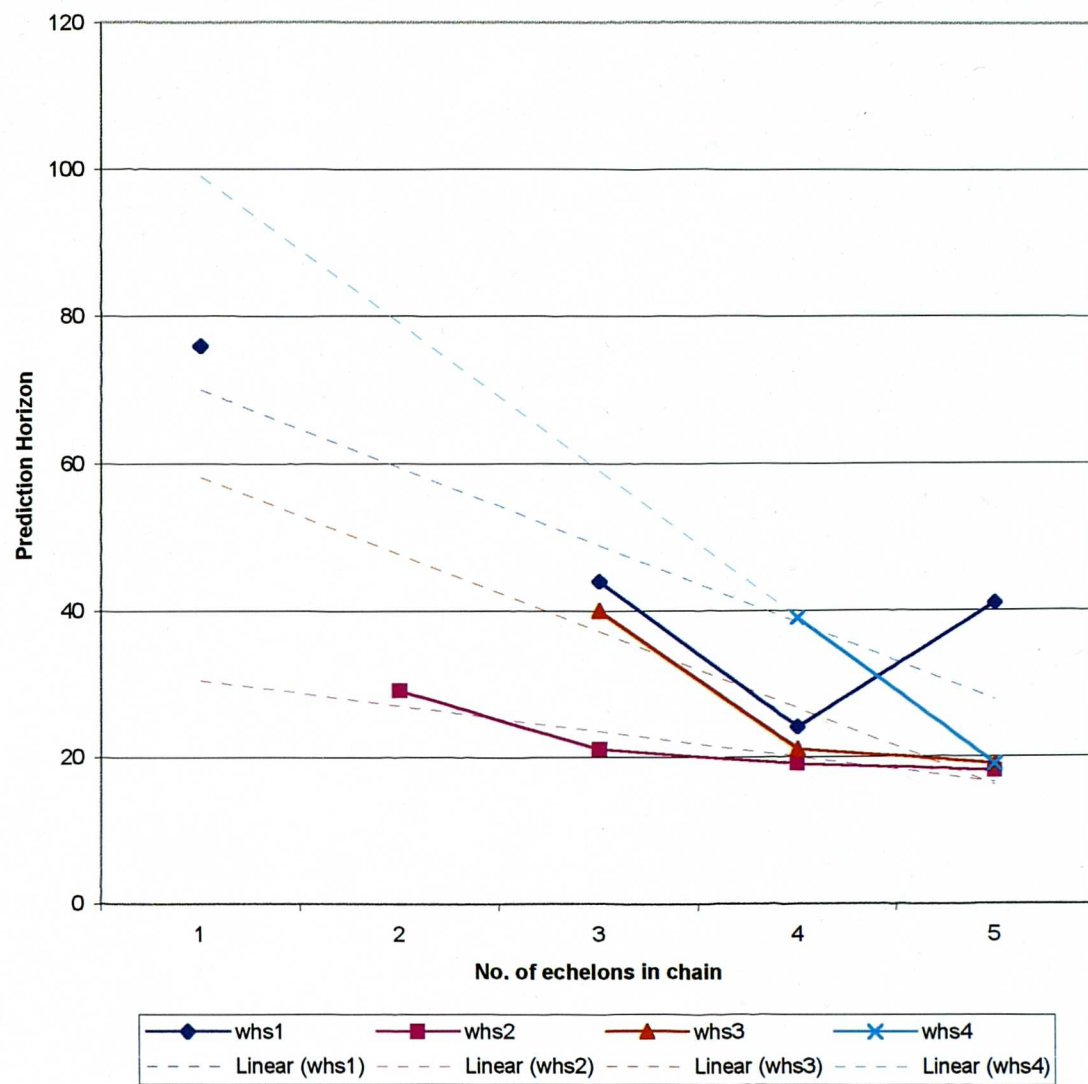


Figure 6.42 – Prediction horizon against number of echelons in supply chain for each warehouse. Demand = 40.

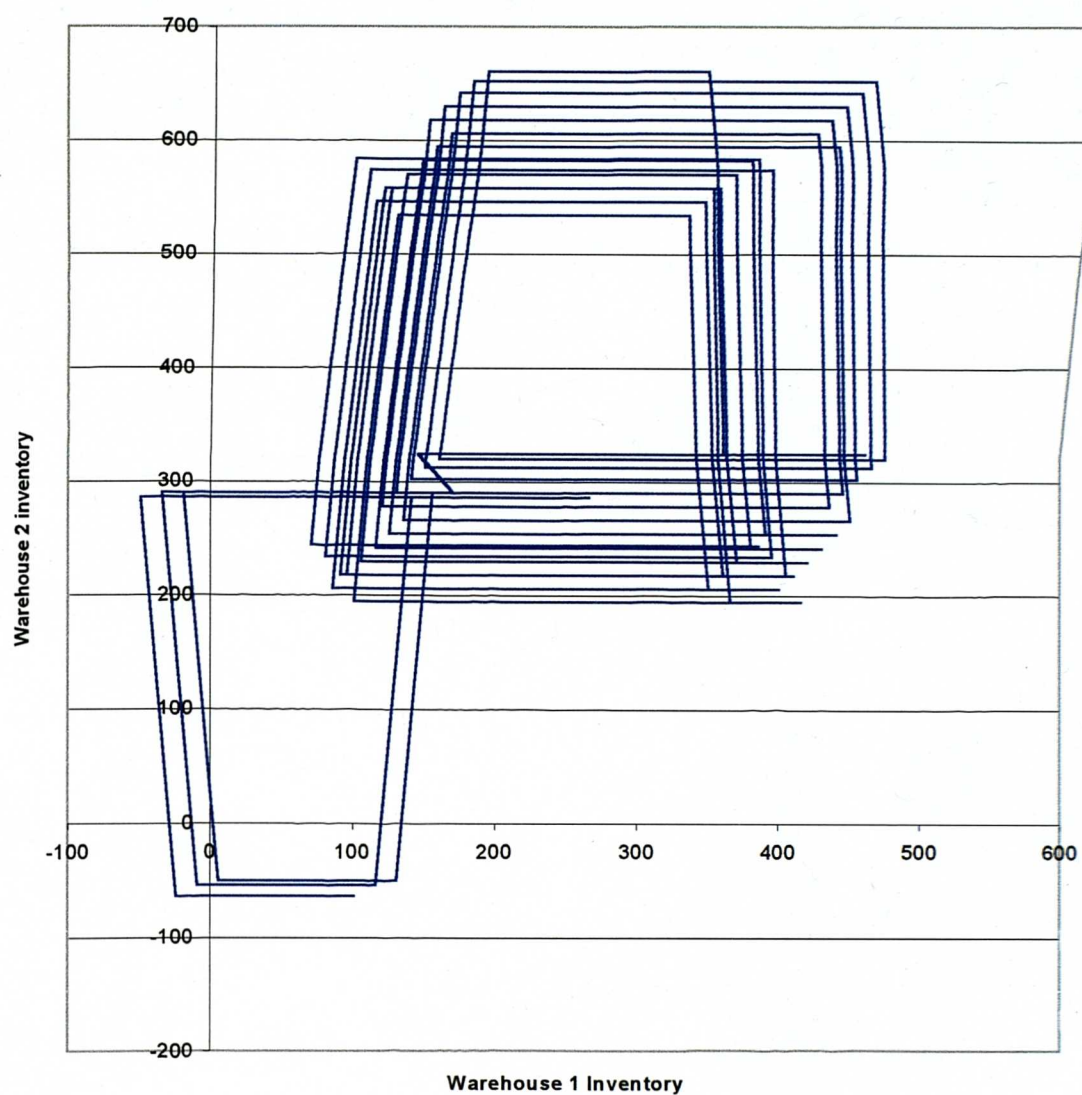


Figure 6.43 – Relationship between Warehouse 1 inventory level and Warehouse 2 inventory level in 5 warehouse supply chain, Demand = 25.

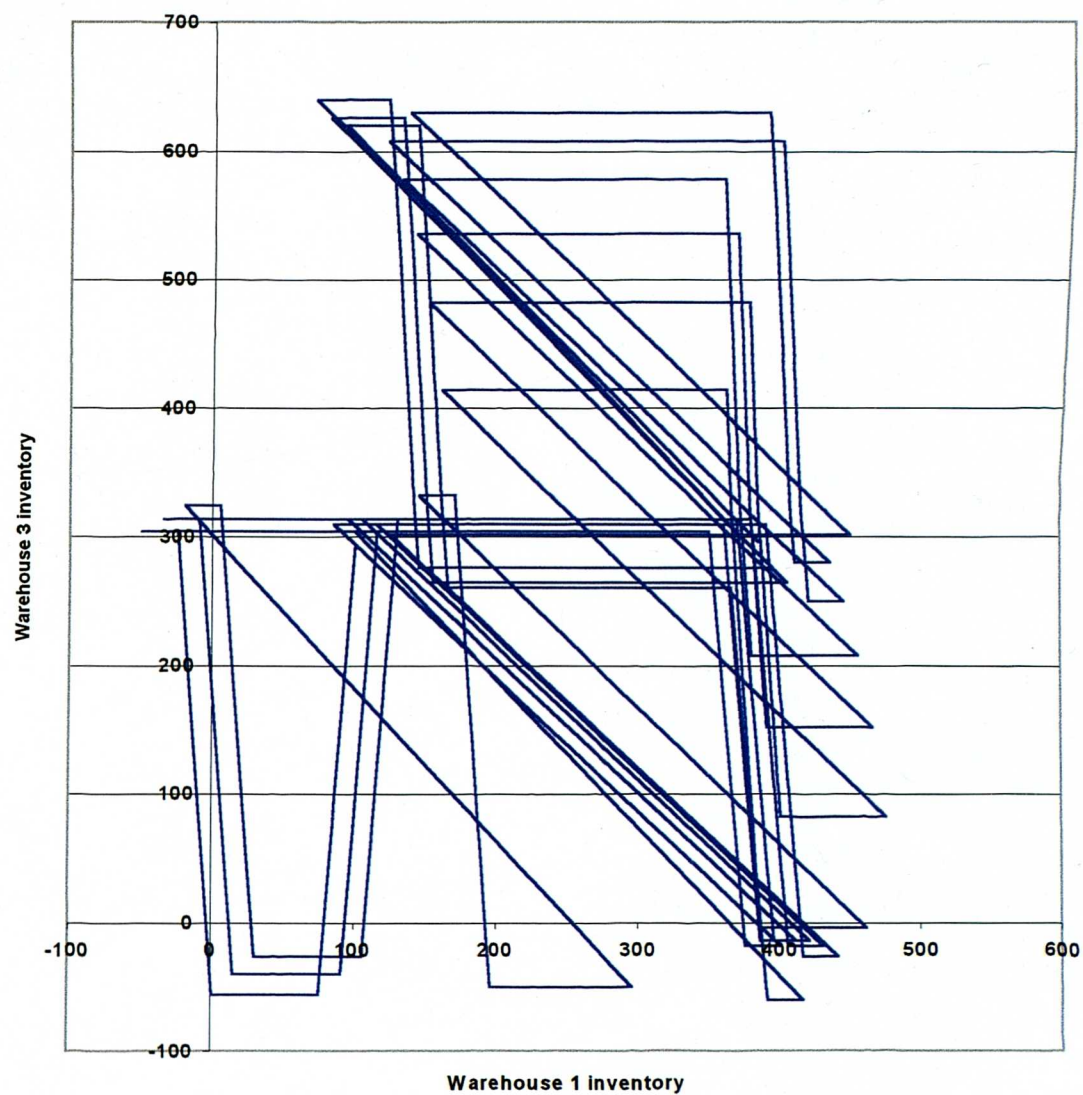


Figure 6.44 – Relationship between Warehouse 1 inventory level and Warehouse 3 inventory level in 5 warehouse supply chain, Demand = 25.

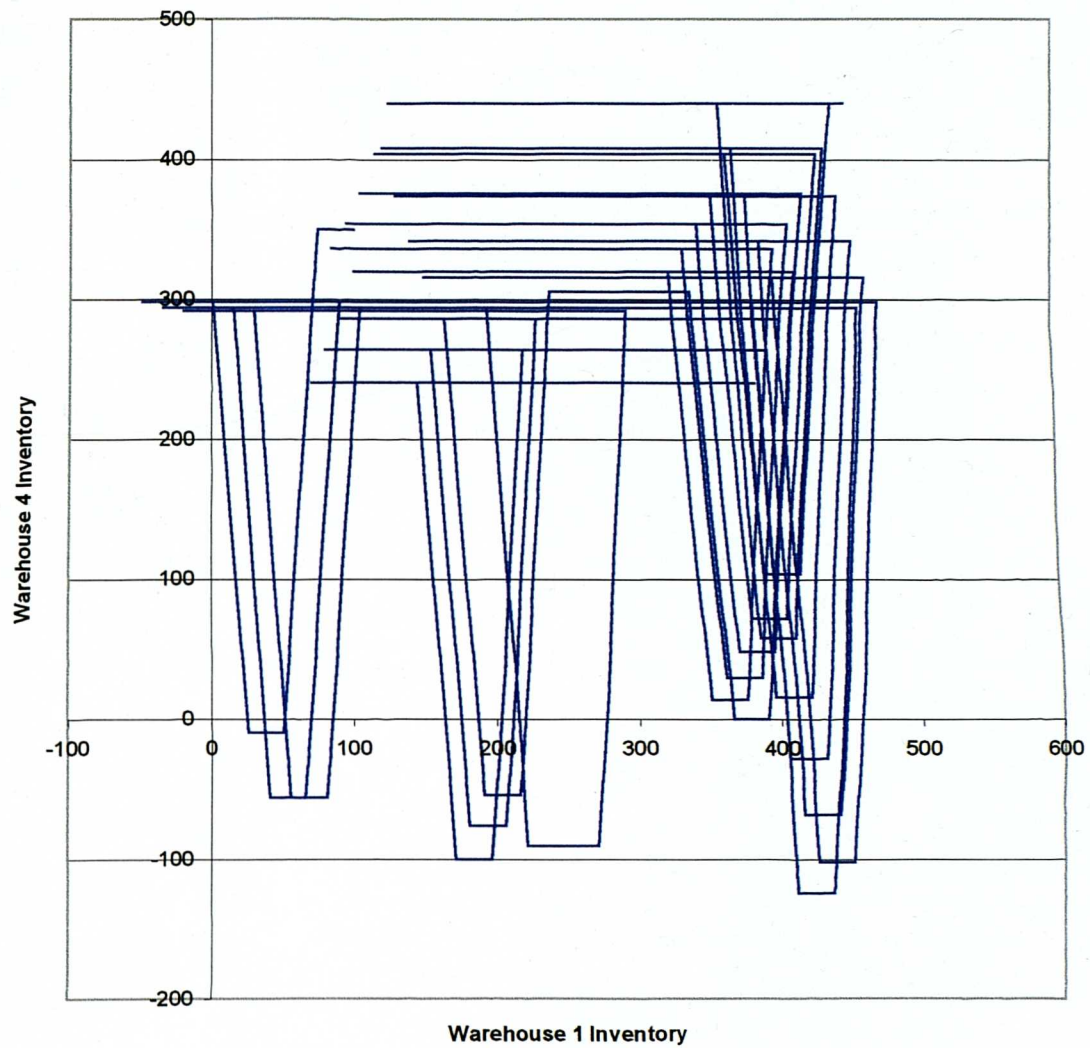


Figure 6.45 – Relationship between Warehouse 1 inventory level and Warehouse 4 inventory level in 5 warehouse supply chain, Demand = 25.

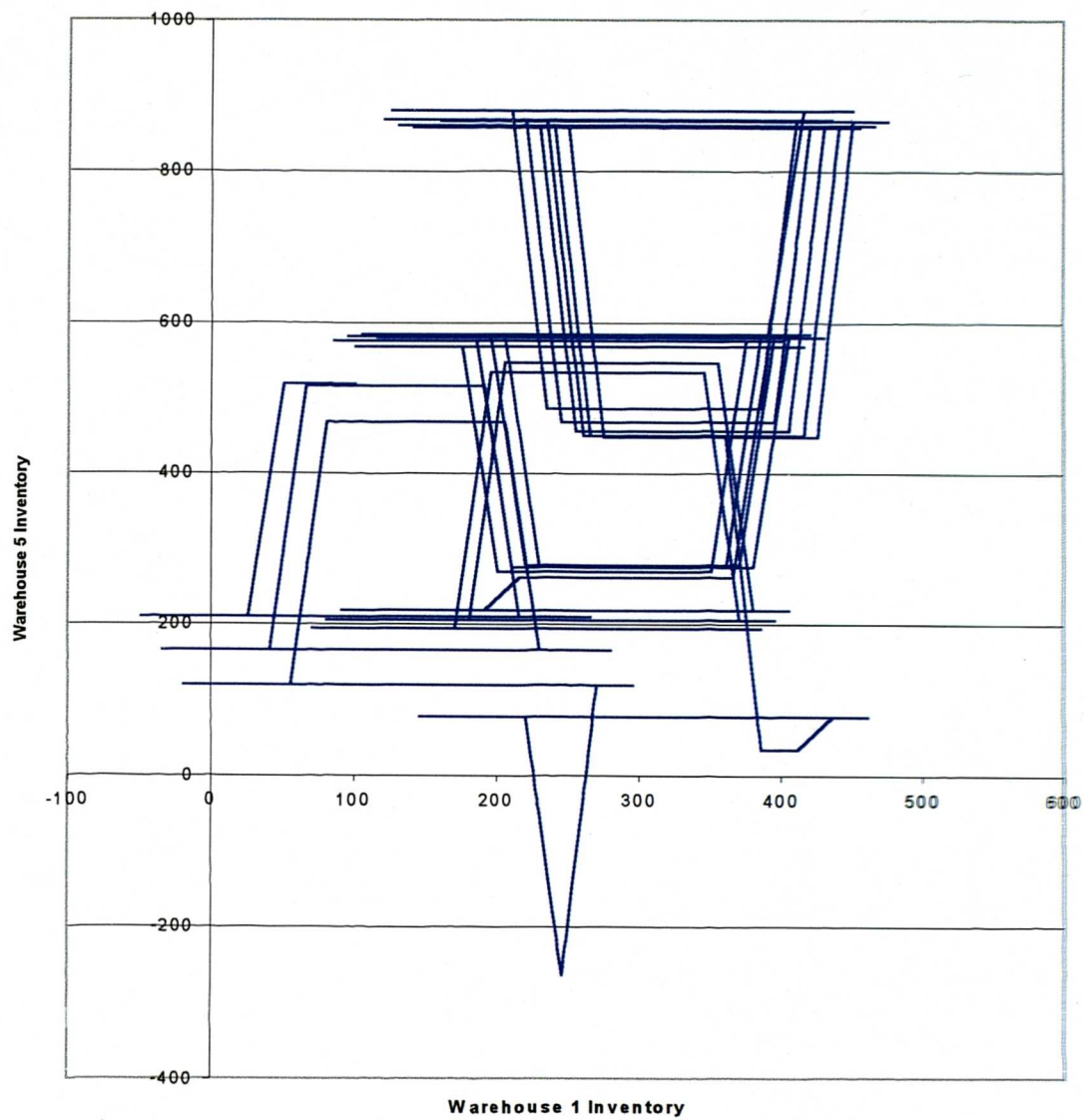


Figure 6.46 – Relationship between Warehouse 1 inventory level and Warehouse 5 inventory level in 5 warehouse supply chain, Demand = 25.

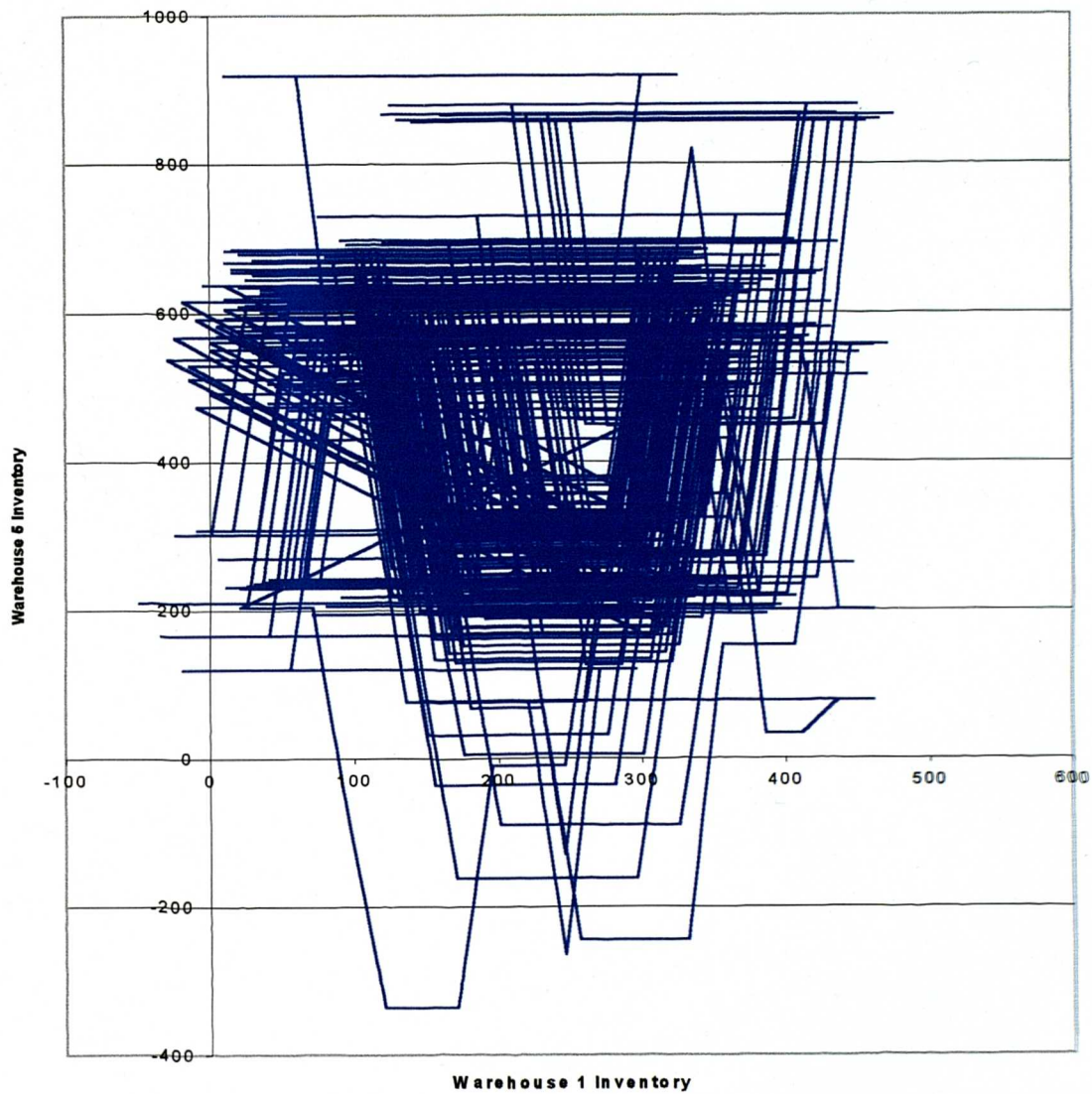


Figure 6.47 – Relationship between Warehouse 1 inventory level and Warehouse 5 inventory level in 5 warehouse supply chain, Demand = 25. (2000 data points).

Due to non-linear chaotic relationship the trajectories eventually cover the phase space.

6.8.4 Results of Investigation 3 – Impact on degree of chaos by increasing supply chain complexity through increasing the number of customer channels.

a) Impact of number of channels on Warehouse 1

Figure 6.48 demonstrates the impact of increasing the number of channels in the supply chain on warehouse 1 for varying levels of demand. The graph demonstrates that the prediction horizon and hence the degree of chaos within the dynamics is not affected by the number of channels within the supply chain. However, the prediction horizon is sensitive to the customer demand level passing through each channel.

b) Impact of number of channels on Warehouse 2

Figure 6.49 shows the prediction horizon for increasing numbers of channels in warehouse 2 (the most upstream warehouse next to the supplier). It can be seen for a daily customer demand on each channel of 25 and 40 that the prediction horizon and hence the degree of chaos is insensitive to the number of echelons. However, for a daily demand of 10 units per channel as the number of channels increase the prediction horizon exhibits a downward trend. This would seem to indicate that the daily demand of 10 is a special case or sensitivity decreases with order size until it reaches a plateau. The trend may indicate that the higher demand levels per channel have forced the warehouse into a slightly different orbit of attraction.

c) Conclusion

Increasing the complexity by increasing the number of channels has no significant effect on the prediction horizon and thus the degree of chaos in warehouse 1. However, warehouse 2 exhibits no significant effect for the higher demand levels but

at the lower demand level of 10 units per day increasing the number of channels results in a reduction of prediction horizon for the data series from the warehouse.

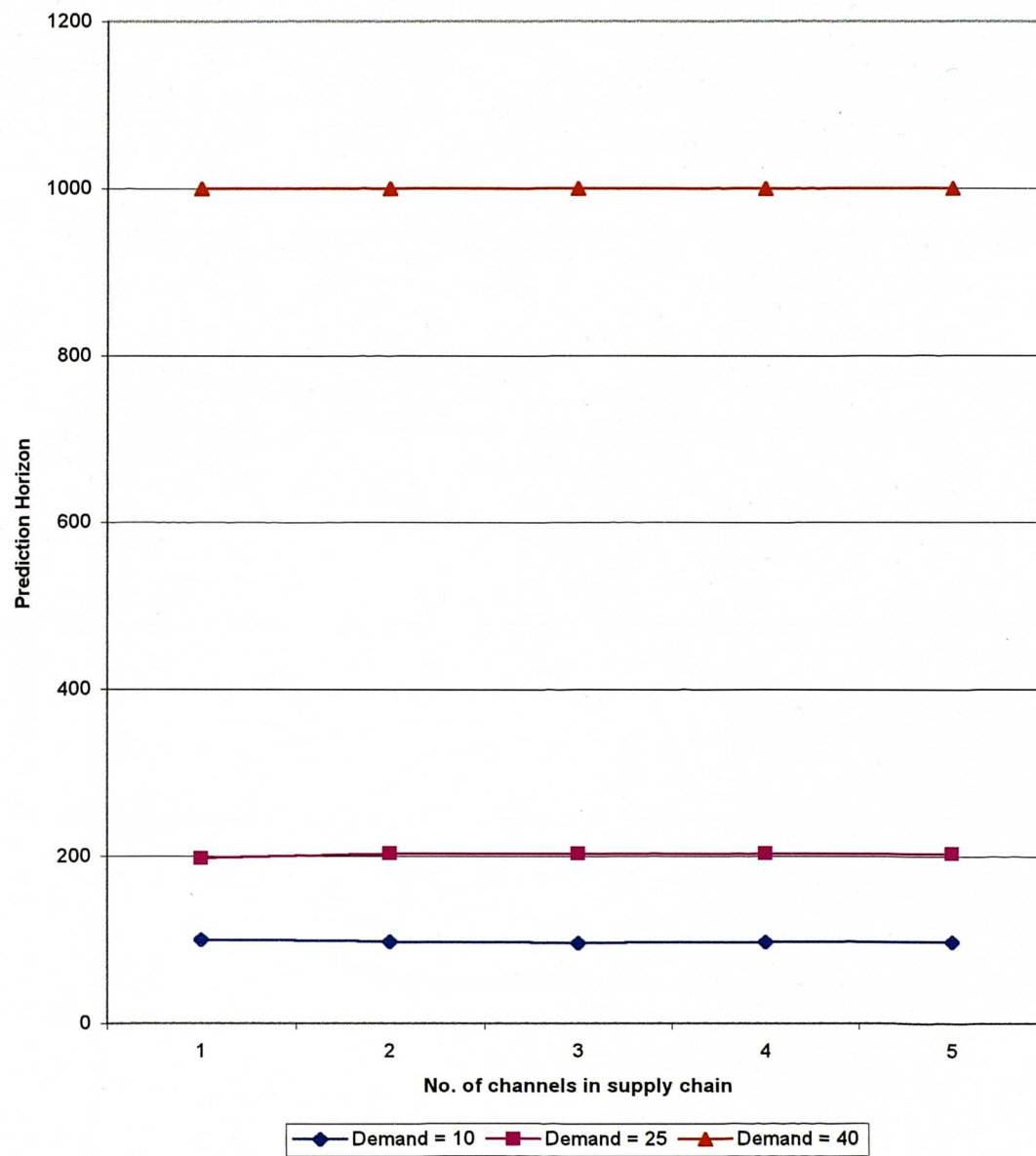


Figure 6.48 – Prediction horizon against number of channels in supply chain for warehouse 1. Demand = 10, 25 and 40.

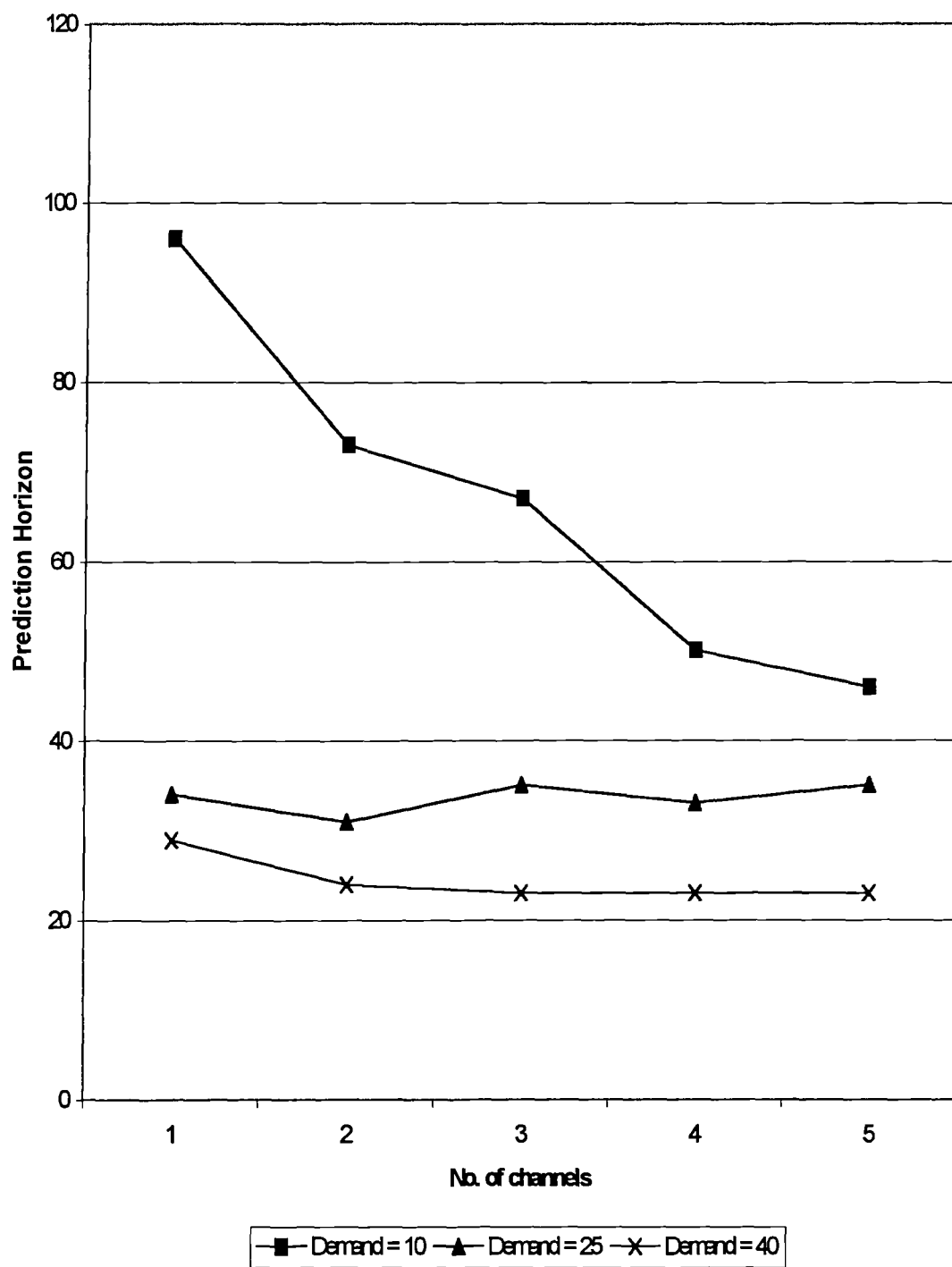


Figure 6.49 – Prediction horizon against number of channels in supply chain for warehouse 2. Demand = 10, 25 and 40.

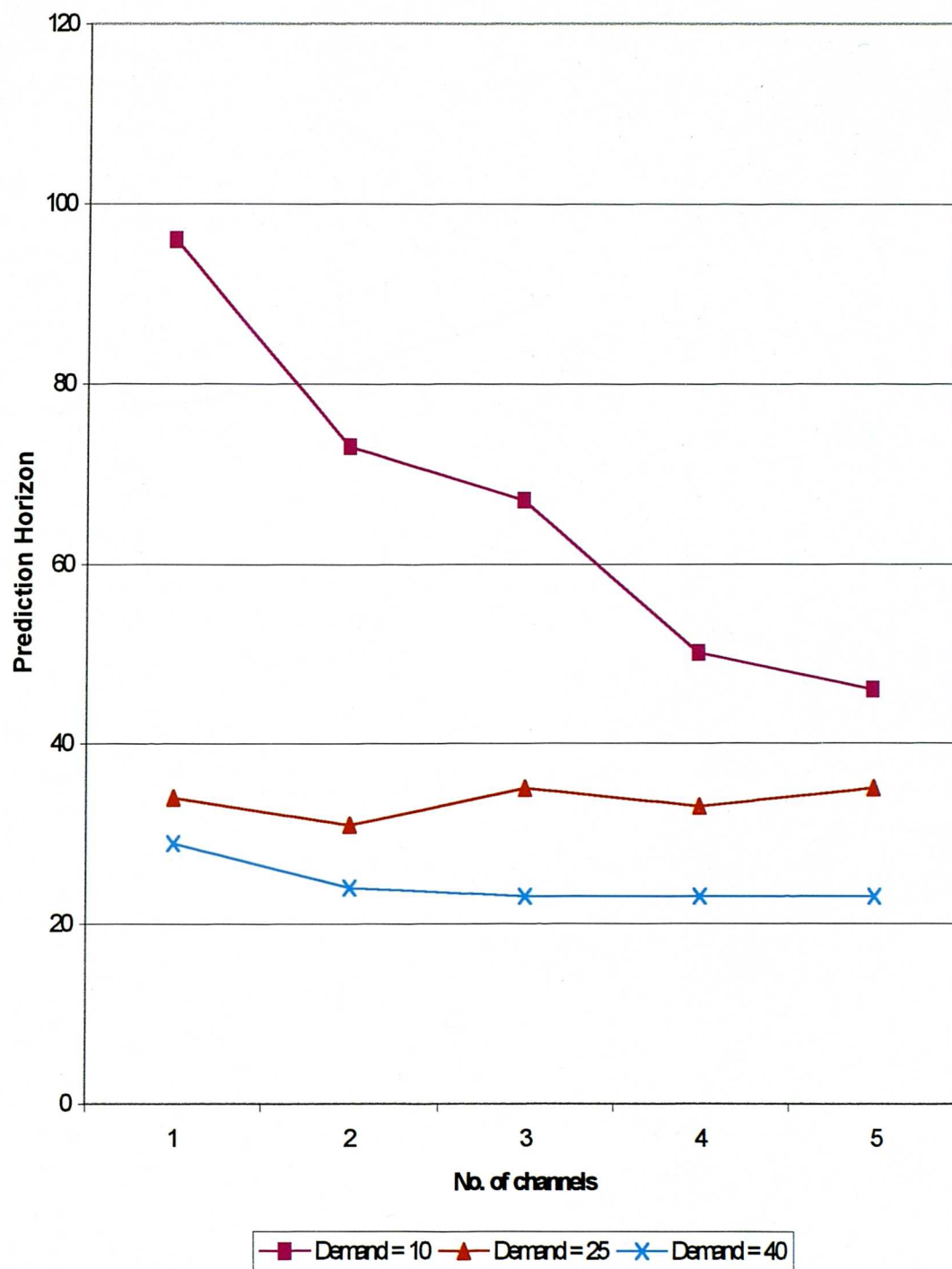


Figure 6.49 – Prediction horizon against number of channels in supply chain for warehouse 2. Demand = 10, 25 and 40.

6.8.5 Results of Investigation 4 – Identification of “Islands of stability”.

a) Effect of increasing daily demand on one-warehouse supply chain.

Figure 6.50 demonstrates the prediction horizon for warehouse 1 in a one-warehouse supply chain (the supplier lead-time is set at 7 days). The graph demonstrates that the degree of chaos and hence prediction horizon varies with demand. Demand levels of 25 and 80 would seem to indicate islands of stability where the data series is stable and effectively can be predicted indefinitely.

b) Effect of increasing daily demand on two-warehouse supply chain.

Figure 6.51 demonstrates the impact of daily demand on prediction horizon for warehouse 1 in a two-warehouse supply chain. Islands of stability occur, for a supplier lead-time of 7 days, at demand level of 40. For a supplier lead-time of 5 days islands of stability are witnessed at demand levels of 20 and 40. (This is in contrast to 25 and 80 for the one warehouse supply chain outlined above). This seems to imply that a change in the number of echelons in the supply chain moves the island of stability.

Figure 6.52 shows the prediction horizon changes for warehouse 2 in the two-warehouse supply chain. No islands of stability are present however lower demand levels on the supply chain tend to produce a slightly higher prediction horizon.

c) Impact of changing supplier lead-time for two-warehouse supply chain.

Figures 6.51 and 6.52 also demonstrate how changing the supplier lead-time impacts on the prediction horizon of the data series from the warehouses. These results reinforce the indications that a change in a parameter within the supply chain impacts

on all echelons in the chain. A particularly interesting finding is that for the shortest supplier lead-time (3 days) the prediction horizon in warehouse 1 is significantly lower than that of the other lead-times. However in warehouse 2 no significant difference is seen. A possible explanation for this is that warehouse 2 carries less cover stock as the supplier lead-time is shorter i.e. the algorithm calculates less stock is required as the supplier can deliver quickly. This then results in warehouse 1 having less inventory buffer in the warehouse supplying it. Therefore if any uncertainty due to chaos occurs warehouse 1 is more liable to be impacted upon, resulting in increased chaos and thus a reduced prediction horizon. This is an example of where the reduction of a lead-time (time compression) does not always result in improved dynamic behaviour.

d) Changing the service level setting for a warehouse 1 in a one-warehouse supply chain.

Figure 6.53 demonstrates the impact of changing the service level setting for warehouse 1 in a one-warehouse supply chain at a daily demand level of 10. It can be seen that islands of stability occur at approximately 98.7% and 99.3%. This provides further evidence that changing one parameter in the supply chain affects the prediction horizon of the system.

e) Conclusion

The above investigation demonstrates that islands of stability can be identified; however these are highly sensitive to parameter settings within the supply chain. This means that islands of stability may be identified but then would move with any small change made to the supply chain. This makes the utilisation of the knowledge of the

location islands of stability to gain benefits for those in the chain particularly difficult.

Further work is required in this area.

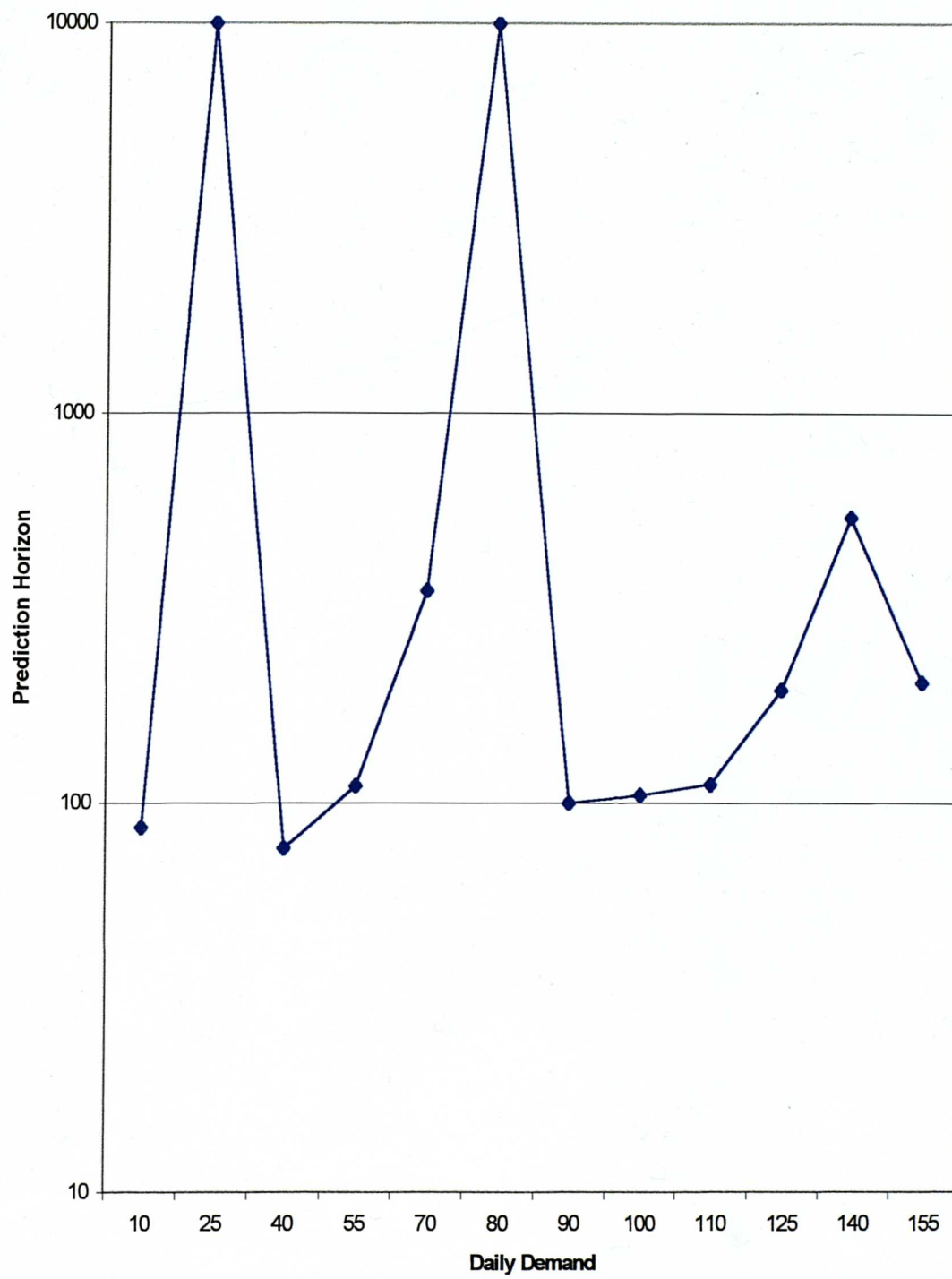


Figure 6.50 – Prediction horizon for Warehouse 1 in one warehouse supply chain with increasing daily demand level.

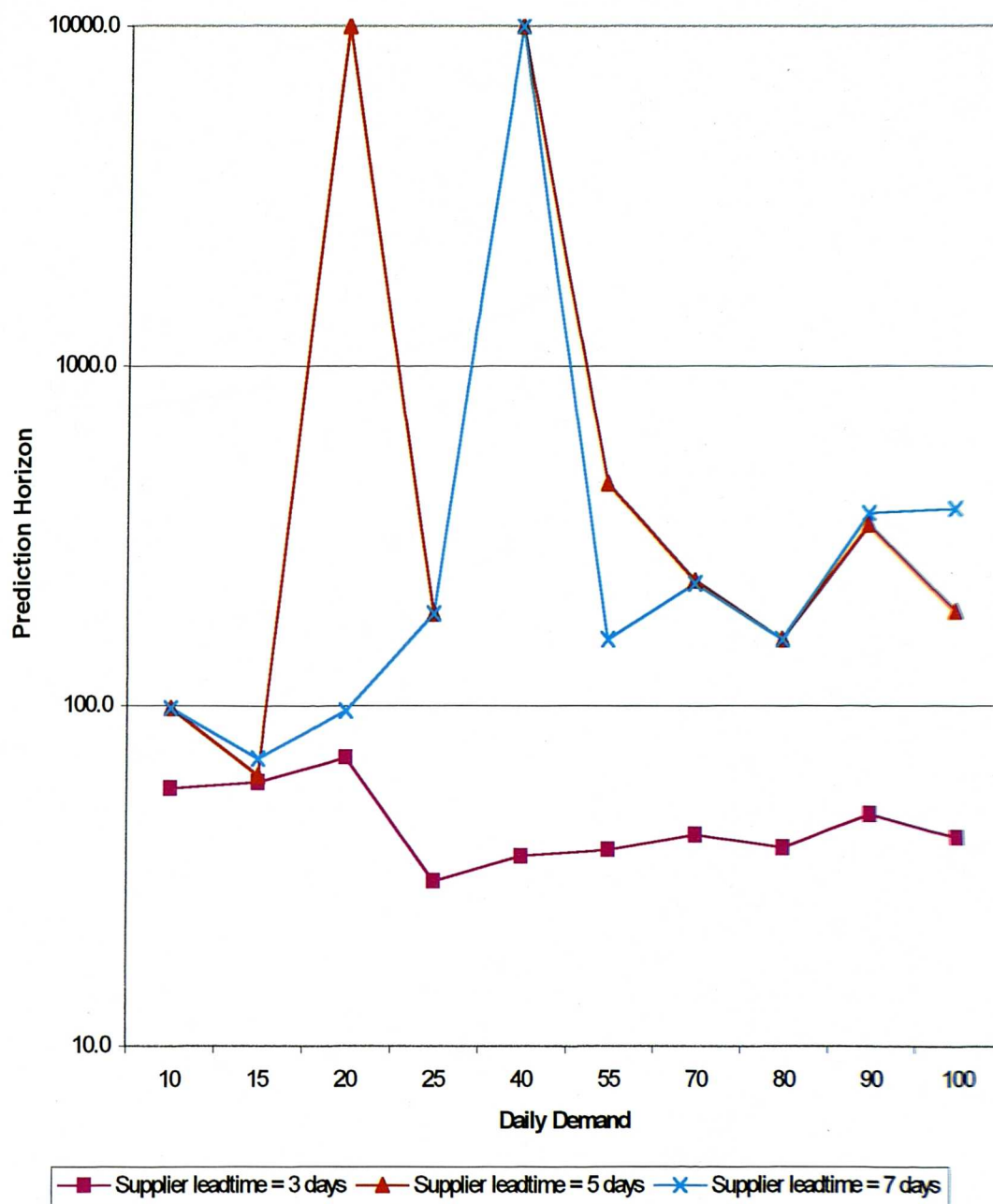


Figure 6.51 – Prediction horizon for Warehouse 1 in two warehouse supply chain with increasing daily demand level and different supplier lead-time.

It is interesting to note that for the shortest lead-time the degree of chaos has increased and subsequently the prediction horizon has reduced. This is the result of the automatic reorder system in the warehouse reducing the amount of safety stock (cover) and this therefore results in a reduced inventory buffer within the system. This can be seen as an example where time compression is not always beneficial.

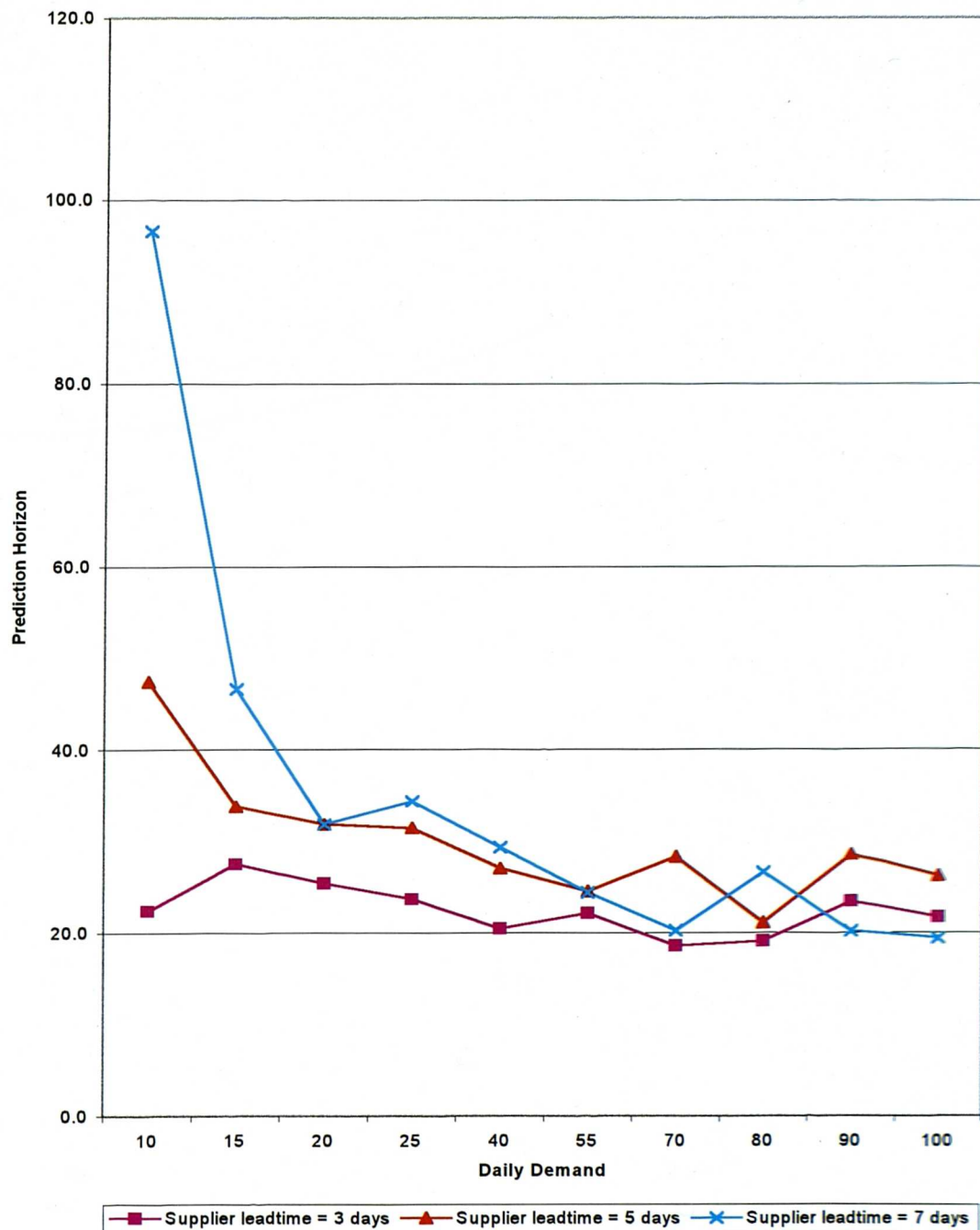


Figure 6.52 – Prediction horizon for Warehouse 2 in two warehouse supply chain with increasing daily demand level and different supplier lead-time.

It is interesting to note that for the shortest lead-time the degree of chaos is not significantly different in contrast to Figure 6.51.

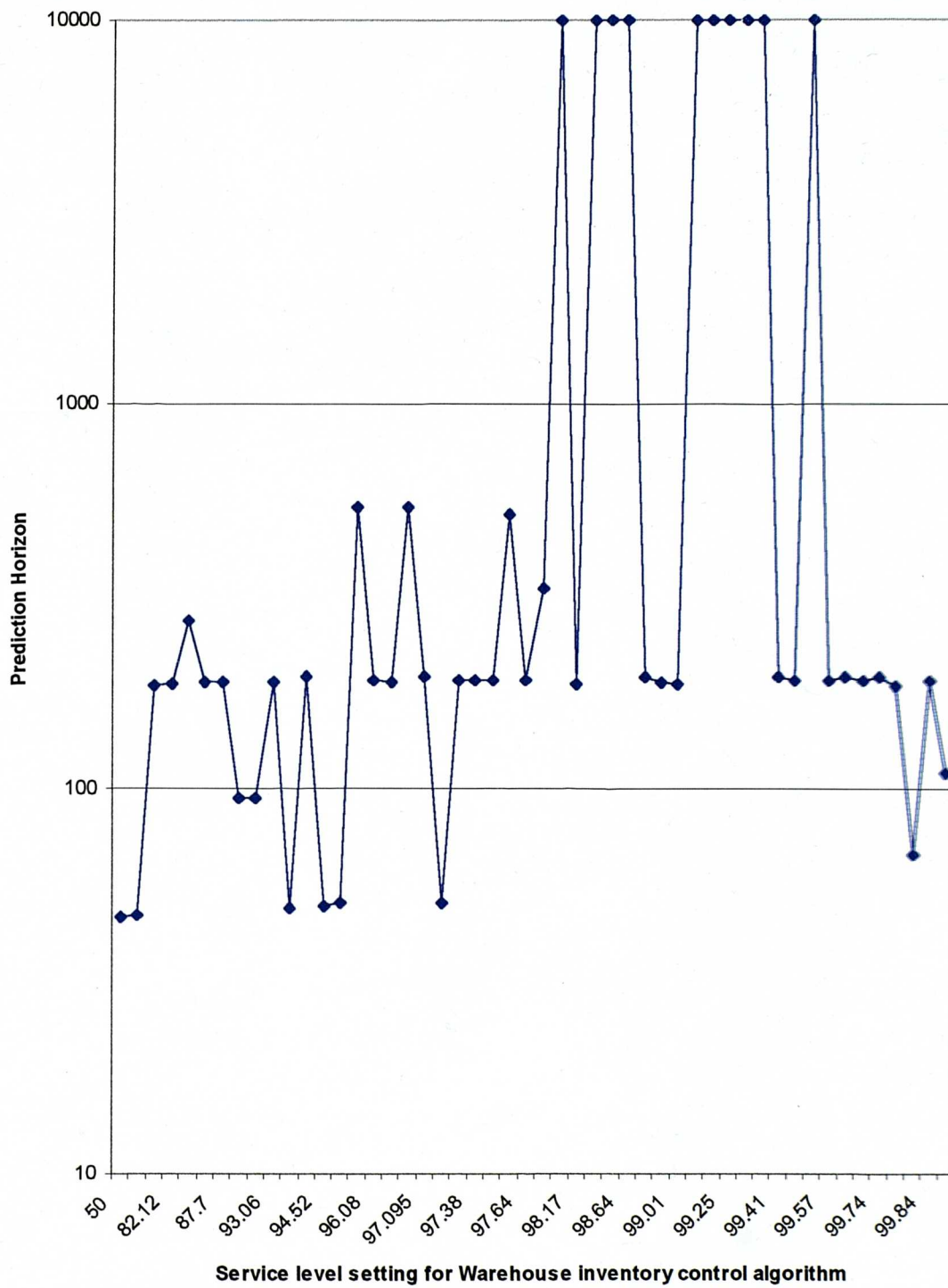


Figure 6.53 – Prediction horizon for different service level settings of warehouse algorithm in one warehouse supply chain.

6.9 Conclusion to Chapter 6

In this Chapter, the simulation methodology for investigating the impact of deterministic chaos on supply chain uncertainty has been explained. The validation process for both the simulation methods and the tools for analysis used for applying the methodology described in chapter 5 has been described.

The investigations addressing the research questions raised in section 4.9 have been described and the results from these investigations have been presented. The use of the average prediction horizon for quantifying the degree of chaos has provided an accessible means of understanding the impact of chaos within the context of supply chain management and hence understanding the degree of uncertainty generated by deterministic chaos within a system.

The implications of these results with reference to the literature will be discussed further in chapter 8.

Chapter 7

Investigation into the generation of supply chain uncertainty by “parallel interactions”.

7.1 Introduction.

In section 1.6.2 the term “parallel interaction” was defined to describe interactions that occur between different channels of the same tier in a supply network. This results in uncertainty being generated within the supply network. The supplier is affected by an occurrence in a parallel supply chain, which at first would seem unrelated.

“Parallel interactions” within the supply chain were observed by Jones [Jones, 1990 p.291] in an automotive supply chain, however no quantitative analysis of this phenomenon was undertaken.

Jones noticed that poor delivery or quality performance from some suppliers in the network affects the efficiency of the good (often Just-in-time) suppliers. Jones suggests that the good suppliers face schedule “ripple” variations caused by the poor suppliers. The supply chain structure investigated by Jones forms the basis for the following investigation.

As discussed in section 3.7 little investigative research has considered sources of uncertainty within supply networks and the subsequent interactions that may generate

uncertainty between suppliers in a supply network. This conclusion is also supported by other published reviews on supply chain research [Thomas, 1996]. However, some analysis has taken place of the effects of uncertainty on serial automated production flow lines [Groover, 1987] and some analogies can be drawn from this body of research and applied to supply chains. This is because there is some similarity as in both cases it is necessary to damp the effects of uncertainty by using buffer stocks. Therefore the analysis becomes one of how buffers influence the levels of utilisation within the system.

The investigations undertaken by Groover focus on the calculation of the efficiency of automated flow lines when breakdowns in the individual machines stop the total process. Since the flow line is made up of a large number of work stations which are often operated as a single mechanism, when failure occurs in one work station it often results in the stoppage of the entire flow line. Groover observes that even if each individual workstation in the flow line is operated in an optimal way, this does not guarantee that the overall flow line efficiency will be optimised. These observations have resulted in Groover advocating a systems approach. This systems approach requires the impact of the number of workstations in the line, and the size and locations of inventory buffers to be assessed for automated flow lines.

Groover's investigation concludes that the line efficiency decreases substantially with the number of workstations. Figure 7.1 shows how the line efficiency alters as the number of workstations increase. The graph is plotted for three different workstation breakdown rates (this figure is the probability that the workstation will break down, 0.001 means the work station breaks down on average every 1000 cycles). Groover

indicates that the introduction of inventory buffers between workstations increases the overall efficiency of the flow line by absorbing the uncertainty.

Analogies can be drawn between the work undertaken by Groover and supply chains. A supply chain is a number of companies rather than work stations but uncertainty in supply will also impact on the overall efficiency of the supply chain. An example of this inefficiency can be witnessed in the small percentage of added value time documented within supply chains.

In this chapter the main research question to be addressed are as follows:

- Does uncertainty from “parallel interactions” have a significant effect on individual suppliers in the supply network?
- How does buffer size impact on the degree of parallel interactions?
- What effect do “rogue” suppliers have on good (e.g. just-in-time) suppliers?
- What impact does uncertainty between forecast and actual demand have on the supply network?

Through addressing these research questions further evidence will be produced to answer the issues raised in section 3.7.

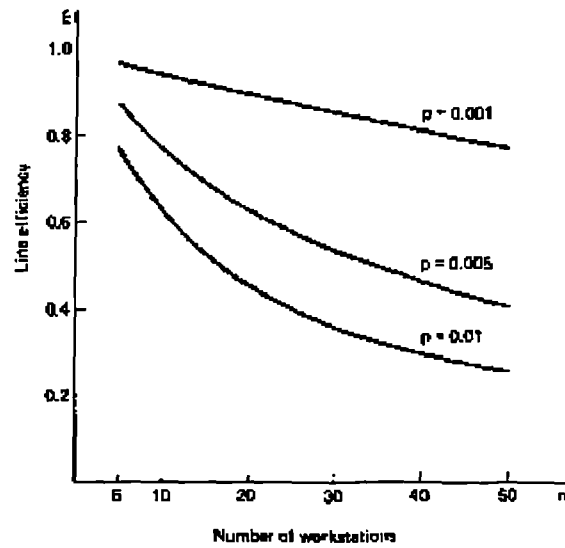


Figure 7.1 – Relationship between line efficiency (E) and the number of workstations (n) for various breakdown rates (p).

Source: Groover, M.P. (1987). "Analysis of automated flow lines." Automation, production systems, and computer integrated manufacture., pp.106-37. Prentice-Hall: London .

7.2 Description of supply chain simulation methodology.

7.2.1 Background to supply chain simulated.

The model represents a simple supply network of four suppliers producing sub-assemblies that are combined by the customer into a finished product. The structure is based on a detailed model developed by Jones [Jones, 1990]. This model was developed to investigate logistics performance within an automotive supply chain.

The supply chain investigated by Jones is that for the manufacture of Rover Metro servo assembly used in the servo assisted brake mechanism of the vehicle. The assembly has been in production at AP (Automotive Products) Brakes Division, Leamington Spa, since the launch of the original Austin Rover Metro. It has continued to be used on the Rover Metro and the Rover 100 models, which is still currently in production. The quantity manufactured per annum is approximately 170,000 units. The assembly consists of 4 key components these are:

- Servo casing and servo support plate known as the “shell and cover”.
- Diaphragm.
- Tandem master cylinder or slave cylinder.
- Fluid reservoir body or fluid tank.

Figure 7.2 depicts a cross-sectional diagram of the servo assembly with these key components identified. A different supplier to AP Brakes Division supplies each of

these key parts. Figure 7.3 shows the structure the supply chain and the name of the suppliers.

The investigation undertaken by Jones indicated that the suppliers were each characterised by different delivery and quality performance. This is summarised in Table 7.1. The table demonstrates that at the time of the investigation some suppliers were seen to exhibit “poor” delivery performance (characterised by irregular deliveries every 2-3 days, and poor schedule adherence). One supplier exhibited “Very good” delivery performance (characterised by Just-in-time deliveries 2 to 3 times per day and good schedule adherence). The supplier exhibiting “good” delivery performance is characterised by just-in-time delivery, 2-3 times per day, and poor schedule adherence. Due to the batch nature of the manufacturing process sometimes severe shortages can occur every 2-3months. Quality was also found to vary between suppliers, “good” quality within this chain was characterised as a customer reject rate of less than 5% of parts (this level of rejection was not seen as a problem to the assembler at the time of the investigation). “Poor” quality resulted in a reject rate by the customer of greater than 20% and was accepted as a major problem by the assembler. The production methods of the suppliers could be classified within two main types, Just in Time and Batch. The batch manufacturer produced large batches of components which may be held as finished goods stock at the supplier while the just in time manufacturers as the name implies manufacture only when needed and carried low finished goods stocks (See [Jones, 1990 pp.187-189, pp.128-132 & p.205]).

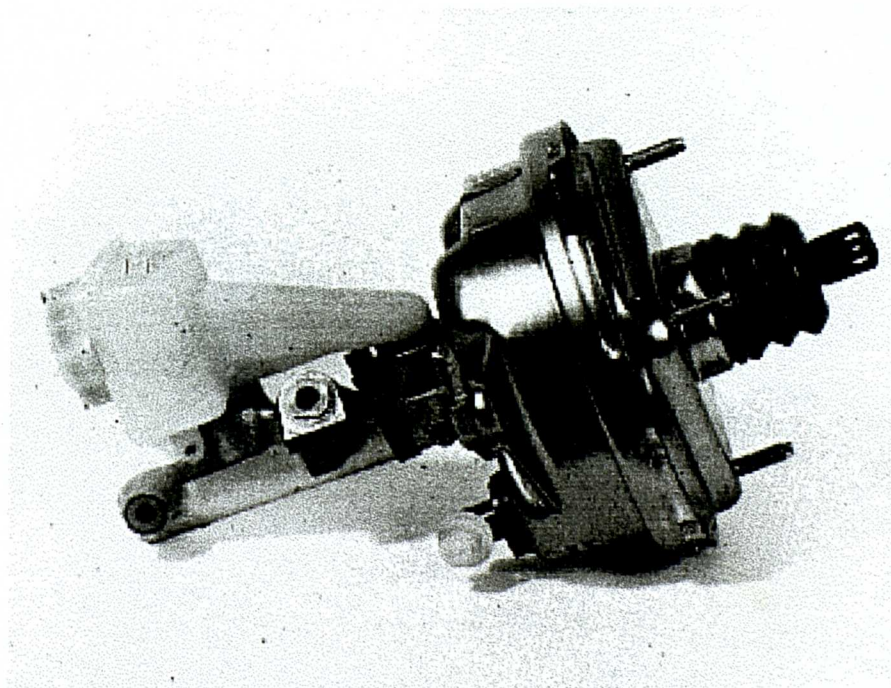
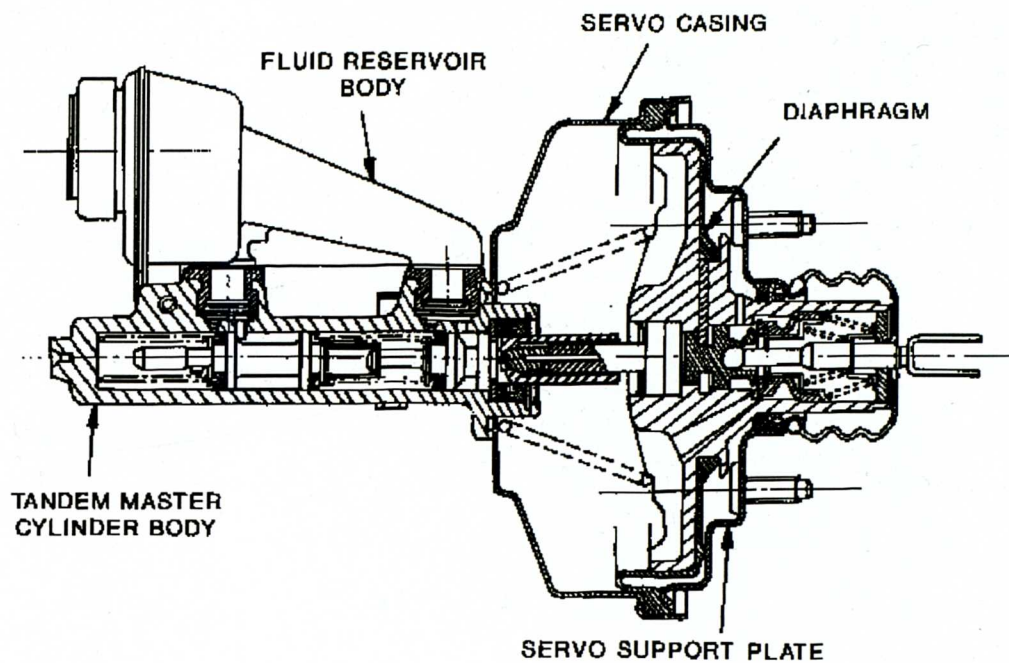


Figure 7.2 – Cross-section and photograph of Servo assembly.

Source: Jones, M.P. (1990). "An investigation into the logistical performance of a partially just-in-time supply chain by the application of discrete event simulation ." MPhil Thesis, University of Warwick.

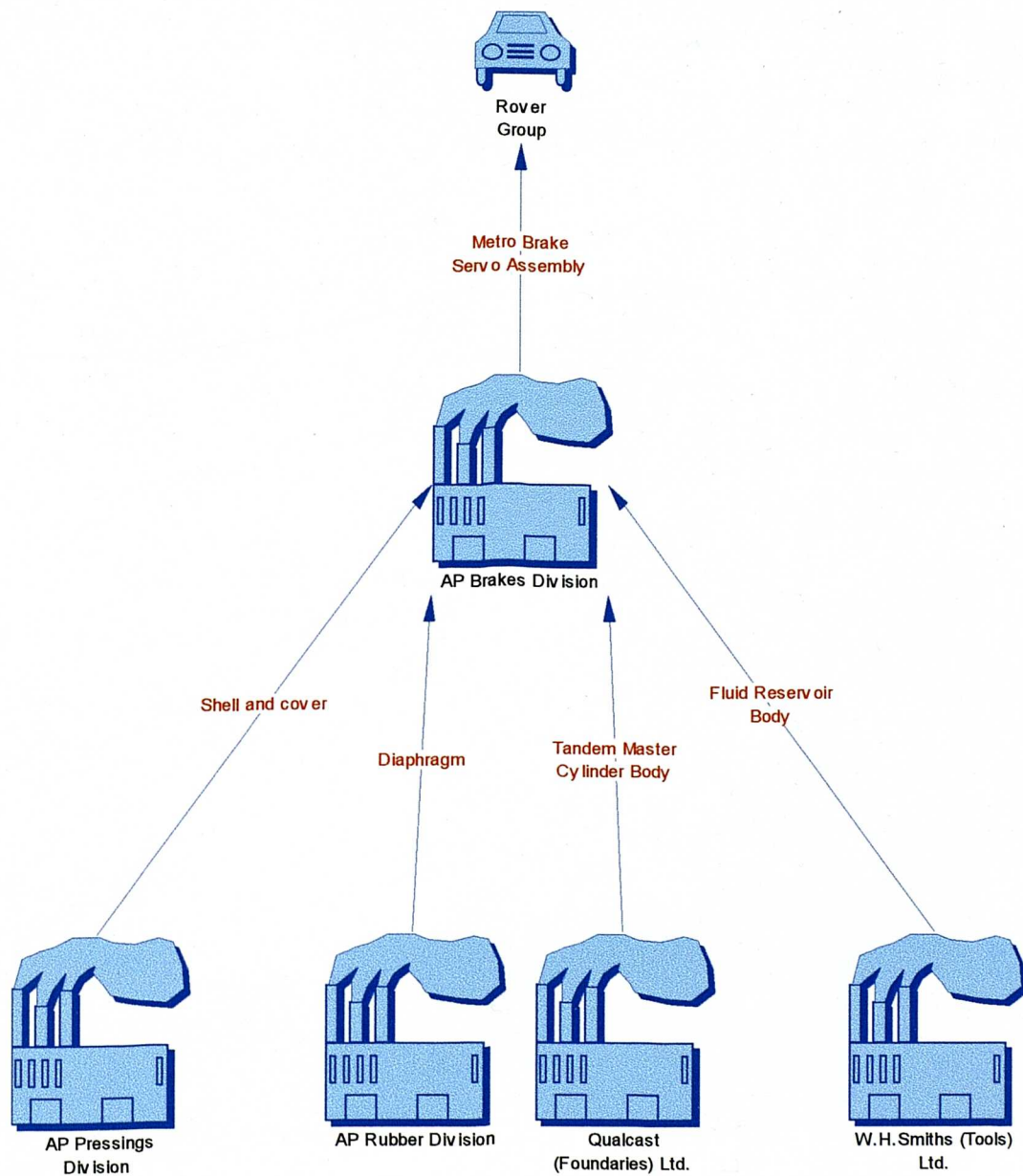


Figure 7.3 – The servo assembly supply network, showing suppliers and main components.

Adapted from [Jones, 1990, Figure 4.2, p.126]

| Component | Supplier Name | Production Type | Delivery characteristic | Quality Characteristic |
|------------------------|---------------------------|-----------------|-------------------------|------------------------|
| "Shell and cover" | AP Pressings Division | Batch | Good | Good. |
| Diaphragm | AP Rubbers Division | Just In Time | Very Good | Good. |
| Tandem Master cylinder | Qualcast (Foundries) Ltd. | Batch | Poor | Good. |
| Fluid Reservoir Body | W.H. Smiths (Tools) Ltd. | Batch | Poor | Poor |

Table 7.1 – Table showing key characteristics of suppliers in servo assembly supply network.

Jones describes the AP Rubbers supply channel as the “JIT stream” because this channel represents a smooth line of flow, running fluently with reduced stock [Jones, 1990 p.190].

7.2.2 Model Description

The model used in this thesis is based on the phase 1 model developed by Jones [Jones, 1990 pp.192-195]. The original model was produced in the simulation language HOCUS. This package is no longer supported, so for the purposes of this investigation the original model was reproduced by the author using Witness a proprietary manufacturing simulation package [AT&T Witness, 1995]. The benefits of using this simulation package are that it is supported by the Simulation Group at the University of Warwick and offered good functionality for the use of random sampling techniques. The package also enabled real-time statistical analysis of the key elements of the model.

The simulation model produced performs in the following way:

a) Supplier “Push” and Assembler “Pull”

The assembler creates demand on the suppliers by taking components out of the suppliers’ stock buffer and combining them into a finished product to be shipped to the end user. (See Figure 7.4)

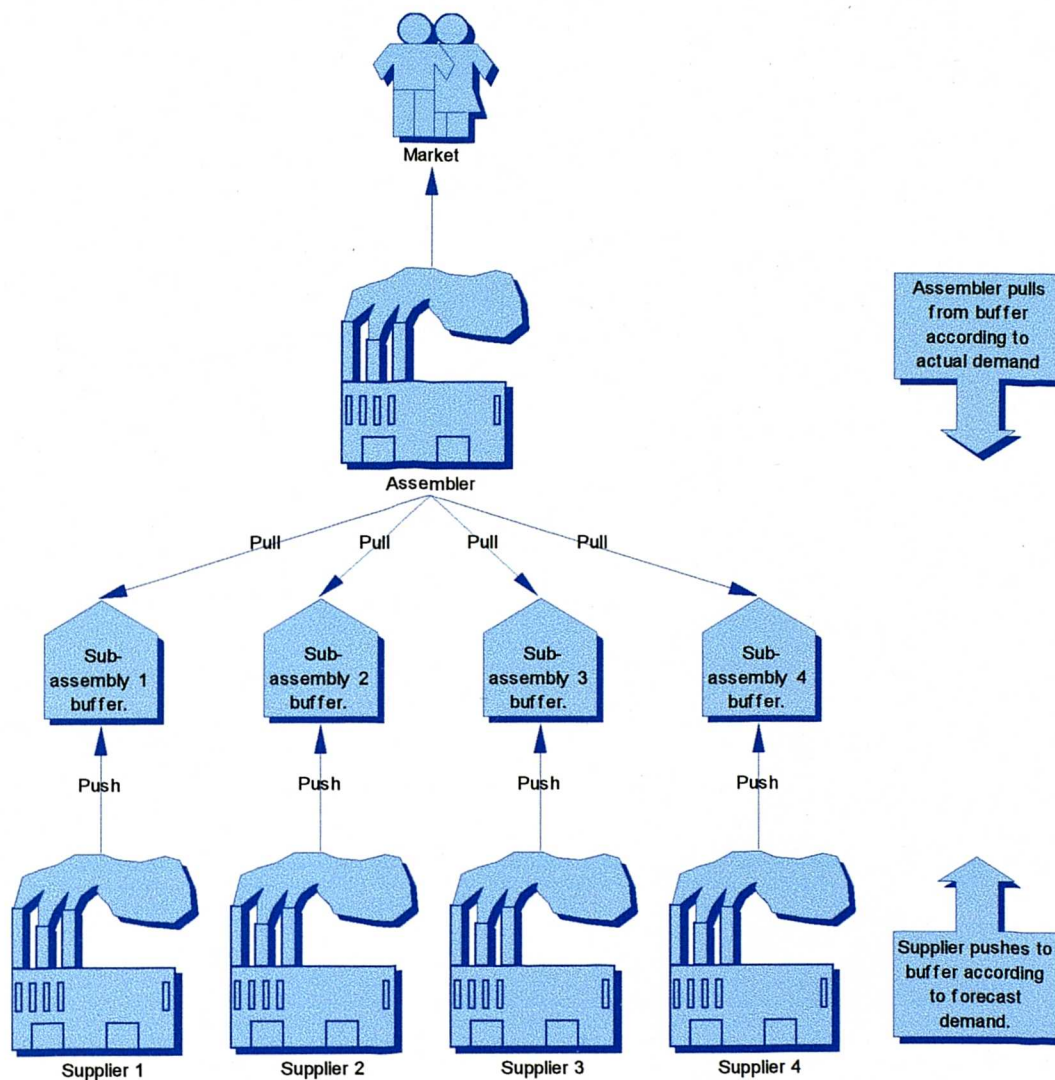


Figure 7.4 - Supply chain network used by author for investigation into "parallel interactions"

(Based on Servo Assembly Supply network described by Max Jones [Jones, 1990] and depicted in Figure 7.3).

The suppliers produce sub-assemblies according to a forecast supplied by the assembler one week before the assembler anticipates they are required. These components therefore fill the supplier's stock buffer so they are readily available for the assembler at the start of the following week. The size of the stock buffer at the suppliers can be altered so the maximum stock present may only be enough to satisfy a small proportion of the weekly demand.

b) Demand and Forecast Creation

The simulation approach used during the experiment is stochastic. The demand and forecast are selected randomly from a specified normal distribution. The distributions have the same mean and standard deviations. However, separate random number streams are used for the demand and forecast selection. This results in the average forecast and demand over time being identical but on a week by week basis the figures will differ.

This procedure replicates what has been observed by Jones [Jones, 1990] and Hill [Hill, 1996] during the analysis of forecast and actual demand for manufactured products. It is observed in the analysis of such data that despite little correlation between forecast and actual demand in the short term, over a longer time period the mean and standard deviation of the actual and forecast demand are equal [Hill, 1996].

c) Supplier output variance.

To emulate the differences in supplier delivery and quality performance in the original supply chain, the model uses a "supplier variability factor" to model the variations in delivery and quality. As experienced in the real world the supplier creates a schedule according to a forecast but due to a variety of circumstances under production and

overproduction may occur. This is caused by problems with maintenance, quality, batch rules, transportation and the demands on production resulting from the requirements of other organisations within the supply network. The number of sub-assemblies produced by a supplier is therefore equal to the forecast multiplied by a supplier variability factor randomly selected on a weekly basis from a normal distribution of mean equal to one.

The supplier variability factor for a good (or JIT) supplier is selected randomly from a normal distribution of mean 1 and standard deviation 0.1. Whereas the supplier variability factor for a poor (or “rogue”) supplier is randomly selected from a normal distribution of mean 1 and standard deviation 0.3. The increased standard deviation for the “rogue” supplier leads to the assembler experiencing a less reliable supply stream of supply compared with the JIT supplier.

c) Simulation Operation

Each week the supplier receives a forecast, this is multiplied by the “supplier variability factor” calculated for that week. This figure indicates the number of sub-assemblies to be produced by that supplier. Calculating the production lead-time to manufacture each component according to the forecast demand enables the generation of a manufacturing schedule. This ensures a robust schedule to produce all the components required in that week. As the components are produced they are pushed to the supplier’s stock buffer. If this buffer becomes full the supplier is forced to stop production and wait until space is available in the buffer. Space is created when the customer takes a sub-assembly out of the stock buffer.

Within the network each supplier operates independently. The degree of “Supplier Variability” will differ between each supplier. A supplier can be made into a “Rogue Supplier” by increasing the standard deviation of that supplier. This results in the week by week output of sub-assemblies being far more variable.

The customer produces according to the actual demand. As with the supplier, the assembler receives the actual demand for the week and calculates the required production lead-time to produce a schedule to manufacture all the required items in that week. The assembler is subjected to no variability. The assembler pulls components out of the various supplier stock buffers. To manufacture the finished assembly one of each sub-assembly is required. If any one sub-assembly is unavailable then the customer can not manufacture. The simulation works continuously, components are taken from the four supplier stock buffers as required to manufacture according to the assemblers schedule.

Figure 7.5 and 7.6 show the flow charts for the assembler and suppliers respectively.

d) Summary

In summary, if a supplier’s inventory buffer is full then the supplier is stopped from producing excess stock. If a supplier’s inventory buffer is empty then the customer can not manufacture a finished component until a sub-assembly is available. The simulation is slightly simplified in that no back orders are created, if the required number of components can not be produced in a given week these are not carried over to the following week.

The uncertainty within the supply network results in various forms of parallel interactions. The impact of the number of highly variable rogue supplies, the buffer

size and the variability of demand and forecast on customer and supplier utilisation has been studied.

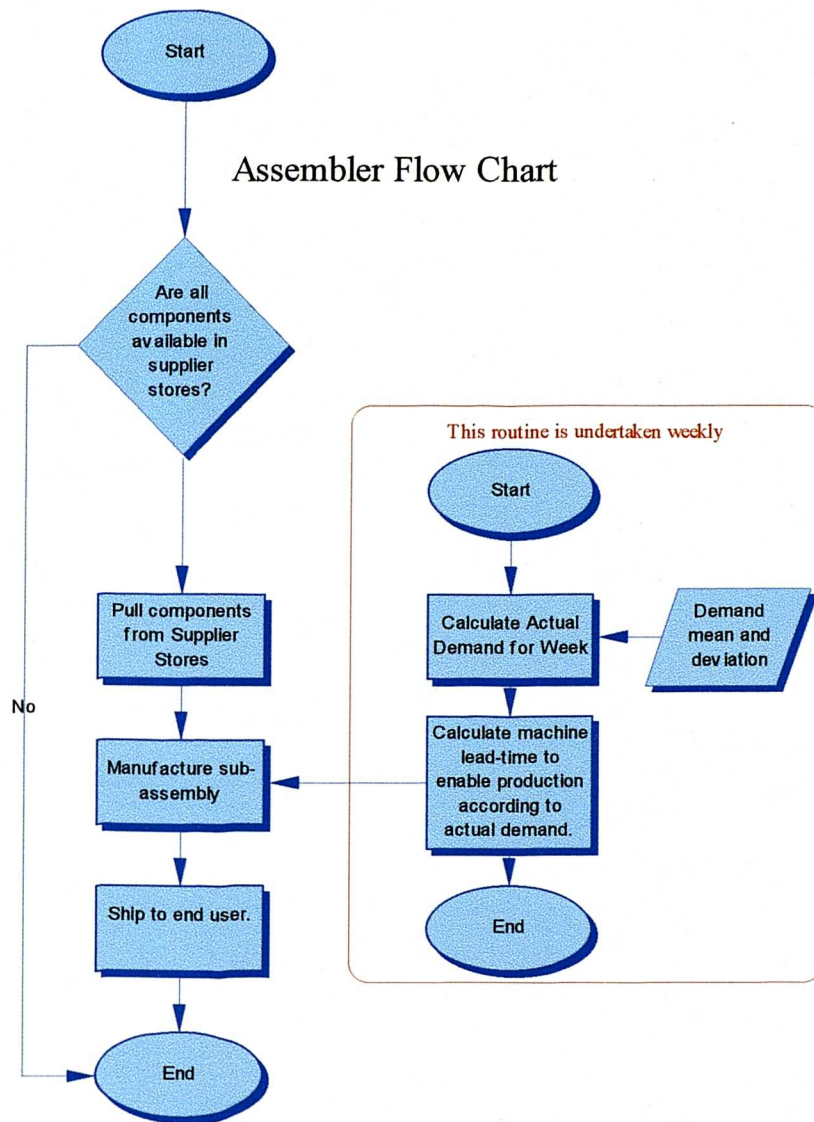


Figure 7.5 – Flowchart depicting simulation control logic of Assembler in supply network.

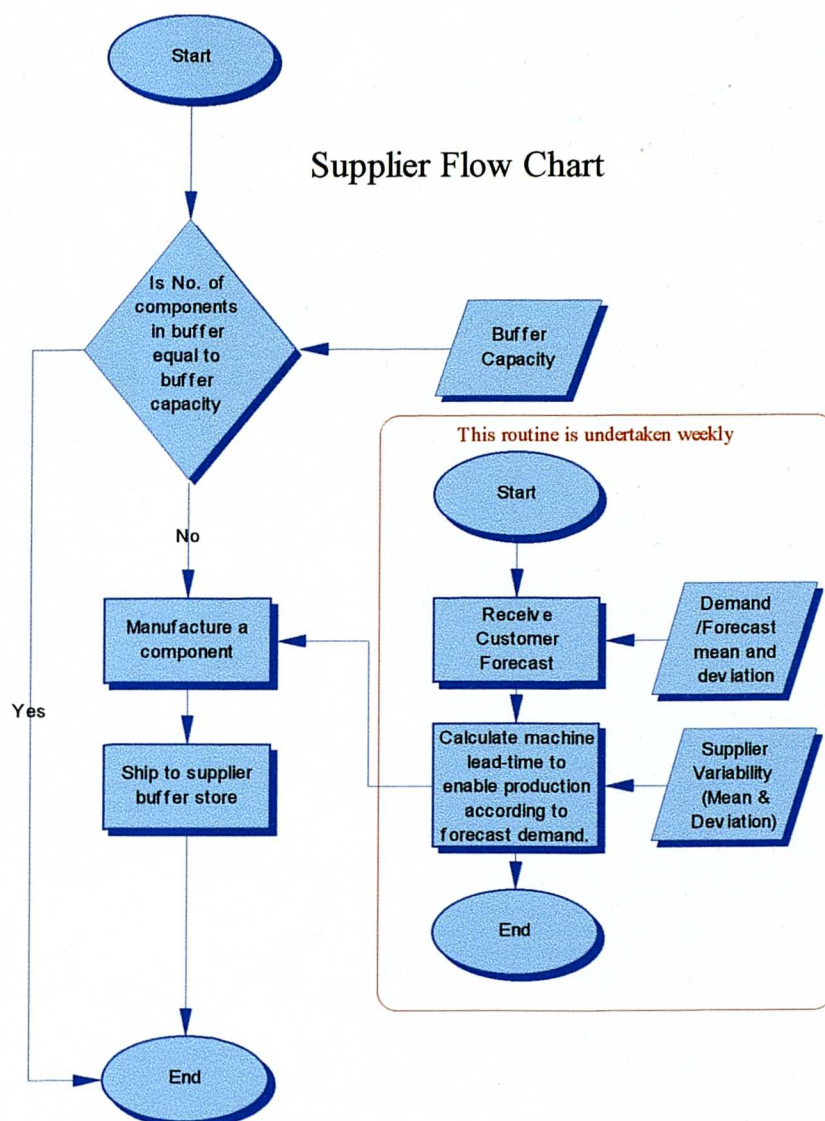


Figure 7.6 – Flowchart depicting simulation control logic of Suppliers in supply network.

7.3 Validation of model

The full validation procedure described in section 6.4 was applied to the simulation models used for this investigation.

As random number streams were used extensively within the simulation model for sampling from distributions step 10 in the 10-stage validation process was given particular emphasis.

From this analysis it was found that one of the random number streams selected produced a cumulative sum graph with a gradient which indicates the numbers produced were not random and exhibited a distinct bias.

By correlating the outputs from suppliers and assemblers other errors in the model were readily identified, for example, if two identical random number streams were used within the model there would be a higher degree of correlation. During validation this technique proved useful.

7.4 Investigation methodology and description of investigations.

The simulation model used was that described in section 7.2. The research questions raised in section 7.1 were addressed by varying one parameter while keeping all other parameters constant.

Both statistical and time series data were gathered from the simulation. The time series data collected included weekly demand and forecasts, weekly production figures for the suppliers and assembler, and the daily amount of inventory within the

buffers. This data was used extensively for the validation of the simulation model. The model was run for 10,000 days, which enabled robust validation and confidence in any statistical analysis.

Statistical data was also gathered from the model and this has been used for subsequent analysis. The data collected was the % utilisation of the suppliers and the assembler. This figure indicates the percentage of time the individual supplier is operating and is not stopped by interactions within the model. The % utilisation figure for a supplier could be used directly to calculate the % time stopped due to any interactions within the network, simply by subtracting the % utilisation figure from 100.

7.4.1 Impact of Forecast/Demand variation.

Two levels of Forecast and Demand variation were selected for the purpose of the analysis with a mean of 50 units of demand per week. The two degrees of Demand/Forecast variability were:

- Demand/Forecast mean = 50 units, Standard Deviation = 1, (Normal Distribution).
- Demand/Forecast mean = 50 units, Standard Deviation = 5, (Normal Distribution).

7.4.2 Impact of no of rogue suppliers on JIT supplier and assembler

The “supplier variability factor” was selected using a normal distribution of mean 1. The standard deviation of the factor was set at two levels, 0.1 and 0.3, for the JIT

supplier and “rogue” supplier respectively. In summary, the “supplier variability factors” are:

- For the JIT supplier: Mean = 1, Standard Deviation = 0.1, (Normal Distribution).
- For the “Rogue” Supplier: Mean = 1, Standard Deviation = 0.3, (Normal Distribution).

To quantify the impact of rogue suppliers on the JIT supplier and the assembler the simulation was run with an increasing number of “rogue” suppliers. Therefore the model was run with 0, 1, 2, 3, and 4 “rogue” suppliers for each buffer size and each level of Demand/Forecast variability.

7.4.3 Impact of inventory buffer size on JIT supplier and assembler.

To investigate the impact of inventory buffers on the “parallel interactions” the maximum inventory buffer size between the assemblers and the supplier was varied. Five buffer sizes were used in the investigation. These, as a percentage of average weekly demand are:

- 10% of average weekly demand (i.e. 5 units maximum).
- 40% of average weekly demand (i.e. 20 units maximum).
- 70% of average weekly demand (i.e. 35 units maximum).
- 100% of average weekly demand (i.e. 50 units maximum).
- 200% of average weekly demand (i.e. 100 units maximum).

7.4.4 Summary

The investigations outlined above resulted in 50 experiments being performed by the author. Each experimental run took approximately 25 minutes. The experiments were therefore initiated using a “Witness batch programme” which enabled 10 experiments to be run overnight, this also required further programming to enable data series reports and statistical analysis reports to be stored for further analysis.

7.5 Analysis of Results

7.5.1 Introduction

The full implications of the findings outlined in this chapter will be discussed within the context of the literature in Chapter 8. The following sections will present the findings of the investigations outlined in section 7.2 and 7.4. (The results are presented in tabular form in Appendix 1).

7.5.2 Impact of the number of “rogue” suppliers on the JIT supplier.

Figures 7.7 and 7.8 demonstrate the percentage of time the JIT supplier is stopped due to interactions generated by supplier variability from an increasing number of “rogue” suppliers in the supply network for Demand/Forecast standard deviations of 1 and 5 respectively.

Both graphs demonstrate that even when very large inventory buffers are available between the assembler and the suppliers some interaction takes place resulting in the JIT supplier being stopped.

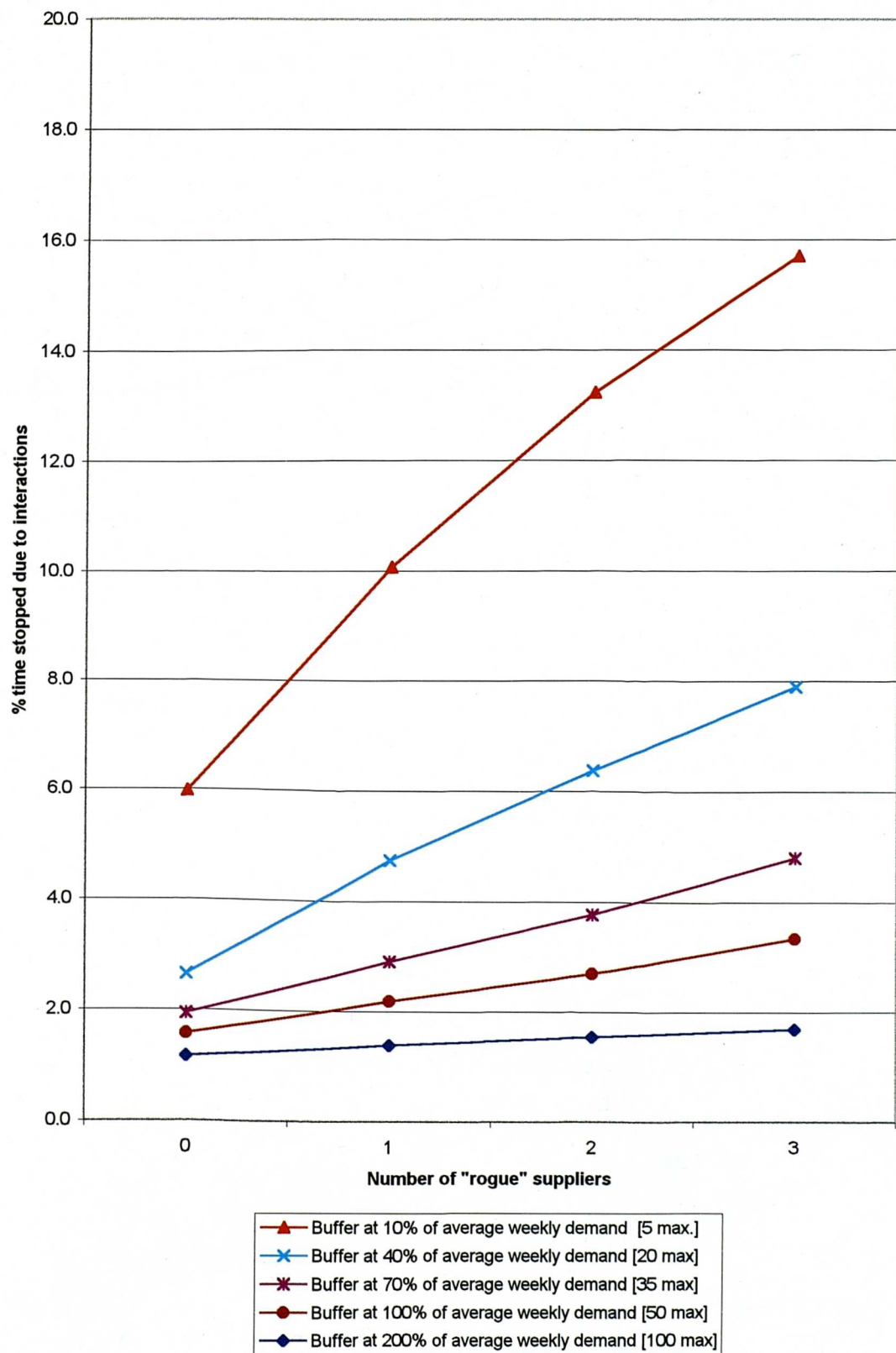


Figure 7.7 – Percentage of time the JIT supplier is stopped due to interactions for an increasing number of "rogue" suppliers in the supply network.

Demand/Forecast standard deviation = 1.

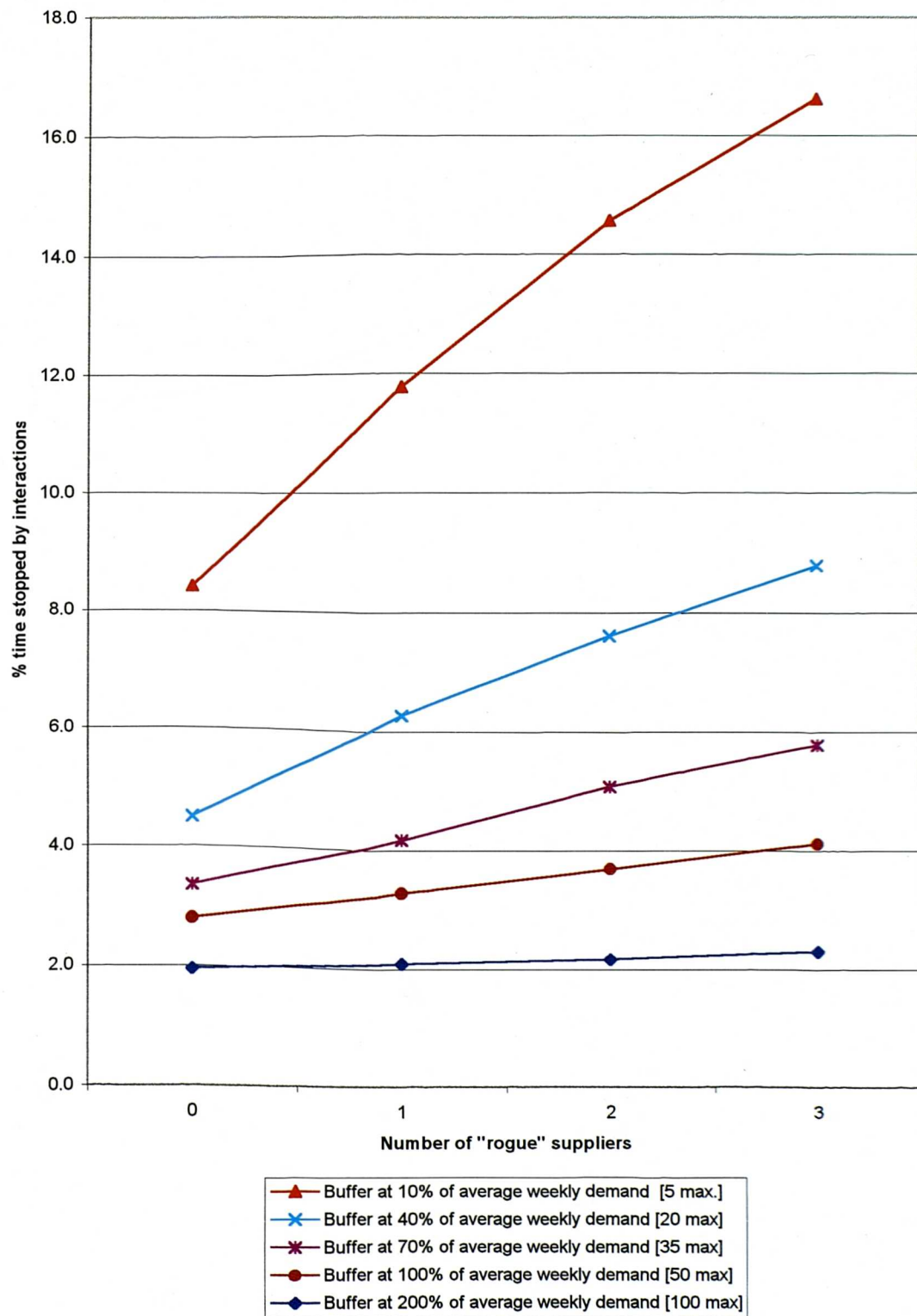


Figure 7.8 – Percentage of time the JIT supplier is stopped due to interactions for an increasing number of “rogue” suppliers in the supply network.

Demand/Forecast standard deviation = 5.

When a small inventory buffer is utilised by the suppliers the JIT supplier becomes very sensitive to interactions generated by the “rogue” suppliers.

In practice these stoppages may result in reduced utilisation of resources or re-scheduling of production to manufacture for other customers.

7.5.3 Impact of the number of “rogue” suppliers on the assembler

Figures 7.9 and 7.10 demonstrate the impact of the number of “rogue” suppliers on the assembler for Demand/Forecast standard deviations of 1 and 5 respectively. The graphs demonstrate that the assembler is stopped by the variability of the suppliers in its supply network.

The stoppages experienced by the assembler are the result of a lack of components being available for manufacture. It can be seen that for large buffer sizes stoppages are less prevalent resulting in a low percentage time stopped due to interactions.

The assembler would, in practice, re-schedule production to accommodate particular component short falls. This re-scheduling activity then results in other suppliers in the network having to re-schedule their activities; thus “parallel interactions” are generated. This is the source of the schedule “ripple” variations observed by Jones [Jones, 1990 p.291].

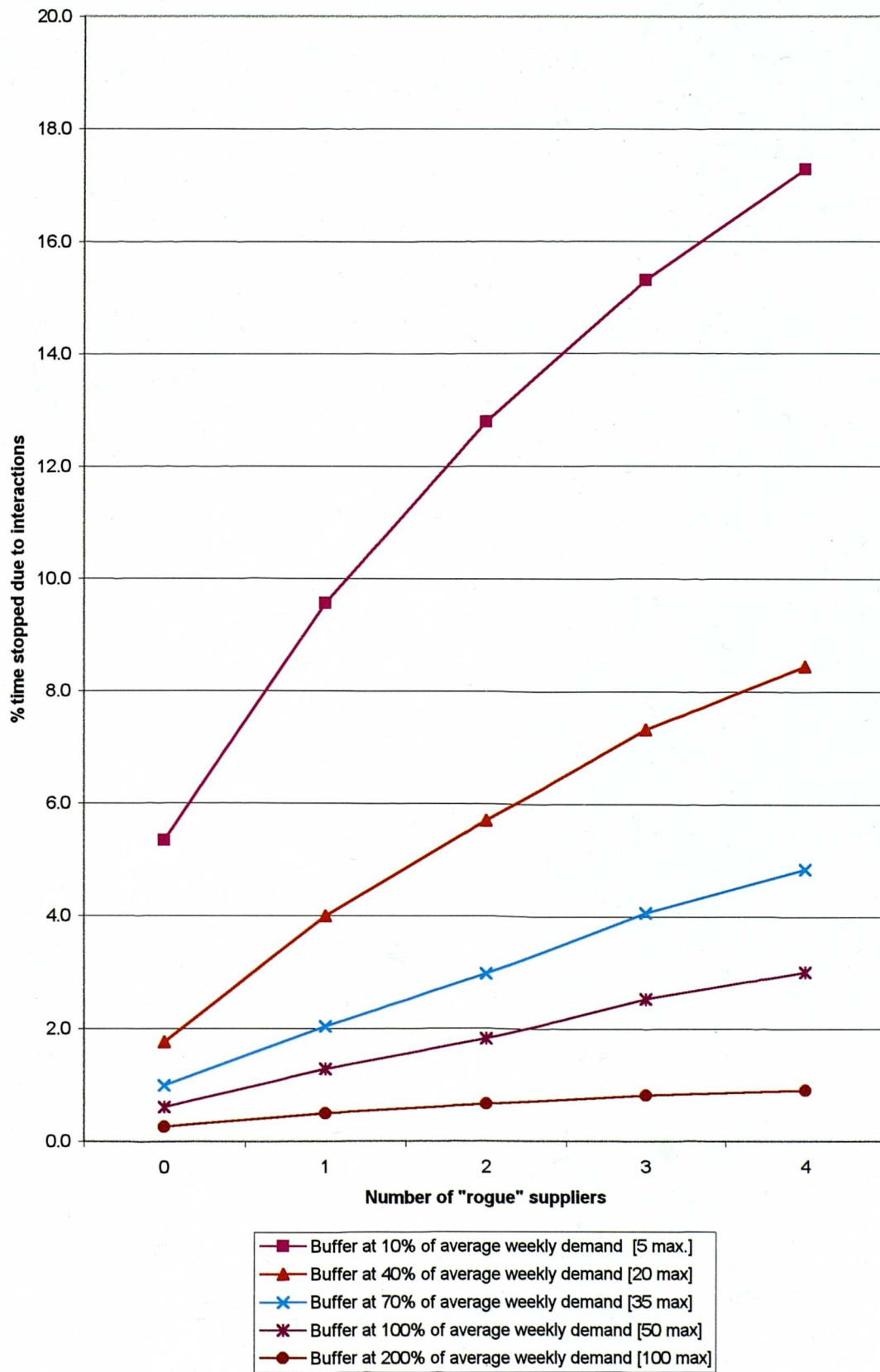


Figure 7.9 – Percentage of time the assembler is stopped due to interactions for an increasing number of “rogue” suppliers in the supply network.

Demand/Forecast standard deviation = 1.

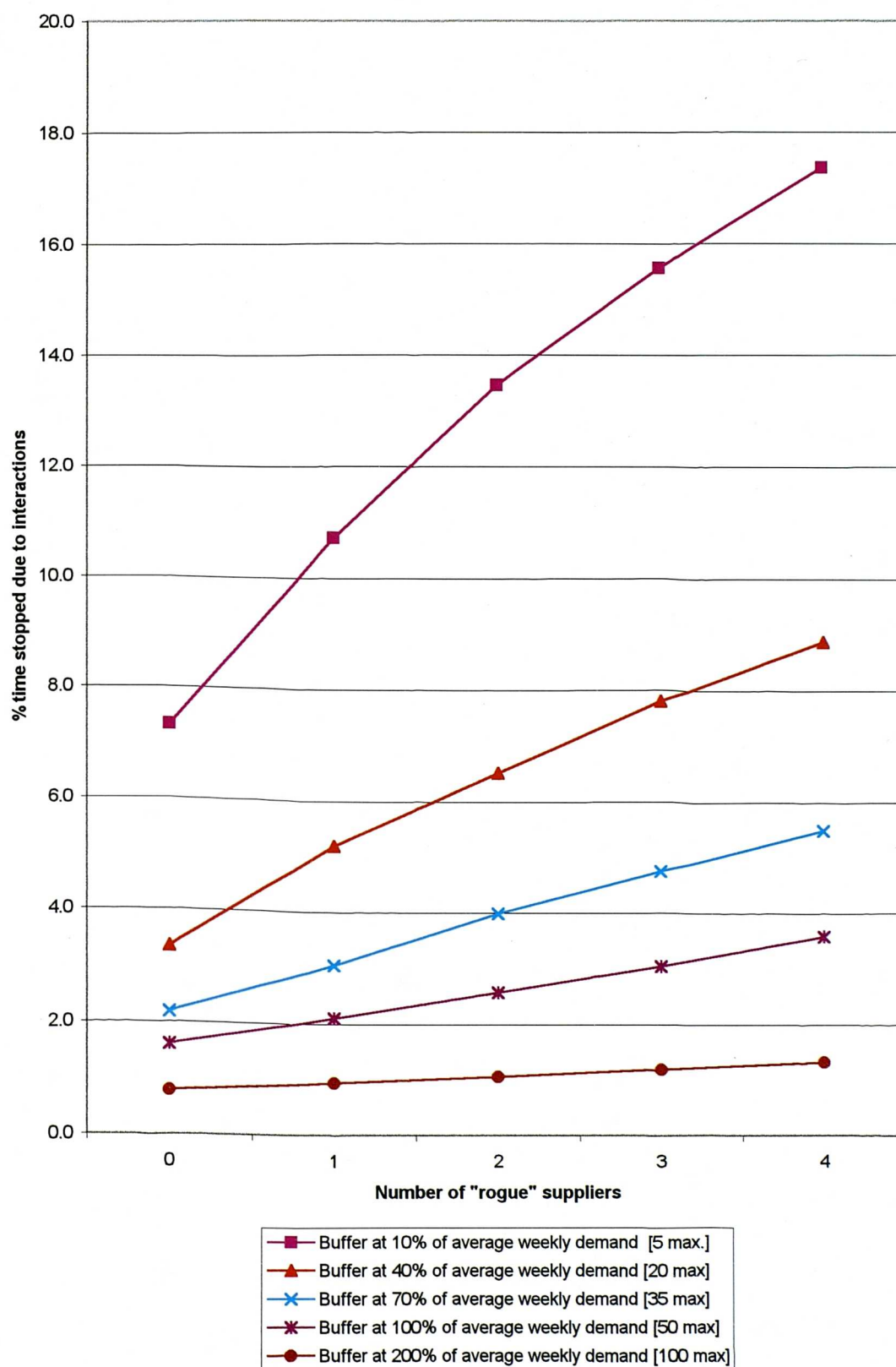


Figure 7.10 – Percentage of time the assembler is stopped due to interactions for an increasing number of “rogue” suppliers in the supply network.

Demand/Forecast standard deviation = 5.

7.5.4 Impact of buffer size on JIT supplier.

Figures 7.11 and 7.12 depict the relationship between the percentage of time the JIT supplier is stopped by interactions and the size of the inventory buffer between the suppliers and the assembler for Demand/Forecast standard deviations of 1 and 5 respectively.

The graphs show that as the inventory buffer increases the stoppages due to interactions are dramatically reduced. Each line on the graph represents a different number of “rogue” suppliers in the network, as the size of the buffer increases these lines converge indicating that the uncertainty caused by “parallel interactions” within the supply network are being absorbed by the inventory.

7.5.5 Impact of buffer size on assembler.

Figures 7.13 and 7.14 show the relationship between the percentage of time the assembler is stopped due to interactions and the inventory buffer size for between the suppliers and the assembler, for Demand/Forecast standard deviations of 1 and 5 respectively.

It can be seen a similar relationship occurs between the percentage of time the assembler is stopped and the percentage of time the supplier is stopped due to interactions, as outlined in section 7.5.4.

As the inventory buffer increases the percentage of time stopped decreases and hence the degree of utilisation for the assembler increases.

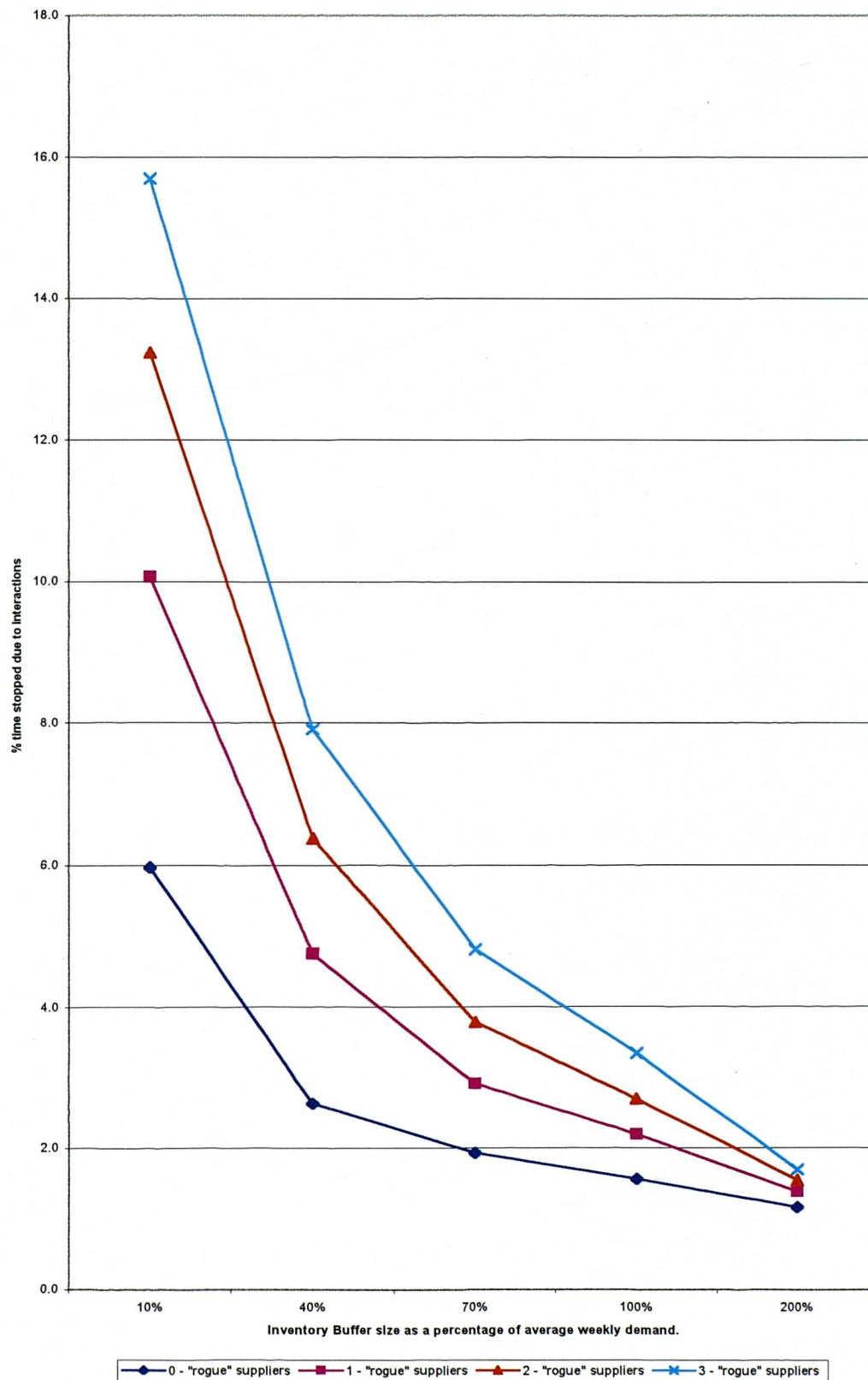


Figure 7.11 – Percentage of time the JIT supplier is stopped due to interactions against the inventory buffer sizes in the supply network.

Demand/Forecast standard deviation = 1.

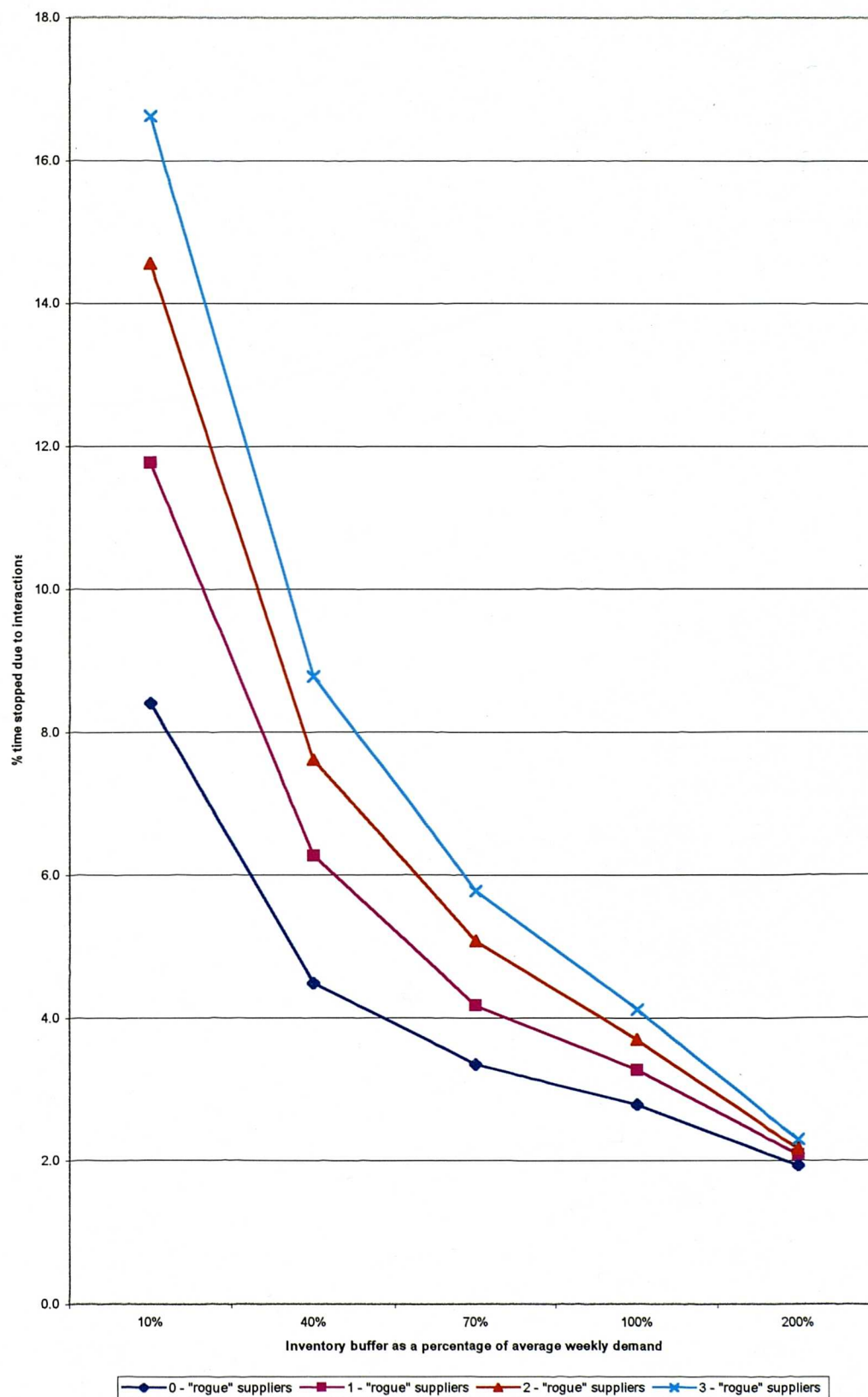


Figure 7.12 – Percentage of time the JIT supplier is stopped due to interactions against the inventory buffer sizes in the supply network.

Demand/Forecast standard deviation = 5.

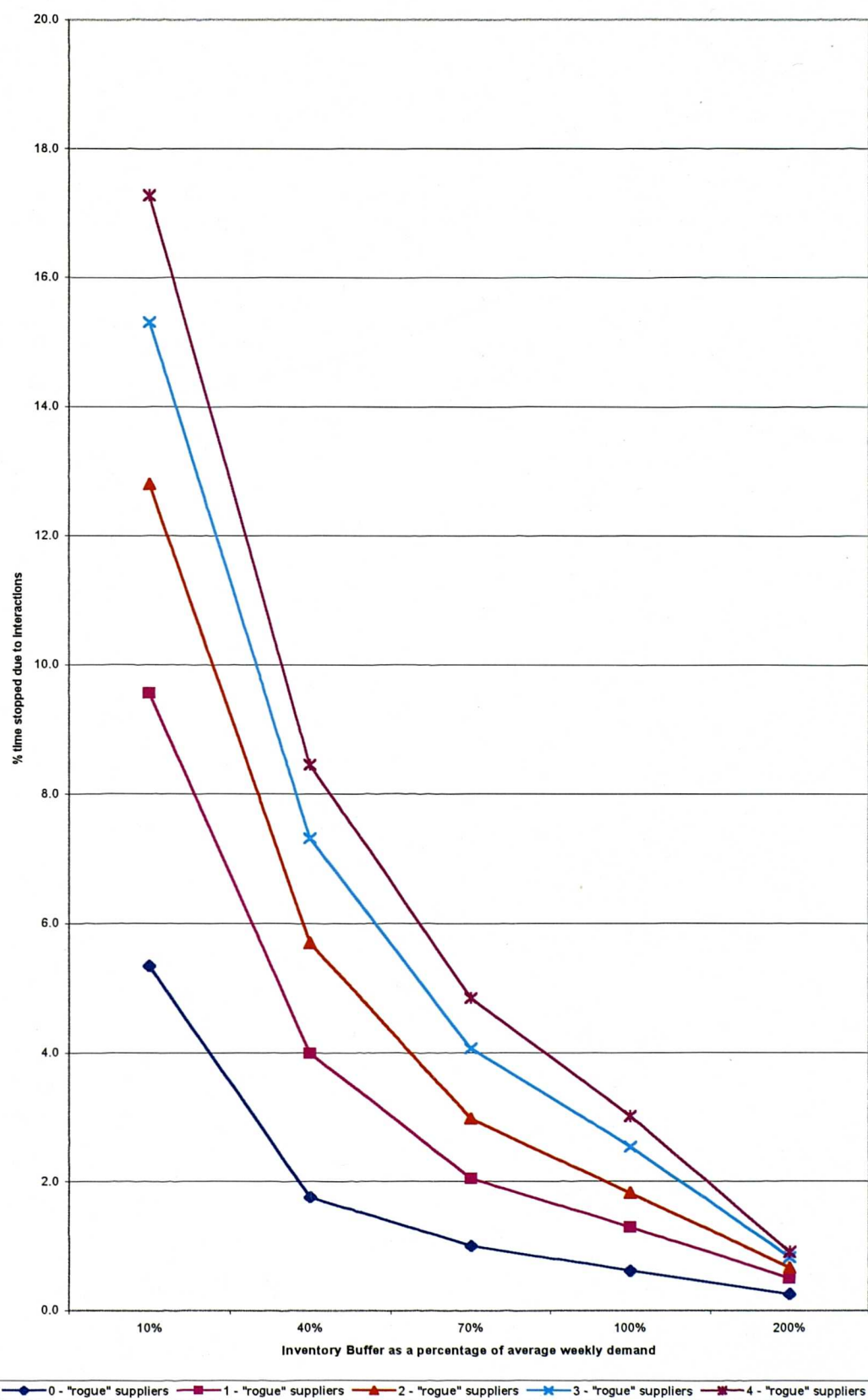


Figure 7.13 – Percentage of time the Assembler is stopped due to interactions against the inventory buffer sizes in the supply network.

Demand/Forecast standard deviation = 1.

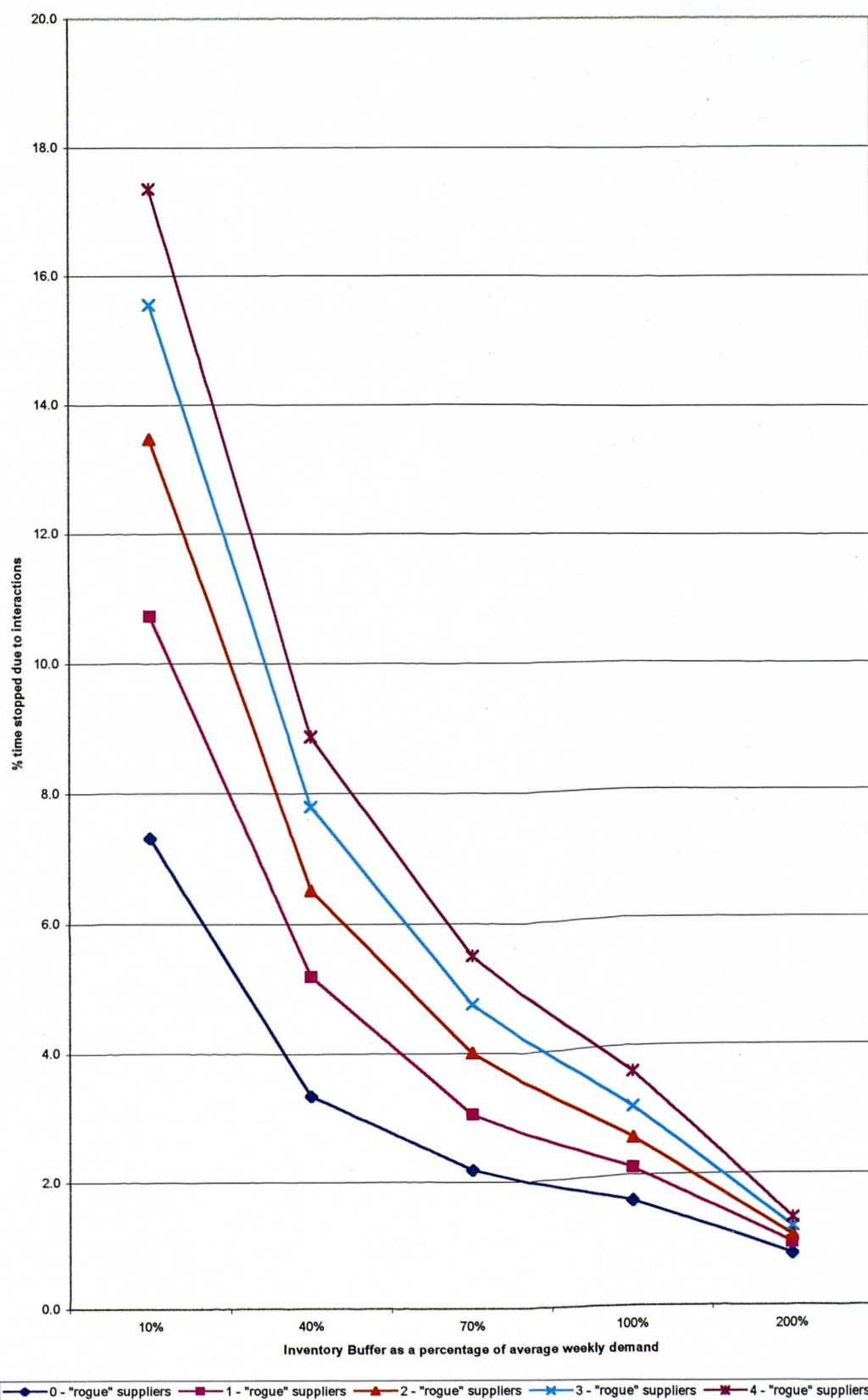


Figure 7.14 – Percentage of time the Assembler is stopped due to interactions against the inventory buffer sizes in the supply network.

Demand/Forecast standard deviation = 5.

7.5.6 Impact of degree of variability between forecast and actual demand on network.

Figures 7.15, 7.16, 7.17 and 7.18 demonstrate the impact the different Demand/Forecast standard deviations have on the percentage time Supplier and assembler are stopped for both varying buffer sizes and numbers of “rogue” suppliers. (Minimum and maximum numbers of “rogue” suppliers and minimum and maximum buffer sizes have been selected for the graphs to enable relationships to be visualised.)

The graphs, in all cases, demonstrate that less variability between the Forecast and Demand reduces the degree of uncertainty and improves the utilisation of both the suppliers and the assembler. Reducing the Forecast and Demand variability results in a reduction in the interactions and thus reduces stoppages.

This result supports and quantifies what is experienced in industry and demonstrates the benefits of improved forecast and demand correlation in the short term.

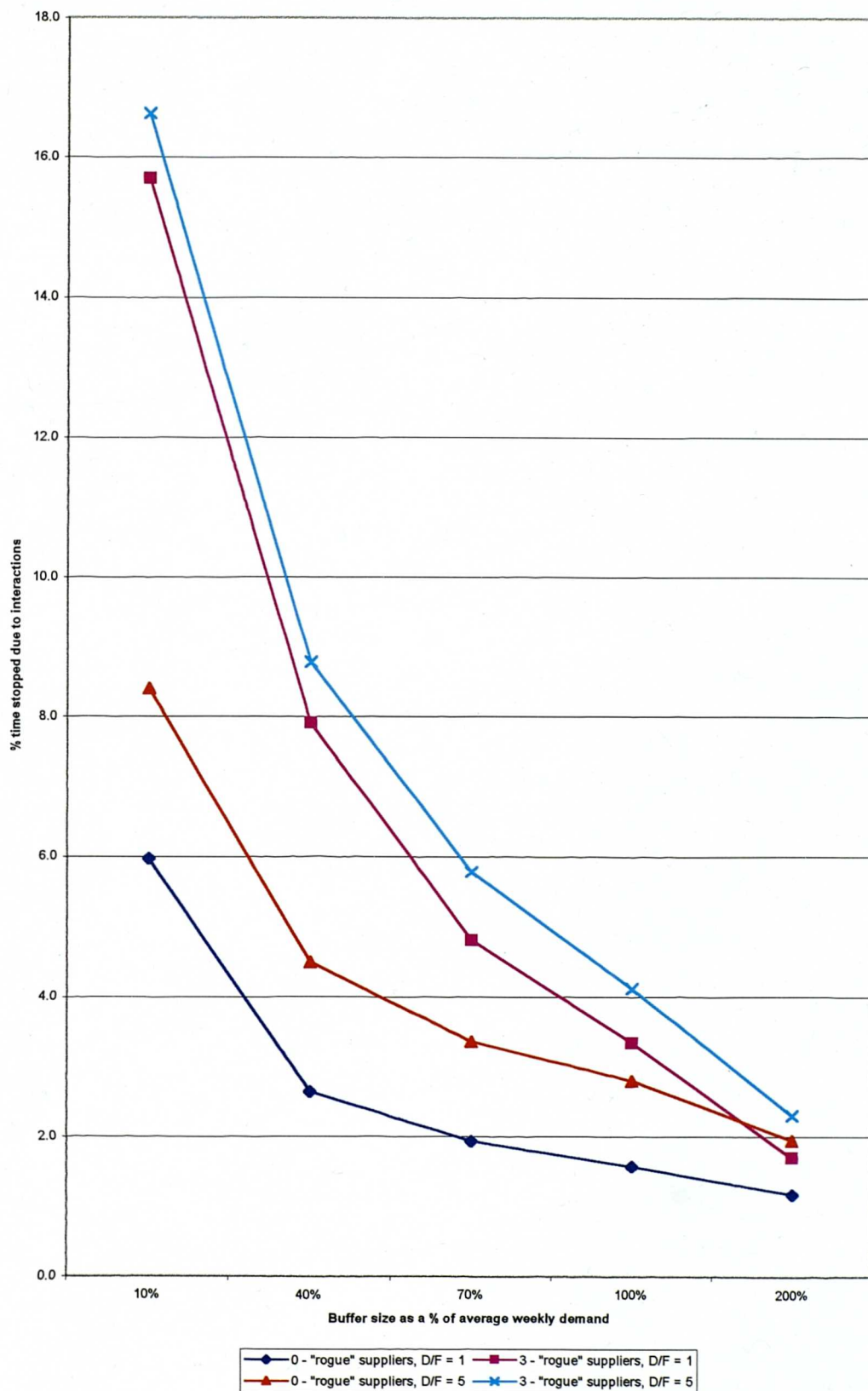


Figure 7.15 – Graph demonstrating impact of Demand/Forecast standard deviation (D/F) on percentage of time the JIT supplier is stopped due to interactions for varying inventory buffer sizes in the supply network.

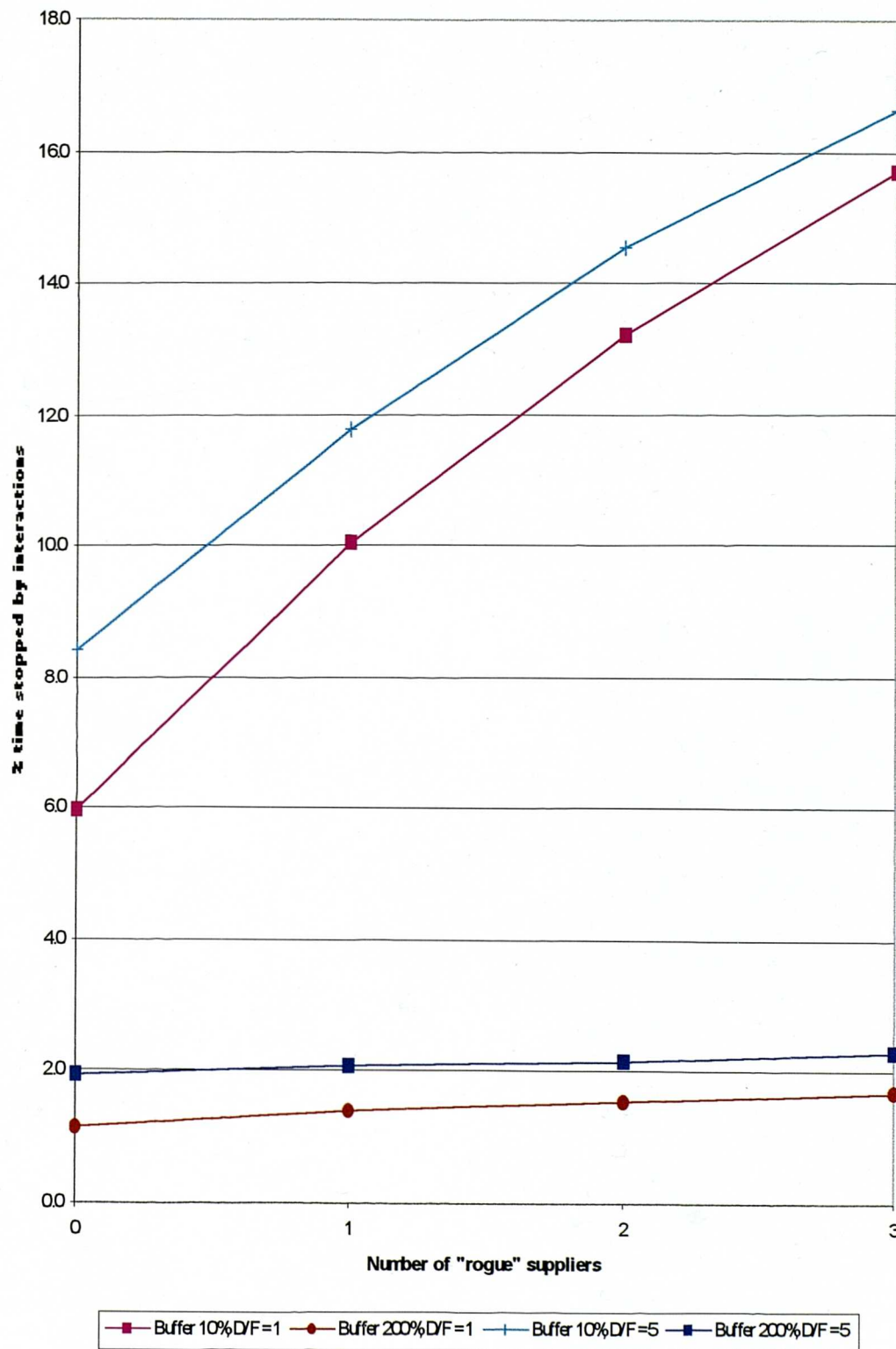


Figure 7.16 – Graph demonstrating impact of Demand/Forecast standard deviation (D/F) on percentage of time the JIT supplier is stopped due to interactions for varying numbers of “rogue” suppliers in the supply network.

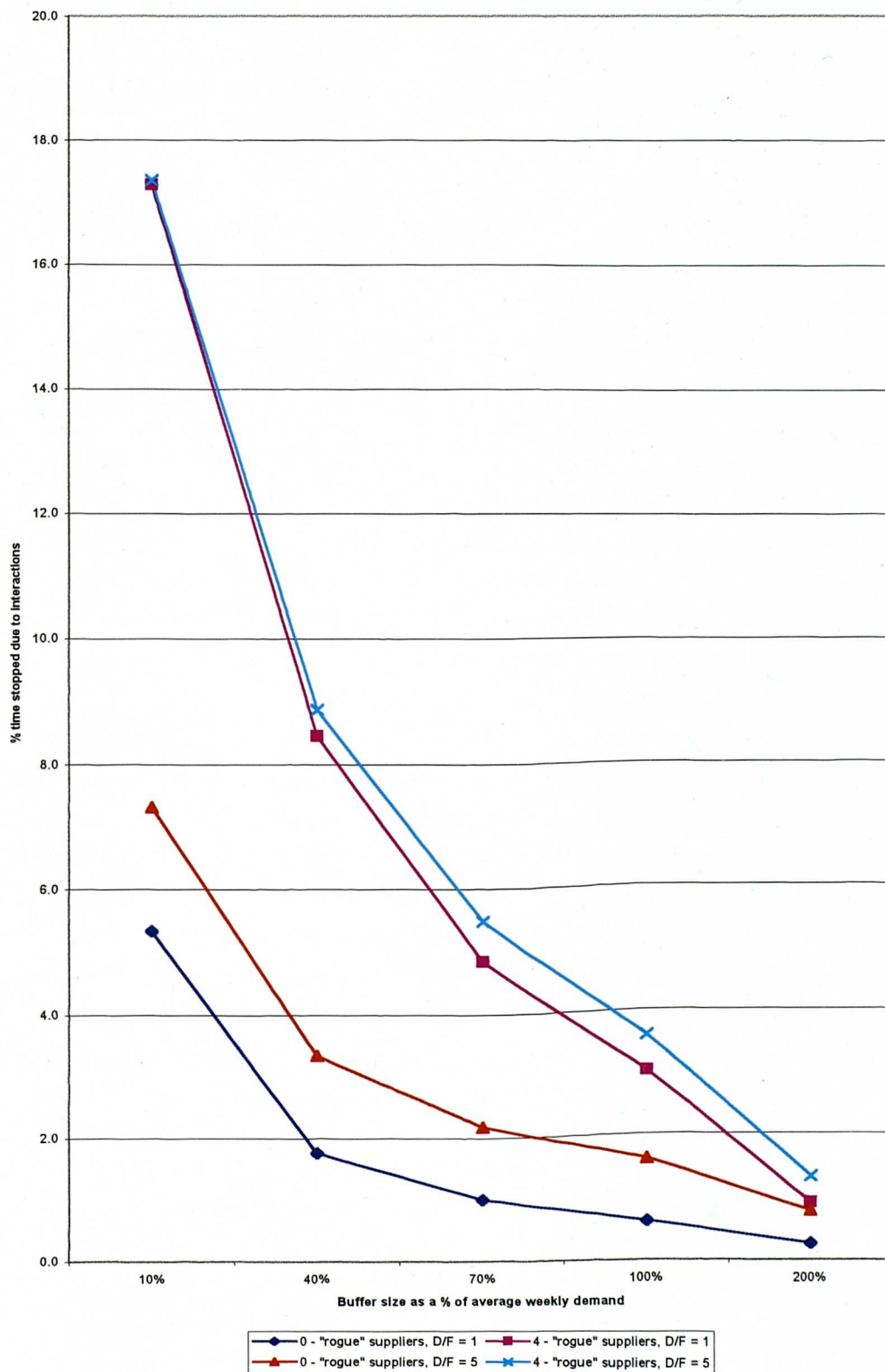


Figure 7.17 – Graph demonstrating impact of Demand/Forecast standard deviation (D/F) on Percentage of time the assembler is stopped due to interactions for varying inventory buffer sizes in the supply network.

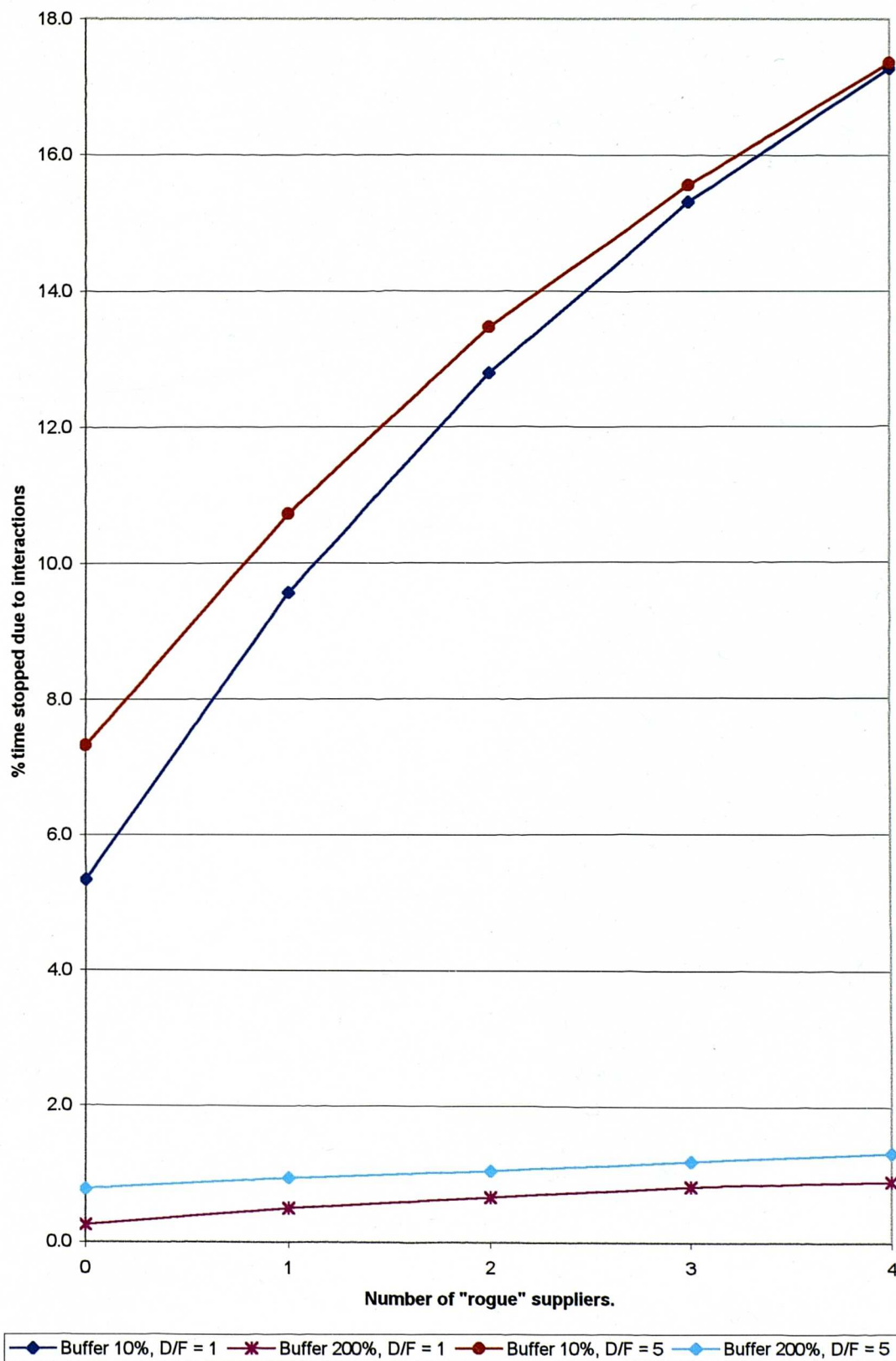


Figure 7.18 – Graph demonstrating impact of Demand/Forecast standard deviation (D/F) on Percentage of time the assembler is stopped due to interactions for varying numbers of “rogue” suppliers in the supply network.

7.7 Conclusion to Chapter 7

The investigation described above demonstrates that “parallel interactions” between suppliers within a supply network do occur. The impact of the interactions on individual suppliers and the assembler has been quantified by calculating the percentage of time the company or assembler would be stopped due to the interactions. In practice, an actual stoppage may not occur but organisations may be forced to re-schedule thus resulting in fluctuations and uncertainties in demand being experienced by suppliers. The “parallel interactions” within the network can be reduced by buffering with inventory, however even for large buffers interactions do occur but less frequently.

The investigation also demonstrates and quantifies the impact of variability between the forecast demand and the actual demand. Increased variability between the forecast and actual demand results in both suppliers and the assembler experiencing increased stoppages due to interactions.

This work also highlights that a JIT supplier within a supply network is susceptible to interactions from “rogue” suppliers that can dramatically impact on the JIT suppliers’ utilisation. Inventory is required to buffer the JIT supplier from such interactions, which may in some situations remove the benefits of operating “just in time”. A “rogue” supplier within a supply network does not only affect the assembler but also other suppliers in the network. This further emphasises the need for a holistic approach to supply chain management recognising that the supply network must be treated as a system and not a collection of individual companies.

Increasing the number of “rogue” suppliers within the network increases the degree of parallel interactions and results in increased stoppages for both the assembler and the suppliers.

In conclusion, “parallel interactions” are a further source of uncertainty within the supply chain and can have a significant impact on all players.

Chapter 8

Final discussion and implications of research.

8.1 Introduction.

In section 1.2 of this dissertation the research problem to be investigated was described as follows:

What are the sources of uncertainty generated internally by systems within the supply chain and what is their impact on supply chain performance?

In chapter 2 the research was set in the context of supply chain management and the drivers for supply chain management and an overview of the current requirements for effective supply chain management are outlined.

Chapter 3 described and reviewed the literature on the generation of amplification and uncertainty through internal processes. The chapter concluded (see section 3.7) that the generation of uncertainty through internal processes has received little attention in recent years. The main focus of the research has been on the Forrester amplification effect in serial supply chains. Little investigative research has considered uncertainty in supply networks and the interactions between suppliers that may generate further sources of uncertainty. The survey also indicated that few attempts have been made to quantify and measure the dynamics generated internally.

Chapter 3 concluded with the following research questions:

- Is a significant amount of uncertainty generated by the internal processes?
- How is uncertainty generated by internal processes and are there other sources of internal uncertainty apart from amplification present?
- Can these effects be quantified for a given system?
- Does deterministic chaos contribute to the uncertainty within the supply chain?

In Chapter 4 this final question was investigated further. A review of the literature describing the historical development of the science and characteristics of deterministic chaos concluded that supply chain environments could potentially be prone to chaotic behaviour. A further review of the application of chaos theory to areas relevant to supply chains was undertaken (see section 4.8). This identified two main areas of literature focusing on management within chaotic environments and the generation of chaos in human decision making behaviour.

In summary the research questions raised by chapter 4 are as follows:

- Work to date has focused on theoretical supply chains; can such behaviour occur in real supply chains?
- Investigations have presumed that management misperceptions occur in the supply chain, does chaotic behaviour occur if no misperceptions about inventory or demand are present?
- Does the degree of chaos in a supply chain increase indefinitely as demand is passed between echelons upstream of the customer?

- If chaos is generated, how does the complexity of the supply chain's structure impact on the amount of chaos present?
- If chaos is generated, is this the overriding mechanism for the generation of uncertainty, and does the chaotic nature of the system override the stochastic shocks that the system is exposed to?
- Can "Islands of stability" be identified and utilised in stabilising or reducing uncertainty?

In order to address the research questions raised in chapter 4 a robust methodology for the identification and quantification of deterministic chaos was researched and developed in chapter 5. It was identified that Lyapunov exponents could be calculated from time series data and these could then be used to calculate the prediction horizon of the data. The prediction horizon can then be used to quantify the degree of uncertainty generated by deterministic chaos within the supply chain..

Chapter 6 documents the investigation methodology for addressing the research questions raised about the generation of uncertainty by a chaotic mechanism in supply chains. The simulation methodology was described and the validation procedure documented. The investigation methodology was described to address the research questions raised by the literature review and four main investigations were undertaken these were:

- Investigation 1 – Is chaos generated within a real supply chain with no misperceptions about orders or inventory?

- Investigation 2 – The impact on the degree of chaos by increasing the supply chain complexity through increasing the number of echelons.
- Investigation 3 – The impact on the degree of chaos by increasing the supply chain complexity through increasing the number of customer channels.
- Investigation 4 – The identification of “Islands of stability”.

The results of these investigations were analysed and discussed. These investigations demonstrated that deterministic chaos is generated within supply chains and can be quantified for a particular system.

In chapter 7 a further area of investigation was described to identify “parallel interactions” between suppliers. The simulation model was based on a real automotive supply chain. The investigations quantified the impact of a highly variable “rogue” supplier on both the down stream assembler and a JIT low variability supplier. The impact of schedule stability and inventory buffer size was also investigated. This demonstrated that “parallel interactions” are a further source of uncertainty within a supply network.

In the following sections the evidence gained from the investigations described above will be discussed in relation to the research questions raised by the review of the literature. The impact of this analysis on the research problem will then be described in relation to supply chain management theory and management policy and conventional practise in such environments. The limitations of the research that were identified during the investigations will be described and finally the implications for further research will be documented.

8.2 Research questions: Conclusion.

In the following section the research questions outlined above will be discussed in relation to the evidence gained from the investigation undertaken in this dissertation.

8.2.1 How is uncertainty generated by internal processes and are there other sources of internal uncertainty present, apart from amplification?

The majority of investigations to date have focused on the generation of uncertainty through demand amplification. This phenomenon does not explain fully the complexity of the dynamics experienced within the supply chain.

Research undertaken by Forrester, Jones and Towill [Forrester, 1961; Jones, 1990; Towill, 1992] have all demonstrated that significant oscillations are generated by the process of demand amplification. This, more recently, has been experienced in world class supply chains by Owen Jones [Jones, 1997] and McGuffog of Nestle [McGuffog, 1997]. This is despite the organisations concerned applying all previously known methods to reduce amplification.

This would seem to indicate that perhaps other mechanisms for the internal generation of uncertainty are present. Parallel interactions and deterministic chaos both offer possible explanations for the complex dynamics being witnessed in world class supply chains where “random” uncertainty due to breakdowns, quality etc are not seen as a significant problem. Internally generated uncertainty under certain circumstances can be the major source of uncertainty experienced in supply chains, producing dynamics far in excess of “random” uncertainty.

The research described in this thesis demonstrates two further sources of uncertainty, deterministic chaos and parallel interactions. Section 6.8.2 demonstrates that deterministic chaos can be readily generated within a real supply chain using commonly used control algorithms. This challenges the previously held theory that chaos is the result of misperceptions in management decision-making [Sterman, 1989b]. The simulation model used in this thesis allowed for no misperceptions about inventory or demand to be present.

Parallel interactions were also shown to have an effect on the degree of uncertainty experienced by all players in the supply chain. It is demonstrated by the literature that uncertainty impacts in a serial way within the supply chain [Groover, 1987], however the analysis of results in section 7.5 demonstrates that uncertainty readily passes in a parallel way across the supply network. These “parallel interactions” are a further source of uncertainty.

In conclusion, there are additional sources of internally generated uncertainty within the supply chain. Three independent yet interacting effects can be identified; amplification, deterministic chaos and parallel interactions.

8.2.2 Is a significant amount of uncertainty generated by the internal supply chain processes?

The investigations into demand amplification carried out by Forrester [Forrester, 1961] and in more recent years Towill [Towill, 1991] demonstrate that significant uncertainty can be generated by amplification. Jones [Jones, 1990] in his investigation of a real automotive supply chain observed that the degree of amplification

experienced exceeded that expected theoretically. There is little doubt that demand amplification can be a source of significant uncertainty within supply chains.

The results of the investigations described in section 6.8 demonstrate that a significant amount of uncertainty can also be generated by the production of deterministic chaos. The non-linear control algorithms at each echelon in the supply chain distort constant predictable customer demand with an infinite prediction horizon. This distortion results in a reduction of the prediction horizon to approximately 20 days (see section 6.8.3a). In addition, the research reviewed in section 4.8.2 demonstrates that human decision making behaviour may also be responsible for chaos within the supply chain due to the misperceptions of the managers [Mosekilde & Larsen, 1988].

Parallel interactions can also be a significant source of uncertainty within the supply chain. In section 7.5.2 and 7.5.3 the number of “rogue” suppliers can be seen to have an impact on the JIT supplier and the assembler. Even with large inventory buffers the parallel interactions have some impact on the utilisation of both the assembler and other suppliers in the network. The results from these sections demonstrate that upwards of 18% of the time suppliers and the assembler can be stopped by parallel interactions or their programmes can be disrupted.

In conclusion, the three sources described above can under certain circumstances generate significant amounts of uncertainty for all players in the supply chain. Any number of these sources within a particular supply chain may generate this uncertainty.

8.2.3 Can these effects be quantified for a given system?

Work by Berry et al [Berry, Towill, & Wadsley, 1994] has quantified the degree of amplification present. The investigations within this thesis demonstrate that both deterministic chaos and parallel interactions can be quantified for a given system.

In practice, the use of simulation enables the production of data for the quantification of these sources of uncertainty. By running the simulation model in a deterministic mode the degree of uncertainty due to chaos can be quantified by the calculation of the prediction horizon [Wilding, 1997]. By running the simulation model in a stochastic mode the degree of disruption due to parallel interactions can be quantified by the percentage of productive time lost due to interactions.

In conclusion, using the methodologies developed in this thesis it is possible to quantify these sources of uncertainty for a given system.

8.2.4 Is uncertainty generated by deterministic chaos in real supply chains?

For all the simulations undertaken within this thesis careful validation procedures have been applied to ensure that the model reflects the key characteristics of real supply chains (see section 6.4).

The results describe in section 6.8.2 demonstrate that deterministic chaos can be generated within the warehouse supply chain investigated. The first warehouse in the supply chain (warehouse 1) shows behaviour that the discriminating statistic and surrogate data analysis would define as chaotic. However, the return plots of the data

seem to demonstrate periodic or quasi-periodic behaviour. There is therefore a strong possibility that chaotic behaviour is present in this warehouse (see section 6.8.2a).

In the second warehouse (warehouse 2) all the tests within the methodology indicate that chaotic behaviour is present (see section 6.8.2b).

In conclusion, real supply chains can under certain conditions generate uncertainty through a deterministic chaos mechanism. These conditions are well within the operating parameters used by industry.

8.2.5 Does chaotic behaviour occur if no misperceptions about inventory or demand are present in the supply chain?

The supply chain model simulated allowed for no misperceptions about inventory and demand and pipeline stock as the model monitors each individual transaction as it passes between each echelon in the supply chain. The data is also sent electronically so that no data errors can occur within the modelled system. In section 6.8.2 it is clearly demonstrated that chaotic behaviour is present within the modelled supply chain.

In conclusion, deterministic chaos can be generated when no misperceptions are present about inventory or demand.

8.2.6 Does degree of chaos in a supply chain increase indefinitely as demand is passed between echelons upstream of customer?

In section 6.8.3a the amplification of chaos within a five-warehouse supply chain is described. It is clear that the prediction horizon of the data series from each echelon

reduces the further upstream one is within the supply chain. However after approximately three echelons the prediction horizon plateaus and does not seem to increase any further, this supports what is observed in real industrial supply chains. Even raw material suppliers obtain some benefit from forecasting. This observation is in contrast to the observations on demand amplification, which increase with each echelon in the supply chain.

In conclusion, the amount of chaos does not increase indefinitely as demand is passed between echelons upstream of the customer.

8.2.7 If chaos is generated, how does the complexity of the supply chain's structure impact on the amount of chaos present?

Within the investigations documented in this thesis, supply chain complexity has been increased in two ways; increasing the number of echelons (see section 6.8.3) and increasing the number of customer channels (see section 6.8.4).

The results demonstrate that increasing the number of echelons in the supply chain has a significant effect on the amount of chaos for all players in the supply chain. Reducing the number of echelons impacts on the degree of chaos experienced in both upstream and downstream echelons. The lower the number of echelons in the supply chain the less the amount of chaos experienced by all players in the supply chain.

The number of customer channels has little effect on the amount of chaos experienced by those in the supply chain. The dynamic behaviour within warehouse 1 remained unchanged as the number of channels was increased (see section 6.8.4a). For warehouse 2 little change was observed as the number of channels was increased

apart from a daily demand level of 10 units which exhibits a downward trend in prediction horizon. This is either a special case or may plateau at one particular value if the number of echelons increase.

In conclusion, for the systems investigated the degree of chaos is more sensitive to the number of echelons in the supply chain than the number of channels. For chaotic behaviour, complexity in the form of “length” of supply chain is of more consequence than that introduced by “breadth” of supply chain i.e. the number of channels. (However the number of “parallel interactions” is a function of the number of channels.)

8.2.8 Is chaos an overriding mechanism for the generation of uncertainty and does the chaotic nature of the system override the stochastic shocks that the system is exposed to?

Deterministic chaos was seen to be an inherent mechanism operating within the supply chains investigated. It was found that for certain levels of demand and parameter settings, stable behaviour could be produced within the supply chains. These “islands of stability” were found to be very sensitive to demand and parameter settings (see section 6.8.5). Stochastic shocks can therefore force the system out of an “island of stability” into a chaotic mode of operation.

The results described in section 6.8.2d demonstrate the impact of a random element within the demand. It can be seen that this seems to have a stabilising effect on the dynamics in the short term. However in the longer term a series of chaotic spikes are observed where the system oscillates significantly more than for the data without

random input. This would seem to indicate that the system has been driven by the stochastic shocks into a different mode of chaotic behaviour.

In conclusion, the uncertainty generated by deterministic chaos can override the impact of stochastic shocks to the system. However it is recognised that further work is needed to obtain more complete answers to the above question.

8.2.9 Can “Islands of stability” be identified and utilised in stabilising or reducing uncertainty?

The results described in section 6.8.5 demonstrate that “islands of stability” can be identified for particular parameter and demand settings. This is analogous to the simple iterated equations outlined in section 4.4.1.8 where “islands of stability” are observed within regions of chaotic operation.

However the results detailed in section 6.8.5 demonstrate that the “islands of stability” are dependent on demand levels, service level constant setting, the structure of the supply chain etc. It would therefore be possible in practice to identify an island of stability but any small change to the system, or random occurrences may cause the system to move into chaotic behaviour.

In conclusion, the investigations carried out in this thesis demonstrate the existence of “islands of stability”. However, further work is required to identify a practical methodology to harness this information for reducing or stabilising supply chain behaviour.

8.3 Research problem: Conclusion.

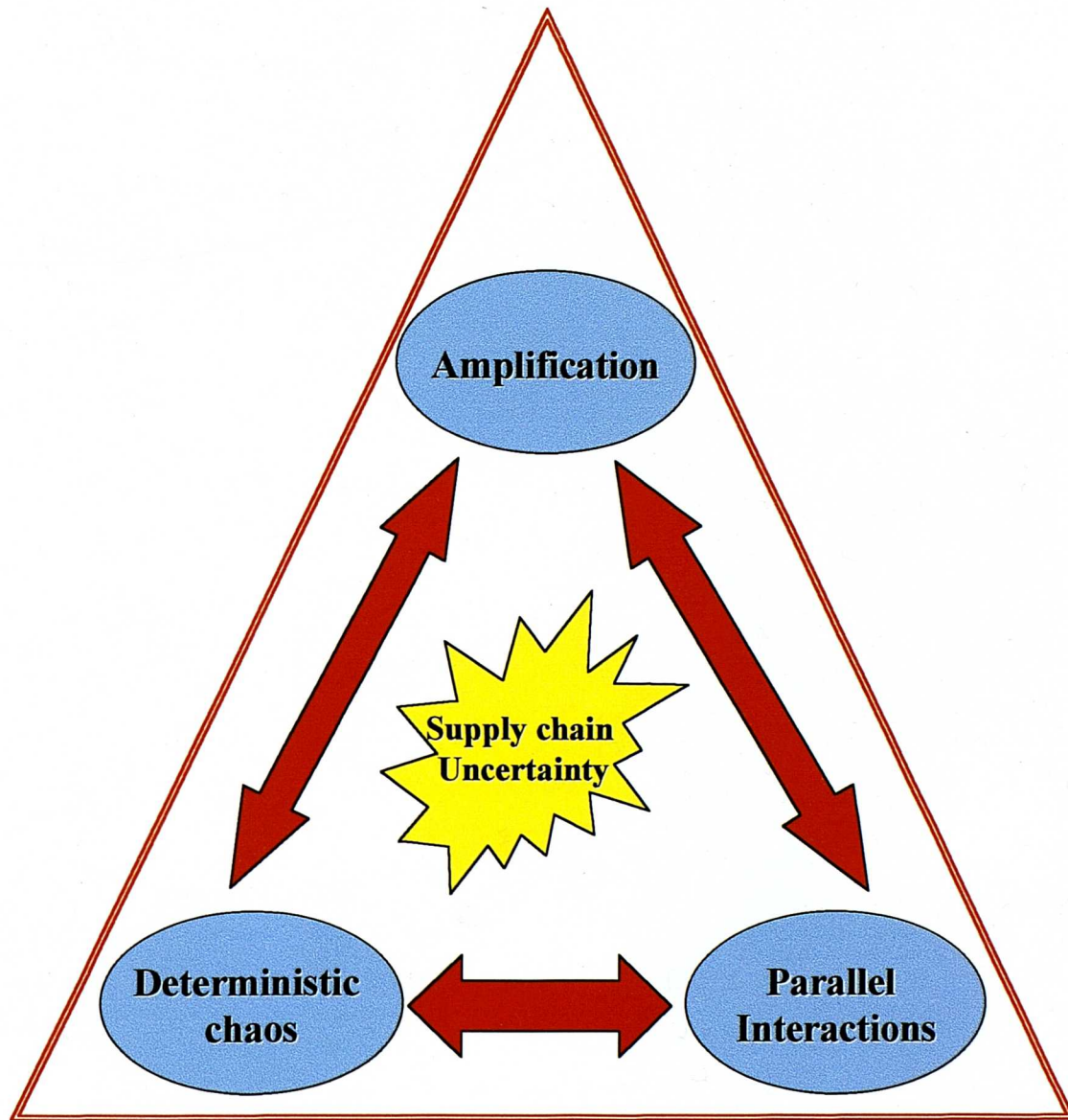
The research problem addressed by this thesis was described in section 1.2 as:

What are the sources of uncertainty generated internally by systems within the supply chain and what is their impact on supply chain performance?

The research documented in this dissertation has identified and quantified two additional sources of uncertainty, in addition to amplification, within supply chains which are generated as a result of a supply chain's systems and overall structure.

Three interacting yet independent effects would seem to cause the dynamic behaviour experienced within supply chains. These are deterministic chaos, parallel interactions and demand amplification. The combination of these effects can significantly increase the degree of uncertainty within a supply chain system.

Figure 8.1 depicts these three effects and their interactions. This "Supply chain complexity triangle" results because each source of uncertainty can act as a stimulus for one of the other sources of behaviour to occur. For example, demand amplification may result in a system operating initially in an "island of stability" to be pushed into a chaotic mode of operation. If the system is operating in a chaotic mode of operation the occurrence of a "chaotic spike" being generated within one echelon may result in demand amplification occurring in the echelons down stream. If, due to the demand amplification and chaos, capacity is exceeded in one supply channel the resulting mis-supply may cause parallel interactions which in turn may result in amplification and chaos. The three interacting phenomena therefore result in complex



The Supply Chain Complexity Triangle

Figure 8.1 – The supply chain complexity triangle.

demand patterns with limited forecast horizons. This uncertainty will result in additional costs being experienced by those in the supply chain.

Unexpected “chaotic spikes” have also been witnessed in a spreadsheet model produced by Levy [Levy, 1994] of a simple supply chain. Levy concludes that, within the chaotic system, dramatic change can occur unexpectedly. Small external changes can occur causing large changes in demand and inventory. The analysis in this thesis provides further evidence that this type of behaviour can occur within real supply chains.

A further paradox identified about the “Supply chain complexity triangle” is that methods to reduce the magnitude of one effect may result in an increase in magnitude in one of the other sources of uncertainty. This was witnessed in the results documented in section 6.6.4, in this investigation the supplier lead-time was reduced, this is known to reduce the degree of amplification generated within a supply chain [Wikner, Towill, & Naim, 1991]. However, the reduction of the lead-time resulted in an increase in the degree of chaos and hence a reduction of the prediction horizon of the data series. This result also confirms the finding of Gordon and Greenspan [Gordon & Greenspan, 1994] who recognised that increasing the time interval between actions moved the system towards stability, therefore the increased supplier lead-time resulted in increased stability i.e. a reduction in chaos. This therefore results in a trade-off between amplification and chaos.

The results of the investigation documented in section 7.5.4 and 7.5.5 demonstrate that parallel interactions can be buffered with increased inventory within the supply chain. However, research undertaken into demand amplification demonstrates that

increasing the amount of inventory cover results in increased amplification [Wikner, Towill, & Naim, 1991]. This trade-off also needs to be recognised.

In conclusion, this investigation has addressed the research problem described above and has resulted in further understanding being gained into the uncertainty experienced within supply chains. The research, however, has identified further avenues of investigation, which will be outlined in chapter 10.

8.4 Implications for theory.

8.4.1 Supply chain strategy

The conclusion that complex forms of behaviour can be generated within supply chains results in the requirement to refocus the ways supply chains are strategically managed. The conventional view that supply chain success is dependent on stability and consensus is challenged.

The complexity experienced in the supply chain can be viewed as a threat and something that needs to be removed or, as authors such as Parker [Parker, 1994], Stacey [Stacey, 1993b] and McMaster [McMaster, 1996] argue, the complexity experienced may force organisations to innovate and learn. If everything were stable organisations would not need to develop new structures or patterns of behaviour. Over time, this would lead to lack of innovation and subsequent loss of competitive advantage.

By understanding the trade-offs within the “supply chain complexity triangle” organisations could potentially improve the quality of service to customers by

ensuring improved availability of goods, and also reduce costs within the system by more effective management of inventory and resources. This therefore improves both cost advantage and value advantage for the organisations.

The analysis undertaken further emphasises the importance of treating the supply chain as a complete system. The whole is not the sum of the parts. Small changes made to optimise one echelon of the supply chain can result in massive changes in other parts of the supply chain. This may subsequently result in the sub-optimisation of the total system performance.

Long term planning within chaotic systems is also particularly difficult. Small disturbances are multiplied over time and because of the non-linear relationships present, the system is very sensitive to initial conditions. Traditional Materials Requirements Planning (MRP) systems used in industry are reliant on long term sales forecasts which are usually inaccurate. This can result in excessive stock holding [Burbidge, 1983].

Tom McGuffog of the international organisation Nestle recently concluded that the complex statistical forecasting packages employed by their organisation do not substantially assist the interpretation of demand [McGuffog, 1997]. He observes that for these systems to be successful there would need to be patterns susceptible to statistical analysis and prognosis. These simple patterns are not observed in practice, and traditional forecasting techniques have had very limited success. These observations add further evidence that the complex dynamics generated may be chaotic in nature.

The benefit of allocating resource to more and more complex models for forecasting may be small. Short-term forecasts and prediction of patterns can be made with reasonable accuracy. Chaotic systems trace repetitive patterns that may make it possible to forecast levels of stock or demand within certain tolerance bands.

Non-linear dynamic analysis can also be used to estimate the forecast horizon of supply chain systems. This has the benefit of focusing resources on forecasting up to that horizon and not wasting resources on trying to forecast past this horizon into the unpredictable future. The use of Lyapunov exponents and the subsequent calculation of the prediction horizon can be used as a technique for quantifying what “short-term” and “long-term” mean within a business environment. Short-term management and strategies can be defined for operation within the prediction horizon. Long-term policies and strategies are defined as those that function outside this forecast horizon.

8.4.1.1 Short-term strategic management

The concept of short-term strategic management may be the most effective strategic approach for management within supply chains [Saisse & Wilding, 1997]. Managers within an organisation need to be aware of the strategic consequences of their daily short-term decisions. These decisions must be aligned with the overall business strategy of the organisation, and this raises the requirement for management tools and techniques.

Product-based competition, labelled mass customisation [Pine, 1993], focuses on increasing customisation of products for individual customers and markets. The most usual way to cope with uncertainty is by building stocks. However this may be not only costly but extremely risky when applied to customised markets where short

product life-cycles are present. Process flexibility is therefore a requirement in such markets. One tool developed for short-term strategic management is an interactive simulation tool called “Jobbing” [Saisse & Wilding, 1997]. “Jobbing” has been installed in three small, make-to-order companies in Brazil [Costa, Hill, & Jardim, 1991a; Costa & Jardim, 1991b].

“Jobbing” is a finite capacity scheduler that uses a discrete simulation algorithm to build alternative production plans in a semi-interactive way. Using the model proposed by Terry Hill [Hill, 1993], the order winning criteria are identified as are the qualifying competitive factors in order to understand how the manufacturing function could best contribute to improve the business performance. As the algorithm takes into consideration the order winning criteria, main constraints and flexibilities involved in the process “Jobbing” can generate many feasible alternative production plans. The algorithm draws information about the resources (machines and workers) structure, capabilities and time availability, bill of materials and routings of the items that will be produced and inventory and shop-floor status, from a central database. The resulting manufacturing plans are therefore strategically aligned with the long-term business strategy.

The “Jobbing” software increases visibility of issues across the internal supply chain of the organisation. This results in more informed logistical decision making in all departments, enabling customers to be served more effectively.

The key focus of this system is short-term decisions related to the long-term business strategy. This type of approach to management within uncertain environments has the potential to be applied across the complete supply chain [Saisse & Wilding, 1997].

8.4.1.2 *Supply chain re-engineering*

A further implication of this work applies to the evolving structure of supply chains. Analysis into automotive parts supply chains is forecasting that by the year 2005 the structure of the supply chain will change dramatically with the requirement for an increase in echelons but a reduction in the number of channels [Disney, Childerhouse, & Naim, 1997]. The findings in this thesis raise a number of key issues about this supply chain re-engineering process. Increasing the number of echelons will result in an increase in the amount of chaos and amplification experienced, but reducing the number of channels will result in a reduction in the number of parallel interactions. The strategists involved in this work would be wise to understand the implications of this trade-off.

8.4.2 *Material logistics*

The purpose of inventory control systems as described by Waters [Waters, 1992 p.16] is as follows;

“Inventory control is based on the use of quantitative models which relate demand, cost and other variables to find optimal values for order quantities, timing of orders and so on”

The implications of this work are that a system which is meant to control and level fluctuations, and consequently buffer the system from instability, can create dynamics which turn a stable predictable, demand pattern into a demand pattern which is unpredictable with occasional explosive changes in demand, so further destabilising the system. Thus a system designed to *optimise* stock holding and order management can actually increase unpredictability and costs incurred across the total supply chain.

Manufacturing planning systems are often run in a batch mode at particular time intervals (for example one every four weeks). This is often a result of the time it takes to do all the calculations and processing. The implications of this investigation are that if the time period between runs of the planning system is greater than the prediction horizon, the planning outside the prediction horizon could be completely inaccurate. By running the planning system with a period of less than the prediction horizon uncertainty due to chaos will be minimised.

However, rather than learning to live with chaos it may be better to remove it all together. The key to the removal of chaos is the use of systems that do not have direct feedback loops. The exponentially smoothed forecasting system used in the warehouse model is one such feedback loop. Simulations using simple re-order point systems do not produce chaotic behaviour as no feedback loops are present, however demand amplification has been shown to be a major drawback with this type of system. Many lean approaches to manufacturing do not rely on complex feedback systems. Focusing on the uninterrupted flow of material that matches the pull from the customer, which is the basis of such techniques, can be seen to eliminate feedback and consequently the conditions required to produce further chaos. However, the misapplication of lean manufacturing, such as wholesale reduction of inventory and lead-times, can result in the system exhibiting increased chaos. Period Batch Control (PBC) is another technique, which, if used appropriately, can remove chaos. It enables parts to be made in balanced product sets that match customer demand. No production of parts should be made for stock intended to cover future requirement [Burbidge, 1983]. Hill [Hill, 1996] discusses the use of Statistical Process Control (SPC) in monitoring demand from customers. He proposes a system where

production is levelled and strategic stocks are used to buffer against uncertainty. SPC is used to quantify the level of risk and calculate the buffer required. This is not altered unless the system is seen to change dramatically. This form of system also relies on pull from customer demand. However inventory is used to strategically buffer fluctuations and thus level production. This would also result in stable demand being passed onto suppliers further down the supply chain.

The removal of chaos by control is a further possibility. Chaotic control uses the characteristic of sensitivity to initial conditions as a control method. This characteristic makes chaotic systems highly susceptible to control, provided that the development of chaos can be analysed in real-time. This analysis can then be used to make small control interventions [Garfinkel et al., 1992]. In some environments it is advantageous to operate the system in chaos, as only small amounts of control are required to get a large effect. If the system is operating in a stable mode larger control inputs are required to achieve the same effect [Shinbrot et al., 1993]. Control is achieved by subjecting the system to small time-dependant perturbations of an available system parameter [Ott, Grebogi, & Yorke, 1990]. This in the context of supply chains could be demand or inventory. The perturbation is timed precisely and of a magnitude to force the system from a chaotic mode of operation into a stable periodic mode of behaviour. A further chaotic control methodology uses weak periodic perturbations which force the system into stable operation [Braiman & Golhirsch, 1991]. Both techniques have been used successfully in a variety of areas including the control of lasers [Roy et al., 1992], animal hearts [Garfinkel et al., 1992] and highly efficient spacecraft propulsion systems [Shinbrot et al., 1993].

8.4.2.1 The flexibility and inventory trade-off

The increased susceptibility to parallel interactions for JIT suppliers demonstrated in this thesis demonstrates the inventory/flexibility trade-off. Inventory can be used to buffer the uncertainty but this may increase the costs for those operating Just-in-time. Organisations implementing Just-in-time therefore need to ensure that their systems are flexible and responsive enough to cope with the increase in uncertainty that may be experienced. This may account for disappointing improvements experienced by many implementing JIT. If Just-in-time inventory systems are to be employed all the business and manufacturing systems need to be reviewed to ensure their flexibility and responsiveness to cope with the possibility of increased uncertainty. This review may result in organisations recognising that inventory buffering and the production techniques outlined above and advocated by Burbidge and Hill being more appropriate.

The inventory/flexibility trade-off also has implications for supplier selection and development. Using the purchasing matrix described by Syson [Syson, 1992](see section 2.5.2) managers need to recognise which organisations will be best suited to JIT and which are suited to inventory buffering. The identification of where flexibility or inventory can be applied to reduce and cope with uncertainty across the supply chain needs to become a key focus.

The JIT2 [Greenblatt, 1994] approach of utilising supplier implants to aid the manufacturing and distribution planning of organisations also reduces uncertainty. This technique effectively results in the organisations being able to view the constraints within both organisations and can result in the reduction of uncertainty across the chain. By concurrently planning the activities of both customer and supplier

and streamlining the communication systems between them, the two parties effectively operate as one echelon within the chain. This therefore removes chaos in the chain and reduces the consequence of parallel interactions.

8.4.3 Information management

Increasingly, industry is investing in faster communication systems and is purchasing “black box” packages for the management of key functions within the supply chain. The human decision making process is increasingly being automated. The interaction of such systems has seen little research to date. The dynamics of such systems are usually explored over a relatively short period of time with performance monitored in detail for, say, 6 months after installation. This is an inadequate time frame to assess such systems. The tendency to produce chaos requires the system to be monitored with care for much longer time periods. The apparently random peaks and troughs in demand and inventory levels cannot be attributed solely to external events, the logic used to control the process can be the causes of such occurrences. This study provides direct evidence that standard computer algorithms used for control within the supply chain can produce deterministic chaos. Simulation of systems and non-linear dynamic analysis of key outputs should be a mandatory part of any supply chain engineering proposal.

One simulation approach currently used in the testing of software in safety critical systems could be readily adapted to the validation of supply chain information systems. The technique called “HILS” (Hardware In Loop Simulation) uses real-time computer simulations based on mathematical models to test control systems [Hanselmann, 1993]. HILS provides a method of testing control systems over the full

range of operating conditions including failure modes, this makes it powerful for testing such systems. Instead of connecting the software to the real components for validation purposes the software is connected to a simulation. The accuracy of the simulation must be such that the information system thinks it is controlling the real system. The benefits of the HILS approach is reduced development time ensuring reliability of all components with complex behaviour [Maclay, 1997]. The technique could be applied within supply chains by networking the actual software systems used within a supply chain and testing the impact of differing simulated demand conditions. This would enable the validation to be over a much longer time period of years rather than weeks, thus generating an understanding of the types of behaviour the system is liable to create. By this method many years of operation can be simulated in a short period of time.

Simple information systems and communications protocols are also of key importance in stabilising dynamic behaviour. McGuffog [McGuffog, 1997] identifies that many institutions have unnecessarily complex processes and procedures which result in costly and inefficient IT systems. EDI messages are often complex and open to interpretation rather than standard in meaning. This has resulted in the concept of SIMPL-EDI and SIMPL-IT being developed and soon to be promoted by the UK Confederation for EDI standards [Fenton, McGuffog, & Wadsley, 1997]. These simple systems aiding communication of data across the whole supply chain will reduce uncertainty and increase the timeliness of information.

8.4.4 Time compression

Time compression has been proved to benefit organisations immensely [Wilding & Beesley, 1995; Wilding & Newton, 1996]. It has been shown that demand amplification is reduced significantly by lead-time reduction but in the system under investigation a trade-off between amplification and chaos is present. The reduction of lead-times, like the reduction of inventory, if undertaken without detailed analysis can lead to the system incurring increased operating costs due to increased unpredictability.

8.4.5 Product Design

Product design can have a major impact on the magnitude of parallel interactions experienced within an organisation. Mather [Mather, 1987] suggests this by advocating design for logistics. Mather proposes that each product should be rated according to the proportion of standard parts and the proportion of parts unique to that product. Products with a high proportion of unique parts should be redesigned. This has been found to reduce the amount of inventory held by organisations and also reduce the degree of uncertainty in supplier schedules. This reduction in uncertainty will be due in part to a reduction in the parallel interactions present. Design for supply chain management [Wilding R.D. & Yazdani, 1997] also allows a standard product to be produced that is customised as late as possible, preferably within the customer's demand time. This therefore removes the need to forecast at an individual product level, hence reducing further schedule instability.

8.5 Implications for policy and practice.

The implications for management when operating within chaotic and uncertain supply chains are as follows [Wilding, 1997]: -

- Dramatic change can occur unexpectedly. Chaotic spikes in demand can occur generated by the system and not as the result of external events.
- Long term planning is very difficult. If long-term plans are made they need to be reviewed on a regular basis.
- Supply chains do not reach stable equilibrium, small perturbations will always prevent equilibrium being achieved.
- Short-term forecasts and prediction of patterns can be made. It is better to allocate resource to the development of effective short-term decision making processes rather than long term.
- Treat the supply chain as a complete system, Small changes made to optimise one echelon of the supply chain can result in massive changes in other parts of the supply chain. Driving down inventory and lead-times may not always improve performance it could result in the system slipping into chaos.
- Remove chaos by focusing on the customer; communicate demand information as far upstream as possible, using simple lean approaches.
- When changing hardware or software platforms, which are critical to an organisation's operation, undertake detailed validation. Computers are prone to chaos.

- Simulation of systems and non-linear dynamic analysis of key outputs should be a mandatory part of any supply chain re-engineering proposal. Search for “Islands of stability”. Remember that if the model generates chaos the real system with increased complexity may do so.

8.6 Limitations of approach.

In section 1.7 a number of known limitations in the approach were described. During the research undertaken in this dissertation a further limitation was identified. This will now be described:

Initially it was hoped that a methodology readily accessible to supply chain managers based in industry could be developed for the analysis of chaos. The methodology used for the detection and quantification of chaos is still relatively complex and would not be accessible to a practitioner based in industry without a working knowledge of the science of chaos. The main limitation is the calculation of the embedding dimensions from finite amounts of data. Despite three techniques (correlation dimension, capacity dimension and false nearest neighbours) being used to gain specific values for the embedding dimension, some data sets still require a degree of qualitative analysis based on experience of other chaotic systems and data sets previously analysed, to gain robust estimates of the embedding dimension.

8.7 Conclusion to chapter 8.

In this chapter the contribution of this research has been described in relation to the original research problem and the research questions gained from the literature. The

implications of the research for supply chain theory have been discussed and the main implications for management policy and practice have also been summarised. During the research a minor limitation with the methodology was found and this has been described. In the final two chapters the main conclusions will be summarised and the implications for further research will be discussed.

Chapter 9

Conclusions

1. A methodology has been developed to document and quantify sources of internally generated uncertainty within an industrial supply chain.
2. In addition to amplification, two additional sources of uncertainty were observed and quantified; namely deterministic chaos and parallel interactions.
3. Deterministic chaos is shown to be readily generated in a simulated warehouse supply chain.
4. The use of Lyapunov exponents calculated from supply chain data series, and the subsequent calculation of the average prediction horizon can be used to quantify the amount of deterministic chaos observed at each echelon in the supply chain.
5. The degree of chaos was found to be dependent on the number of echelons in the supply chain. The number of channels in the warehouse supply chain had little overall effect.
6. The number of echelons in the supply chain impacts on the amount of chaos witnessed by all members of the supply chain.

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7. Islands of stability can be observed for particular supply chains but these are highly dependent on the number of organisations and the settings of all parameters in the system.
 8. Parallel interactions occur between suppliers in the same tier, these interactions impact on the utilisation of all organisations in the chain. A rogue supplier in the supply chain impacts on the performance of the whole system and the individual suppliers.
 9. Schedule stability also impacts on the utilisation of the suppliers in the chain.
 10. Three interacting yet independent effects have been identified creating a “supply chain complexity triangle” these effects are amplification, deterministic chaos and parallel interactions.

Chapter 10

Implications for further research

Further research arises from the experimental work undertaken and also the final discussion.

10.1 Further research from experimental work.

The application of chaos theory and non-linear dynamic analysis to supply chain systems is still very much in its infancy. This thesis has demonstrated that greater understanding and benefits can be gained by the application of such an analytical approach.

One key area requiring further work is the identification of “islands of stability”. Although some attempt was made to identify the location of islands of stability in this dissertation, shortage of time limited a complete analysis involving changing every variable in the systems and observing if certain parameter settings produced stable behaviour for all modes of operation. The research outlined in this dissertation would seem to indicate the amount of chaos is extremely sensitive to the parameter settings of all echelons in the supply chain, so the practical benefits achieved by a complete analysis may be small. A full analysis will require a significant increase in the number of simulation runs.

The limitation on the amount of data points being readily available for analysis due to the size of the Windows clipboard should also be addressed. This will enable more accurate values of embedding dimensions and Lyapunov exponents to be calculated. These can then be used to assess in more detail the minimum number of data points required to gain reliable values of embedding dimensions and Lyapunov exponents. The investigations undertaken in this dissertation would seem to indicate that approximately 1000 data points are adequate but this requires more detailed analysis.

10.2 Further research from final discussion.

One area of further work that can be readily undertaken is carrying out an equivalent analysis to that documented in this thesis on different warehouse control algorithms, for example, periodic review and re-order point systems. This would enable a comparison between the performance of different warehouse systems from the perspective of the supply chain complexity triangle.

The application of the Hardware-in-loop-simulation approach is worthy of further investigation. Proprietary MRP and warehouse control packages could be investigated within a laboratory by networking a number of computers. This would enable the analysts to observe the interactions between the various packages being tested and would act as a practical test environment. This could also be used as a simulator for managers to practise supply chain decision-making.

A further area of investigation, which would prove beneficial to this area of research, would be investigating the potential of applying chaotic control methods to stabilise the dynamics. The use of small perturbations to move the supply chain from chaotic

to stable modes of operation could prove beneficial. Investigations into this chaotic control would gain additional evidence on the impact of stochastic shocks to the systems.

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Appendix 1

Results data from Chapters 6 and 7

Results data from Investigations 2 and 3, Chapter 6.

Results of Investigations 2 and 3 (Chapter 6)

| File Name | Embedding Dimension | Lyapunov Exponent | Prediction Horizon |
|-----------|---------------------|-------------------|--------------------|
| 1c101 | 3 | 0.142 | 98.6 |
| 1c102 | 5 | 0.145 | 96.6 |
| 1c251 | 3 | 0.071 | 197.2 |
| 1c252 | 6 | 0.407 | 34.4 |
| 1c401 | 3 | 0 | #DIV/0! |
| 1c402 | 6 | 0.477 | 29.4 |
| 2c101 | 3 | 0.145 | 96.6 |
| 2c102 | 5 | 0.191 | 73.3 |
| 2c251 | 3 | 0.069 | 202.9 |
| 2c252 | 6 | 0.455 | 30.8 |
| 2c401 | 3 | 0 | #DIV/0! |
| 2c402 | 6 | 0.581 | 24.1 |
| 3c101 | 3 | 0.146 | 95.9 |
| 3c102 | 5 | 0.208 | 67.3 |
| 3c251 | 3 | 0.069 | 202.9 |
| 3c252 | 6 | 0.401 | 34.9 |
| 3c401 | 3 | 0 | #DIV/0! |
| 3c402 | 6 | 0.6 | 23.3 |
| 4c101 | 3 | 0.144 | 97.2 |
| 4c102 | 5 | 0.281 | 49.8 |
| 4c251 | 3 | 0.069 | 202.9 |
| 4c252 | 6 | 0.428 | 32.7 |
| 4c401 | 3 | 0 | #DIV/0! |
| 4c402 | 6 | 0.598 | 23.4 |
| 5c101 | 3 | 0.144 | 97.2 |
| 5c102 | 5 | 0.303 | 46.2 |
| 5c251 | 3 | 0.069 | 202.9 |
| 5c252 | 6 | 0.402 | 34.8 |
| 5c401 | 3 | 0 | #DIV/0! |
| 5c402 | 6 | 0.6 | 23.3 |
| 1s101 | 3 | 0.162 | 86.4 |
| 1s251 | 3 | 0 | #DIV/0! |
| 1s401 | 3 | 0.185 | 75.7 |
| 2s101 | 3 | 0.142 | 98.6 |
| 2s102 | 5 | 0.362 | 38.7 |
| 2s251 | 3 | 0.071 | 197.2 |
| 2s252 | 6 | 0.407 | 34.4 |
| 2s401 | 3 | 0 | #DIV/0! |
| 2s402 | 6 | 0.477 | 29.4 |
| 3s101 | 4 | 0.231 | 60.6 |
| 3s102 | 6 | 0.599 | 23.4 |
| 3s103 | 6 | 0.221 | 63.3 |
| 3s251 | 4 | 0.351 | 39.9 |
| 3s252 | 6 | 0.697 | 20.1 |
| 3s253 | 6 | 0.3 | 46.7 |
| 3s401 | 4 | 0.316 | 44.3 |
| 3s402 | 6 | 0.679 | 20.6 |
| 3s403 | 6 | 0.347 | 40.3 |
| 4s101 | 4 | 0.329 | 42.6 |
| 4s102 | 6 | 0.738 | 19.0 |
| 4s103 | 6 | 0.629 | 22.3 |
| 4s104 | 6 | 0.388 | 36.1 |
| 4s251 | 4 | 0.258 | 54.3 |
| 4s252 | 6 | 0.65 | 21.5 |
| 4s253 | 6 | 0.745 | 18.8 |
| 4s254 | 6 | 0.371 | 37.7 |
| 4s401 | 4 | 0.591 | 23.7 |
| 4s402 | 6 | 0.754 | 18.6 |
| 4s403 | 6 | 0.662 | 21.1 |
| 4s404 | 6 | 0.357 | 39.2 |
| 5s101 | 4 | 0.242 | 57.9 |
| 5s102 | 6 | 0.789 | 17.7 |
| 5s103 | 6 | 0.625 | 22.4 |
| 5s104 | 6 | 0.553 | 25.3 |
| 5s105 | 6 | 0.341 | 41.1 |
| 5s251 | 5 | 0.351 | 39.9 |
| 5s252 | 6 | 0.629 | 22.3 |
| 5s253 | 6 | 0.697 | 20.1 |
| 5s254 | 6 | 0.759 | 18.4 |
| 5s255 | 6 | 0.367 | 38.1 |
| 5s401 | 4 | 0.344 | 40.7 |
| 5s402 | 5 | 0.786 | 17.8 |
| 5s403 | 6 | 0.747 | 18.7 |
| 5s404 | 6 | 0.746 | 18.8 |
| 5s405 | 6 | 0.39 | 35.9 |

File Interpretation

File name: 3s104 = 3 warehouses in Series, Demand = 10, Warehouse No. 4
File name: 3c102 = 3 Channels, Demand = 10, Warehouse No. 2

Results data from Investigation 4, Chapter 6.

Results of Investigation 4 (Chapter 6)**Single Warehouse Supply Chain**

Order Quantity Lyapunov Exponent Prediction Horizon.

| | | |
|-----|-------|---------|
| 10 | 0.162 | 86 |
| 25 | 0 | #DIV/0! |
| 40 | 0.183 | 77 |
| 55 | 0.127 | 110 |
| 70 | 0.04 | 350 |
| 80 | 0 | #DIV/0! |
| 90 | 0.14 | 100 |
| 100 | 0.134 | 104 |
| 110 | 0.126 | 111 |
| 125 | 0.072 | 194 |
| 140 | 0.026 | 538 |
| 155 | 0.069 | 203 |

Two Warehouse Supply Chain**Lyapunov Exponents**

| Order Quantity | Supplier Lead-time | | |
|----------------|--------------------|--------|--------|
| | 3 days | 5 days | 7 days |
| 10 | 0.627 | 0.295 | 0.145 |
| 15 | 0.509 | 0.414 | 0.3 |
| 20 | 0.551 | 0.439 | 0.439 |
| 25 | 0.592 | 0.445 | 0.407 |
| 40 | 0.685 | 0.518 | 0.477 |
| 55 | 0.633 | 0.571 | 0.573 |
| 70 | 0.755 | 0.495 | 0.693 |
| 80 | 0.734 | 0.664 | 0.525 |
| 90 | 0.598 | 0.49 | 0.694 |
| 100 | 0.647 | 0.533 | 0.723 |

Warehouse 1

| Order Quantity | 3 days 5 days 7 days | | |
|----------------|----------------------|--------|--------|
| | 3 days | 5 days | 7 days |
| 10 | 0.246 | 0.143 | 0.143 |
| 15 | 0.235 | 0.225 | 0.2 |
| 20 | 0.199 | 0 | 0.145 |
| 25 | 0.46 | 0.075 | 0.075 |
| 40 | 0.388 | 0 | 0 |
| 55 | 0.371 | 0.031 | 0.089 |
| 70 | 0.335 | 0.06 | 0.061 |
| 80 | 0.366 | 0.089 | 0.089 |
| 90 | 0.291 | 0.041 | 0.038 |
| 100 | 0.341 | 0.074 | 0.037 |

Prediction Horizon

| Order Quantity | Supplier Lead-time | | |
|----------------|--------------------|--------|--------|
| | 3 days | 5 days | 7 days |
| 10 | 22.3 | 47.5 | 96.6 |
| 15 | 27.5 | 33.8 | 46.7 |
| 20 | 25.4 | 31.9 | 31.9 |
| 25 | 23.6 | 31.5 | 34.4 |
| 40 | 20.4 | 27.0 | 29.4 |
| 55 | 22.1 | 24.5 | 24.4 |
| 70 | 18.5 | 28.3 | 20.2 |
| 80 | 19.1 | 21.1 | 26.7 |
| 90 | 23.4 | 28.6 | 20.2 |
| 100 | 21.6 | 26.3 | 19.4 |

| Order Quantity | 3 days 5 days 7 days | | |
|----------------|----------------------|---------|---------|
| | 3 days | 5 days | 7 days |
| 10 | 56.9 | 97.9 | 97.9 |
| 15 | 59.6 | 62.2 | 70.0 |
| 20 | 70.4 | #DIV/0! | 96.6 |
| 25 | 30.4 | 186.7 | 186.7 |
| 40 | 36.1 | #DIV/0! | #DIV/0! |
| 55 | 37.7 | 451.6 | 157.3 |
| 70 | 41.8 | 233.3 | 229.5 |
| 80 | 38.3 | 157.3 | 157.3 |
| 90 | 48.1 | 341.5 | 368.4 |
| 100 | 41.1 | 189.2 | 378.4 |

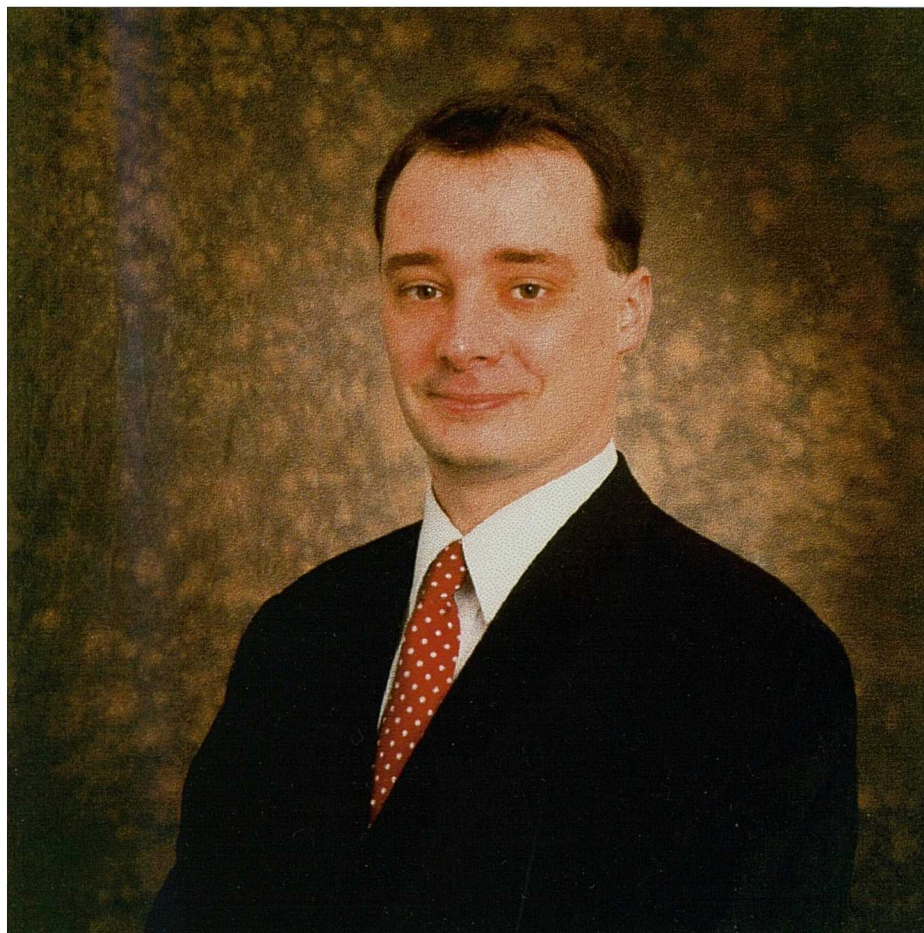
Results of Investigation 4 (Chapter 6)

| k | Service Level % | Lypunov Exponent | Prediction Horizon. |
|----------|------------------------|-------------------------|----------------------------|
| 0 | 50 | 0.303 | 46 |
| 0.42 | 66.28 | 0.299 | 47 |
| 0.84 | 79.95 | 0.076 | 184 |
| 0.92 | 82.12 | 0.075 | 187 |
| 1 | 84.13 | 0.051 | 275 |
| 1.04 | 85.08 | 0.074 | 189 |
| 1.16 | 87.7 | 0.074 | 189 |
| 1.28 | 89.97 | 0.148 | 95 |
| 1.38 | 91.62 | 0.148 | 95 |
| 1.48 | 93.06 | 0.074 | 189 |
| 1.52 | 93.57 | 0.287 | 49 |
| 1.56 | 94.06 | 0.072 | 194 |
| 1.6 | 94.52 | 0.282 | 50 |
| 1.64 | 94.95 | 0.278 | 50 |
| 1.7 | 95.54 | 0.026 | 538 |
| 1.76 | 96.08 | 0.073 | 192 |
| 1.82 | 96.56 | 0.074 | 189 |
| 1.88 | 96.99 | 0.026 | 538 |
| 1.895 | 97.095 | 0.072 | 194 |
| 1.91 | 97.19 | 0.277 | 51 |
| 1.925 | 97.32 | 0.073 | 192 |
| 1.94 | 97.38 | 0.073 | 192 |
| 1.955 | 97.5 | 0.073 | 192 |
| 1.97 | 97.56 | 0.027 | 519 |
| 1.985 | 97.64 | 0.073 | 192 |
| 2 | 97.72 | 0.042 | 333 |
| 2.045 | 97.96 | 0 | #DIV/0! |
| 2.09 | 98.17 | 0.075 | 187 |
| 2.13 | 98.34 | 0 | #DIV/0! |
| 2.17 | 98.5 | 0 | #DIV/0! |
| 2.21 | 98.64 | 0 | #DIV/0! |
| 2.25 | 98.78 | 0.072 | 194 |
| 2.29 | 98.9 | 0.074 | 189 |
| 2.33 | 99.01 | 0.075 | 187 |
| 2.365 | 99.1 | 0 | #DIV/0! |
| 2.4 | 99.18 | 0 | #DIV/0! |
| 2.43 | 99.25 | 0 | #DIV/0! |
| 2.46 | 99.31 | 0 | #DIV/0! |
| 2.49 | 99.36 | 0 | #DIV/0! |
| 2.52 | 99.41 | 0.072 | 194 |
| 2.55 | 99.46 | 0.073 | 192 |
| 2.58 | 99.51 | 0 | #DIV/0! |
| 2.635 | 99.57 | 0.073 | 192 |
| 2.69 | 99.64 | 0.072 | 194 |
| 2.74 | 99.69 | 0.073 | 192 |
| 2.79 | 99.74 | 0.072 | 194 |
| 2.845 | 99.775 | 0.076 | 184 |
| 2.9 | 99.81 | 0.207 | 68 |
| 2.95 | 99.84 | 0.073 | 192 |
| 3 | 99.98 | 0.127 | 110 |

Results data of Parallel Interaction investigations, Chapter 7.

Results of Parallel interaction investigations (Chapter 7)

| Demand/Forecast Dev. | No. of Rogue Suppliers. | % Utilisation of suppliers and assembler. | | | | |
|----------------------|-------------------------|---|-------|-------|-------|-------|
| | | Sup1 | Sup2 | Sup3 | Sup4 | Asse. |
| 1 | 0 | 98.83 | 98.84 | 99.29 | 99.09 | 99.74 |
| 1 | 1 | 98.61 | 98.63 | 99.08 | 93.83 | 99.50 |
| 1 | 2 | 98.45 | 98.46 | 94.15 | 93.71 | 99.34 |
| 1 | 3 | 98.30 | 92.91 | 94.03 | 93.60 | 99.18 |
| 1 | 4 | 92.85 | 92.86 | 93.99 | 93.56 | 99.10 |
| 5 | 0 | 98.06 | 98.14 | 98.54 | 98.31 | 99.22 |
| 5 | 1 | 97.91 | 98.00 | 98.42 | 93.37 | 99.06 |
| 5 | 2 | 97.83 | 97.92 | 93.83 | 93.30 | 98.95 |
| 5 | 3 | 97.70 | 92.58 | 93.70 | 93.17 | 98.81 |
| 5 | 4 | 92.34 | 92.48 | 93.60 | 93.06 | 98.68 |
| 1 | 0 | 98.43 | 98.43 | 98.89 | 98.69 | 99.39 |
| 1 | 1 | 97.81 | 97.81 | 98.27 | 93.36 | 98.71 |
| 1 | 2 | 97.31 | 97.31 | 93.37 | 92.95 | 98.18 |
| 1 | 3 | 96.66 | 91.81 | 92.86 | 92.49 | 97.47 |
| 1 | 4 | 91.37 | 91.45 | 92.55 | 92.16 | 96.99 |
| 5 | 0 | 97.20 | 97.29 | 97.71 | 97.48 | 98.40 |
| 5 | 1 | 96.72 | 96.82 | 97.22 | 92.55 | 97.90 |
| 5 | 2 | 96.30 | 96.38 | 92.70 | 92.23 | 97.43 |
| 5 | 3 | 95.88 | 91.34 | 92.32 | 91.90 | 96.95 |
| 5 | 4 | 90.70 | 90.94 | 91.97 | 91.49 | 96.41 |
| 1 | 0 | 98.07 | 98.07 | 98.52 | 98.31 | 99.00 |
| 1 | 1 | 97.09 | 97.08 | 97.53 | 92.84 | 97.96 |
| 1 | 2 | 96.22 | 96.21 | 92.63 | 92.16 | 97.03 |
| 1 | 3 | 95.19 | 90.70 | 91.84 | 91.38 | 95.93 |
| 1 | 4 | 90.11 | 90.16 | 91.27 | 90.78 | 95.15 |
| 5 | 0 | 96.64 | 96.74 | 97.14 | 96.91 | 97.82 |
| 5 | 1 | 95.83 | 95.91 | 96.31 | 91.96 | 96.95 |
| 5 | 2 | 94.92 | 94.99 | 91.71 | 91.20 | 96.00 |
| 5 | 3 | 94.22 | 90.03 | 91.13 | 90.64 | 95.24 |
| 5 | 4 | 89.35 | 89.50 | 90.60 | 90.07 | 94.51 |
| 1 | 0 | 97.36 | 97.37 | 97.82 | 97.61 | 98.24 |
| 1 | 1 | 95.25 | 95.28 | 92.04 | 95.49 | 96.01 |
| 1 | 2 | 93.62 | 93.64 | 90.73 | 90.22 | 94.30 |
| 1 | 3 | 92.09 | 88.51 | 89.48 | 88.99 | 92.68 |
| 1 | 4 | 87.45 | 87.62 | 88.60 | 88.10 | 91.55 |
| 5 | 0 | 95.51 | 95.58 | 96.01 | 95.78 | 96.66 |
| 5 | 1 | 93.73 | 93.79 | 90.90 | 93.99 | 94.81 |
| 5 | 2 | 92.39 | 92.46 | 89.80 | 89.28 | 93.48 |
| 5 | 3 | 91.22 | 87.80 | 88.85 | 88.29 | 92.20 |
| 5 | 4 | 86.76 | 86.94 | 87.97 | 87.42 | 91.13 |
| 1 | 0 | 94.03 | 94.06 | 94.49 | 94.26 | 94.66 |
| 1 | 1 | 89.94 | 89.96 | 88.15 | 90.16 | 90.44 |
| 1 | 2 | 86.77 | 86.81 | 85.45 | 84.83 | 87.21 |
| 1 | 3 | 84.30 | 82.43 | 83.25 | 82.73 | 84.69 |
| 1 | 4 | 80.39 | 80.75 | 81.56 | 81.00 | 82.72 |
| 5 | 0 | 91.59 | 91.63 | 92.03 | 91.81 | 92.68 |
| 5 | 1 | 88.23 | 88.26 | 86.65 | 88.45 | 89.28 |
| 5 | 2 | 85.44 | 85.50 | 84.27 | 83.75 | 86.53 |
| 5 | 3 | 83.38 | 81.67 | 82.45 | 81.96 | 84.44 |
| 5 | 4 | 79.67 | 80.08 | 80.87 | 80.32 | 82.64 |



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