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THE EFFECT OF INTERNAL STATIC MANUFACTURING COMPLEXITY ON MANUFACTURING PERFORMANCE

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ABSTRACT

Manufacturing systems are complex. They consist of many interrelated subsystems and elements. This study investigates the effect on performance due to the complexity resulting from system design, i.e. internal static manufacturing complexity. The quantitative measure, ISMC, consisting of eight measurable complexity elements is proposed. This new measure of complexity was then tested with another existing measure of internal static manufacturing complexity proposed by Frizelle and Woodcock (1995).

A large set of simulation experiments, each modeling a general batch-type manufacturing system, was employed to test the effects of the overall complexity measure, ISMC, and the eight individual elements on five measures of manufacturing performance. The experimental design included two levels for each of the eight static complexity elements and two levels for the environmental variable, due date tightness.

The results indicated that neither the proposed measure, ISMC, nor the prior Frizelle and Woodcock's measure demonstrate a practical level of predictive validity. Three of the eight individual components making up ISMC were correlated to manufacturing performance. These were the breadth of the product structures, the depth of the product structures, and the number of different end-products in a manufacturing system.

DEDICATION

I dedicate this to my wife, Terri, and my children, Davis, Elliot, and Hayes, for their sacrifice and support over the past seven years. Whether they realize it or not, they forwent much, in time, attention, and material possessions, for me to complete this.

I also recognize the great working of the one true God, who directed me to seek this degree, who provided greatly for our care, who blessed me with the Clemson faculty and this dissertation committee, and who enabled me to fulfill one of my greatest earthly desires – a career that I hope to enjoy all the days of my life.

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I am also grateful to Dr. LaForge for his support throughout my time during my dissertation. His recommendation to compare ISMC to Frizelle and Woocock's H made a tremendous difference in the value of my research. I also appreciate the opportunity he provided me to supervise the Manufacturing Management Laboratory as a graduate assistant. It was a great teaching experience for me to bring theory and practice together in a non traditional setting. I recognize that by working with and around Dr. LaForge, I learned as much about teaching as I did about research

I wish to thank Dr. Steve Cantrell for his help with the statistical analysis throughout my efforts. Also, I thank Dr. Mark McKnew for his committee work, but even more for having done an excellent job preparing me for my research through his simulation course. I did not have to ask him many questions because I was well-equipped to design, program and run these simulations.

TABLE OF CONTENTS

Table of Contents (Continued)

Table of Contents (Continued)

LIST OF TABLES

List of Tables (Continued)

List of Tables (Continued)

List of Tables (Continued)

LIST OF FIGURES

List of Figures (Continued)

Figure | Page

CHAPTER I

INTRODUCTION

Complexity is difficult to define. Although we all have a sense of complexity, and can intuitively acknowledge differences in the level of complexity between systems (e. g. an automobile engine and a bicycle) an operational definition is not easy to articulate. Simon (1962) defined complexity by saying that a complex system has a large number of parts, whose relationships are not "simple". Simple meaning "single, small"[1], or "having or composed of only one thing, element, or part"[2].

Manufacturing systems have many elements and there are many relationships among those elements. The relationships are not simple relationships. For example, when viewing a single department relative to its workload (queue of jobs), it may appear simple. However, since departments in a production system are interrelated, and job routings may vary, the overall manufacturing operation is extremely complex.

Manufacturing systems are complex because of the many elements and subsystems of a manufacturing operation and their interactions. The design of a production system greatly affects the degree of complexity a system will have, e.g. the

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[1] "simple" The American Heritage Dictionary of the English Language, 4th ed. Boston: Houghton Mifflin, 2000. www.bartleby.com/61/. July, 28, 2003.

[2] "simple" The Concise Oxford Dictionary. Ed. Judy Pearsall. Oxford University Press, 2001. Oxford Reference Online. Oxford University. http://www.oxfordreference.com. July 28, 2003.

number and type of machines or type of layout. This study investigates how the various elements of design complexity, called static complexity, influence manufacturing performance.

Manufacturing complexity can be separated into two constituents – static and dynamic complexity (Frizelle and Woodcock, 1995). Desmukh, Talvage, and Barash (1998, p.645) define static complexity as being a "function of the structure of the system, connective patterns, variety of components, and strength of interactions." So, static complexity is the complexity in a system that is due to the factory structure or design, e.g. number of products, number of machines.

Dynamic complexity deals with the uncertainty of a system as it moves through time (Desmukh et al., 1998). Unpredictable events, like machine breakdowns and quality failures, are two common examples of what would be considered elements of dynamic complexity in a manufacturing system. Philosophies such as total productive maintenance (TPM) and total quality management (TQM) address some of the issues associated with dynamic complexity by reducing the number of unpredictable events.

Another important distinction about complexity is whether it is internal or external. The elements of manufacturing system complexity that are in the direct control of system managers are considered to be internal complexity. The products to be offered, the type and amount of equipment, the degree of vertical integration, the quality system design, and the maintenance plan are examples of decisions that affect internal manufacturing complexity. Those things that are outside the direct control of management are part of external complexity, e.g. customer orders and government regulations.

Manufacturing complexity, as an overall theory, has not received much research attention. This is probably due to the difficulty in defining complexity. This does not make manufacturing complexity unimportant. For example lean manufacturing recognizes the impact of complexity and focused on simplifying the manufacturing system. Organizations that adopt the lean manufacturing philosophy are, in part, trying to reduce the complexity in the manufacturing system. Also, some techniques eschewed in the area of operations management such as product simplification and cellular manufacturing can be seen as reducing static complexity. Product simplification efforts review product designs to eliminate any unnecessary components and identify common subsystems which can be used in many of the manufacturer's products, i.e. reducing the number of elements in its system. One of the main advantages of employing a cellular manufacturing layout is the reduction in the number of parts manufactured by each smaller system (cell), these parts being grouped by component and routing commonality. This reduces the complexity in the overall operation by dividing it into smaller, less complex units, i.e. the number of parts and the number of relationships.

Since there has been little past research analyzing the relationship of complexity to performance, this study limits its scope of research to one category of manufacturing complexity with the intent to create a basis for future research. This research effort focuses only on internal static manufacturing complexity. The inclusion of dynamic and external elements of manufacturing complexity would make it difficult to effectively analyze and interpret the results. This study of internal static manufacturing complexity examines many of the important management decisions about system design, (e.g. product design and process design).

The objectives of this research are: to identify the relevant elements of internal static manufacturing complexity; to develop a valid quantitative measure from those elements; to test the proposed quantitative measure; and to identify those individual complexity elements that have a significant impact on performance.

The Current Study

Frizelle and Woodcock (1995) and Desmukh et al. (1998) have proposed and evaluated measures for static complexity using the concept of entropy developed from the field of information theory. Both related static complexity solely to the queue length at machines. In basing their measure of complexity upon an entropic measure, potential users would likely have difficulty gaining an intuitive understanding of the measure. Furthermore, the vast data requirements and the intensive computational effort involved in applying their proposed measure reduce its potential adoption by practicing managers.

It is important that any measure of internal static manufacturing complexity be practical (data is relatively easy to obtain), understandable to managers and researchers, and useful in explaining manufacturing phenomena. In this study, an alternative measure of internal static manufacturing complexity will be developed, which addresses these important attributes for a practical measure.

The proposed model, shown in Figure 1.1, identifies quantifiable elements of internal static manufacturing complexity, many of which have been considered in past research (i.e. Collier, 1981; Benton and Srivastava, 1993; Wacker and Treleven, 1986). These elements are combined to form a quantitative measure of internal static manufacturing complexity. The model predicts that internal static manufacturing

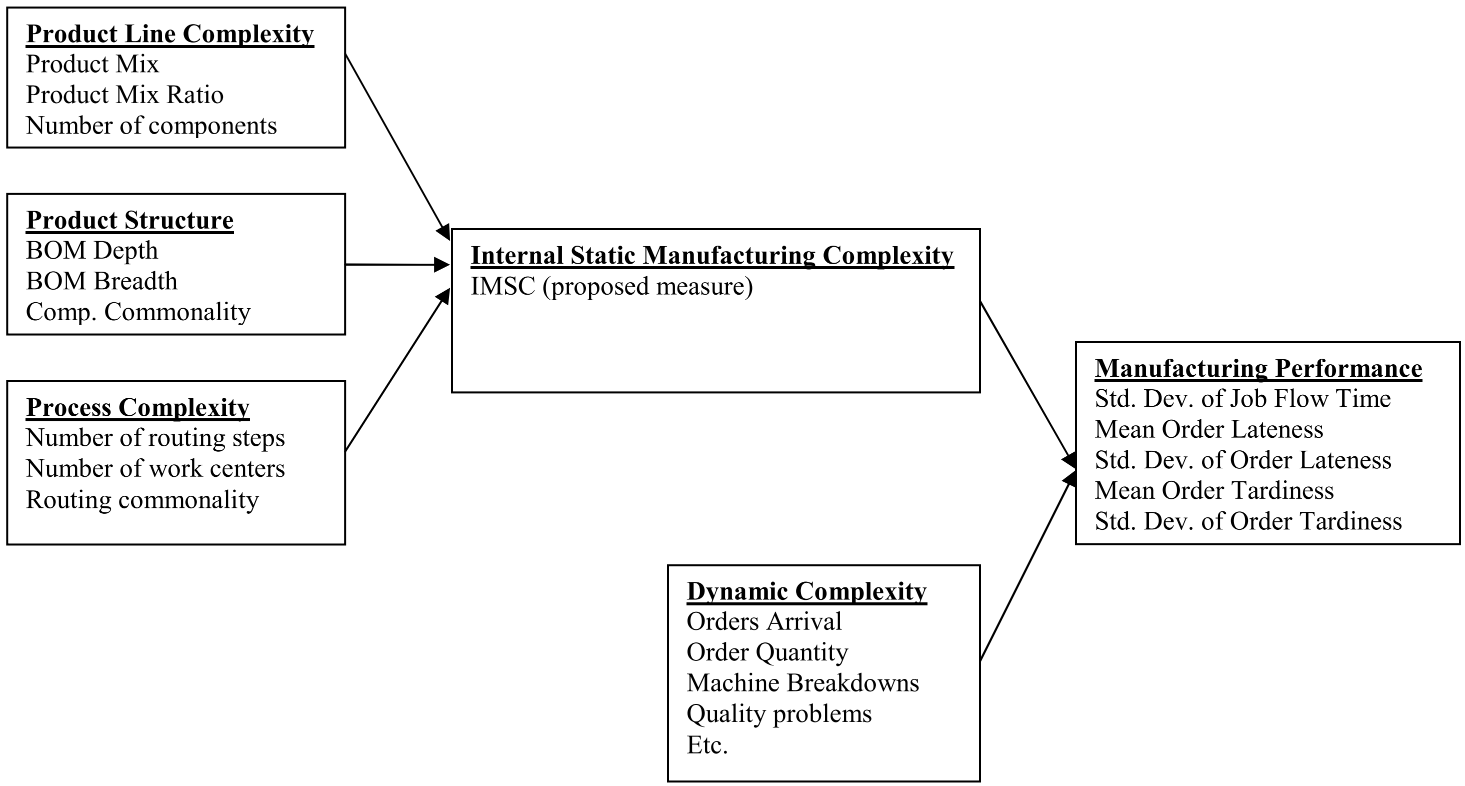

Figure 1.1 The Proposed Theoretical Model for Measuring the Effects of Manufacturing Complexity on Manufacturing Performance

complexity affects manufacturing performance. The model recognizes that dynamic complexity also affects manufacturing performance.

Research Questions

The primary purpose of this research is to develop and test a practical measure of internal static manufacturing complexity. This measure will then be used to investigate two related questions. The first is:

> Do systems with lower levels of internal static manufacturing complexity have better manufacturing performance?

In this study, it is theorized that two manufacturing operations that face the same external circumstances, having the same product mix, and having the same resources (machines and labor), but having different levels of internal static manufacturing complexity (system design), will have different performance. In fact, the system with lower internal static manufacturing complexity should have better performance.

The second research question is:

> Which elements of internal static manufacturing complexity have a greater impact on manufacturing performance?

This asks, if everything was equally easy to change, which element(s) should a manager address first to obtain the largest “payback”? This seeks to identify the complexity elements (e.g. number of components, component commonality, and number of routing steps) that have the greatest effect on performance.

Contribution of Research

By developing a quantitative measure of internal static manufacturing complexity that integrates the manufacturing complexity elements identified in past research and testing its predictive validity, this research determines whether this specific measure of internal static manufacturing complexity, ISMC, is useful. If so, ISMC can assist theory development by providing a way to control for complexity differences between systems or industries when conducting other manufacturing performance research.

A quantitative measure for internal static manufacturing complexity that is related to performance would aid them in making decisions about system design. They could determine how to allocate limited resources in order to make the largest possible impact on complexity, and thereby, system performance. Managers could evaluate how decisions regarding system changes would affect manufacturing complexity. They could also use the measure to benchmark themselves internally and externally.

The remaining chapters are organized as follows: Chapter II contains a review of literature regarding complexity and forms and operational definition for complexity. In Chapter II the elements of internal static manufacturing complexity are identified from past research and a framework is developed for internal static manufacturing. In Chapter III, a quantitative measure for internal static manufacturing complexity is proposed. Research methodology is proposed to address the research questions. The results of the research experiments using simulation of a batch manufacturing environment are presented In Chapter IV. Lastly, Chapter V discusses the conclusions of this research study and recommends possible areas for future research.

CHAPTER II

REVIEW OF THE LITERATURE

The first step in understanding manufacturing complexity is to define complexity. In this section, a general definition of complexity is adopted from past literature in the areas of physics, general systems theory, philosophy and medicine. This definition is used to develop an operational definition of complexity by identifying three dimensions of a complex system – numerosity, intricacy, and states.

A framework is developed from past literature which identifies and categorizes the important aspects of a manufacturing system that create complexity. These aspects of manufacturing complexity are then categorized as being either internal or external sources of complexity based on the extent to which they are under managerial control. The aspects comprising manufacturing complexity are further classified as elements of static or dynamic complexity.

Complexity

As previously stated, complexity is difficult to define. We all have a sense of complexity, and can intuitively perceive differences in the level of complexity between systems. So, in order to measure complexity, the first step is to articulate an operational definition of complexity.

The Oxford Dictionary defines the term complex as "consisting of many different and connected parts" and "not easy to analyze or understand"[3]. However, the scientific community admits that there is no single generally accepted definition of complexity (Flood, 1987; Klir, 1985; Lofgren, 1977; Ashby 1973; Simon 1962). Stein (1988) says that "complexity is almost a theological concept; many people talk about it, but nobody knows what it really is." (p. xiii) Although complexity is admittedly difficult to define, Casti (1979) has provided a good general definition of system complexity. He defines a complex system as one that has a counterintuitive, unpredictable or complicated structure and behavior.

Measuring Complexity

Stein (1988) states that the first step in understanding complexity is to identify and measure the properties, or dimensions, of complex systems. There have been two major approaches to this. One way that researchers have considered measuring complexity is by measuring the length of the shortest description of a system (Klir, 1985; Lofgren, 1977; Ashby 1973; Simon 1962). Longer descriptions indicate greater complexity exists. However, determining what is the shortest complete description of a system is subjective. A more precise, or scientific, way of defining complexity would be by what causes descriptions to be long, i.e. the dimensions of a system.

A second approach to measuring complexity considers the number of elements in the system and the number and type of relationships between these elements (Flood,

[3] "complex •adj." The Concise Oxford Dictionary. Ed. Judy Pearsall. Oxford University Press, 2001. Oxford Reference Online. Oxford University. http://www.oxfordreference.com. August 28, 2003.

1987; Klir, 1985; Lofgren, 1977). This notion can be linked to Simon (1962) who says that a complex system has a large number of parts, whose relationships are not "simple". Simple means "single, small"[4], or "having or composed of only one thing, element, or part"[5]. Lofgren, in his discussion of measuring complexity, termed these two elements of complexity *numerosity* (number of items) and *intricacy* (relationships of the parts).

According to Klir (1985) there is a third element of the definition of complexity – the *states* that a system element can attain. The state of a system element is the condition or mode of that element, e.g. on or off. How one system element relates to other system elements is affected by its state and the states of the other system elements at a given point in time, thereby contributing to the complexity of a system.

These two approaches to operationalize complexity may at first appear to be distinct. Since increasing the number elements and relationships in a system increases the length of the description required for completely describing a system, these approaches are clearly related. This research uses the latter approach of measuring complexity to examine existing literature about manufacturing complexity

Manufacturing Complexity

A manufacturing system is composed of numerous elements, (i.e. numerosity) – products, components, machines, work centers, etc. The number of relationships among the elements in a manufacturing system (i.e. intricacy) is often evident in system

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[4] "simple." *The American Heritage® Dictionary of the English Language,* 4th ed. Boston: Houghton Mifflin, 2000. www.bartleby.com/61/. July, 28, 2003.

[5] "simple" *The Concise Oxford Dictionary*. Ed. Judy Pearsall. Oxford University Press, 2001. *Oxford Reference Online*. Oxford University. http://www.oxfordreference.com. July 28, 2003.

documents like the bills-of-materials (BOM), routings, and the facility layout. The manufacturing system's elements can have different conditions (i.e. states). For example, machines has four states. A machine may be processing work, out of work, inoperable, (e.g. broken down), or being set-up.

Both Frizelle and Woodcock (1995) and Deshmukh et al. (1998) subdivide manufacturing complexity into static and dynamic complexity. Static, or structural, complexity refers to the complexity resulting from the system design. Deshmukh et al. (1998) define static complexity as being a "function of the structure of the system, connective patterns, variety of components, and strength of interactions." (p.645)

Dynamic, or operational, complexity stems from the dynamic nature of system resources that cause uncertainty of a system as it moves through time (Deshmukh et al., 1998). Only with the passing of time do the system components have an opportunity to change states. Dynamic complexity would include elements of manufacturing complexity that change states. Examples of aspects of a manufacturing system that can be classified as part of dynamic complexity are machine breakdowns and rejection of an order due to poor quality.

Another important distinction to make is that of internal versus external control. The elements of manufacturing system complexity that are in the direct control of system managers are considered internal complexity aspects. The products to be offered, the type and amount of equipment, the degree of vertical integration, the quality system design, and the maintenance plan are examples of decisions that affect internal manufacturing complexity. Those things that are outside of the direct control of management can add external complexity, e.g. customer orders and government regulations.

All of the identified previous research about manufacturing complexity is shown in Table 2.1. The general topic each study examines is given in column two. This table identifies the aspects of manufacturing complexity included in each article's research (column 3). It then classifies how each aspect of internal manufacturing complexity was measured, i.e. numerosity, intricacy, or states. The type of manufacturing complexity that was measured in the study is represented in Table 2.1 by an "S" for static or "D" for dynamic. The last column denotes aspects of manufacturing complexity that are external.

As shown in Table 2.1, Kotha and Orne (1989) develop a generic manufacturing strategy paradigm in which they propose a construct for manufacturing complexity. Cooper, Sinha, and Sullivan (1992), Frizelle and Woodcock (1995), and Desmukh, Talvage, and Barash (1998) propose measures for manufacturing complexity, but do not test them. Calinescu, Efstathiou, Schirn and Bermejo (1998) evaluate two potential measures of manufacturing complexity. Khurana (1999) presents a typology of manufacturing complexity in his study on the technological process complexity of the color picture tube industry.

Table 2.1 Aspects of Manufacturing Complexity Identified in Past Research

			Internal Complexity component			
Article (Year)	Topic	Aspect of Complexity	Numerosity	Intricacy	States	External
Kotha & Orne (1989)	Generic Manufacturing Strategy	Product complexity	S	S		
		Product Mix Ratio	S			D
		Product Mix	S			
		Integration between processes		S		
Cooper et al. (1992)	Manufacturing complexity in semiconductor fabrication	Product Mix	S			
		Process complexity	S	S		
		Cycle Time *				
Frizelle & Woodcock (1995)	Manufacturing complexity index	Number of machines/resources	S			
		Product Mix	S			
		Number of components	S			
		Product Mix	S/D			
		Queue length	D		D	
		Machine status			D	
Deshmukh et al. (1998)	Static manufacturing complexity index for FMS	Product Mix	S			
		Number of operations	S			
		Number of machines	S			
		Routings		S		
		Processing times		S		
		Product Mix	S			

* Cycle time is an outcome of system performance. It is not a measure of system complexity
** Does note exhibit numerosity, intricacy or states.

S = Static complexity
D= Dynamic complexity

Table 2.1 Aspects of Manufacturing Complexity Identified in Past Research (Continued)

			Internal Complexity component			
Article (Year)	Topic	Aspect of Complexity	Numerosity	Relationships	States	External
Calinescu et al. (1998)	Comparison of two mfg complexity measures	Product Mix	S			
		Number of components	S			
		Cycle Time *				
		Lot Sizes	S/D			
		Routings	S	S		
		Number of machines/resources	S			
		Layout	S			
		Set-up time **				
		Dynamicism, variability, environmental uncertainty	D		D	D
Khurana (1999)	Technological process complexity	Product mix	S			
		Environmental complexity				D
		Product complexity	S	S		
		Process complexity	S	S/D		

* Cycle time is an outcome of system performance. It is not a measure of system complexity
** Does note exhibit numerosity, intricacy or states.

S = Static complexity
D= Dynamic complexity

From this literature, 12 distinct aspects of static internal manufacturing complexity were identified. Table 2.2 reorganizes the information in Table 2.1 to identify which research involved each of these 12 aspects of internal static manufacturing complexity.

The first of these aspects of manufacturing complexity is the number of end-products, called product mix. It is addressed by all six articles regarding manufacturing complexity. It is measured by counting the number of active products produced by a system. Product mix is considered an internal aspect of manufacturing complexity because it is determined by management. The breadth of a product line is usually a strategic decision to increase competitiveness. Offering a larger product mix may increase market share and profitability by increasing overall sales or by spreading overhead costs across greater output. A larger product mix increases system complexity because it increases the number of elements in the manufacturing system (numerosity) and the number and type of relationships (intricacy) of the elements.

Table 2.2 Aspects of Manufacturing Complexity Organized by Complexity Element

Aspect of Internal Static Manufacturing Complexity	Article
Product mix	Kotha and Orne (1989) Cooper et al (1992) Frizelle & Woodcock (1995) Calinescu et al (1998) Deshmukh, et al. (1998) Khurana (1999)
Product mix ratio	Kotha and Orne (1989) Frizelle & Woodcock (1995) Deshmukh, et al. (1998)
Number of components	Frizelle & Woodcock (1995) Calinescu et al (1998)
Product complexity	Kotha and Orne (1989) Khurana (1999)
Process complexity	Cooper et al (1992) Khurana (1999)
Integration between processes	Kotha and Orne (1989)
Number of machines/resources	Frizelle & Woodcock (1995) Calinescu et al (1998) Deshmukh, et al. (1998)
Routings	Calinescu et al (1998) Deshmukh, et al. (1998)
Processing times	Deshmukh, et al. (1998)
Layout	Calinescu et al (1998)
Set-up time	Calinescu et al (1998)
Lot Sizes	Calinescu et al (1998)

Since a system may be producing more items than simply the end-products, e.g. subassemblies or fabricated parts, Frizelle and Woodcock (1995) and Calinescu et al. (1998) include not only the number of end-products, but also the number component parts produced by a system. Whether to make or buy a component is a system design decision. The number of components manufactured to support the end-products has an impact on system complexity similar to that of the number of end-products. The product mix and the number of internally produced components add to internal static complexity by increasing its *numerosity*. As the number of items manufactured (or assembled) increases, more equipment is required, more diverse processes exist and there is more interaction in the product flow, hence greater internal static manufacturing complexity.

The product mix ratio is the proportion of unit sales (numerosity) of each end-product in the product line for a business unit. Kotha and Orne (1989) purport that a system has a different amount of complexity when the product volume is spread out across the entire product line than when a few products have high volumes. Frizelle and Woodcock (1995) indirectly use the product mix ratio in their measure of static manufacturing complexity. They use the probability of a product being in queue for a machine. This probability, in essence, is the distribution of the product mix after considering the manufacturing routings. Deshmukh et al. (1998) utilize a matrix of product mix percentages to determine the average processing requirements for a flexible manufacturing system.

Kotha and Orne (1989) and Khurana (1999) address the issue of product complexity, the fourth aspect listed in Table 2.2. The authors in both articles discussed how some products are more complex than others, i.e. their inherent complexity. Kotha and Orne (1989) suggest that the complexity of products could be evaluated subjectively. They illustrate this by simply saying that a sports car is more complex than a base-model economy sedan. Khurana (1999) proposes that assembled products should be classified as being more complex than fabricated products. This concept of product complexity relies on the subjective determination of which products are more complex. This reduces its reliability as a measure.

Another aspect of manufacturing complexity in Table 2.2 is process complexity. Cooper et al. (1992) and Khurana (1999) did not provide an operational definition, but argue that there are inherent differences in the "degree of difficulty" of individual manufacturing processes. Neither author proposes an objective method of measuring process complexity. They measure process complexity subjectively, which reduces its reliability as a measure.

Kotha and Orne (1989) identify "level of interconnection" in their discussion of their process complexity construct. The "level of interconnection" is meant to capture the integration between processes. It considers the discontinuity, technological interdependence, and product-mix flexibility of the manufacturing processes. Their research was theoretical development of a manufacturing strategy framework in which one dimension is process complexity. In their definition of the "level of interconnection", there is no link to any of the definitional elements of complexity, i.e. numerosity, intricacy, or states. They did not attempt to quantify their factors.

As shown in Table 2.2, three complexity researchers (Frizelle and Woodcock, 1995; Deshmukh et al., 1998; Calinescu et al., 1998) identify the number of machines or processing resources as part of manufacturing complexity. Since management has some discretion over process design (i.e. number of machines or workstations) and since the number of machines or resources is independent of time, the number of machines or resources is an element of internal static manufacturing complexity.

Frizelle and Woodcock (1995) indicate that one way to reduce static complexity is to reduce the number of processing resources. By lowering static complexity, they suggest that there is less “resistance to flow” in the system. Deshmukh et al. (1998) use the number of machines in their proposed measure of internal static manufacturing complexity. It is one of three of their numerosity variables, the others being the number of products and the number of operations. Calinescu et al. (1998) do not propose a complexity measure, but recognize that the number of resources is an important element of plant structure.

Manufacturing routings are identified by Deshmukh et al. (1998) and Calinescu et al. (1998) as being another important aspect of internal static manufacturing complexity. Routings are the specific sequence of operations required to assemble or manufacture an item. The routing is a simple way of describing the specific relationship that a product has to the processes in a manufacturing system. It also has a numerosity component – the number of steps or operations. Deshmukh et al. (1998) thought that the sequence of steps and the number of steps in a routing were both important to measure so they recorded them in separate matrices when calculating static complexity. It is evident that routings have both numerosity and intricacy dimensions. Routings are an internal aspect of manufacturing complexity because they can be altered by management through process redesign efforts, i.e. elimination of steps or combining process steps. So, manufacturing routings can be classified as a component of internal static manufacturing complexity.

Deshmukh et al. (1998) included processing times in their static complexity measure. However, processing time is a measure of time, and does not express numerosity, intricacy, or state. It is also not clear how differences in processing times between two manufacturing systems can create complexity.

As part of their definition of "product structure", Calinescu et al. (1998) includes plant layout - the eighth of 12 identified complexity aspects in Table 2-2. The facility layout is a static internal complexity element. The "design" decisions of locating equipment are directed by plant management (internal). A layout is defined as the structure of the manufacturing system, and is not affected by the passing of time, i.e. it is static. The plant layout defines the relationship, or interconnection, of processes. Although recognizing the potential impact of layout on manufacturing complexity, Calinescu et al. (1998) did not propose a method to measure it.

Calinescu et al. (1998), as part of a general construct of "plant structure" include set-up times. From a system design perspective, set-up time is determined by technological process selection, and thus, appears to be an element of internal complexity. However, the set-up time encountered in a system is determined as time is passing. The number of set-ups, a possible component of a numerosity measure of complexity, cannot be calculated or fairly estimated at a static point in time. The sequence of batches, jobs, or items will determine both the total number of set-ups and the total set-up time for a system. The total set-up time is unpredictable for a given system design exposed to stochastic events, e.g. customer order arrivals. Therefore, equipment set-up (time or quantity) exhibits qualities of both static and dynamic complexity.

Lot-size is also one of the concepts listed by Calinescu et al. (1998) as being part of their "plant structure" construct. Calinescu et al. (1998) do not explain why lot-size is a relevant element of internal static manufacturing complexity nor do they develop a measure for manufacturing complexity. It is true that management makes the lot-size decisions, which means that lot-sizing is an internal aspect of manufacturing complexity. At the same time, the production lot-size for an item is often a dynamic decision that depends upon customer order size or system status. In addition, the cost structure of a system is not fully in the control of management. Certain industries require different levels of technological investment, e.g. continuous flow industries. Like set-up time, lot size can be considered as being an aspect of both static and dynamic complexity.

Measures of Manufacturing Complexity

Only three researchers reviewed in Table 2.2 (Cooper et al., 1992; Frizelle and Woodcock, 1995; and Deshmukh et al., 1998) developed quantitative measures for manufacturing complexity. Cooper et al. (1992) develop a complexity measure they call "total net die equivalent" (TNDE). In their measure, they evaluated product mix, the relative complexity of each product, the relative complexity of each process technology, and the process-flow characteristics. Their formulation is given as:

$$\text{TNDE}(j)=\sum V(i,j)*PPI(i)*PFLOW(i,j), \tag{1}$$

where PP(i) is the product process index of the i^{th} chip type; V(i,j) is the volume of chip type i in the j^{th} period; and PFLOW(i,j) is the flow index. The TDNE measure was specifically designed for the semiconductor industry and, as such, is difficult to generalize.

Both Frizelle and Woodcock (1995) and Deshmukh et al. (1998) propose measures for internal manufacturing complexity using entropy-based formulations. This methodology was adapted from information theory research (Shannon, 1948). An entropic measure attempts to quantify the amount of uncertainty associated with a system. The general form for quantifying entropy is given in Equation (2):

$$H(S) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{2}$$

The entropy, H(S), is the sum of the weighted probabilities of a state or event. In this equation, there is a probability (p) assigned to each possible state (i) which is weighted by the $\log_2$ of the probability of the i^{th} state. The base of 2 for the log function is used because the states are considered binary, i.e. each state can be either occurring or not occurring.

Frizelle and Woodcock (1995) propose an entropic formulation for both internal dynamic and internal static manufacturing complexity. Equation (3) gives their formulation for internal dynamic manufacturing complexity.

$$\begin{aligned} H(S) = {} & -P\log_2 P - (1-P)P\log_2(1-P) \\ & -(1-P)\left(\sum_{j=1}^{M^q}\sum_{i=1}^{N_j^q} p_{ij}^q \log_2 p_{ij}^q + \sum_{j=1}^{M^m}\sum_{i=1}^{N_j^m} p_{ij}^m \log_2 p_{ij}^m + \sum_{j=1}^{M^b}\sum_{i=1}^{N_j^b} p_{ij}^b \log_2 p_{ij}^b \right) \end{aligned} \tag{3}$$

Frizelle and Woodcock (1995) evaluate manufacturing complexity based upon the probabilistic blocking effect of a production system. The queue length represents the state of a machine and is given by the probability p^q. The term $p^q{}_{ij}$ is the probability that machine *j* has state *i*, where *i* represents a queue length greater than one. The probability of machine *j* working or being idle is called the "makestate", and is represented by the term $p^{m}{}_{ij}$. And $p^{b}{}_{ij}$ is the probability of an unplanned state occurring on machine j, e.g. breakdowns or quality rejects. P represents the probability that the system is in control; that it is operating within predefined limits. For Frizelle and Woodcock (1995), the system is in control when there is no queue at any machine.

For static complexity, Frizelle and Woodcock (1995), set $P = 0$, stating that control elements apply only to dynamic systems. Their formulation for the internal static manufacturing complexity is given in Equation (4).

$$H(S) = -\sum_{j=1}^{M}\sum_{i=1}^{N_j} p_{ij} \log_2 p_{ij} \tag{4}$$

where p_{ij} is the probability that product i is running on machine j. Frizelle and Woodcock (1995) suggest that the greater the number of products or machines in a system the greater the internal static manufacturing complexity. They note that because it is scaled by $\log_2$, the addition of each new product or machine has a reduced impact on complexity. That is to say that the marginal impact of adding a product or machine is less for large systems than small systems.

In their conceptualization of their internal manufacturing complexity measures, Frizelle and Woodcock (1995) consider complexity as being "resistance" to the flow of production. Since the results of the calculations are unitless, they propose that these units be called equivalent product process (*epp*). According to Frizelle and Woodcock (1995), *epp* expresses the level of resistance to flow in a system, which represents the level of internal manufacturing complexity.

Deshmukh et al. (1998) also formulates an entropic measure for internal static manufacturing complexity. However, their measure is designed only to be applied to flexible manufacturing systems (FMS). The measure proposed by Deshmukh et al.

(1998) does not consider product structure. Also, despite being published four years after Frizelle and Woodcock (1995), Deshmukh et al. (1998) does not reference nor build upon this prior research.

Product Mix

All six research articles from Table 2.2 identified end-product variety, referred to as product mix or product line breadth, as an important aspect of internal static complexity. An additional eight studies were identified that also investigated the impact of product mix on manufacturing performance. These are shown in Table 2.3. Of these eight articles, five were identified by Ramdas (2003) in his review of research on product variety. This section summarizes the results of these studies.

The past research that investigated the effect of product variety on manufacturing performance is shown in Table 2.3. For each article, the table identities the type of research performed and the research findings. It is interesting to note that all of the identified past research on product mix has used some type of empirical research methodology.

In the first study shown in Table 2.3, Kaisa, The Japanese Corporation, Abegglen and Stalk (1985) recognize that a broad product line is a source of complexity for manufacturing plants. They state that "With increasing complexity comes an increased number of parts, greater material handlings and inventories, more diverse process flows, higher supervision requirements, an increase of errors and defects, and smaller batches produced in shorter runs" (Abegglen and Stalk, 1985, p. 80). Abegglen and Stalk (1985) link product line complexity to the need for more frequent set-ups, and the increased overhead associated with those set-ups. The extra efforts associated with scheduling, material handling and expediting are examples they cite as being drivers of increased overhead. Using a Toyota forklift factory as anecdotal evidence, they show that by focusing their efforts on a narrower product line, hence lowering factory complexity, Toyota was able to reduce manufacturing costs by 18%.

Foster and Gupta (1990) study the relationship between cost drivers and manufacturing overhead (MOH). They examine MOH because MOH can also represent a sizeable portion of total manufacturing costs. In their sample of 37 electronics facilities belonging to one parent company, MOH made up an average of 39% of total manufacturing cost.

Complexity-based cost drivers are one of the three "classes" of cost drivers that Foster and Gupta (1990) investigate. The other two classes are volume-based and efficiency-based cost drivers. The complexity-based cost drivers were divided into five categories: product design, procurement, manufacturing process, product range (i.e. product mix), and distribution complexity.

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Table 2.3 Past Studies that Investigated Product Mix

Authors (Year)	Type of Study	Findings
Ramdas (2003)	Literature Review	Proposes a framework for variety-related decisions in a firm. Identifies areas for future research in product variety including dimensions of variety, product architecture, degree of customization and points of variegation
Abegglen and Stalk (1985)	Field Study	Narrower product mix leads to reduction in total MFG costs
Foster and Gupta (1990)	Survey	Product mix positively correlated to total Manufacturing Overhead
Kekre and Srinivasan (1990)	Analysis of PIMS data	Mixed results
Ittner and MacDuffie (1995)	MIT Automotive empirical study	Part complexity significantly related to direct labor hours and overhead hours per vehicle
MacDuffie, Sethuraman, and Fisher (1996)	MIT Automotive empirical study	Part complexity significantly related to direct labor hours per vehicle
Fisher and Ittner (1999)	Single plant study	Option <u>variability</u> negatively affects overhead hours per car and inventory
Bozarth and Edwards (1997)	Survey	Product mix had significant negative relationship with manufacturing performance
Anderson (1995)	Case studies in three textile plants	Product line heterogeneity increased manufacturing overhead through increased set-ups and greater raw material variety.

Although the primary conclusion was that volume-based cost drivers have the largest impact on MOH, Foster and Gupta (1990) speculate that the high correlation of volume-based variables with MOH could be driven by complexity factors. There were significant correlations between MOH and several complexity factors within the five categories. Two factors measuring product variety had significant correlation with MOH - the number of products offered and number of products accounting for 80% of business. Other complexity factors that had significant correlations included the number of components, the bill of materials depth, and the extent of vertical integration.

Kekre and Srinivasan (1990) investigate the benefits and cost implications of product mix. Their results provide mixed support for their hypotheses that (1) greater product mix leads to higher direct costs, (2) total inventory increases with greater product mix, and (3) greater product mix adversely affects a firm's ROI.

They evaluate their hypotheses using data from the Profit Impact of Marketing Strategies (PIMS) database. Their results indicated that there was a slight decrease in manufacturing cost as product mix increased, the opposite of what was hypothesized. They also found no significant relationship between product mix and total inventory. Regarding the direct effect of product mix on ROI, their results show that there was a significant, but small, negative effect of a broader product line on ROI only for the firms classified as industrial goods providers.

Although their hypotheses were not supported, Kekre and Srinivasan (1990) believe that having a broader product line will still negatively impact performance. They suggest that firms that must offer a broad product line may employ strategies that mitigate these negative effects such as implementing cellular manufacturing, applying

Just-in-Time and Lean manufacturing practices, using focused factories, and designing products with a high degree of part commonality. Kekre and Srinivasan (1990) acknowledge that the PIMS data does not capture information regarding these strategies.

Using data from the MIT International Motor Vehicle Program study, Ittner and MacDuffie (1995) and MacDuffie, Sethuraman, and Fisher (1996) evaluate the impact from product variety on performance in automotive assembly plants. Ittner and MacDuffie (1995) examine the effects of product mix complexity on direct and indirect labor requirements in automobile assembly. They measure product mix complexity with three measures – model mix complexity, option complexity and parts complexity. Each one is a scaled measure ranging from 0 to 100, where 0 is assigned to the plant with the least complexity and 100 to the plant with the greatest complexity. Model mix complexity measures the major differences between models based upon the number of platforms, drive trains and export variations. Option complexity is based upon the percent of vehicles assembled with a given option (from a limited list of 11 options). Parts complexity is a combined measure of four elements – parts/component variation, number of parts to the assembly area, percent of common parts across models, and the number of suppliers to the assembly area.

From the results of their regression analysis, Ittner and MacDuffie (1995) find that parts complexity was a determinant of both direct labor hours per car and indirect labor hours per car. Options complexity only had a significant relationship with indirect labor hours per car. The authors contend that the option bundling programs and the line scheduling algorithms employed by many of the plants reduced the effects of option mix on direct labor, but could not entirely shield them from the need for increased materials handling and production control. Model mix had no significant relationship with either type of labor content. Ittner and MacDuffie (1995) say that this is due to the dedicated or automated lines common in the automobile assembly industry.

MacDuffie, Sethuraman, and Fisher (1996) in a sister study to Ittner and MacDuffie (1995), investigate the effects of product complexity on plant productivity and quality performance. Product complexity is a combination of four measures. The first three, model mix complexity, parts complexity, and option content (complexity), are identical to those of Ittner and MacDuffie (1995). MacDuffie et al.(1996) add a fourth measure termed option variability, which measures the extent to which a vehicle contains a given option. They contend that the variability in options creates workload imbalances, thus reducing productivity in assembly.

In the study by MacDuffie et al.(1996), parts complexity again was directly related to direct labor productivity. They surmise that as the number of components and subassemblies increase, there is an increase in the labor and effort expended to manage and assemble them. Option content, in agreement with the prior research by Ittner and MacDuffie (1995), is related to the labor productivity – more options yielded lower productivity.

An interesting outcome from MacDuffie et al.(1996) is that, contrary to their expectation, option variability had a significant negative regression coefficient. This would mean that as variability in options increased, labor hours per vehicle decreased. While they can not provide a conceptual explanation for this result, they speculate that plants that deal with greater option variability have developed capabilities to cope with it.

Fisher and Ittner (1999) continue the investigation on the impact of product variety on automobile assembly plant performance. They use empirical data from a single plant and a follow-up simulation to examine relationships between option content and variability and performance. Option content is measured as the average number of options per car, limited to a set of eight options actively tracked by the management of the study plant. Option variability is calculated as the standard deviation in the number of options installed (of the eight tracked options).

Fisher and Ittner (1999) suggest that product variation in mixed-model assembly causes variation in process times at the different stations of an assembly line. They note that scheduling (sequencing) of models is employed to help reduce the effects of product variation by reducing downtime that results from repeated long processing time requirements at stations (one auto after another). The results concur with their thinking. There is not a significant relationship between option content and any of their measures of performance. However, option variability has a significant, adverse effect on output (cars per hour), total labor hours per car, overhead labor hours per car and inventory. Fisher and Ittner (1999) note the plant that was studied used excess labor capacity as a tactical response to combat the affect of variability. Increases in option variability lead to increases in excess capacity. This single plant result conflicts with that of prior research in automotive assembly plants (MacDuffie et al., 1996) where option variability had a significant positive impact on productivity.

The results of the follow-up simulation by Fisher and Ittner (1999) provide two important insights. First, the results support those from the empirical study regarding option variability. As option variability increase, labor requirements per car increase.

Secondly, random variation in the process (i.e. process time variation, defective parts, and poor quality from preceding workstation) was determined to be a larger contributor to the negative affects than product variety, since scheduling can be used to mitigate the affects of known variation. Fisher and Ittner (1999) suggest that this makes product mix variation an important element in any measure of product variety.

Bozarth and Edwards (1997) perform empirical research to test their proposed model relating market requirements focus and manufacturing focus to plant performance. Their survey includes 24 manufacturing plants that were original equipment suppliers (OEMs) in the automotive industry. They measure the manufacturing focus construct using two measures of product similarity, two measures of similarity among work cells, and a measure of strategic orientation. Market requirements focus is measured by the number of major customers (those that make up 80% of the plants dollar volume), variability in customers needs (made up of six variables), number of product lines (i.e. PLB), and variability in level of customization. Bozarth and Edwards (1997) develop a combined plant performance measure consisting of six criteria - cost, conformance, quality, delivery speed and reliability, product range, and design capability. All dependent and independent variables are perceived measures, either obtained as estimates or from questions using a Likert scale.

The result of the Bozarth and Edwards (1997) study shows a significant, negative relationship between the number of product lines (i.e. product mix) and their plant performance measure. They suggest that this result indicates that more product lines inhibit performance. They also find that product homogeneity, as measured by similarity of processing requirements, is related to higher plant performance. Lastly, Bozarth and

Edwards (1997) find that efforts identified as "plant-within-a-plant" like cellular manufacturing, are related to improved plant performance.

In a three-plant case study, Anderson (1995) investigates the effects of product mix heterogeneity on manufacturing costs. Anderson (1995) and Bozarth and Edwards (1997) are the only studies that seek to differentiate products by degree of similarity. The research study by Anderson (1995) involves three textile manufacturing facilities with different levels of production line variety. One plant focused on high volume, very similar textile products. The second plant experienced greater variety of heterogeneous fabrics than the first. The third plant's niche was to introduce new products frequently and therefore had the highest levels of product heterogeneity. The study measured product heterogeneity using variables specific to textile manufacturing that the author developed through interviews with plant personnel. The results suggest that increases in MOH were associated with greater product mix through increases in total set-up time, and the diversity in process and quality requirements.

Although there have been some mixed results on the effect of product variety, several important points can be drawn from past research. First, product mix (number of end-products) appears to have an impact on system performance. Secondly, because a larger product mix increases the number of components in a system, system complexity increases and more overhead is required to help manage the ensuing effects. Lastly, from Fisher and Ittner (1999), consideration must be given to the variation of demand for the products in the product line. As they imply, it may be the variation in the demand of the products across the breadth of the product line that has a significant effect on plant performance.

Product Mix Ratio

The product mix ratio represents the distribution of unit sales across the product line for a business unit (Deshmukh et al.,1998). It can be viewed as both an aspect of internal static or external dynamic complexity. The actual product mix ratio is affected by the environment (external) via customer demand for the products. As time passes, customer order volumes do not exactly match the forecasts or schedules, and dynamic decisions are made to adjust to these variations. These are external dynamic complexity issues.

At the same time, the product mix ratio is often a management decision (internal), determined by capacity planning and marketing decisions. Product volume estimates are made periodically, and "static" decisions are made using them, i.e. layout, machine and labor requirements. Articles regarding manufacturing complexity that have included the concept of product mix ratio (Kotha and Orne, 1989; Frizelle and Woodcock, 1994; and Deshmukh et al., 1998) have considered it part of static complexity.

Although they do not quantitatively measure manufacturing complexity, Kotha and Orne (1989) assert that a system in which the product volume is spread across the entire product line will have a different amount of complexity than a system having a few products with high volumes. Frizelle and Woodcock (1995) make no conclusions about the effect of the product mix ratio on manufacturing complexity, but use it indirectly in their measure of static manufacturing complexity. They use the probability of a product being in queue for a machine, which, in essence, is the product mix ratio after considering the manufacturing routings.

Likewise, Deshmukh et al. (1998) include product mix ratio in their formulation. They make no suggestions of the impact of the product mix ratio. They utilize a matrix of product mix percentages to determine the average processing requirements for a flexible manufacturing system.

Product Complexity

According to Kotha and Orne (1989) and Khurana (1999), product complexity is an important determinant of manufacturing complexity. Product complexity is created via the number of components and their relationships to one another. A bill of materials (BOM), or product structure, is an expression of the relationships among products and components in a manufacturing system. A BOM has both numerosity and intricacy dimensions.

A BOM can be measured by numerosity in the number of levels (i.e. Veral and LaForge, 1985; Benton and Srivastava, 1985; 1993;) or the total number of components (i.e. Sum et al., 1993). Its intricacy can be measured by its breadth of components (Benton and Srivastava, 1985; 1993; Fry et al., 1989), Although a BOM represents the specific relationships of components to a "parent", when considering all the BOMs in a system, other relationships can also be measured, e.g. component commonality (Sum et al., 1993; Collier, 1981; 1982; Wacker and Treleven, 1986).

Veral and LaForge (1985) introduce product complexity when they include it as a factor in their study of the performance of four lot-sizing rules in a multi-level manufacturing environment. In this study, they define product complexity as "the maximum number of levels of dependent relationships (depth) in a product structure"

(p. 60). The three other factors investigated are value-added, variability of demand, and order/set-up cost. Using simulation, Veral and LaForge (1985) evaluate the performance of lot-sizing rules on four products whose product structure ranged from two to five levels. The performance measure used to evaluate the four lot-sizing rules was inventory cost relative to that of a baseline rule, i.e. the Wagner-Whitin model. The results show that the relative performance of lot-sizing rules was not significantly affected by product complexity. They make no inference about the overall effect of product complexity, because the analysis was based upon a relative measure and not an absolute measure of cost.

In their research on lot-sizing rules in a multi-level environment, Benton and Srivastava (1985) evaluate product complexity in terms of both breadth and depth of the product structure. They define product structure breadth as the number of immediate components for a parent item. Similar to Veral and LaForge (1985), Benton and Srivastava (1985) define product structure depth as the number of levels in the product structure for an end-product. One minor difference between the two studies is that Benton and Srivastava (1985) do not consider the end-item, but include all other levels.

Benton and Srivastava (1985) conduct their investigation employing a simulation involving four contrived product structures These product structures have a variety of depths and breadths. Using holding costs as the dependent variable, the results from their study led Benton and Srivastava (1985) to conclude that product structure complexity does not alter the performance of lot sizing rules. This is consistent with Veral and LaForge (1985). However, product structure complexity was statistically significant as a main effect and in all two-way interactions. These results indicate that product structure complexity likely affects performance. Their data on mean total cost indicates that product structure depth has an inverse relationship with mean total system cost.

In 1993, Benton and Srivastava continue their research in product structure complexity and lot-sizing. They developed a quantitative measure of product structure complexity that included the number of operations performed, i.e. processing steps. The product structure complexity index (PSCI) is a multiplicative function of the number of levels per parent (depth), the number of items per parent (breadth) and the number of operations per end item. They used the same contrived products from Benton and Srivastava (1985) and assume that there is only one operation required at each parent node in a product structure.

Utilizing simulation, Benton and Srivastava (1993) test the hypotheses regarding their three study factors - lot-size rules, product structure complexity and inventory capacity limits. They use total manufacturing cost (set-up, holding and excess inventory storage space) and fill rate as the dependent variables. In their results, all experimental factors have significant main effects and two-level interactions with both performance measures. In general, the results indicate that as PSCI increases so do the total system costs, therefore Benton and Srivastava (1993) conclude that as product structure complexity increases, so do system costs.

It is interesting to note that the data from Benton and Srivastava (1993) show that the fill rate increases as the PSCI increases. Intuitively, a PSCI should have an inverse relationship with fill rate due to multi-level planning and performance issues. As the complexity of products increases it should be more difficult to coordinate material arrivals at each successive level in order to complete orders on-time. It would be expected that fill rate would decline as product complexity increased

Sum, Png, and Yang (1993) identify three factors useful in measuring product structure complexity during their investigation of the interaction of product structure complexity with lot-sizing rules (RU). The three factors are (1) the total number of items in all products structures (NI), (2) the maximum number of levels in all product structures (LV), and (3) a commonality index (CI). In their simulation model, Sum et al. (1993) include 180 different product structures, far greater than other studies (Veral and LaForge, 1985; Benton and Srivastava, 1985 & 1993). As in Veral and LaForge (1985), performance is measured as the ratio of total cost of the specific lot-sizing rule to the total cost of the baseline lot-sizing rule (the Wagner-Whitin model). Sum et al. (1993) also report the mean total cost for each lot-size rule that they evaluated. Sum et al. (1993) find that all factors have significant main effects, 2-level interactions, and 3-level interactions with the exception of NI*LV*RU. As in prior research, the ranking of the lot-sizing rules is not affected by product structure complexity. At the same time, the individual factors of product structure complexity are shown to have a significant relationship to total cost performance. Based upon follow-up analysis of the interactions of NI, LV, and CI, Sum et al. (1993) suggest that CI (component commonality) has a greater effect on performance than NI or LV.

In a study on lot-sizing rules in an assembly shop, Russell and Taylor (1985) include product structure complexity as a way to define an assembly environment. They define product structure complexity by the number of levels in the product structure, the number of components, and the number of operations per component. Purchased items are not considered part of the product structure. They do not propose a complexity "index", but contrive five end-products with a mix of product structure complexity attributes. In their simulation, the five end-products range in having product structures with either two or three levels, four or five components, and one to three operations. Mean flow time, mean tardiness, RMS of tardiness, percent tardy and assembly delay are the five dependent variables.

The objective of the Russell and Taylor (1985) study is to investigate the performance of lot-sizing rules in an assembly environment, which is described by a given set of characteristics including product structure complexity. It is after they completed the initial experiment that Russell and Taylor (1985) perform sensitivity analysis to evaluate the effect of "tall" and "flat" product structures. They conclude that "tall-structured jobs were more difficult to process in an assembly shop than flat-structured jobs, by every measure of performance" (p.208).

Continuing research on assembly shops, Fry, Oliff, Minor, and Leong (1989) evaluate the effect of product structure on priority dispatching rules. The authors compare 10 different product structures representing flat, tall and complex product structures in a simulated assembly job shop. Three items had flat BOMs, each having a single level and containing from two to eight components. The three items with tall BOMs had two, four or six levels, each level having two components – one purchased item and one manufactured item. The two items with complex product structures (a.k.a. BOMs) had three levels and either two or three components at each level.

The definition of product structure by Fry et al. (1989) includes the routing steps required for each component in the BOM. Each manufactured item has a routing with a randomly selected number of operations ranging from one to four. Components are processed in batches in a job shop environment made up of six machines (work centers). These components are assembled into the final product at one of four assembly work stations.

Fry et al. (1989) show that the performance of sequencing rules is affected by the product structure. Of all the rules evaluated, they identify the earliest job due date rule as the only rule consistently in the top performing rules across each of the 10 product structures. The author's conclusions regarding the effects of product structure are similar to those of Russell and Taylor (1985). Taller product structures tend to be tardier than flat product structures across all of the dispatching rules that were examined.

Regarding product structure complexity, past literature indicates that depth and breadth, and component commonality can affect system cost, flow time and customer service (e.g. tardiness and fill rate). Past research has not investigated the extent of the effects of either depth or breadth. It has typically been an environmental factor in research experiments. These past studies investigated other management issues, e.g. lot-sizing rules or dispatching rules, but have not examined the effects of product structure complexity in detail. The inclusion of product structure complexity is obviously important and the analysis of its impact on performance is extremely relevant.

Component Commonality

Kekre and Srivansivan (1990) speculate that designing products that share parts may help to reduce internal static manufacturing complexity. When products or subassemblies share components, it is referred to as component commonality (Collier, 1981). Collier (1981) recognizes that component commonality in product structures could affect production process performance by way of the materials plan. In his 1981 research, Collier studies the effects of commonality on system cost and work center load. To do this, Collier develops a "degree of commonality" index (DCI). It is designed to "reflect the number of common parent items per average distinct component part" (Collier, 1981, p.87). Collier proposes the following formulation of DCI:

$$DCI = \frac{\sum_{j=1}^{d} \Phi_j}{d}, \tag{5}$$

where $\sum_{j=1}^{d} \Phi_j$ is the number of parents for each component in the set of d components used to make all the firm's end-products.

In a simulation experiment, Collier (1981) uses three lot-sizing rules (economic order quantity, least total cost, and lot-for-lot) to evaluate the effects of four sets of product structures with the degree of component commonality ranging from no commonality (DCI = 1.0) to high commonality (DCI = 2.5). Each set consists of three end-products with identical product structures, the same part routings, set-up and processing times, and planning lead times. The degree of commonality is altered for each set of product structures by changing the number of common components with the product set. The results of the simulation show that higher levels of component commonality lead to reduced system costs (inventory carrying and set-up costs) and lower average workloads. Collier (1981) finds that fewer set-ups occurred due to the use of common parts, thus there was a reduction in average workloads. The negative effect of commonality observed by Collier (1981) is that it creates greater workload variation when either the economic order quantity or least total cost lot sizing approaches were employed. Collier suggests that greater component commonality leads to larger lot sizes and a lumpier material plan.

In 1982 Collier applies his commonality index in research on the relationship of component commonality and safety stock level. His experiment includes six levels of commonality ranging from no commonality (DCI = 1.0) to high commonality (DCI = 12.0) and two safety factors ($k = 0.84$ and $k = 1.75$). The safety factor, k, is related to service level by a formulation proposed in this same article. Collier (1982) utilizes a simulation experiment to measure the effect of component commonality, measured by DCI, on total safety stock in an MRP environment. According to Collier, the results suggest that greater component commonality reduces the safety stock quantities for components at any given constant service level. Using three practical examples, he demonstrates that increasing component commonality reduces the safety stock requirements for components needed to maintain a certain service level. In turn, he shows that this relationship between component commonality and component safety stock will lead to a reduction in inventory costs.

Baker (1985) and Baker, Magazine, and Nuttle (1986) contend that commonality makes predicting service level performance difficult. Collier (1982) had purported that lower amounts of safety stock of components were required when commonality existed. Baker (1985) agrees with this, but demonstrates that service level cannot be directly calculated for the end-products that shared common components as Collier (1982) formulated.

Using some simple product structures for examples, Baker (1985) tests Collier's (1982) conclusion regarding the relationship of component commonality and component safety stocks. He explores these issues in an assemble-to-order manufacturing environment. Component safety stocks are used to maintain a target service level. Using three end-products each with a 2-level product structure, Baker demonstrates that under Collier's (1982) safety factor approach, greater component commonality does reduce component safety stock requirements. He demonstrates this for both the cases of within-product and between-product component commonality. He also shows that end-products with correlated demand permit commonality to have a larger positive impact on safety stock requirements.

The problem that Baker (1985) identifies with the theoretical relationship of commonality and safety stock is that the calculation of safety stock using the "k-factor" is not valid when there is between-product component commonality. Baker (1985) states that the impact of component commonality is multidimensional, making it difficult to determine the actual service level for end-products. He concludes that the service level performance can be negatively affected for systems with between-product component commonality, thus Collier's (1982) formulation for determining service level cannot be used.

Baker et al. (1986) continues the investigation of commonality and safety stock in an assemble-to-order environment. They formulate and solve an optimization problem for two end-products, a two-level product structure with two components per end-product. The objective function is to minimize total component safety stock. Using an example with two end-products, Baker et al. (1986) demonstrate qualitatively that the safety stock of the common components decreases when compared to having individual unique components. At the same time, when there is between-product commonality, the safety stock of non-common components must increase in order to maintain a minimum service level.

Guerrero (1985) investigates the effects of component commonality on system performance in three production environments – make-to-order, assemble-to-order, and make-to-stock. In his simulation model, Guerrero constructs two alternate 3-level product structures, one set with commonality (referred to as high commonality) and the other without commonality (referred to as low commonality). Lot sizing rules, either Wagner-Whitin or lot-for-lot, are designated to each level of the product structure according to the production environment. Performance measures are the total cost (set up and holding) and the variance of work-in-process inventory. According to Guerrero (1985), significantly lower total cost occurred in the case of high commonality. However, in the case of commonality, work-in-process load variance was greater, suggesting to Guerrero (1985) that high commonality can cause lumpy requirements for those items "in common".

Weaknesses in Collier's (1981) DCI are identified by Wacker and Treleven (1986). Since the DCI is a cardinal measure, not a relative measure, Wacker and Treleven (1986) suggest that the measure cannot be used to compare the affects of component commonality across organizations. They also state that the DCI does not identify the source of the commonality, i.e. within-product or between-products.

In order to resolve the first of these weaknesses in the DCI, Wacker and Treleven (1986) propose the Total Component Commonality Index (TCCI), given as:

$$TCCI = 1 - \frac{d-1}{\sum_{j=1}^{d} \Phi_j - 1} \tag{6}$$

As in Collier (1981), $\sum_{j=1}^{d} \Phi_j$ represents the number of parents for each component in the set of d components used to make all the firm's end-products. TCCI can only range from zero to one. A TCCI of zero represents a group of products having no commonality. A TCCI of one signifies complete commonality, i.e. one component used everywhere. Since TCCI measures the relative degree of component commonality in a system, Wacker and Treleven (1986) suggest it may be used when comparing different systems.

Wacker and Treleven (1986) go on to formally define two types of component commonality that can exist and proposed methods to measure them. Baker (1985) informally identified these in the examples he used to demonstrate the affect of commonality on component safety stock. According to Wacker and Treleven (1986), *within-product* component commonality occurs when there are multiple uses of the same component within the product structure of a single end-product. *Between-product* component commonality is the amount of component standardization among all end-products. The indices proposed by Wacker and Treleven (1986) to measure within-product or between-product commonality are designed to evaluate an individual end-product. Their within-product constant commonality index (WCCI) measures the within-product commonality for a single end-product. The between-product constant commonality index (BCCI) measures the component commonality, ideally, for a new product or new product family.

Many other commonality indices are proposed in Wacker and Treleven (1986). These include measures for average commonality within a single product structure level, and indices for total, within-product and between-product commonality for purchased parts. Details of these have not been included here because they are not relevant for the proposed research.

Vakharia, Pamenter, and Sanchez (1996) further investigate the affects on work center workloads due to component commonality that are identified in Collier (1981) and Guerrero (1985). In their experiment, two types of commonality are used as two of the study factors – within-product and between-product commonality using commonality. In their experimental design, Vakharia et al. (1996) use 10 end-products. Product structures are established for the set of 10 end-products in order to achieve two levels of component commonality for each within-product and between-product commonality. At the "low" setting, each end-product had none of the specific commonality. At the "high" setting, the commonality is set at 0.2308 for the specific type of commonality, as measured by Wacker and Treleven's (1986) TCCI. When both factors, i.e. within-product and between-product commonality, are at their high setting, the overall TCCI is 0.4616.

The four other study factors in Vakharia et al. (1996) are the number of work centers, set-up time, correlation of end-product demand, and variance of end-product demand. The authors include five levels of the number of work centers ranging from 1 to 150 work centers. By doing this, the authors believe they would be able to analyze the average load and load variance at the work center level in a more realistic simulation.

Vakharia et al. (1996) investigate the affects of correlation and variation in demand, because these were not examined by Collier (1981, 1982) or Guerrero (1985). They also include set-up time as a factor because they believe that component commonality may reduce total processing requirements by reducing the number of total set-ups, because components can be released in larger batches.

The results of Vakharia et al. (1996) support those of Collier (1981) and Guerrero (1985). When either type of commonality was introduced, average processing time per work center decreased and the standard deviation of work center processing time increased. Vakharia et al. (1996) attribute the reduction in average processing time to the reduction of the total number of set-ups that was due to the increased commonality. According to Vakharia et al. (1996), all study factors have a significant relationship to the average standard deviation of work center processing time except set-up time. Set-up time is only significant in the experiment using the economic order quantity (EOQ) as the lot-sizing rule. The authors also investigate the effects of commonality on holding costs when the EOQ lot-sizing rule was used. As anticipated by Vakharia et al. (1996), holding costs are lower under both types of commonality.

Of the previously discussed commonality research (Collier 1981, 1982; Baker, 1985; Baker et al., 1986), only Baker (1985) and Vakharia et al. (1996) considered correlated demand for end-products in their studies. Eynan (1996) performs detailed research on the impact of demand correlation and component commonality on cost. Eynan generates product demand for the two end-products assuming a bivariate probability distribution. Using two simple product structures (with and without commonality), Eynan shows that, at each service level of the experiment, inventory of common components decreases as correlation decreases from ρ = 1 (perfectly correlated demand). For specialized components (non-common), there is a bowl effect as correlation of demand moves from ρ = 1 to ρ = -1. Inventory is highest at these extremes, and is reduced as correlations moves to ρ = 0, i.e. totally independent demands. Eynan (1996) suggests that his analysis also revealed that the savings in purchasing cost resulting from the commonality increases as demand correlation decreases from ρ = 1. Eynan (1996) concludes that commonality leads to lower total component inventory, but depends on the degree of correlation of end-product demands.

Component commonality was identified by Sum et al (1993) as having a greater impact on mean total cost than the number of items and the number of levels in a product structure. Collier (1981) and Wacker and Treleven (1986) proposed indices for measuring component commonality. The findings in past research into component commonality have indicated that the total inventory cost decreases as commonality increases (Collier, 1981; Guerrero, 1985). Studies on assemble-to-order environments have shown that employing component commonality reduces safety stock requirements for components (Collier, 1982; Baker, 1985; Baker et al., 1986; Enyan, 1996). Enyan (1996) and Vakharia et al. (1996) demonstrated that correlation of demand is an important consideration when evaluating the effects of component commonality.

Number of Machines

As shown in Table 2-2, only three researchers identified the number of machines or production resources as a relevant aspect of internal static manufacturing complexity. They are Calinescu et al. (1998), Frizelle and Woodcock (1995) and Deshmuhk et al.

(1998). Calinescu et al. (1998) recommended including the number of machines or production resources as part of a measure of manufacturing complexity, but did not propose a quantitative measure.

Frizelle and Woodcock's (1995) measure of internal static manufacturing complexity was given in Equation 3. As previously discussed, the authors suggest that their measure expresses the "resistance to flow" in a system due to queuing at each machine. As such, this number of machines is implicitly evaluated in their calculation of manufacturing complexity as they sum their computation across all machines in the system.

Deshmukh et al. (1998) considers resources in a system (i.e. machines) only to specify the machines eligible to perform an operation and the corresponding processing times for each operation in a product's routing. The numeric quantity of machines in a facility is not directly part of their formulation. This is because their measure of internal static complexity is designed strictly for flexible manufacturing systems.

Routing Complexity

Routing commonality occurs when manufactured items have routings with steps in the same sequence. The similarity of flows among items should require less management intervention since the reduction in variety of flow should make the system more predictable. As stated earlier, unpredictability is an essential part of the general definition of system complexity (Casti, 1979).

As shown in Table 2.2, only Calinescu et al. (1998) and Deshmukh et al. (1998) identify routings as a source of internal static manufacturing complexity. However, Calinescu et al. (1998) discuss their perspective on the components of manufacturing complexity, but do not formulate a quantitative measure for it. Deshmukh et al. (1998) use a matrix that includes precedence of operations and processing times. This is the equivalent of a manufacturing routing. They go on to capture numerosity and intricacy via *routing commonality* in an intermediary matrix used for calculating static manufacturing complexity. The matrix is counting the number of times an operation sequence occurs, i.e. two consecutive operations with the same precedence.

Monahan and Smunt (1999) investigate the impact of flow dominance (routing commonality) on performance in a batch operating environment. Their main objective is to consider the effects of transforming a batch process layout to a cellular layout, where cells are formed to support products with a high degree of routing commonality. In their study, Monahan and Smunt (1999) do not develop a measure of routing commonality, but contrive sets of routings that reflect three distinct situations. These are: (1) all routings have the same sequence, (2) most (10/12) routings have the same sequence, and (3) all product routings are different. In addition to the degree of routing commonality, the five other study factors are set-up time (five levels), variation of processing times (four levels), number of machines per work center (three levels), lot size (five levels) and number of products (three levels). The combination of these factors is evaluated using computer simulation. Capacity utilization is controlled in each experiment by adjusting the arrival rate of orders to maintain a utilization level of 60%.

Using mean flow time as the performance measure, Monahan and Smunt (1999) find that systems with 100% routing commonality or a high degree of commonality generally outperformed the systems with random routings and no commonality. The one exception acknowledged by the authors occurs at the highest level of processing time variation, where the random routing environment has lower mean flow time than the systems with high levels of routing commonality. Monahan and Smunt (1999) establish that routing commonality is important, but they do not develop a quantitative measure for routing complexity.

Layout complexity

Calinescu et al. (1998) alone considers layout a relevant aspect of internal static manufacturing complexity. However, they do not propose a quantitative measure for layout complexity. There has been other research investigating the benefits of using layout algorithms like CRAFT versus using a visual method. From this stream of research there have been several quantitative measures developed for layout complexity (Vollman and Buffa, 1966; Block, 1979; Gupta and Deisenroth, 1981; Herroelen and Van Gils, 1985). These layout complexity measures attempt to quantify the dominance of product flow in a plant by evaluating the product routings for commonality. A high level of difference in the routings would lead to recommending a visual layout approach. A lower value of complexity indicated that a mathematical algorithm, like CRAFT, would likely provide results superior to a visual-based approach.

These studies were not discussed in the prior section on routing complexity, because, in each case, the proposed measures all try to measure the degree to which there is ***one*** dominant flow. It cannot identify if there are multiple “common” flows or routings. Within this body of research, no method is proposed to quantitatively assign a complexity value to a layout. So, this body of research does not provide a means to evaluate the relative complexity of layout alternatives.

Process Complexity

As previously discussed, Cooper et al. (1992) and Khurana (1999) identify process complexity as a relevant aspect of internal static manufacturing complexity. Both associate process complexity with the "degree of difficulty" of individual manufacturing processes. However, neither Cooper et al. (1992) nor Khurana (1999) propose an objective method of measuring process complexity; it is something they evaluate subjectively. Both suggest measuring process complexity at the process or machine level. The process or machine level of detail is beyond that intended in this research, which is to develop and test an objective, plant-level, quantitative measure for internal static manufacturing complexity.

Treleven and Wacker (1987) formulate measures for process commonality; something that they believe affects process complexity. They state that "the number and diversity of processes reflect the complexity of the internal planning and control system." Televen and Wacker (1987) create three measures for each of the three separate components of process commonality – lot-sizing, sequencing, and expediting.

Their lot-sizing component evaluates the weighted average set-up time at a work center, where each product's set-up is weighted by its percentage of the total product mix. According to Televen and Wacker (1987), set-up time is the major determinant of lot-size.

Their sequencing component measures the degree that sequencing can affect production throughput at a work center due to set-up dependency. Manufactured items with a low process commonality index (meaning they have high commonality) have low set-up times. Their process commonality index is high when there are large differences in the set-up times of jobs.

Lastly, the expediting component of process commonality is designed to measure the probability of each product having to be expedited. According to Televen and Wacker (1987), this component reflects a plant's schedule flexibility.

Using the three individual process commonality measures, Televen and Wacker (1987) propose that managers look to improve the work centers with the worst process commonality, i.e. the highest index values. However, these measures cannot be combined into an overall measure of plant-level process complexity. Their three measures are designed to be applied to the individual work centers.

Ashby (1973) and Klir (1985) assert that system complexity depends on the point of view of the observer. The current study is concerned with the overall plant structure, and not the detailed level of the complexity of each individual machine or process. At the plant-level, process complexity will be addressed by the layout and manufacturing routing aspects of internal static manufacturing complexity.

Summary

Manufacturing systems are complex, because they are unpredictable and have complicated structures and behaviors (Casti, 1979). Past literature has identified three elements that can be used to measure complexity – numerosity, intricacy, and states.

Manufacturing complexity consists of both internal and external complexity. Internal complexity is caused by the elements of a manufacturing system under management control, e.g. quality system design, facility layout and product design. External complexity relates to the impact to the system by actions outside managerial control, e.g. customer demand.

Deshmukh et al. (1998) and Frizelle and Woodcock (1995) subdivide manufacturing complexity into static and dynamic complexity. Static complexity refers to the complexity resulting from the system structure or design. Dynamic complexity stems from the dynamic nature of system resources that causes uncertainty of a system as it moves through time (Deshmukh et al., 1998). Dynamic complexity would include aspects of manufacturing complexity that have elements that change states, like machine breakdowns.

Only three of the past studies attempted to quantify a measure for internal static manufacturing complexity (Cooper et al., 1992; Frizelle and Woodcock, 1995; and Deshmukh et al., 1998). Cooper et al. (1992) develop a measure to be used in the semiconductor wafer manufacturing industry, limiting its applicability.

Frizelle and Woodcock (1995) and Deshmukh et al. (1998) each propose an entropy-based formulation for manufacturing complexity derived from information theory research. Frizelle and Woodcock (1995) incorporate only some of the aspects of internal static manufacturing complexity that have been identified from literature. They are number of machines, product mix, and product mix ratio. They refer to the result of their computation as equivalent product processes, a measure of the "resistance" to the flow of production.

Deshmukh et al. (1998) formulation captures more aspects of manufacturing complexity than that of Frizelle and Woodcock (1995). They incorporate in their measure of product mix, product mix ratio, routings, processing times, and number of machines. However, their measure is directed solely at quantifying the internal static complexity of flexible manufacturing systems, thus limiting its applicability.

From past research on manufacturing complexity, twelve distinct aspects of static internal manufacturing complexity were identified. These are product mix, product mix ratio, the number of components, product complexity, process complexity, integration between processes, the number of machines or resources, manufacturing routings, processing time, plant layout, set-up time, and lot-size. Some of these aspects of complexity have been studied independently in past research.

The extent to which the product mix creates complexity has shown some mixed results. Because greater product mix increases the number of components and processes in a system, internal static manufacturing complexity increases and plant performance is affected. In past studies, greater product mix has been shown to be negatively related to manufacturing performance (Foster and Gupta, 1990; Ittner and MacDuffie, 1995; Bozarth and Edwards, 1997). Kekre and Srinivasan (1990) suspected that this relationship would be demonstrated in their study, but obtained results to the contrary.

Product mix can also include a level of similarity among its products that may make a difference in performance. Anderson (1995) and Bozarth and Edwards (1997) obtained results to indicate that product heterogeneity negatively influences manufacturing performance.

Product complexity has been measured in the past by various measures of the product structure (Veral and LaForge, 1985; Benton and Srivastava, 1985; 1993; Sum et al., 1993). In all cases in which it was a study variable, product structure complexity had a significant effect on performance. Product structure depth, breadth, and total number of parts have been components of product complexity measures in past research. However, a consistent measurement of product structure complexity does not exist.

Along with product structure depth and breadth, the sharing of components among products is an element of product complexity. Collier (1981) and Wacker and Treleven (1986) propose quantitative measure for component commonality. In studies in assemble-to-order manufacturing environments, aggregate component inventory has been shown to be lower when component commonality exists (Collier, 1982; Baker; 1985; Baker et al., 1986). Collier (1981) and Guerreo (1985) conclude from their results that higher commonality leads to reduced total system costs, but with a greater amount of workload variability at work centers.

Routing complexity can be reflected in the number of routing steps or commonality among item routings. Very little research has been done on routing complexity. Monahan and Smunt (1999) find that systems with high levels of routing commonality outperformed systems with random routings.

The limited and somewhat incomplete development of quantitative manufacturing complexity measures leaves considerable room for further research. The literature has isolated the relevant aspects of internal static manufacturing complexity. Utilizing the operational definition of complexity in conjunction with these aspects of manufacturing complexity will permit the development of a more complete formulation for static internal manufacturing complexity.

CHAPTER III

RESEARCH DESIGN

The purposes of this chapter are to describe the development of a quantitative measure for internal static manufacturing complexity and to explain the experimental design used to evaluate this measure. A practical quantitative measure is proposed based upon many of the aspects of internal static manufacturing complexity identified in Chapter II.

A simulation model was developed for a batch manufacturing environment. System performance was evaluated at different levels of the factors taken from the proposed quantitative measure.

Requirements for a Useful Complexity Measure

While researchers may be willing to use measures that are difficult to compute and require data that is difficult to obtain, most practicing managers want to be able to obtain the data quickly and be able to use the data in a clear, step-by-step analysis. Typically, managers are not willing to apply a measure if they must invest hundreds of man-hours for data collection each time they want to compute it. This means that a complexity measure must use data that is reasonably easy to obtain. It must also be objective data that can be obtained reliably by multiple observers of the system. Data available from computerized business systems like bills of materials, routing, inventory masters, and product demand are examples of this type of objective data that are easily obtained.

Calinescu et al. (1998) evaluated Frizelle and Woodcock's (1994) entropic measure of manufacturing complexity and found that obtaining and analyzing the data for Frizelle and Woodcock's measure was very time-consuming. They could not calculate the static complexity for all parts in the system due to the vast number of parts, the unavailability of information, and the sheer impracticality of the resources required to obtain the data. As far as the results of the calculations, Calinescu et al. (1998) concluded more was learned as a result of gathering the required data than was provided in the analysis of the computed complexity measures.

For any system measure to be useful, it must of course be a valid measure of the system being studied. According to Nunnally and Bernstein (1994), validity "denotes the scientific utility of a measuring instrument, broadly statable in terms of how well it measures what it purports to measure" (p.83). There are two pertinent types of validity pertaining to the development of a measure for internal static manufacturing complexity – construct validity and predictive validity (Nunnally and Bernstein, 1994). Construct validity applies to variables that are abstract, or constructed. In this research, internal static manufacturing complexity is a construct created from nine observable variables in a manufacturing system. Since the variables forming the proposed measure, ISMC, were identified from past literature on manufacturing complexity it is assumed that ISMC is a valid construct.

Predictive validity stems from the ability of a measure to "predict" the outcome that was theorized. In this research the proposed measure is tested to ascertain its predictive validity, i.e. performance worsens as internal static manufacturing increases.

Future construct validation for the proposed measure results from the analysis of the results of this study. Once the proposed measure is shown to have predictive validity, further analysis is performed to verify the importance of each of the observable variables that form the measure.

Frizelle (1996) argued that, in addition to validity, a useful complexity measure needs to be composed of separable, additive components. By being separable and additive the manufacturing complexity measure allows easy analysis of complexity change for alternative system designs.

Any complexity measure should provide the practitioner a tool to compare system designs and to measure improvement. It must have an intuitive formulation, so that managers can easily recognize what degree of affect that systems changes will have on the measure. They will want to know whether it will increase or decrease, and by how much.

At the same time, a measure of complexity should permit researchers to quantitatively analyze the relationships between system design and system performance. A useful quantitative measure of manufacturing complexity should be able to be applied to within- and across-industry research. Therefore, a quantitative measure for internal static manufacturing complexity should:

1. require data that is practical to obtain
2. utilize objective data

3. be intuitive to managers and system designers
4. be able to be used in academic research for performing within and across industry research
5. be a valid measure of complexity

These form the guiding principles for the quantitative measure proposed in this research.

A Measure of Internal Static Manufacturing Complexity

In Chapter II, twelve relevant aspects of internal static manufacturing complexity were discussed. Past attempts to quantify manufacturing complexity have included some, but never all of these aspects. This was because some of these elements are difficult to objectively assess, like process complexity, or are not easily quantified, e.g. layout complexity.

In this study, the complexity of a system is determined by the numerosity of elements and relationships, the intricacy of the relationships, and the different states that system elements can have. Although the most complete measurement of complexity would include all of these dimensions, it may be only possible or even practical to measure just a portion of a system's complexity. The first measurement task should be to measure those elements of complexity that managers can control.

The quantitative measure for internal static manufacturing complexity proposed in this research is composed of three components – product line complexity, product structure complexity and process complexity. These three components incorporate seven of the twelve relevant aspects identified in Chapter II. Table 3.1 lists the aspects of manufacturing complexity associated with the three components of the proposed measure.

Process complexity, as identified in past research, has been based upon a subjective evaluation of individual processes, (e.g. operations), that can somehow be combined to form the overall manufacturing process (e.g. Cooper et al, 1992; Khurana, 1999). In this research, a more "plant scale" view is preferred. Similarly, the number of machines/resources is at a more detailed level than desired for this initial attempt to quantify complexity. At the same time, from a "plant scale" viewpoint, these two measures can be viewed as objectively measuring the overall manufacturing process complexity. Therefore, in this study, these two concepts are combined such that process complexity is measured by the number of work centers in the manufacturing system.

Table 3.1 The Three Components of Internal Static Manufacturing Complexity

ISMC Component	Aspect of internal static manufacturing complexity
Product Line Complexity	Number of end-products Number of components Product Mix Ratio
Product Structure Complexity	Product complexity
Process Complexity	Process complexity Routings Number of machines/resources

Layout complexity could not be integrated in the proposed measure of complexity. None of the three prior attempts to quantify manufacturing complexity included layout complexity. It is difficult to quantify layout complexity, because layout complexity does not have any evident numerosity or intricacy elements. Because no quantifiable element of layout complexity has been identified, it was not included in the proposed measure of internal static manufacturing complexity.

Processing time is also not included in the proposed measure for internal static manufacturing complexity in this study. Although Deshmukh et al. (1998) include processing times in their static complexity measure, processing time is a measure of time, and does not express numerosity, intricacy, or state. It is also not clear how differences in processing times between two manufacturing systems can create complexity. Therefore, processing time has been excluded form the formulation of the proposed measure.

Calinescu et al. (1998) suggested that a measure of manufacturing complexity include set-up times. In the previous chapter, set-up time was identified as being both static and dynamic in nature. Since set-up time is determined by technological process selection, it appears to be an element of internal complexity. However, the set-up time encountered in a system is determined as time is passing. The number of set-ups, a possible component of a numerosity measure of complexity, cannot be calculated or fairly estimated at a static point in time. The sequence of batches, jobs, or items will determine both the total number of set-ups and the total set-up time for a system. The total set-up time is unpredictable for a given system design exposed to stochastic events, e.g. customer order arrivals. Therefore, equipment set-up (time or quantity) is considered in this research to be an aspect of dynamic complexity and will not be included in the proposed formulation for internal static manufacturing complexity.

Calinescu et al. (1998) also suggest that lot-size as being part of their "plant structure" construct. They do not explain why lot-size is a relevant element of internal static manufacturing complexity nor do they develop a measure for manufacturing complexity. As discussed in Chapter II, lot size can be considered as being an aspect of both static and dynamic complexity. Because this is an exploratory study, the aspects that have dynamic complexity associated with them are not being considered in the proposed measure. Therefore, lot size has also been excluded.

Lastly, the integration between processes was not included in the proposed measure of internal static manufacturing complexity. Kotha and Orne (1989) identify "level of interconnection" in their discussion of their process complexity construct attempting to capture the integration between processes. It considers the discontinuity, technological interdependence, and product-mix flexibility of the manufacturing processes. They did not attempt to quantify these factors. As such, their concept was not included in an objective quantitative measure for internal static manufacturing complexity.

ISMC Explained

The product line complexity component of the proposed measure, ISMC, is the total number of manufactured items, which accounts for the end items (i.e. product mix) and the manufactured components. The term manufactured is used to include components that are assembled or fabricated or both. This portion of product line complexity can simply be stated as:

$$|E| + |C|, \tag{7}$$

where $|E|$ represents the total number of end items and $|C|$ represents the total number of manufactured components.

The product line complexity factor must also account for the affect of the product mix ratio. As will be shown in the next section, the product mix ratio is taken into consideration by using it to weight the impact of each product on the product and process complexity components of ISMC. However, when a system has products which all have the same breadth and depth, the product mix ratio will have no effect on ISMC. The product mix ratio will also have no impact on ISMC when all products have the same number of routing steps. Therefore, the ISMC formulation must include a mathematical expression to ensure that the product mix ratio is reflected in ISMC under all conditions. As the difference between the proportions of production volume becomes smaller, the internal static manufacturing complexity of a system increases because more set-ups are likely to be needed, which will likely increase the unpredictability of flow times, and, hence, other performance measures.

A simple mathematical factor to account for differences in the proportion of production volume is proposed. The proportion of volume of the largest volume product is compared to the average proportion of the remaining products. This product mix factor should also have numerical bounds of its maximum and minimum effect on ISMC. To limit the impact of product mix ratio on total ISMC, it was permitted to, at its maximum, double the sum of product and process complexity when all products have equal proportions of production volume, i.e. the most complex situation. When there is only one product, ISMC was to not increased, because one product is the “simplest” product mix. This factor is calculated using this formula:

$$2-\left[\frac{MAX(Q_i)}{|E|-1}-\left(1-\frac{MAX(Q_i)}{|E|-1}\right)\right] \tag{8}$$

where $|E|$ is the number of distinct end-items and $MAX(Q_i)$ is the maximum volume of all products.

Thus the complete product line complexity factor is given as:

$$(|E|+|C|)\times\left\{2-\left[\frac{MAX(Q_i)}{|E|-1}-\left(1-\frac{MAX(Q_i)}{|E|-1}\right)\right]\right\} \tag{9}$$

Product structure complexity is comprised of the following elements: (1) the weighed average product structure depth, (2) the weighed average product structure breadth, and (3) the component commonality multiplier.

The proposed mathematical formulation for product structure complexity is:

$$\frac{\sum_{i=1}^{e}(Q_i\times d_i)}{\sum_{i=1}^{e}Q_i}\times\frac{\sum_{i=1}^{e}(Q_i\times b_i)}{\sum_{i=1}^{e}Q_i}\times(2-CCI)\,, \tag{10}$$

where e is the number of distinct end-items, Q_i represents the total requirements (e.g. annual) for the i^{th} end-item, d_i is the number of levels in the product structure for the i^{th} end item, b_i is the breadth of the product structure of the i^{th} end item, and CCI is the component commonality index.

The first subcomponent of equation (10) is the weighted average product structure depth. For this study, the depth of a product structure, or bill of materials, is the number of levels of manufactured items in the product structure for an end item. The individual contribution of the product structure depth for each end item is weighted by its percent of total volume, which is the product mix ratio. This is used to prevent a low volume product with an appreciably deeper or shallower product structure than the rest of the product line from having an undue influence on the valuation of the entire system.

Because this study is strictly concerned with the impact of the design of a manufacturing system, the purchased component level is excluded from the product structure depth and breadth values. The number of levels in a product structure is a numerosity component of product complexity. The number of levels evaluates the added complexity taken on by a firm that has decided to "make" their components and subassemblies. The number of levels assesses the degree of vertical integration within the manufacturing system under evaluation.

The second subcomponent of the formulation for product structure complexity is the weighted average product structure breadth. The breadth of the product structure is also a numerosity measure of product complexity. It is determined by counting the number of manufactured components at the end of each "branch" of the product structure. As stated previously, the purchased materials are truncated from the product structure in this study. As in the product structure depth calculation, the breadth of the product structure for each end item is weighted by the product mix ratio.

The third subcomponent of product structure complexity is the component commonality multiplier. It employs a commonality index that measures the influence of component commonality on internal static manufacturing complexity. Component commonality is a measure of the intricacy, or relationships, among the bills of materials for manufactured items in a manufacturing system.

The CCI, as proposed, is a measure that can range from zero, (no commonality), to one, (one item used everywhere). It represents the average commonality of components among the end-products in a manufacturing system. The formulation for CCI is as follows:

$$CCI = 1 - \frac{|C| - 1}{\sum_{j=1}^{|C|} \theta_j - 1}, \tag{11}$$

where $|C|$ represents the total number of distinct manufactured components, and θ_j represents the number of occurrences of the j^{th} component in all product structures for all active end-products. An "active" end product has a product mix ratio greater than zero. This equation assumes that there are a minimum of two distinct components or two end-products.

In order to have the result equal a value of one for the case of total component commonality, one must be subtracted from both the number of distinct components (|C|) and the total occurrences of each component in all product structures ($\Sigma\ \theta_j$). Total component commonality can only occur when there is one distinct component used in every end product.

In equation (10), the CCI is subtracted from two so that it would become one when there was complete commonality and not increase the value of product structure complexity in the proposed measure. When there is no commonality, the term becomes two, which serves to double the value for product structure.

The decision to double complexity when there is no component commonality is subjective. A factor is needed that will be large enough to represent a meaningful increase in complexity as component commonality decreases. At the same time, it cannot dominate the result of the overall product structure complexity calculation.

Some alternatives for the component commonality factor were developed and evaluated. All alternatives were developed such that in the case of perfect commonality, no increase to the product structure measure occurred, i.e. the result was equal to one. For all but two alternatives, when component commonality is low, the multiplier is too large. A large component commonality factor would indicate that commonality is the driving factor in product structure complexity. Since the relative affect of component commonality on complexity, and thereby performance, is not known, four of the alternative formulations were not acceptable for the proposed measure of product structure complexity.

The two alternatives that were considered acceptable were (2-CCI) and $\log_2(CCI)+1$. The resulting calculations are very similar. Since the differences in the factors are relatively small, the linear formulation was selected. A linear function is likely to be more intuitive to persons who utilize this measure than a logarithmic function. However, one could make a case for the logarithmic formulation, because the multiplier increases at an increasing rate as component commonality approaches zero. This may better represent the way component commonality affects product structure complexity and system performance.

The process complexity component is composed of three elements. They are: (1) the weighted average number of routing steps associated with end items, (2) the total number of work centers in the manufacturing system, and (3) the routing commonality multiplier.

The proposed formula for the process complexity is:

$$\frac{\sum_{i=1}^{e}\left[Q_i \times \frac{Steps(E_i) + \sum_{j}^{|C_i|} Steps(C_{ij})}{|C_i| + 1}\right]}{\sum_{i=1}^{e} Q_i} \times |WC| \times (2 - RC), \tag{12}$$

where e is the number of distinct end-items, E_i represents the i^{th} end-item, $|C_i|$ is the number of manufactured components in the i^{th} end-item, C_{ij} represents the j^{th} manufactured component of the i^{th} end-item, Q_i represents the requirements for the i^{th} end-item, $|WC|$ is the number of work centers, and RC is the routing commonality.

The first subcomponent of equation (12) is the weighted average number of routing steps, or operations. This is a numerosity element that takes the average of the number of individual operations required for the end item and all the manufactured components in its product structure. It attempts to measure the complexity of coordinating the flow of production needed as the number of sequential operations increases for manufactured items. Like product structure depth and breadth, the average number of routing steps for each end item is weighted by the product mix ratio.

The number of work centers in a manufacturing system is the second subcomponent of the formulation for process complexity in equation (12) As an alternative to counting the number of resources or machines, in this study a larger unit of evaluation, the number of work centers, is counted. This was selected because it represents the level at which the lowest level of management (first line supervision) is implemented to mitigate the effects of manufacturing complexity. A work center is usually a group of equipment with a common point of management. It may be a group of similar equipment that shares a common queue and a single manager (or supervisor). It may be a group technology cell, again sharing a common queue and manager. A manager may be responsible for multiple work centers, dependent on the size of the work centers and the overall size of the manufacturing system. This research defines a work center as a group of equipment and workstations that share a common queue and manager.

The third subcomponent of product structure complexity is the routing commonality multiplier. Routing commonality is the percentage of identical routings in the set of all active routings. Routings are considered identical when the have the same sequence of operations at the same work centers. Routing commonality is an attempt to measure the intricacy among the routings for manufactured items in a manufacturing system. Identical routings have the same sequence of operations at the same work centers. Complexity increases as the similarity among routings decreases.

Routings typically include the operation time and set-up time. Differences in these times are not considered when determining if routings are identical. Routing commonality is calculated as:

$$RC = \frac{number\ of\ identical\ active\ routings}{total\ active\ routings} \tag{13}$$

In equation (13), the RC index was subtracted from two so that it would become one when there was perfect commonality and, therefore, it would not increase the value of process complexity in the proposed measure. When there is no commonality among routings, this term’s value becomes two, thus doubles the calculated amount of process complexity. The rationale for using this linear formulation is the same as for that discussed for the component commonality multiplier for the product structure complexity component. The overall measure of internal static manufacturing complexity (ISMC) is given in equation (14).

$$ISMC = \left(|E| + |C|\right) \times \left\{2 - \left[\frac{MAX(Q_i)}{|E|-1} - \left(1 - \frac{MAX(Q_i)}{|E|-1}\right)\right]\right\} \times \tag{14}$$

$$\left(\left\{\frac{\sum_{i=1}^{e}(Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} \times \frac{\sum_{i=1}^{e}(Q_i \times b_i)}{\sum_{i=1}^{e} Q_i} \times (2 - CCI)\right\} + \left\{\frac{\sum_{i=1}^{e}\left[Q_i \times \frac{Steps(E_i) + \sum_{j}^{|C_i|} Steps(C_{ij})}{|C_i| + 1}\right]}{\sum_{i=1}^{e} Q_i} \times |WC| \times (2 - RC)\right\}\right)$$

In equation (14), the three subcomponents, product, product structure and process complexity, are combined multiplicatively and additively. The components in equation (14) are kept separate. Frizelle (1996) argued that a useful complexity measure needs to have separable, additive components. By being separable and additive the manufacturing complexity measure would then allow easy analysis of change as complexity for alternative system design changes. In this measure, managers can easily evaluate the relative impact on complexity of changes in the product structure or the process design. For academic research, the individual components could be applied depending on the focus of the research. Individually, product structure complexity and process complexity are multiplied by the product line complexity. This is done to distinguish between systems with similar product structures having appreciably different amount of end items and manufactured components. The product structure and process complexity components are multiplied by the product line complexity component and then added together.

ISMC is a ratio measure. The numeric results dictate a strict order of the internal static manufacturing complexity of systems under comparison. The larger the value of ISMC, then the more complex a system's structure is. Also, the differences, or interval, between values for ISMC is important. For example, systems with ISMC that differ by 1000 are further apart in complexity than system whose ISMC differs by 100. And, lastly, ISMC has a specific origin, i.e. zero. ISMC can range from zero to positive infinity.

ISMC is unitless and does not have a specific interpretation unlike Frizelle and Woodcock (1995) whose created there own unit, *epp* – equivalent product processes. ISMC provides a value of the unpredictability and the level of complication of the system's structure (Casti, 1979). As such, it is useful for comparison of manufacturing systems, benchmarking a single manufacturing system, and evaluating management decisions as to how they affect manufacturing complexity.

Performance Measures

According to Casti (1979), the behavior of a complex system is difficult to predict. Variation is a measure of unpredictability. The greater the variation in a system, the greater is its unpredictability. Therefore it is important to include performance measures that capture the level of unpredictability in a system, which may be done by evaluating the variance of system measures.

One measure of system performance would be mean flow time. Companies are interested in having stable mean flow times so that they may have a better estimate of their manufacturing lead time. As the variation of mean flow time increases, the more “slack” must be built into the manufacturing lead time to ensure on-time delivery to the customer. Speed of delivery is one way companies compete (Hill, 1994), so having lower lead time is important.

Another measure of system performance would be lateness (Baker 1974). Lateness is the difference between the order completion date and the order due date. Lateness may be positive, i.e. the order is late, or negative, meaning the order was completed early. It is desirable to have an average lateness close to zero, indicating that orders “on average” ship on their due date. At the same time it is desirable that the variance in lateness be small so that the system doesn’t have orders that ship very late or are completed early and must be held in inventory for a long time. Therefore, both mean lateness and the standard deviation of lateness are relevant performance measures for this study.

Tardiness is another important measure of system performance (Baker 1974). Tardiness views performance from the customer’s perspective. It measures the amount of time that an order is completed after its assigned order due date. If an order is completed early, then it has a tardiness value of zero, i.e. it was shipped on time. In order to maintain high levels of customer satisfaction, companies want to reduce the amount of tardiness. Ideally, they want to have all orders ship on the assigned due dates and have no tardiness. System performance can be measured by the mean of the tardiness for a system. A low mean tardiness indicates that the system is closer to the goal of shipping on time. Likewise, it is important to monitor the standard deviation of tardiness, so that the degree of unpredictability of systems can be evaluated. Both mean tardiness and standard deviation of tardiness are included as performance measure in this study.

Hypothesized Performance

There are nine variables that are part of the proposed measure of internal static manufacturing complexity. In the theoretical model presented in Chapter I (Fig 1.1), internal static manufacturing complexity is shown as having a direct influence (relationship) on manufacturing system performance. The objective of this research is to test the proposed measure of ISMC for its predictive validity, i.e. to see if it reflects the impact of the manufacturing system's design on its performance. Given the way this measure has been developed, and the results from past literature, some anticipated relationships between internal static manufacturing complexity and system performance are developed here. The hypotheses below are made regarding the overall effect of the system design as captured by the proposed measure on manufacturing system performance.

As ISMC increases all the performance measure should deteriorate. The underlying assumption of this model is that manufacturing performance worsens as ISMC increases, regardless of the source of complexity, i.e. the individual element in equation (14). So the following null hypotheses are proposed.

$H_0$1: An increased value of ISMC does not affect system performance.

$H_0$1A: An increased value of ISMC does not increase the standard deviation of flow times measured from the beginning of the lowest level component until the completion of the end product.

$H_0$1B: An increased value of ISMC does not increase the mean lateness of end-products.

$H_0$1C: An increased value of ISMC does not increase the standard deviation of lateness of end-products.

$H_0$1D: An increased value of ISMC does not increase the mean tardiness of end-products.

$H_0$1E: An increased value of ISMC does not increase the standard deviation of tardiness of end-products.

Because ISMC is a conglomeration of many elements of static complexity, the hypothesized effect of each element on shop performance can only be discussed in terms of the effects that each complexity source may have on performance.

One way ISMC can increase is through an increase in the variety of end-products, i.e. product mix. More end-products will likely lead to the requirement for more components, i.e. greater variety, to be manufactured. The increase in end-products and manufactured components leads to a greater number of routings that are likely to be diverse. There will be greater opportunity for shop congestion, thereby increasing flow time variability. As flow time variance increases, the variance of lateness and tardiness will increase. Since tardiness can only vary positively, increases in the variance of tardiness will mean there will be an increase in mean tardiness.

As the product mix ratio moves from having a dominant end product to being more evenly spread among all products, there is likely to be more interaction among the product and component flows. The queuing at each work center will become unpredictable. There will be shifting bottlenecks as shop congestion increases, leading to an increase in flow time variance. As flow time variance increases, the variance of lateness and tardiness also will increase.

Lower commonality among manufactured components increases ISMC. With less component commonality there will be more manufacturing orders having diverse routings. This increases shop congestion and contributes to variation in flow times

(Vakharia et al., 1996). As flow time variance increases, the variance of lateness and tardiness also will increase. An increase in the variance of tardiness will mean there will be an increase in mean tardiness.

As product structures become broader and deeper, the timing of component completion times affects the ability to release the order for the parent parts. The mis-timing of manufacturing order arrivals will likely lead to the delayed completion of components needed for the parent part, thereby increasing the lateness and tardiness of an order for an end product (Russell and Taylor, 1985).

ISMC increases when the average number of routing steps in the product structure of end-products increases. More routing steps will lead to more required set-ups and more opportunity to queue at work centers during the flow of a manufacturing order for all manufactured items. Flow times will vary due to the unpredictability of the queuing that occurs, increasing the variance of flow time. As flow time variance increases, the variance of lateness and tardiness also will increase. An increase in the variance of tardiness will mean there will be an increase in mean tardiness.

When there are more work centers in a manufacturing system ISMC increases. Assuming the same overall shop utilization, having a greater number of work centers increases the opportunity of bottleneck shifting. This increases unpredictability of manufacturing order flow times, hence increasing the variation of flow times. As flow time variance increases, the variance of lateness and tardiness also will increase. An increase in the variance of tardiness will mean there will be an increase in mean tardiness.

As routing commonality decreases, complexity increases, because there are more diverse routings, which can lead to shifting bottlenecks. Shifting bottlenecks leads to less predictability of flow times, meaning increased variation of flow time (Monahan and Smunt, 1999). As flow time variance increases, the variance of lateness and variance of tardiness also will increase. An increase in the variance of tardiness will mean there will be an increase in mean tardiness.

The many elements of ISMC are interrelated, it is difficult to project which element would have greater effects than others. However, it is unlikely that each element has an equal impact on system performance, so the following null hypotheses are made.

$H_0$2: No element (experimental factor) has an effect on system performance.

$H_0$2A: No element (experimental factor) has an effect on the standard deviation of flow times.

$H_0$2B: No element (experimental factor) has an effect on the mean lateness of end-products.

$H_0$2C: No element (experimental factor) has an effect on the standard deviation of lateness of end-products.

$H_0$2D: No element (experimental factor) has an effect on the mean tardiness of end-products.

$H_0$2E: No element (experimental factor) has an effect on the standard deviation of tardiness of end-products.

From the formulation of ISMC it appears that the number of end-products would likely have the greatest impact because it is a multiplicand in both the product structure and process complexity components. One reason that this may not be the case is that the formulation of the proposed measure for ISMC was not designed to weight any of the sources of complexity more than the others. It was simply a way of describing complexity based upon the operational definition and the objectives established for a useful measure. The relative effect of the elements is an objective of this study.

Another reason that it is difficult to predict the impact of an individual element on ISMC is that they can be interrelated. For example, increasing component commonality will not only reduce the component commonality factor, but it will reduce the number of manufactured components in the system. Also, as components are replaced by common components, there will be some effect to both the weighted average number of routing steps and the routing commonality factor. Therefore, no specific prediction about the relative impact of each element of ISMC on an operation's performance is made.

The third concern of the current research is the predictive validity of ISMC as compared to the only other identified measure of internal static manufacturing complexity. Frizelle and Woodcock (1995) proposed the entropy-based measure, H, discussed in Chapter II. The null hypothesis to address this research question is:

$H_0$3: ISMC is not a better predictor of overall manufacturing performance than the Frizelle and Woodcock's, H.

$H_0$3A: ISMC is not a better predictor of the standard deviation of flow time end-products than H.

$H_0$3B: ISMC is not a better predictor of the mean lateness of end-products than H.

$H_0$3C: ISMC is not a better predictor of the standard deviation of lateness of end-products than H.

$H_0$3D: ISMC is not a better predictor of the mean tardiness of end-products than H.

$H_0$3E: ISMC is not a better predictor of the standard deviation of tardiness of end-products than H.

The Simulated Shop

The simulated shop will model a batch processing system. In this type of system, a manufacturing order, i.e. batch, remains together as it flows through all assigned operations in the production process. At an individual operation (i.e. routing step), the individual units in a manufacturing order may be processed one at a time, but no unit moves to the next operation until all units have been completed at that operation.

Batch processing systems are one of the four main process types identified by Hayes and Wheelwright (1979). It is important to study this manufacturing setting because it constitutes a large percentage of actual industry application. In a survey by Safizadeh, Ritzman, Sharma, and Wood (1996), the largest potion of their respondents (32%) identified themselves as primarily batch shops. Batch shops would also be more likely to experience a wider range of the elements making up ISMC.

In the proposed simulated shop, orders for end items are randomly created. The end product and quantity attributes are assigned to each order as it is created. The bills of materials and routings are set in advance for each item. The quantity of specific parts and the duration of each routing step is a function of the randomly generated order size. Once the orders are generated, due dates are set using total work content of the critical path (TWKCP) and order release timing is determined working backward from the order due date for the end product.

Order Due Dates

TWKCP is the sum of all the operation times in the longest chain of the product structure. In this study, the longest chain is the product structure branch with the largest total per unit processing time. The estimate for the total processing time will include a set-up time at each operation plus the run time for the order at each operation.

The TWKCP method (as in Fry et al, 1989) was selected for setting due dates because it considers that operations occurring on the other branches of the product structure may occur in parallel to those of the critical path. Due dates using TWKCP are established by the following equation:

$$DD_i = k * TWKCP, \tag{15}$$

where DD_i is the due date for the i^{th} order, k is an allowance factor (i.e. due date tightness factor), and TWKCP is the sum of the processing times on the critical path. The due date tightness factor, k, is one of the experimental factors.

Experimental Factors

Since this is the first such experimental study on a measure for internal static manufacturing complexity, it was considered an exploratory study. This study was seeking to determine the value of such a measure by examining the relationship of ISMC to system performance and evaluating the relative effect of the individual elements of the measure on performance. Therefore, only two levels of each variable were established – a low and a high level. By using high and low levels, the existence of any effect on system performance should be evident.

The experimental factors include all variable elements of the proposed ISMC equation. Table 3.2 displays the factors and their experimental settings.

Table 3.2 Experimental Factor Levels

Factor	Levels: High	Levels: Low
Product Mix – No. of End-products (PM)	5	2
Product Mix Ratio (PMR)	All equal	1 Dominant/Others
Product Structure Depth (D)	5	2
Product Structure Breadth (B)	5	2
Component Commonality (CC)	~30 %	0 %
Number of Routing Steps (RS)	10	4
Number of Work Centers (WC)	10	4
Routing Commonality (RC)	~50 %	0 %
Due Date Tightness Factor (k)	30% orders late	10% orders late

Product Mix

As stated in Table 3.2, the low and high factor settings for product mix are two and five end-products, respectively. These levels were selected in order to have a sufficient difference between the levels to be able to perceive a difference in performance, if one exists. The low setting had to be a minimum of two in order to permit the alterations necessary to achieve the desired amount of component commonality. At the same time the high setting was kept to a level that made product structure development manageable.

Product Mix ratio

In Table 3.2, the settings for Product Mix Ratio (PMR) are given. The low setting is the case when there is a dominant end-product, that is, one end-product having a large proportion of unit sales. At both levels of PMR, the percent volume of the dominant end-product was four times greater than the proportion of the other end-product(s). The non-dominant end-products had equal proportions, i.e. the same unit volumes. At the high factor setting, all end-products had an equal proportion of the total unit sales volume.

When the Product Mix (PM) factor is at the low setting, E-1 (Product 1) had 80% and E-2 (Product 2) had 20% of the volume. At the high setting of the Product Mix (PM), E-1 had 50% of the volume and the remaining four end-products (E-2, E-3, E-4, and E-5) each had 12.5% of the total unit volume.

Product Structures

Product Structures for each manufactured item, i.e. end-product or component, were prepared in advance corresponding to the levels of the three product structure factors - the number of levels in the product structure (depth), the breadth of the product structure, and component commonality. Because this was an exploratory study, the usage of each component was set at one unit per parent.

Number of Levels in the Product Structure – Product Structure Depth

There were two levels of product structure depth, two and five. The high level for product structure depth was set to five levels to have sufficient difference between the low and high settings to allow the measurement of a significant difference in performance, if one does exist.

At each setting, all the product structures for end-products were formed to have exactly two or five levels. This was done for simplicity of experimental design. Maintaining this type of consistency reduces the possible artificial interactions between factors, since some of the factors are interrelated, e.g. component commonality and the number of routing steps,

Although, in reality, a system could be designed where all components or raw materials are purchased, two levels are needed in order to test the effect of component commonality. Recall, this study is solely concerned with the complexity due to internal system design. Therefore purchasing complexity was excluded.

Product Structure Breadth

There were two levels of product structure breadth, two and five. In order to obtain a reasonable high setting for component commonality, the end-products had to have a minimum product structure breadth of two. The high level for product structure breadth was set to five levels to have sufficient difference between the low and high settings to allow the measurement of a significant difference in performance, if one does exist.

Again, at each setting for product structure breadth, all the product structures for end-products were formed to have a breadth of exactly two or five. As previously stated, this was done for the simplicity of experimental design.

Component Commonality

There were two levels of component commonality. The low setting is no commonality and the high setting is set to approximately 0.30. A CCI of 0.30 results in having approximately 30% of the components shared within the product structures of a system. This was believed to be a level that would be high considering that only manufactured components are being considered in this research.

Formation of Experimental Product Structures

The product structures are given in Appendix B. Product structures for each manufactured item for the high level of the product structure depth, the high level of product structure breadth, and at the low level of component commonality were generated first. To be consistent, the first two end-products at each experimental setting were identical for the low and high settings of product mix (PM). There were five end-products having two levels of product structure depth, two levels of product structure breadth, and two levels of component commonality (5 x 2 x 2 x 2) resulting in a total of 40 products structures.

The product structures for the low level of product structure depth and breadth and the high level of component commonality were created as variants based upon the initial sets of product structures. To the extent possible, the components within the product structures for end-products and the relationships of these components, i.e. their product structures, were maintained across the experiment. For example the product structure for Product 1 (E-1), at the high level of product structure depth and breadth, included manufacturing components C-101 and C-102. At the low setting for depth and breadth, E-1, also included C-101 and C-102. This was done to attempt to have an equitable comparison at the product structure factor settings. One exception was made to end-product E-3 where C-112 was replaced by C-113 in order to achieve the high setting of component commonality.

The five product structures that were designed to be deep and broad were generated to have "branching" occur at various levels among the product structures in order to obtain diversity in the experiment. These product structures also were designed so that the number of components at the lowest level ranged from two to five to avoid accidentally biasing the experiment. Each of these product structures had nine components to avoid incurring variation due to the number of components. Having nine components permitted enough opportunity for achieving the high setting for component commonality but simplified the process of generating product structures.

The product structures created to achieve low product structure breadth and high product structure depth were deigned is a similar manner. The product structures were generated to have "branching" occur at different levels. An attempt was made to keep the total components in each product structure at five. Five components was the maximum that can occur if the assembly "branching" occurs at the lowest level. Four of the five product structures had five components each. However, to permit the opportunity to achieve the high setting of component commonality the product structure for product E-5 had to be constructed with eight components.

As stated, it was not possible to achieve the same number of components in all product structures within the low setting of product structure breadth and the high setting of component commonality. It was not possible to design product structures with high product structure breadth and depth and have only five components. Also, it was not possible to achieve a total number of components equal to nine when the products structure breadth was at its low setting, because the maximum number of components at the low setting of product structure breadth and high setting of product structure depth is eight. Additionally, there was only one product structure design that can be made having eight components. So, maintaining an equal number of components for the two settings of product structure breadth at the high setting of depth was not possible.

The tree structure for each end-product at the high setting for component commonality was identical to those with no commonality with the exception that now some components were shared “in common” with other product structures. Component commonality was designed to occur at a variety of levels in the product structures. To the extent possible, the relationships in the product structures of components were kept consistent across experiments in order to model reality. For example, if a level three item, i.e. C-301 in Product E-1, was exchanged for a level three item, i.e. C-303 from Product E-2, the level four items (C-402) associated with the level three item in Product E-2 would also become part of Product E-1’s product structure (see Figures B.3 and B.7).

Components were exchanged in the product structures to obtain a CCI as close to 0.30 as reasonable. Among the other settings for the product structure variables (PM, B and D), the CCI ranged from 0.29 to 0.33. These differences were due to having different numbers of components in the product structures and to trying to make logical replacements of components that included any associated “child” components, as previously discussed.

A variety of components were made common among the end-products, but none were common with more than three end-products. An alternative to this would be to make just one or two components common throughout all product structures. The primary motivation for choosing the former design was to avoid any biasing affect of selecting the same few items to be common in all end-products.

Routings

Routings were prepared in advance for each item corresponding to the levels of the three routing factors - the number of routing steps, the number of work centers, and the routing commonality. Routings for each manufactured item for the high level of the number of steps at the low level of routing commonality were generated first. Routings were then varied based upon these initial routings to create the routings for the low level of routing steps and the high level of routing commonality.

Number of Work Centers

There were two levels of the number of work centers, four work centers being the low setting and 10 being the high setting. This was supported from past literature. Monahan and Smunt (1999), in their study in routing commonality, experimented with six and 12 work centers. Fry et al. (1989), used 10 work centers in their study of product structure complexity and dispatching rules. In their study on dispatching rules in a hybrid flow shop, Barman and LaForge (1998) included six work centers.

In the preparation of the routings for the low setting of routing commonality, routing steps were randomly assigned to a work center for each level of the number of work centers.

Routing Steps

The low and high settings for the number of routing steps (RS) were four and 10 steps. Past literature has selected the number of steps to be in this range. Monahan and Smunt (1999) selected six routing steps for their research on routing commonality. Barman and LaForge (1998) used a range of four to six operations.

Routing Commonality

At the high level of routing commonality, manufactured items were selected so that 50% of the routings had an identical sequence. To the extent possible, the same items were selected among the various sets of product structures for the setting for product structure depth, product structure breadth, and component commonality. Routing commonality was achieved by assigning the sequence of work centers visited in an item's routing to the same sequence of another item. The original processing times were maintained in the same sequence as the original routing.

Formation of Experimental Routings

Routings were generated randomly for each manufactured item. Routings for the high level of RS were created first. For each routing step, a work center was randomly assigned, each having an equal likelihood (uniform) of being assigned. The only rule was that consecutive routing steps could not be assigned to the same work center.

Processing times were composed of a set-up time *per order* and a run time *per unit*. The set-up time is set arbitrarily to 1.0 hour. Set-up time was included in the shop design to determine the effect of component commonality. When manufacturing orders for the same item are processed consecutively they will require a single set-up. To avoid introducing a bias to the experiment, the same set-up time (1 hour) was designated for all items for all operations.

Run times per unit for each item for each step were generated randomly using a uniform distribution with a mean or 0.1 and end points of 0.05 and 0.15 hours. The mean of 0.1 hours was chosen to make the average ratio of set-up to unit run time equal to 10. This was in line with the setting developed by Krajewski et al. (1987) from information obtained from practicing managers. The set-up to run ratio was deemed to be more important than actual time, because shop utilization will be adjusted by altering the arrival rate of orders (explained in detail in a subsequent section).

For each manufactured item, the routing sequence of work centers visited and processing times were generated for the high setting of RS and WC and the low setting for RC. Routings for the low setting RS are created for each manufactured item by truncating the routing for the high setting of RS. The run time portion of the processing time was adjusted proportionally for each routing step so that the total of the run times was the same for high and low settings for the number of routing steps. This was done to ensure an equitable basis of comparison for the mean lateness and mean tardiness performance measures.

For the low setting of WC, the processing times were maintained in their initial sequence, but work centers were randomly assigned using the low setting. Again, this was done to ensure an equitable basis of comparison for the mean lateness and mean tardiness performance measures.

Routings for the low setting RS and low setting of WC were created the same as with the high setting of WC. The routings were created for each manufactured item by truncating the routing for the high level of RS and the run time portion of the processing time was adjusted proportionally for each routing step so that the total of the run times was the same for high and low settings for the number of routing steps.

To achieve the high setting for routing commonality (RC), items were selected within the product structures created based upon the four experimental factors for product structure. The items selected were selected from a variety of end-products and at a variety of levels within the products structure. This was done to avoid biasing the experiment. Items were arbitrarily made to have common routings to achieve the following objectives: attain the high setting of routing commonality; have items with common routings at various product structure levels; selected items were changed across all product structure settings. To the extent possible, these objectives were met.

Routing were made "common" in the product structures to obtain a RC as close to 0.50 as reasonable. The routing commonality ratio (RC) ranged from 0.44 to 0.80. These differences were due to differences in the numbers of components in the products structures and in order to make the most logical choices of items that were to have common routings.

As stated previously, two items have a common routing when the sequence of work centers visited is identical. The run-times did not have to be the same. At the high setting for routing commonality, when an item was selected to have a common routing with another item, the processing time were maintained in their original sequence, but the work centers were changed to match those of the item selected to have the common routing.

Environmental Settings

Due Date Tightness (k)

Three of the five performance measures evaluated order completion date compared to order due date. As stated previously, due dates were set using TWKCP. The due date tightness will impact the amount of tardiness produced by a system. Therefore it was also considered an experimental factor, having two levels. At the high level due dates were "tight", having a lower value for k than when due dates are loose. The due date tightness factor, k, was established in preliminary runs of the experimental manufacturing system deemed to be the "simplest" (PM=low, PMR=low, D=low, B=low, CC=high, RS=low, WC=low, RC=high). The low setting was set such that, after the warm-up period, approximately 10% of the orders were tardy. The high setting for k was set, for this "simplest" case, when approximately 30% of the orders were tardy.

Utilization

In order to ensure that each experimental condition was being compared fairly, the shop utilization we held constant. Past studies (e.g., Barrett and Barman, 1986) have shown that shop utilization affects performance. For this study, the average utilization at the bottleneck work center was set at 85%. This has been a common mid-range setting used in the past (Barman, 1998; Pierreval and Mebarki, 1997; Fry et al., 1989).

Work center utilization is affected when the number of work centers is altered. More work centers increases the total available capacity in the shop. Also, when routing commonality increases, the shop utilization could be affected. To maintain consistent mean shop utilization, the mean order arrival interval was adjusted (e.g. Barman, 1998; Kanet and Haya, 1982).

The time between order arrivals was determined by sampling from the exponential distribution with a predetermined mean as done in similar studies (e.g. Barman and LaForge, 1998; Fry et al., 1989; Kanet and Haya, 1982). The mean of the distribution was established using preliminary simulation runs to achieve the desired bottleneck utilization.

Order Generation

Orders were generated to include an order quantity for each end-product in the product mix. The average total order size was approximately 200 units. The average order size for each end-product was based upon the specific product mix ratio for the experimental run. For example, at the low settings for PM and PMR, the mean order quantity for each end-product, E-1 and E-2, was 160 units and 40 units, respectively.

As in many real manufacturing environments, the simulated system encountered variation in order sizes. This was accomplished using a coefficient of variation of 0.30 for the demand for each end-product. The coefficient of variation is equal to the standard deviation of a distribution divided by its mean. The orders sizes were generated using a truncated normal distribution where the minimum order size is zero and the maximum is twice the mean order size. A coefficient of variation of 0.30, assuming a normal distribution, permited the opportunity for order sizes to be zero, but this probability would be extremely small. Approximately 68% of order sizes should randomly occur between ± 30% of the mean order size and approximately 95% of order sizes should be between ± 60%.

Orders were generated during the simulation run based upon the mean time between order arrivals. To make experimental conditions as consistent as possible, each end-product was assigned a specific random number stream to be used in all experimental runs. Therefore, for experiments having the same settings of PM and PMR, order sequence and quantity was identical for each end-product.

Order Release

The release dates for manufacturing orders for components at the end of each product structure branch were calculated using the total work content (TWK) method (Goodwin and Goodwin, 1982) as soon as an order arrives. Since changes to customer orders were not permitted once an order was received, these manufacturing order release dates were not changed.

The order release for the lowest level component on the critical path of a product structure coincided with the order arrival date, because the due date was set using the TWKCP method. Because the critical path is the branch in a product structure with the greatest number of operations, (i.e. routing steps), and not the greatest processing time, it was possible that the TWK for another branch was greater than that of the critical path. In those cases, manufacturing orders for those items were released at the order arrival time, too. By using the same allowance factor, k, for manufacturing order releases, orders had the same opportunity to complete as their "sister" items in the product structure.

Parent items in the product structure were released at the time that the latest manufacturing order for child items was completed. This gave the manufacturing orders for parent items an opportunity to be released early or late, thus providing clearer evidence of the impact of system complexity on performance. If the order release for parent items were set using some other release rule, e.g. TWK, it might have artificially inflated the flow time, lateness and tardiness statistics.

Order Sequencing

A dispatch rule that is simple to employ in industry practice as well as simulation experiments is earliest job due date (EDD). In the experimental scenario, each order for end-products is considered to be the "job". The EDD dispatch rule was used at each work center to select the next manufacturing order to process. EDD for orders has been shown to be in the group of best performing dispatch rules under a wide range of product structure complexity in an assembly shop (Fry et al., 1989). This allowed each experiment the best chance of performing well under the experimental conditions. So, the primary reason for late order completion was due to the system design, i.e. internal static manufacturing complexity.

Other factors

In a manufacturing system there are many factors that can be included when modeling a particular system. In this study, to reduce the "noise" in the statistical analysis, most of the environmental factors were made constant. The transfer time for moving a manufacturing order between work centers was ignored (i.e. transfer time = 0). There was a single server (i.e. machine) at each work center. There was no maximum queue size at any queuing point, e.g. work center.

Simulation

Simulation was appropriate for this experiment since this is an exploratory study evaluating a proposed metric for internal static manufacturing complexity. The number of variables is relatively large. It would be nearly impossible to control the environmental factors if an empirical study were to be made.

As part of the simulation process, three crucial steps in the simulation development process recommended by Pritsker (1986) are model verification, model validation, and tactical planning. Verification of the model establishes that the computer program executes as intended (Law and Kelton, 2000). Validation ensures that the model closely matches the system being modeled (Law and Kelton, 2000). According to Pritsker (1986), tactical planning involves setting the starting conditions of simulation runs and selecting a method to reduce variance of the mean of the dependent variable.

Verification

Verification of the final simulation model was done using the "trace" reports from Visual SLAM. One order for each item was simulated individually in the computer model. The intermediate reports indicating the arrival and departure times from specific activities were compared with manual calculations. By this, the routing sequence, set-up time and run-times were verified.

To verify that the product structures were working as designed, one order for each end-product was initiated into the simulation. "Output" nodes were inserted before the queue locations where the child item manufacturing orders waited to be matched and released as the parent manufacturing order. Report data was reviewed to see if the "match" function and parent order release occurred correctly.

Validation

The proposed simulated manufacturing system was designed to evaluate the impact of internal static manufacturing complexity on a batch manufacturing environment. It was not intended to depict a specific manufacturing system.

External validity of any simulated system rests on its realistic nature. While the experimental settings were primarily established to enable the identification of relationships between the independent variables of internal static manufacturing complexity and the dependent variables of system performance, some degree of realism must also exist.

Many of the settings were validated by their use in prior research, e.g. utilization and set-up/run ratio. Others like products structure depth and number of work centers have not been as clearly justified.

The past industry experience of this researcher supported, hence validated, some of the experimental levels. For example, the printed circuit board (PCB) fabrication process typically required more than 10 routing steps at 10 different work centers. PCBs subcomponents (called “innerlayers”) were manufactured internally, making a two level product structure with breadth ranging from two to 14 different innerlayer part numbers. Due to the custom nature of PCB electrical layout, there was little (near zero) component commonality.

At a consumer handtool plant, differences in end-products often occurred late in the manufacturing process. Thus the product structures often were a single, “chain-link” of manufactured items often going four levels deep. The number of routing steps at each level ranged from two to over 10. There was also a mild level of component commonality.

In one electronics assembly plant, plastic housings were molded that were assembled to the printed circuit board assembly (PCBA). The molding process involved a single routing step and one work center. This is below the low level used in the proposed system, but this plastic housing was only one of many items manufactured or assembled in this plant. The PCBA process often involved more than 10 operations visiting a minimum of four different work centers.

Thus, even from this limited amount of experience, the experimental levels included in the simulated system have external validation.

Steady State Determination

A simulation run begins in an empty state, i.e. entities in the system. The warm-up, or transient, period is the time when a simulated system goes from the empty state at time=0, to a "steady state", where the mean distribution of matches within the steady state are approximately the same (Law and Kelton, 2000). To avoid the impact of the transient state to the performance variable statistics, the performance data collected during the transient state is cleared prior to starting the data collection for the experiment.

Law and Kelton (2000) recommend a procedure for determining the steady state of a stochastic process. Observations of random variables are collected in batches (time intervals) and plotted (variable vs. time). Steady state can be observed when the mean of the random variable for successive batches become approximately the same.

For this study, a pilot simulation run was made at each of the 256 experimental combinations to determine the "worst case" time until steady state is achieved. Average queue length and mean flow times for individual manufacturing orders were collected in 50 hour intervals and plotted to identify the end of the transient period.

Number of Replications

Replication of experiments was used to capture the variance of dependent variables. Pilot simulation runs were made to determine the experimental combination that exhibited the longest transient period. This transient period will be the basis for determining the size and number of replications.

The batch means method was used to make the simulation runs for each experimental combination. The batch means method employs a single long simulation run where all the replications are extracted (Law and Kelton, 2000). After reaching steady state, statistics were collected for a predetermined number of distinct batches, or replications. Each batch was assumed to be independent of the other batches.

Determining the number of replications needed to reduce the variance of sample means is not simple. It often involves a reiterative process (Law and Kelton, 2000) and can lead to requiring a large number of replications. Based upon his research, Schmeiser (1982) recommends that from 10 to 30 replications be conducted. Pritsker (1986) developed a formula to determine the minimum number of replications needed in order to achieve a predetermined confidence range for the sample mean.

$$I \geq \left(\frac{t_{\frac{\alpha}{2}, I-1} S_x}{g} \right)^2 \text{, where} \qquad (16)$$

I = number of independent replications

$t_{\alpha/2,\, I\text{-}1}$ = Student's t value with I-1 degrees of freedom

S_x = sample standard deviation of the dependent variable, and

g = half-width of the confident interval for the sample mean

Pritsker (1986) goes on to restate g in terms of the standard deviation of the population by setting $g = v\sigma_x$, where v is the fraction of the standard deviation that forms the half-width of the confidence interval for the sample means. In this study it was desired to have a 90% confidence interval. At 15 replications, the 90% confidence interval results in achieving μ_x between $(\overline{X} + .55\sigma_X, \overline{X} - .55\sigma_X)$. Therefore, using the batch means method, each experiment run had 15 independent replications (i.e. batches).

Avoiding Censored Data

Censoring of data occurs by missing the start and completion of some orders when the start of the collection of statistics is based upon simulation time (Blackstone et al., 1982). By using this method, the lateness and tardiness statistics do not apply to the same set of orders, thus making an unfair comparison. To avoid this, Blackstone et al. (1982) recommend that the statistics for the same group of orders be evaluated. However, they recognize that as experimental factors change, the shop changes, i.e. the processing of orders (timing and sequence) will not be the same from experiment to experiment, thus altering the conditions of systems being compared. Even so, Blackstone et al. (1982) recommend using a methodology that avoids censoring data.

Pilot simulation runs were made to identify when steady state occurs for the worst-case experiment. When steady state was reached for the worst-case, the simulation will be continued for an additional five times that duration. During the steady state period the average orders per hour were determined. The number of orders in a replication for all experiments was the time to clear the transient period for the worst-case multiplied by the average orders per hour. Thus, for every replication in every experimental run, the same number of orders will be evaluated. The longest transient period observed was 28,500 hours. This yielded an average of 91 orders. To ensure a long enough observation period, the replication size used was 200 orders, more that twice as long as the warm-up period. For each experiment, data was collected beginning with order 201 and ended with order 400.

In order to maintain independence of batches, an interval equal to one replication batch was left between batches where statistics will not be collected. This was the same for all experiments. For example, statistics for the second replication were be collected for 200 orders beginning with order number 601, having ignored orders 401 through 600. Using this methodology maintained synchronization of the random number streams for all experimental runs, and kept the experiments as similar as possible.

Statistical Hypotheses and Data Analysis

In order to answer the first research question proposed in Chapter 1, $H_0 1$ was developed. Basically, the data will be evaluated to identify the existence of a relationship between the proposed measure, ISMC, and manufacturing performance, which is a multivariate dependent variable. This relationship may be tested either by employing MANOVA with ISMC as the independent variable or using multiple regression viewing ISMC as the DV. Both will be used to aid in interpretation of results, but the objective is to determine if ISMC have predictive validity.

It is anticipated that ISMC will have a significant relationship with manufacturing performance. In this case, subsequent univariate tests will be performed for each performance measure to determine which performance measures are significantly related to ISMC. Linear regression will be used to test significance.

The second research question seeks to determine which experimental factors, the individual aspects of manufacturing complexity that make up ISMC, are related to manufacturing performance. Therefore, $H_0 2$ was proposed to evaluate the means of each experiment factor to determine if they are equal to zero. This will be tested using MANOVA (a 2 x 2 x 2 x 2 x 2 x 2 x 2 x 2 x 2 model). Since this exploratory research, the analysis will be limited to testing the effects of each factor, the due date tightness factor, k, and the interaction of each factors with k. A set of univariate ANOVA tests will then be conducted for any significant effects revealed in the MANOVA test. This protects against having an inflated Type I error resulting from multiple univariate tests on correlated dependent variables (Tabachnick and Fidell, 2000).

For the third hypothesis, the same analysis will be performed for H as is planned for ISMC. A MANOVA will be conducted using H instead of ISMC. Follow-up univariate ANOVAs will be performed for each of the five individual performance measures. Subsequently, a statistical test will be conducted to compare R-squared for ISMC to that for H. It is anticipated that the R-squared for ISMC will be higher and statistically different from the R-squared for H. for all measures of manufacturing performance.

Summary

In this chapter a quantitative measure for internal static manufacturing complexity was proposed based upon the important aspects of manufacturing complexity identified in literature. Each element of the proposed measure was considered an experimental variable each having two levels. This experimental design requires 512 experiments with 15 replications made in each experiment for a total of 7,680 independent runs.

A simulated batch manufacturing system was proposed as the basis for the experiment. Both complexity measures, ISMC and H, will be calculated for each experiment. Performance measures to be evaluated are mean job flow time, mean and standard deviation of lateness, and mean and standard deviation of tardiness.

CHAPTER IV

RESULTS

The results of the statistical analysis are presented in this chapter. Data was collected from the simulation using AweSim modeling software as described in the previous chapter. Each of the three research questions is addressed through statistical tests. A complete discussion of the results of these tests follows.

Data Preparation

An initial review of the data revealed that the dependent variables (DVs) had skewness and kurtosis that might affect the normality assumption and homoscedasticity requirement for using regression and ANOVA techniques. Table 4.1 provides the dependent variable names to be used throughout the discussion of the statistical analysis. Table 4.2 lists the descriptive statistics for each DV. Histograms were generated for each DV to visually analyze the results. These histograms helped to identify the appropriate transformation for each variable (Tabachnick and Fidell, 2001). All DVs had histograms that were mound-shaped and skewed to the right. This indicated that either the logarithm or square root transformation would be likely to produce normality. After trying these two standard transformations on each variable, each DV was transformed as $Y = Y^{1/2}$ because this reduced both skewness and kurtosis for each DV. The descriptive statistics for the transformed DVs are given in Table 4.3.

Table 4.1 Dependent Variable Abbreviations

Performance Measure	Untransformed Variable	Transformed Variable
Standard Deviation of Order Flow Time	S_{FT}	SQRT_S_{FT}
Mean Order Lateness	L_{Mean}	SQRT_L_{Mean}
Standard Deviation of Order Lateness	S_L	SQRT_S_L
Mean Order Tardiness	T_{Mean}	SQRT_T_{Mean}
Standard Deviation of Order Tardiness	S_T	SQRT_S_T

Table 4.2 Descriptive Statistics for Untransformed Dependent Variables

Dependent Variable	Mean	Standard Deviation	Minimum	Maximum	Range	Skewness	Kurtosis
S_{FT}	799.1	431.7	73.6	3143.9	3070.3	1.059	1.996
L_{Mean}	522.8	524.9	-534.5	3077.2	3611.7	0.992	0.979
S_L	673.9	437.3	51.7	3089.1	3037.4	1.191	2.104
T_{Mean}	579.7	492.3	0	3078.8	3078.8	1.198	1.372
S_T	633.9	444.5	0	3047.3	3047.3	1.131	1.832

Table 4.3 Descriptive Statistics for Transformed Dependent Variables

Dependent Variable	Mean	Standard Deviation	Minimum	Maximum	Range	Skewness	Kurtosis
SQRT_S_{FT}	27.25	7.54	8.58	56.07	47.49	0.241	-0.016
SQRT_L_{Mean}	31.56	7.87	0.72	60.10	59.38	0.343	-0.023
SQRT_S_L	24.62	8.25	7.19	55.58	48.39	0.325	-0.188
SQRT_T_{Mean}	21.72	10.38	0.00	55.49	55.49	0.223	-0.512
SQRT_S_T	23.54	8.94	0.00	55.20	55.20	0.137	-0.221

One independent variable (IV), ISMC, had high skewness (2.093) and kurtosis (5.577) statistics. Additionally, scatter plots of ISMC with each transformed DV indicated potential heteroscedasticity. Therefore, ISMC was transformed using the standard transformation, $Y = LOG_{10}(Y)$, since this transformation reduced both skewness and kurtosis. Table 4.4 shows the descriptive statistics for ISMC before and after transformation.

Table 4.4 Descriptive Statistics for ISMC – Before and After Transformation

Variable	Mean	Standard Deviation	Minimum	Maximum	Range	Skewness	Kurtosis
ISMC	3963.9	3860.3	181.1	25000	24818.9	2.093	5.577
LOG_ISMC	3.41	0.41	2.26	4.40	2.14	-0.169	-0.363

H, the measure of static manufacturing complexity proposed by Frizelle and Woodcock (1995), did not need to be transformed. The skewness and kurtosis, as provided in Table 4.5, were already acceptable, because they were less than one. The standard transformations were attempted to see if improvement was possible, but there was no satisfactory improvement to skewness and kurtosis.

Table 4.5 Descriptive Statistics for H

Variable	Mean	Standard Deviation	Minimum	Maximum	Range	Skewness	Kurtosis
H	21.65	9.31	8.16	49.5	41.34	0.890	0.032

Factor Analysis

After transforming the DVs, an inspection of the bivariate correlations indicated that all five DVs were highly correlated with each other. As shown in Table 4.6, many of the bivariate correlations between DVs exceeded 0.90. High amounts of multicolinearity between DVs can confound statistical test results using the MANOVA method (Tabachnick and Fidell, 2001). Therefore, factor analysis was used to create a single factor that represents overall manufacturing performance. Using SPSS 13.0 statistical software, principle components analysis extracted a single factor (referred to as F_{DV}) from the transformed DVs explaining 92.4% of the variation in the five DVs. Tables 4.7 and 4.8 summarize the results of the factor analysis. A similar factor analysis was performed using the untransformed DVs. Since the distribution of the transformed DV scores reduced skewness and kurtosis, these factors scores were preferred to those from the untransformed DVs. Table 4.9 provides descriptive statistics for both the untransformed and transformed factor.

Table 4.6 Coefficients of Correlation for Transformed Dependent Variables

	$SQRT\_S_{FT}$	$SQRT\_L_{Mean}$	$SQRT\_S_{L}$	$SQRT\_T_{Mean}$	$SQRT\_S_{T}$
$SQRT\_S_{FT}$	-				
$SQRT\_L_{Mean}$	0.762	-			
$SQRT\_S_{L}$	0.901	0.892	-		
$SQRT\_T_{Mean}$	0.800	0.982	0.943	-	
$SQRT\_S_{T}$	0.879	0.928	0.989	0.963	-

Table 4.7 Results of Principle Components Analysis for Transformed Dependent Variables

Component	Eigenvalues	% Variance
1	4.621	92.425
2	0.292	5.850
3	0.072	1.433
4	0.010	0.206
5	0.004	0.086

Table 4.8 Factor Loadings

DV	Loading
SQRT_S_{FT}	0.901
SQRT_L_{Mean}	0.951
SQRT_S_L	0.984
SQRT_T_{Mean}	0.977
SQRT_S_T	0.991

Table 4.9 Descriptive Statistics for the Dependent Variable Factor using transformed and untransformed values for the Dependent Variables

Factor scores from	Mean	Standard Deviation	Min.	Max.	Range	Skewness	Kurtosis
Untransformed DVs	0.00	1.00	-1.436	5.027	6.464	1.106	1.333
Transformed DVs	0.00	1.00	-2.253	3.520	5.773	0.342	-0.353

Alterations to the Planned Statistical Analysis

Since the statistical analysis was performed using F_{DV} as a single dependent variable, it was necessary to deviate from the statistical methodology proposed in Chapter III. The first hypothesis was tested by using linear regression. F_{DV} served as the dependent variable and ISMC was the independent variable. The planned post hoc test to examine the effect of the due date tightness setting was conducted by adding k, the due date tightness factor, to the regression model as the second independent variable.

The second hypothesis was tested using ANOVA instead of a MANOVA. The first test conducted included F_{DV} as the dependent variable and the eight complexity elements as the independent variables. The due date tightness factor became a ninth independent variable in the ANOVA model during the planned post hoc test.

The same regression analyses conducted for ISMC was repeated for Frizelle and Woodcock's (1995) complexity measure, H. The statistical test proposed in Chapter III to compare the strength of relationship between ISMC and performance to that between H and performance was not affected and did not have to be changed.

Tests of Hypothesis 1

One of the objectives of this research is to test the proposed measure of ISMC for its predictive validity, i.e. to see if it reflects the impact of the manufacturing system's design on its performance. Using the single factor of all DVs, F_{DV}, multiple regression analysis was employed to evaluate $H1_0$, that ISMC was not related to manufacturing performance. The general linear model for the regression model used in the "omnibus" test is: $F_{DV} = \beta_0 + \beta_1 LOG\_ISMC + \varepsilon$

The "Omnibus" Regression Results

The results of the regression analysis are presented in Table 4.10. For this analysis, coefficients of variables with p-values less than .01 indicate that the variable is statistically related to the performance measure. The omnibus model is statistically significant having a p-value less than .001. The null hypothesis for H_01 is rejected and it is inferred that ISMC is related to manufacturing performance. Follow-up regression analyses were conducted on the individual manufacturing performance measures, the DVs, to evaluate hypotheses H1a-H1e.

Table 4.10 Omnibus Regression Results for ISMC

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	182.66	1	182.66	187.089	0.000	0.024
Residual	7496.34	7678	0.98			
Total	7679.00					

Variable	Coefficients b	Standard error	t	Significance
Constant	-1.271	0.094	-13.578	0.000
LOG_ISMC	3.720	0.027	13.678	0.000

Standard Deviation of Flow Time

The regression results for the individual DVs are presented in Tables 4.11 through 4.15. LOG_ISMC is significant for each performance measure. $H_0$1a is rejected. It can be inferred that there is a relationship between ISMC and the standard deviation of flow time. The adjusted R^2 for the model involving the standard deviation of flow time, SQRT_s_{FT}, was .009. This means that LOG_ISMC explained less than 1% of the variation in SQRT_s_{FT}. The coefficient of LOG_ISMC is positive indicating that as ISMC increases, order flow time becomes less predictable because the standard deviation of flow time increases.

Table 4.11 Regression Results for ISMC: DV = SQRT_s_{FT}

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	4173.37	1	4173.37	74.129	0.000	0.009
Residual	432259.42	7678	56.30			
Total	436432.79	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	21.167	0.711	29.777	0.000
LOG_ISMC	1.779	0.207	8.610	0.000

Mean Lateness

The hypothesis $H_0 1b$, stating that there is not a relationship between ISMC and the mean lateness is rejected. LOG_ISMC explained 3% of the variation in the mean lateness variable, $SQRT\_L_{MEAN}$. The estimated regression coefficient for LOG_ISMC was positive, thus indicating a positive relationship exists between ISMC and mean lateness. As ISMC increased, mean order lateness tended also to increase.

Table 4.12 Regression Results for ISMC: DV = $SQRT\_L_{MEAN}$

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	14249.56	1	14249.56	237.026	0.000	0.030
Residual	461586.11	7678	60.12			
Total	475835.67	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	20.330	0.735	27.674	0.000
LOG_ISMC	3.287	0.214	15.396	0.000

Standard Deviation of Lateness

$H_0 1c$ is also rejected in favor of the alternative hypothesis that ISMC is related to the standard deviation of lateness. The regression results for the standard deviation of lateness, $SQRT\_s_L$ show that LOG_ISMC explained 1.8% of the variation in $SQRT\_s_L$. Since the coefficient of LOG_ISMC is positive, these results suggest that as ISMC increased, the variation in order lateness increased.

Mean Tardiness

The regression model involving mean tardiness was statistically significant at the .01 level allowing $H_0$1d to be rejected and supporting the idea that ISMC and mean tardiness are related. The adjusted R^2 for this regression model shows that LOG_ISMC explained 3.2 % of the variation in the dependent variable, $SQRT\_T_{Mean}$. The coefficient of LOG_ISMC was also positive suggesting that when ISMC increased, mean order tardiness tended to increase.

Table 4.13 Regression Results for ISMC: DV = $SQRT\_s_L$

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	9512.41	1	9512.41	142.437	0.000	0.018
Residual	512762.42	7678	66.78			
Total	522274.83	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	15.442	0.774	19.944	0.000
LOG_ISMC	2.686	0.225	11.935	0.000

Standard Deviation of Tardiness

$H_0$1e is also rejected in favor of its alternative hypothesis, that ISMC is related to the standard deviation of tardiness. The LOG_ISMC explained 2.3% of the variation in $SQRT\_S_T$ and the positive coefficient of LOG_ISMC suggested that as ISMC increased, the variation in order tardiness increased.

Table 4.14. Regression Results for ISMC: DV = SQRT_T_{MEAN}

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	26679.48	1	26679.48	255.797	0.000	0.032
Residual	800811.61	7678	104.30			
Total	827491.08	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	6.362	0.968	6.575	0.000
LOG_ISMC	4.498	0.281	15.994	0.000

Table 4.15 Regression Results for ISMC: DV = SQRT_s_T

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	14398.05	1	14398.05	184.578	0.000	0.023
Residual	598923.35	7678	78.01			
Total	613321.41	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	12.252	0.837	14.642	0.000
LOG_ISMC	3.304	0.243	13.586	0.000

Post hoc Analyses

Two additional moderating factors might have had a large influence on the performance measures. Two levels of due date tightness were evaluated for each of the 256 experimental systems. It is expected that systems where due dates were set "tighter" would have higher mean lateness and mean tardiness. It is more important to see if ISMC predicts performance differently depending on the level of due date tightness used, i.e. is the interaction of ISMC with the due date tightness factor, k, statistically significant?

The second possible moderating factor, the mean protective work center capacity, was examined after completion of the experiments. Although the research design attempted to control for the effect of utilization level of each experiment, it is possible the differences in work center utilization may have affected performance. Recall, shop utilization for each experiment was established by setting the mean arrival rate for orders such that the average long-run bottleneck utilization was 85%. Differences in mean utilization between work centers could not be controlled, because the routings (sequence of work centers and unit production time) were randomly generated and order size and arrival was also random. Lawrence and Buss (1994) showed that these utilization differences, referred to as protective capacity, can significantly affect mean flow times. Changes in mean flow times will likely affect the other four performance measures in this study. Therefore, the protective capacity level of the system was considered in the analysis. This protective capacity variable, PC, was calculated as the mean difference in utilization between the bottleneck work center and the long-run mean utilization of all of the other work centers. Since this was a post hoc consideration, detailed utilization data had not been recorded for all replication during the actual experimental runs so the mean PC was calculated using the utilization data from the preliminary simulation runs. So, all the replications in each experimental cell used the same calculated PC.

After calculating the mean PC for each experiment cell, a visual evaluation of the results showed that the distribution of mean PC values was acceptably close to normal. The descriptive statistics are provided in Table 4.16. Both skewness and kurtosis were below 1.0. The mean PC ranged from .56 to .016. So, in under at least one set of experimental conditions, the average protective capacity between the bottleneck work center and all other work centers was 56%. This is a large amount of protective capacity compared to the extreme of having a mean protective capacity of 1.6%.

Table 4.16 Descriptive Statistics for PC

Variable	Mean	Standard Deviation	Minimum	Maximum	Range	Skewness	Kurtosis
PC	3963.9	3860.3	181.1	25000	24818.9	2.093	5.577

A new regression model was used to evaluate the impact of these factors. The revised model included k and PC and their possible interactions with ISMC. To protect against increased opportunity for Type I error, an omnibus regression test was performed using the factor created from the five dependent variables, F_{DV}. The general linear model for the regression model used in the revised “omnibus” test is given by:

$$F_{DV} = \beta_0 + \beta_1 LOG\_ISMC + \beta_2 k + \beta_3(LOG\_ISMC*k) + \beta_4(PC) + \beta_5(LOG\_ISMC*PC)$$

$+ \varepsilon$.

The results of this test are presented in Table 4.17. For this analysis, coefficients of variables with p-values less than .01 indicate that the variable is statistically related to the performance measure. Both the due date tightness factor (k) and ISMC were significant. In addition, the utilization variable, PC, and the interaction between PC and ISMC were also significant. The interaction between k and ISMC was not significant, meaning that ISMC "predicts" manufacturing performance in the same manner when due dates were set "tight" or "loose". This interaction, therefore, was not included in the follow-up regression tests on the individual manufacturing performance measures.

<u>Follow-up Tests – Hierarchical Regression Results</u>

In the follow-up regression analysis for each of the DVs, hierarchical regression was used to evaluate the relationship of ISMC to each performance measure. Since ISMC is the variable of primary interest, ISMC was the first variable entered into the regression analysis. The due date tightness factor, k, was a planned environmental factor, so k was entered second in the regression analysis. PC entered third, followed by ISMC*PC because these were considered after the conclusion of the experiments. The adjusted R^2 for each step in the regression was compared to the prior regressions as each variable was added. Tables 4.18 through 4.22 contain a summary of the regression results for the five individual performance measures (DVs).

Table 4.17 Omnibus Regression Results for ISMC - Revised Model

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	1984.16	5	396.83	534.745	0.000	0.258
Residual	5694.84	7674	0.74			
Total	7679	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	-2.795	0.215	-13.019	0.000
LOG_ISMC	1.039	0.063	16.552	0.000
k	0.498	0.163	3.051	0.002
LOG_ISMC*k	-0.064	0.047	-1.353	0.176
PC	8.906	0.759	11.729	0.000
LOG_ISMC*PC	-3.739	0.228	-16.381	0.000

Table 4.18 Hierarchical Regressions for ISMC: DV = $SQRT\_S_{FT}$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
LOG_ISMC	0.098	0.098	0.027	0.348
	(<0.000)	(<0.000)	(0.147)	(<0.000)
k		-0.013	-	-
		(0.247)	-	-
PC			-0.33	1.091
			(<0.000)	(<0.000)
LOG_ISMC*PC				-1.395
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.009	0.009	0.113	0.134
Increase to R^2	-	0.000	0.104	0.021
F statistic	-	-	395.46	47.64
p-value of F statistic	-	-	0.000	0.000

The first of the individual performance measures is the standard deviation of flow time. LOG_ISMC explained 0.9 % of the total variation in $SQRT\_S_{FT}$. The due date tightness factor, k, was not statistically significant. This was expected since flow time of an order is not affected by the tightness of due dates. PC increased the proportion of variation explained by the regression model to 11.3 %, supporting the past research findings that PC can have a large impact on flow times (Lawrence and Buss, 1994). The interaction of ISMC and PC was also significant and increased the model's performance by another 2.1 %, meaning that the affect of ISMC on predictability of flow times depends on the amount of protective capacity at work centers.

As shown in Tables 4.19 through 4.22, the four remaining performance measures have similar results. As expected, all variables are statistically significant, including k, since each of these variables measures the shop's ability to meet due dates. The amount of variation explained by ISMC alone ranged from 1.8 % to 3.2 %. The level of due date tightness, k, increased adjusted R^2 from between 0.6 % to 6.3 % When PC is included in the regression model, the change to the adjusted R^2 ranged from 17 % to 21 %. As in the analysis of $SQRT\_S_{FT}$, these results also support the findings of Lawrence and Buss (1994). The regression coefficient for PC in Model 3 for the five measures of manufacturing performance indicates that as the mean protective capacity (PC) increased, the individual performance measure improved.

Table 4.19. Hierarchical Regressions for ISMC: DV = SQRT_L_{Mean}

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
LOG_ISMC	0.173	0.173	0.072	0.466
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.251	0.251	0.251
		(<0.000)	(<0.000)	(<0.000)
PC			-0.469	1.273
			(<0.000)	(<0.000)
LOG_ISMC*PC				-1.710
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.030	0.093	0.303	0.334
Increase to R^2	-	0.063	0.210	0.031
F statistic	-	469.08	730.83	55.26
p-value of F statistic	-	0.000	0.000	0.000

Table 4.20 Hierarchical Regressions for ISMC: DV = SQRT_S_L

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
LOG_ISMC	0.135	0.135	0.045	0.378
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.080	0.080	0.080
		(<0.000)	(<0.000)	(<0.000)
PC			-0.422	1.056
			(<0.000)	(<0.000)
LOG_ISMC*PC				-1.452
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.018	0.024	0.194	0.216
Increase to R^2	-	0.006	0.170	0.022
F statistic	-	45.23	636.64	45.35
p-value of F statistic	-	0.000	0.000	0.000

Table 4.21 Hierarchical Regressions for ISMC: DV = $SQRT\_T_{Mean}$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
LOG_ISMC	0.180	0.180	0.079	0.428
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.212	0.212	0.212
		(<0.000)	(<0.000)	(<0.000)
PC			-0.470	1.078
			(<0.000)	(<0.000)
LOG_ISMC*PC				-1.520
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.032	0.077	0.288	0.312
Increase to R^2	-	0.045	0.211	0.024
F statistic	-	334.37	747.27	43.70
p-value of F statistic	-	0.000	0.000	0.000

Table 4.22. Hierarchical Regressions for ISMC: DV = $SQRT\_S_T$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
LOG_ISMC	0.153	0.153	0.058	0.386
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.133	0.133	0.133
		(<0.000)	(<0.000)	(<0.000)
PC			-0.444	1.010
			(<0.000)	(<0.000)
LOG_ISMC*PC				-1.428
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.023	0.041	0.229	0.250
Increase to R^2	-	0.018	0.188	0.021
F statistic	-	134.99	691.78	41.41
p-value of F statistic	-	0.000	0.000	0.000

The interaction of ISMC with PC increased the adjusted R^2 for all individual performance measures. The improvement ranged between 2.2 % and 3.1 %. This indicates that there is practical significance in the effect that PC has on how ISMC predicts performance. More importantly, for all individual performance measures, after evaluating the regression coefficients resulting from Model 4, when PC is relatively small, as ISMC increased, performance decreased. However, for a large number of experiments, when the interaction of ISMC and PC is considered the regression coefficients demonstrate that as ISMC increased, performance increased. This is contrary to the theory underlying measuring internal static manufacturing complexity. Table 4.23 summarizes the "turning point" values for PC where ISMC begins to "reverse predict" performance and the percentage of experiments in which the PC was greater than the turning point value.

Table 4.23 Evaluation of LOG_ISMC*PC Interaction - Turning Points Values for PC

	$SQRT\_S_{FT}$	$SQRT\_L_{Mean}$	$SQRT\_S_{L}$	$SQRT\_T_{Mean}$	$SQRT\_S_{T}$
Turning Point for PC *	0.251	0.274	0.262	0.284	0.272
% Above **	46.5	41.8	44.5	38.3	41.8

* The values for PC above which ISMC predicts improved performance with increased complexity

** The percentage of experiments with a mean PC greater than the turning point value

These results also support the effect of PC observed in model 3. With minimal exception, as PC increases, manufacturing performance improves (i.e. the performance measure decreases). Table 4.24 shows the cut-off point for ISMC where the reverse occurs. Again, this occurs in not more that 10 cases, depending on the performance measure. A real manufacturing system is not likely have a value of ISMC as small as these, so PC appears to act consistent when the interaction with ISMC is considered.

Table 4.24 Evaluation of LOG_ISMC*PC Interaction - Turning Points Values for PC

	$SQRT\_S_{FT}$	$SQRT\_L_{Mean}$	$SQRT\_S_{L}$	$SQRT\_T_{Mean}$	$SQRT\_S_{T}$
Turning Point for PC *	0.251	0.274	0.262	0.284	0.272
% Above **	46.5	41.8	44.5	38.3	41.8

* The value for ISMC **below** which PC predicts reduced performance with increases in PC

Summarized results for Hypothesis 1

As ISMC increased, all five measures of manufacturing performance worsened. However, the low value for adjusted R^2, indicates that ISMC explained very little of the variation in performance.

In the post hoc analyses it was found that the average protective capacity in a system (PC) had a sizeable effect on manufacturing performance, supporting the research of Lawrence and Buss (1994). As PC increased, manufacturing performance improved across all performance measures. Additionally, the interaction between ISMC and PC was statistically significant, meaning that ISMC affects performance differently depending on the amount of protective capacity in a system. At relatively high levels of mean protective capacity, (i.e. PC exceeded 25%), systems with higher ISMC scores performed better than systems with lower ISMC.

Tests of Hypothesis 2

The second hypothesis, H2, examined which of the eight complexity factors composing ISMC listed were related to manufacturing performance. These eight factors and their abbreviations are found in Table 4.25. A limited ANOVA was used to statistically test for relationships between the categorical variables (high and low), and the factor score of the performance measures (the DVs), which was a continuous variable. As was done for H1, an "omnibus" test was performed first using the factor of the DVs derived from the factor analysis, F_{DV}. The general linear model for this regression model is given by:

$$F_{DV} = \mu + k + P + B + D + CC + PMR + OP + WC + RC + \varepsilon$$

The statistical null hypothesis for this research question is:

$$H2_0: k = P = B = D = CC = PMR = OP = WC = RC = 0$$

The results of the ANOVA are presented in Table 4.26. For this analysis, variables with p-values less than .01 indicate that the variable is statistically related to the performance measure. The p-value for the model was approximately 0, so the null hypothesis for H2 was rejected. Six of the eight factors were shown to be statistically related to the overall manufacturing performance measure factor, F_{DV}. These were P, D, B, PMR, WC, and RC.

Table 4.25 Individual Internal Manufacturing Static Complexity Factors

Factor	Description
P	Number of end-products produced
D	Levels in product structure
B	Breadth of product structure
CC	Component commonality index
PMR	Product mix ratio
OPS	Number of routing steps (operations)
WC	Number of work centers in the system
RC	Routing commonality index

Table 4.26 Omnibus Regression Results for Internal Static Manufacturing Complexity Factors

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Significance
Corrected Model	4,228.05	8	528.51	1,174.801	0.000
Intercept	0.00	1	0.00	0.000	1.000
P	58.52	1	58.52	130.072	**0.000**
D	729.40	1	729.40	1,621.369	**0.000**
B	1,194.87	1	1,194.87	2,656.043	**0.000**
CC	1.50	1	1.50	3.332	0.068
PMR	18.54	1	18.54	41.203	**0.000**
OPS	0.13	1	0.13	0.288	0.592
WC	2,220.83	1	2,220.83	4,936.604	**0.000**
RC	4.27	1	4.27	9.499	**0.002**
Error	3,450.95	7671	0.45		
Total	7,679.00	7680			
Corrected Total	7,679.00	7679			

R Squared = .551 (Adjusted R Squared = .550)

Follow-up ANOVAs were conducted for the individual manufacturing performance measures to evaluate the six factors that were statistically significant in the omnibus test. In the discussion of the results for each of these tests, the effect size is presented using the transformed variable while the meaning of the effect is expressed using the untransformed variable.

Standard Deviation of Flow Time

Table 4.27 summarizes the ANOVA results for the first performance measure, the standard deviation of flow time, SQRT_s_{FT}. The adjusted R^2 for the models is .621, meaning that the individual variables explain 62% of the variation in SQRT_s_{FT}. All six factors identified in the omnibus model were significant in this model – P, D, B, PMR, WC, and RC. Of these, three factors had a relatively large effect size as measured using η^2 (eta-squared) – B, D, and WC. η^2 is the approximate squared correlation between the individual independent variable and the dependent variable, i.e. the proportion of the variation in the dependent variable uniquely explained by change in the level of the factor. Combined, these three factors explained over 58% of the variation in SQRT_s_{FT}. A discussion of each significant factor follows.

Table 4.27 ANOVA Results for SQRT_s_{FT}

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Significance	Eta Squared
Corrected Model	271,034.47	8	33,879.31	1,571.287	0.000	
Intercept	5,700,645.73	1	5,700,645.73	264,389.935	0.000	
P	10,311.37	1	10,311.37	478.230	**0.000**	**0.024**
D	109,480.50	1	109,480.50	5,077.590	**0.000**	**0.251**
B	52,372.49	1	52,372.49	2,428.981	**0.000**	**0.120**
CC	0.67	1	0.67	0.031	0.860	0.000
PMR	4,266.55	1	4,266.55	197.878	**0.000**	**0.010**
OPS	0.38	1	0.38	0.017	0.895	0.000
WC	94,436.65	1	94,436.65	4,379.872	**0.000**	**0.216**
RC	165.87	1	165.87	7.693	**0.006**	**0.000**
Error	165,398.33	7671	21.56			0.379
Total	6,137,078.53	7680				1.000
Corrected Total	436,432.79	7679				

R Squared = .621 (Adjusted R Squared = .621)

<u>P: Number of End-products</u>

The number of end-products produced in a manufacturing system, P, accounted for 2.4% ($\eta^2 = 0.024$) of the variation in SQRT_s_{FT}. Table 4.28 summarizes the marginal means for the six significant factors. From these results, when the factor P increased from two to five products, the s_{FT} decreased from a mean of 861 to 737 hours. This indicates that as a greater number of end-products were produced in a manufacturing system, the variability in flow times tended to decrease, i.e. it improved. Although this is significant, this was not as anticipated. The calculations for ISMC were based on the assumption that more products implied more internal static manufacturing complexity, which, in turn, should mean less predictability of flow times, i.e. greater fluctuation in flow times.

Table 4.28 Marginal Means for s_{FT}

Factor	Low	High
P	860.83	737.36
D	599.52	998.68
B	661.13	937.07
PMR	836.78	761.42
WC	997.91	600.28
RC	803.95	794.25

D: Depth of Product Structure

The depth of the product structure, D, explained the greatest amount of variation in SQRT_s_{FT} of any of the complexity factors. It had a η^2 of .251. As D increased from two to five levels of items in the product structure, s_{FT} increased from an average of 599 hours to 1000 hours. This supports the notion that systems with more product structure levels, and therefore greater complexity, have greater variability in flow times of orders.

B: Breadth of Product Structure

The breadth of the product structure, B, was one of the three largest contributing factors in explaining variation in SQRT_s_{FT}. It uniquely explained 12% (η^2 = 0.120) of that variation. As B went from its low setting to high setting, s_{FT} increased from an average of 661 hours to 937 hours. As was anticipated, the breadth of the product structure indicates that systems having wider product structures have less predictability in the flow times of orders.

PMR: Product Mix Ratio

Although statistically significant, the PMR factor had a relatively small effect size with a η^2 of 0.01. The mean s_{FT} decreased from 837 to 761 hours when PMR went from having a highly dominant end-product to having no dominant end product. This was the reverse of what was anticipated. This result indicates that having a balanced demand of products, as opposed to a demand with a highly dominant product, leads to a more predictable flow time for orders.

WC: Number of Work Centers

The number of work centers comprising a manufacturing system, WC, explained nearly 22% ($\eta^2 = 0.216$) of the variation in SQRT_s_{FT}. It is the second largest contributor to explaining the predictability of flow time. As the number of work centers increased from four to ten, the mean s_{FT} decreased from 998 to 600 hours. The development of ISMC assumed that having more work centers in a manufacturing system would lead to higher variability in the flow times for orders. The results indicate the opposite. Having a greater number of work centers in a system, from the static design standpoint, did not negatively affect the variability of flow time, rather it resulted in improved performance. Variability was lower in systems that had more work centers.

RC: Routing Commonality

Although statistically significant, RC explained virtually no change in SQRT_s_{FT}. RC had a η^2 that was less than 0.001. As RC went from its low to high setting, s_{FT} decreased from an average of 804 to 794 hours. In these experiments, the flow time was more predictable when no routings were "common" than when some items shared "common" routings with other items.

Mean Lateness

The ANOVA results for mean lateness are presented in Table 4.29. The six factors identified in the omnibus model were all significant predictors of SQRT_L_{MEAN}. The adjusted R^2 for the model containing all internal manufacturing static complexity factors was 0.503. The factors B and WC explained a large portion of the variation in mean lateness, a total of 41.3%. A discussion of each statistically significant complexity factor follows.

P: Number of End-products

The number of end-products produced in a manufacturing system, P, had an η^2 of 0.064, meaning that this factor accounted for 6.4% of the variation in SQRT_s_{FT}. Table 4.30 summarizes the marginal means for the six significant factors. As the number of products increased from two to five products, the s_{FT} increased from a mean of 408 to 638 hours. This indicates that as a greater number of end-products were produced in a manufacturing system, the mean lateness increased. This supported the idea that as static complexity increases due to having more end-products, performance declines.

Table 4.29 ANOVA Results for L_{Mean}

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Significance	Eta Squared
Corrected Model	239,710.72	8	29,963.84	973.436	0.000	
Intercept	7,648,449.42	1	7,648,449.42	248,475.459	0.000	
P	30,277.37	1	30,277.37	983.622	**0.000**	**0.064**
D	11,894.09	1	11,894.09	386.404	**0.000**	**0.025**
B	68,935.46	1	68,935.46	2,239.509	**0.000**	**0.145**
CC	65.60	1	65.60	2.131	0.144	0.000
PMR	568.62	1	568.62	18.473	**0.000**	**0.001**
OPS	17.21	1	17.21	0.559	0.455	0.000
WC	127,725.98	1	127,725.98	4,149.439	**0.000**	**0.268**
RC	226.38	1	226.38	7.355	**0.007**	**0.000**
Error	236,124.95	7671	30.78			0.496
Total	8,124,285.09	7680				1.000
Corrected Total	475,835.67	7679				

R Squared = .504 (Adjusted R Squared = .503)

Table 4.30 Marginal Means for L_{MEAN}

Factor	Low	High
P	407.97	637.73
D	440.51	605.19
B	333.20	712.49
PMR	496.63	549.07
WC	791.08	254.62
RC	531.42	514.28

D: Depth of Product Structure

The factor, D, explained 2.5% of the variation in mean lateness ($\eta^2 = 0.025$). As the number of levels in the product structures in a manufacturing system increased from two to five, the average mean lateness increased from 441 to 605 hours. This was as anticipated. As static complexity increases due to a system having more levels in product structures, performance was negatively affected.

B: Breadth of Product Structure

The depth of the product structure, B, was one of the two largest contributing factors in explaining variation in mean lateness. It had an η^2 of 0.145, nearly one third of the total variation explained by the model containing all factors. As the breadth of the product structure increased from two to five, the average L_{Mean} increased from 333 to 713 hours. As was anticipated, when the breadth of the product structure increased, performance worsened.

PMR: Product Mix Ratio

As was the case with SQRT_s_{FT}, PMR was statistically significant, but had an extremely small effect size. It uniquely explained only 0.1% of the variation in SQRT_L_{MEAN} (η^2 = 0.001). As PMR went from its low to high setting, the average mean lateness increased from 497 to 549 hours. As expected, mean lateness was negatively affected for systems that were more complex due to having a balanced demand for its end-products (more complex) than those with one more dominant end product (less complex).

WC: Number of Work Centers

The number of work centers comprising a manufacturing system, WC, explained the largest amount of the variation in mean lateness. It explained 26.8% of the variation in SQRT_L_{MEAN} (η^2 = 0.268). As the number of work centers increased from four to ten, the average mean lateness decreased from 791 to 255 hours. As was the case with S_{FT}, this was the opposite of what was anticipated. In these experiments, as complexity increased by having more work centers in a system, the mean lateness of orders improved.

RC: Routing Commonality

Although statistically significant, RC explained virtually no change in SQRT_L_{Mean}. RC had an η^2 of less than 0.001. When routing commonality went from its low to high setting, the average L_{Mean} decreased from 531 to 514 hours. This indicates that although static complexity increased due to a system having no routing commonality, performance improved, as measured by mean lateness. This was not as expected.

Standard Deviation of Lateness

Table 4.31 provides the ANOVA results for the SQRT_S_L. The adjusted R^2 for the model containing all factors making up ISMC was 0.546. Only five of the factors that were significant in the omnibus model were statistically significant for SQRT_S_L. In this model, P, the number of end-products, was not statistically significant at the 1% level. The factors D, B and WC had large effect sizes, combining to explain over 53% of the variation in SQRT_S_L. A discussion of each statistically significant factor follows.

Table 4.31. ANOVA Results for SQRT_ S_L

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Significance	Eta Squared
Corrected Model	285,448.40	8	35,681.05	1,155.738	0.000	
Intercept	4,653,592.04	1	4,653,592.04	150,733.621	0.000	
P	180.94	1	180.94	5.861	0.016	0.000
D	55,331.77	1	55,331.77	1,792.241	**0.000**	**0.106**
B	74,978.20	1	74,978.20	2,428.605	**0.000**	**0.144**
CC	156.78	1	156.78	5.078	0.024	0.000
PMR	7,172.06	1	7,172.06	232.309	**0.000**	**0.014**
OPS	1.54	1	1.54	0.050	0.823	0.000
WC	147,383.89	1	147,383.89	4,773.884	**0.000**	**0.282**
RC	243.21	1	243.21	7.878	**0.005**	**0.000**
Error	236,826.43	7671	30.87			0.453
Total	5,175,866.87	7680				1.000
Corrected Total	522,274.83	7679				

R Squared = .547 (Adjusted R Squared = .546)

D: Depth of Product Structure

The depth of the product structure, D, explained nearly 11% of the total variation in SQRT_S_L ($\eta^2 = 0.106$). As anticipated, as the depth of the product structure increased, the average variability in mean order lateness increased, i.e. performance declined. Table 4.32 displays the marginal means for each of the statistically significant factors. When the number of levels in the product structure changed from two to five in the experimental systems, the average s_L increased from 541 to 807 hours.

Table 4.32 Marginal Means for s_L

Factor	Low	High
P	N.S.	
D	540.93	806.95
B	523.47	824.41
PMR	630.50	717.38
WC	898.60	449.29
RC	679.42	668.46

B: Breadth of Product Structure

The complexity factor, B, had an η^2 of 0.144. This means that breadth explains the second largest portion of the variance in lateness. As expected, systems with narrow product structures had more predictable mean lateness than systems with broad products structures. The mean s_L was 523 hours for experiments at the low setting for B, compared to 824 hours for experiments at the high setting.

PMR: Product Mix Ratio

The PMR factor explained 1.4% of the variation in SQRT_s_L. In experiments at the low setting for PMR, (i.e., a dominant end product), the average s_L was 631 hours. At the high complexity setting for PMR, the mean s_L was 717 hours. The results were as expected. Systems that are more complex (i.e., they have a balanced demand for their end-products) had a higher standard deviation of order lateness than systems with a dominant end product.

WC: Number of Work Centers

The number of work centers in a system, WC, uniquely explained the greatest amount of variation in SQRT_s_L. WC explained over 28% of the total variation in this performance measure. However, the marginal means show that as the number of work centers in a system increased, variation in the mean order lateness decreased, meaning the system was more predictable in terms of mean order lateness. At the low complexity setting for WC (i.e., fewer work centers), the s_L was 899 hours compared to 449 hours at its high complexity setting.

RC: Routing Commonality

Once again, routing commonality was statistically significant, but explained virtually no change in manufacturing performance as measured by s_L. RC had an η^2 less than 0.001. The relationship of RC to variability of order lateness was opposite of what was anticipated. Experiments with some routing commonality (low complexity) had a mean s_L of 679 hours. Those systems with no routing commonality had slightly less variability having a mean s_L of 668 hours.

Mean Tardiness

The ANOVA results for mean lateness are presented in Table 4.33. All six factors identified in the omnibus model were significant predictors of SQRT_T_{MEAN}. The adjusted R^2 for the model including all internal manufacturing static complexity factors was 0.529, explaining more the half of the variation in the DV. Two factors, B and WC, explained a substantial portion of the variation in mean tardiness - a total of 43.5%. A discussion of each statistically significant complexity factor follows.

Table 4.33 ANOVA Results for $SQRT\_T_{Mean}$

Tests of Between-Subjects Effects						
Source	Type III Sum of Squares	df	Mean Square	F	Significance	Eta Squared
Corrected Model	438,370.69	8	54,796.34	1,080.238	0.000	
Intercept	3,624,668.52	1	3,624,668.52	71,455.602	0.000	
P	32,342.91	1	32,342.91	637.598	**0.000**	**0.039**
D	36,058.45	1	36,058.45	710.845	**0.000**	**0.044**
B	127,361.54	1	127,361.54	2,510.766	**0.000**	**0.154**
CC	309.48	1	309.48	6.101	0.014	0.000
PMR	9,102.13	1	9,102.13	179.437	**0.000**	**0.011**
OPS	0.30	1	0.30	0.006	0.939	0.000
WC	232,646.44	1	232,646.44	4,586.320	**0.000**	**0.281**
RC	549.44	1	549.44	10.831	**0.001**	**0.001**
Error	389,120.40	7671	50.73			0.470
Total	4,452,159.61	7680				1.000
Corrected Total	827,491.08	7679				

R Squared = .530 (Adjusted R Squared = .529)

<u>P: Number of End-products</u>

The complexity factor, P, explained 3.9% of the variation in T_{MEAN}. As shown in the Table 4.34, when comparing experiments at the low setting for P to those with the high setting, the average T_{MEAN} increased from 502 to 657 hours. As expected, systems with more end-products tended to have higher mean order tardiness.

D: Depth of Product Structure

The depth of product structure, D, explained 4.4% of the variation in mean tardiness ($\eta^2 = 0.044$). In these experiments, systems with shallow product structures had an average T_{MEAN} of 488 hours opposed to 671 for systems with deep product structures. Performance declined in terms of mean tardiness as static complexity increased due to the depth of product structures. This was the expected result.

Table 4.34 Marginal Means for T_{MEAN}

Factor	Low	High
P	502.35	657.07
D	488.42	671.00
B	407.01	752.41
PMR	531.53	627.89
WC	831.66	327.76
RC	586.60	572.81

B: Breadth of Product Structure

The depth of the product structure, B, had an η^2 of 0.154. Systems with a narrow product structure (lower complexity) outperformed those with broad product structures (higher complexity). When B was at the low setting, the average T_{MEAN} was 407 hours in contrast to 752 hours for experiments when B was at the high setting. The purported relationship existed because performance was worse, as measured by mean tardiness, when product structures were broad as opposed to narrow.

PMR: Product Mix Ratio

The PMR factor had an η^2 of 0.011. The average mean tardiness was lower for experiments with PMR at the low complexity setting (T_{MEAN} = 532 hours) than at the high complexity setting (T_{MEAN} = 628 hours). These results support the expectation that systems with a dominant end product demand had better mean order tardiness than systems without a dominant end product.

WC: Number of Work Centers

Over 28% of the variation in mean tardiness (SQRT_T_{MEAN}) was explained by the factor WC. The average T_{MEAN} of systems with fewer work centers (lower complexity) was 832 hours. This is much higher than the 328 hours observed for systems with more work centers. This was the opposite of what was anticipated. These results indicate that systems with more work centers with the same bottleneck utilization (85%) had better performance than systems with fewer work centers.

RC: Routing Commonality

While RC was statistically significant, it explained virtually no change in SQRT_T_{Mean}. RC explained 0.1% of the variation in SQRT_T_{Mean} (η^2 = 0.001). Observing the marginal means, performance was better for systems with no routing commonality than for those with some commonality in routings. The average mean tardiness was 587 hours at the low complexity setting, slightly higher than the 573 hours at the high complexity setting for RC. This was contrary to what was anticipated.

Standard Deviation of Tardiness

The ANOVA results for the $SQRT\_S_T$ are shown in Table 4.35. The model with all complexity factors explains 55% of the variation in the DV. The six factors significant in the omnibus model were also statistically significant predictors of $SQRT\_S_T$. Over 53% of the total variation in the DV is explained by three primary factors – D, B and WC. The remaining three factors, P, PMR, and RC, combined to explain less than 2% of $SQRT\_S_T$. Following is a discussion of each significant complexity factor.

Table 4.35. ANOVA Results for $SQRT\_ S_T$

Tests of Between-Subjects Effects

Source	Type III Sum of Squares	df	Mean Square	F	Significance	Eta Squared
Corrected Model	337,509.77	8	42,188.72	1,173.372	0.000	
Intercept	4,255,181.35	1	4,255,181.35	118,347.056	0.000	
P	5,128.55	1	5,128.55	142.638	**0.000**	**0.008**
D	55,570.51	1	55,570.51	1,545.553	**0.000**	**0.091**
B	96,295.29	1	96,295.29	2,678.209	**0.000**	**0.157**
CC	215.59	1	215.59	5.996	0.014	0.000
PMR	2,682.00	1	2,682.00	74.593	**0.000**	**0.004**
OPS	105.29	1	105.29	2.928	0.087	0.000
WC	177,143.80	1	177,143.80	4,926.805	**0.000**	**0.289**
RC	368.74	1	368.74	10.256	**0.001**	**0.001**
Error	275,811.64	7671	35.96			0.450
Total	4,868,502.75	7680				1.000
Corrected Total	613,321.41	7679				

R Squared = .550 (Adjusted R Squared = .550)

P: Number of End-products

The number of end-products produced in a manufacturing system, P, accounted for only 0.8% of the variation in SQRT_s_T. The marginal means for the statistically significant complexity factors is provided in Table 4.36. At the low setting for P the average s_T was 609 hours. At the high complexity setting for P, the mean s_T was only 659 hours. Contrary to what was anticipated, the results indicate that systems with more end-products (i.e. more complex) have more predictable mean order tardiness than do systems with fewer end-products (i.e. less complex).

Table 4.36 Marginal Means for s_T

Factor	Low	High
P	608.94	658.90
D	506.67	761.17
B	474.37	793.47
PMR	608.48	659.36
WC	866.27	401.57
RC	639.92	627.92

D: Depth of Product Structure

The depth of the product structure, D, had a η^2 of 9.1%. Variability in mean tardiness was greater for systems with deep product structures than systems with shallow product structures. The mean s_T was 507 hours for systems at the high setting for D compared to 761 hours for systems at the low setting. This is consistent with expectations.

B: Breadth of Product Structure

The complexity factor, B, had an η^2 of 0.157 meaning this factor uniquely explains nearly 16% of the variation in this performance measure. As anticipated, systems with narrow product structures encountered less variability in mean order tardiness than the systems with broad product structures. When B was at its low setting, the mean s_T was 474 hours. At the high setting for B, the mean s_T was 793 hours, substantially higher.

PMR: Product Mix Ratio

The PMR factor explained 0.4% of the variation in SQRT_s_T. In experiments conducted at the low setting of PMR, mean s_T was 608 hours compared to 659 hours at the high setting. This is consistent with the expectation that systems with low complexity due to having a dominant end product are more predictable in terms of mean tardiness than system with no dominant end product.

WC: Number of Work Centers

Once again the number of work centers in a system, WC, uniquely explained the greatest amount of variation in performance – 28.9%. As with all previous performance measures, the results are contrary to what was expected. As the number of work centers increased, performance improved, i.e. s_T decreased. At the low complexity setting for WC, s_T was 866 hours. At the high setting for WC, s_T was only 402 hours.

RC: Routing Commonality

As is the case for the previous four performance measures, the routing commonality factor, RC, was statistically significant, but explained virtually none of the variation in SQRT_s_T. RC had an η^2 of 0.001. Contrary to what was anticipated, but consistent with all other DVs, as static complexity increased by reducing the amount of routing commonality, performance improved. Systems with less routing commonality, i.e. more complex, were more predictable in terms of mean tardiness. The average s_T for systems at the low complexity setting for RC was 640 hours. For system at the high complexity setting for RC, the mean s_T was slightly diminished at 628 hours.

Post hoc Analysis

A post hoc analysis was conducted of the findings related to hypothesis 2. The influence of due date "tightness" and the mean protective capacity were examined to determine if they could explain the results. Systems where management sets "tighter" due dates may explain a sizeable portion of the variation observed in the manufacturing performance measures and change how we interpret the influence of the factors comprising ISMC. Additionally, the amount of mean protective capacity may similarly help to explain system performance and moderate the affect of these complexity factors. From these concerns, these factors were included in a set of ANCOVA models to test for observable affects on manufacturing performance. The covariate, PC, will be used to adjust DV scores in order to remove undesirable variance, i.e. noise, and clarify the effects due to factors and their interactions (Tabachnik and Fidell, 2001).

The revised model included k and PC and the interaction of k with the eight experimental factors. The general linear model for the ANCOVA model used in the revised "omnibus" test is given by:

$$
\begin{aligned}
F_{DV} = {} & \mu + P + B + D + CC + PMR + OP + WC + RC + k \\
& + k*P + k*B + k*D + k*CC + k*PMR + k*OP + k*WC + k*RC + PC \\
& + \varepsilon
\end{aligned}
$$

The new statistical null hypothesis is:

$$
\begin{aligned}
H1_0\text{: } & P = B = D = CC = PMR = OP = WC = RC = k = k*P = k*B = k*D = k*CC \\
& = k*PMR = k*OP = k*WC = k*RC = PC = 0
\end{aligned}
$$

<u>The "Omnibus" ANCOVA Results</u>

The results of the ANCOVA are presented in Table 4.37. For this analysis, variables with p-values less than .01 indicate that the variable is statistically related to the performance measure. The null hypothesis for the revised H2 is rejected because at least one factor is shown to be statistically related to manufacturing performance. Seven of the eight factors were shown to be related to the overall manufacturing performance measure factor, F_{DV}. These were P, D, B, PMR, OPS, WC, and RC. Additionally, the due date tightness factor, k, the covariate, PC, and two interactions, k*P and k*D, were statistically significant in the omnibus test.

Table 4.37 ANCOVA Results for the Omnibus model

Tests of Between-Subjects Effects

Dependent Variable: Factor Score of transformed DVs

Source	Type III Sum of Squares	df	Mean Square	F	Significance
Corrected Model	4,498.24	18	249.90	601.900	0.000
Intercept	86.24	1	86.24	207.716	0.000
P	136.15	1	136.15	327.925	**0.000**
D	816.96	1	816.96	1,967.677	**0.000**
B	1,274.33	1	1,274.33	3,069.281	**0.000**
CC	1.21	1	1.21	2.913	0.088
PMR	34.60	1	34.60	83.325	**0.000**
OPS	31.91	1	31.91	76.861	**0.000**
WC	1,191.68	1	1,191.68	2,870.212	**0.000**
RC	3.27	1	3.27	7.876	**0.005**
k	149.27	1	149.27	359.535	**0.000**
k * P	17.00	1	17.00	40.936	**0.000**
k * D	8.01	1	8.01	19.287	**0.000**
k * B	1.48	1	1.48	3.563	0.059
k * CC	0.03	1	0.03	0.080	0.778
k * PMR	1.75	1	1.75	4.215	0.040
k * OPS	0.07	1	0.07	0.160	0.690
k * WC	0.99	1	0.99	2.382	0.123
k * RC	0.00	1	0.00	0.010	0.922
Mean_PC	91.58	1	91.58	220.586	**0.000**
Error	3,180.76	7,661	0.42		
Total	7,679.00	7,680			
Corrected Total	7,679.00	7,679			

R Squared = .586 (Adjusted R Squared = .585)

Follow-up Tests

In the follow-up tests to determine which complexity factors were important to explaining each performance measure, an ANCOVA was conducted for each DV. Only significant effects that resulted from the omnibus ANCOVA were analyzed. A summary of the ANOCOVAs is found in Table 4.38.

Due date tightness factor - k

As expected, neither the due date tightness factor, k, nor any of the interactions with k were statistically significant for the dependent variable $SQRT\_S_{FT}$. The tightness of due dates should not affect flow time either in terms of mean flow time or variation in flow time. For the remaining four DVs, k, k*P, and k*D were statistically significant. The due date tightness factor, k, explained 7.3% and 5.1% of the variation in mean lateness ($SQRT\_L_{Mean}$) and mean tardiness ($SQRT\_T_{Mean}$), respectively. It explained only 0.7% and 2.0% of the variation in $SQRT\_s_L$ and $SQRT\_s_T$, respectively.

By including the due date tightness factor, k, all statistical models explained more of the variation in manufacturing performance. This result was entirely expected, because k was included as an experimental factor.

Protective capacity - PC

In order to evaluate the impact of including the interaction effects associated with k and the effect of PC, the three statistical models were compared. Model 1 is the original ANOVA with the eight research factors. Model 2 adds the due date tightness factor and corresponding interactions. Model 3 is the ANCOVA model that incorporates PC into Model 2. Similar to hierarchical regression, the statistical significance in the change to adjusted R^2 was tested. Tables 4.39 through 4.43 summarizes the effect size (η^2) and significance for each factor and the results of the tests for change in adjusted R^2, first, between Model 1 and Model 2, then between Model 2 and Model 3.

Table 4.38 ANCOVA Summary Results for Individual Performance Measures

	SQRT_S_{FT}		SQRT_L_{Mean}		SQRT_S_L		SQRT_T_{Mean}		SQRT_S_T	
Factor	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared
P	**0.000**	**0.004**	**0.000**	**0.075**	**0.000**	**0.008**	**0.000**	**0.053**	**0.000**	**0.021**
D	**0.000**	**0.291**	**0.000**	**0.035**	**0.000**	**0.132**	**0.000**	**0.058**	**0.000**	**0.114**
B	**0.000**	**0.147**	**0.000**	**0.171**	**0.000**	**0.174**	**0.000**	**0.182**	**0.000**	**0.188**
CC	0.000	0.001	0.259	0.000	0.101	0.000	0.629	0.000	0.292	0.000
PMR	**0.000**	**0.006**	**0.000**	**0.003**	**0.000**	**0.020**	**0.000**	**0.016**	**0.000**	**0.008**
OPS	**0.000**	**0.006**	**0.000**	**0.002**	**0.000**	**0.006**	**0.000**	**0.004**	**0.000**	**0.004**
WC	**0.000**	**0.144**	**0.000**	**0.150**	**0.000**	**0.177**	**0.000**	**0.161**	**0.000**	**0.174**
RC	0.018	0.000	**0.008**	**0.000**	0.014	0.000	**0.002**	**0.001**	**0.003**	**0.001**
k	0.056	0.000	**0.000**	**0.073**	**0.000**	**0.007**	**0.000**	**0.051**	**0.000**	**0.020**
k * P	0.058	0.000	**0.000**	**0.009**	**0.000**	**0.001**	**0.000**	**0.003**	**0.000**	**0.005**
k * D	0.133	0.000	**0.000**	**0.004**	**0.000**	**0.001**	**0.000**	**0.002**	**0.000**	**0.001**
k * B	0.410	0.000	0.018	0.000	0.133	0.000	0.109	0.000	0.000	0.001
k * CC	0.779	0.000	0.802	0.000	0.706	0.000	0.697	0.000	0.580	0.000
k * PMR	0.001	0.001	0.387	0.000	0.000	0.002	0.000	0.001	0.000	0.001
k * OPS	0.749	0.000	0.179	0.000	0.829	0.000	0.619	0.000	0.565	0.000
k * WC	0.029	0.000	0.153	0.000	0.072	0.000	0.184	0.000	0.000	0.001
k * RC	0.974	0.000	0.945	0.000	0.906	0.000	0.964	0.000	0.731	0.000
Mean_PC	**0.000**		**0.000**		**0.000**		**0.000**		**0.000**	
Adjusted R^2	0.636		0.584		0.571		0.588		0.586	

It should be noted that no effect size was calculated for PC, because it is a covariate providing adjustment to the means of the other effects in the model. The effect size for the main and interaction effects was calculated by dividing the sum of squares for the effect by the adjusted total sum of squares. The adjusted total sum of squares is the total of the sum of squares for all main and interaction effects and the sum of squares error. The calculated sum of squares for the covariate is excluded (Tabachnick and Fidell, 2001).

As expected, including k and its interaction with the eight complexity factors did not make any difference to s_{FT} since flow time is not a measure of comparison to the order's due date. However, for the remaining four performance measures, the models that included k are better at explaining performance. The largest increases in adjusted R^2 occurred for mean lateness and mean tardiness performance measures, which increased by 7.5% and 5% respectively. The due date tightness factor also helped to explain more of the variation in performance for s_L and s_T. Adjusted R^2 for these measures increased by 1% and 2.5% respectively.

Continuing the discussion of the significant interactions involving k, as seen in Tables 4.40 through 4.43, the effect size, η^2, for each of the interactions was always less than 1%, meaning that, although the interactions are statistically significant, they played a very small role in explaining the change in performance. The adjusted marginal means for the interactions are shown in Table 4.44. When comparing the marginal means for the k*P interaction, across all four of the later performance measures, regardless of the level of k, systems with more end-products performed worse than systems with fewer end-products. Similarly for the k*D interaction, regardless of k, systems with more levels in their product structures were outperformed by system with fewer levels. The effect of D and P were both as expected.

Referring to the marginal means for both the k*P and k*D interactions in Table 4.44, for all four performance measures in which these interactions were significant, performance was better in systems where due dates were set "loose" compared to systems where dues dates were set "tight". For mean lateness and mean tardiness, this was anticipated. When due dates are set tighter, these measures should increase. This explains the larger effect size of k for these two performance measures.

As seen in the results from Model 3 for all performance measures, the covariate, PC, was statistically significant, meaning that the differences in the amount of mean protective capacity do help explain variation in performance. In addition to being statistically significant, the inclusion of PC provided a clearer picture of the effects of some of the other factors.

In comparing the results of these models, the three factors that constantly contributed to explaining the largest variation in performance were affected by the addition of the covariate, PC, into the statistical model. For all performance measures, the effect size of factor D was larger in the presence of the covariate. With the exception of s_{FT}, the effect size for product structure breadth, B, was also larger when the affect of PC was considered. The more interesting finding pertained to the factor WC. In all cases, the effect size of WC decreased substantially. The smallest decrease was 7% for SQRT_s_{FT}. For SQRT_T_{MEAN} and SQRT_L_{MEAN}, the effect size of WC decreased by 12%. This indicates that a substantial portion of what originally was attributed to WC was due to differences in PC.

Table 4.39 ANOVA/ANCOVA Model Comparisons: DV = SQRT_s_{FT}

Factor	Effect Size (η^2) & significance Model 1	Model 2	Model 3
P	0.024	0.024	0.004
	(<0.000)	**(<0.000)**	**(<0.000)**
D	0.251	0.251	0.291
	(<0.000)	**(<0.000)**	**(<0.000)**
B	0.120	0.120	0.147
	(<0.000)	**(<0.000)**	**(<0.000)**
CC	0.000	0.000	0.001
	(0.860)	(0.860)	**(<0.000)**
PMR	0.010	0.010	0.006
	(<0.000)	**(<0.000)**	**(<0.000)**
OPS	0.000	0.000	0.006
	(0.895)	(0.895)	**(<0.000)**
WC	0.216	0.216	0.144
	(<0.000)	**(<0.000)**	**(<0.000)**
RC	0.000	0.000	0.000
	(0.006)	**(0.006)**	(0.018)
k	-	0.000	0.000
	-	(0.061)	(0.056)
k * P	-	0.000	0.000
	-	(0.063)	(0.058)
k * D	-	0.000	0.000
	-	(0.140)	(0.133)
k * B	-	0.000	0.000
	-	(0.419)	(0.410)
k * CC	-	0.000	0.000
	-	(0.783)	(0.779)
k * PMR	-	0.001	0.001
	-	(0.001)	(0.001)
k * OPS	-	0.000	0.000
	-	(0.754)	(0.749)
k * WC	-	0.000	0.000
	-	(0.033)	(0.029)
k * RC	-	0.000	0.000
	-	(0.974)	(0.974)
Mean_PC	-	-	N/A
	-	-	**(<0.000)**
Adjusted R^2	0.621	0.621	0.636
Increase to R^2	-	0.000	0.015
F statistic	-	-	2.56
p-value of F statistic	-	-	**0.000**

Table 4.40. ANOVA/ANCOVA Model Comparisons: DV = $SQRT\_L_{MEAN}$

Factor	Effect Size (η^2) & significance Model 1	Model 2	Model 3
P	0.064	0.064	0.075
	(<0.000)	**(<0.000)**	**(<0.000)**
D	0.025	0.025	0.035
	(<0.000)	**(<0.000)**	**(<0.000)**
B	0.145	0.145	0.171
	(<0.000)	**(<0.000)**	**(<0.000)**
CC	0.000	0.000	0.000
	(0.144)	(0.113)	(0.259)
PMR	0.001	0.001	0.003
	(<0.000)	**(<0.000)**	**(<0.000)**
OPS	0.000	0.000	0.002
	(0.455)	(0.417)	**(<0.000)**
WC	0.268	0.268	0.150
	(<0.000)	**(<0.000)**	**(<0.000)**
RC	0.000	0.000	0.000
	(0.007)	**(0.003)**	**(0.008)**
k	-	0.063	0.073
	-	**(<0.000)**	**(<0.000)**
k * P	-	0.007	0.009
	-	**(<0.000)**	**(<0.000)**
k * D	-	0.004	0.004
	-	**(<0.000)**	**(<0.000)**
k * B	-	0.000	0.000
	-	(0.019)	(0.018)
k * CC	-	0.000	0.000
	-	(0.804)	(0.802)
k * PMR	-	0.000	0.000
	-	(0.391)	(0.387)
k * OPS	-	0.000	0.000
	-	(0.183)	(0.179)
k * WC	-	0.000	0.000
	-	(0.156)	(0.153)
k * RC	-	0.000	0.000
	-	(0.945)	(0.945)
Mean_PC	-	-	N/A
	-	-	**(<0.000)**
Adjusted R^2	0.503	0.578	0.584
Increase to R^2	-	0.075	0.006
F statistic	-	35.66	1.14
p-value of F statistic	-	**0.000**	0.306

Table 4.41 ANOVA/ANCOVA Model Comparisons: DV = SQRT_s_L

Factor	Effect Size (η^2) & significance Model 1	Model 2	Model 3
P	0.000	0.000	0.008
	(0.016)	(0.014)	**(<0.000)**
D	0.106	0.106	0.132
	(<0.000)	**(<0.000)**	**(<0.000)**
B	0.144	0.144	0.174
	(<0.000)	**(<0.000)**	**(<0.000)**
CC	0.000	0.000	0.000
	(0.024)	(0.023)	(0.101)
PMR	0.014	0.014	0.020
	(<0.000)	**(<0.000)**	**(<0.000)**
OPS	0.000	0.000	0.006
	(0.823)	(0.821)	**(<0.000)**
WC	0.282	0.282	0.177
	(<0.000)	**(<0.000)**	**(<0.000)**
RC	0.000	0.000	0.000
	(0.005)	**(0.005)**	(0.014)
k	-	0.006	0.007
	-	**(<0.000)**	**(<0.000)**
k * P	-	0.001	0.001
	-	**(<0.000)**	**(<0.000)**
k * D	-	0.001	0.001
	-	**(<0.000)**	**(<0.000)**
k * B	-	0.000	0.000
	-	(0.140)	(0.133)
k * CC	-	0.000	0.000
	-	(0.711)	(0.706)
k * PMR	-	0.002	0.002
	-	(<0.000)	(<0.000)
k * OPS	-	0.000	0.000
	-	(0.832)	(0.829)
k * WC	-	0.000	1.000
	-	(0.077)	(0.072)
k * RC	-	0.000	1.000
	-	(0.907)	(0.906)
Mean_PC	-	-	N/A
	-	-	**(<0.000)**
Adjusted R^2	0.546	0.556	0.571
Increase to R^2	-	0.010	0.015
F statistic	-	4.34	2.99
p-value of F statistic	-	**0.000**	**0.000**

Table 4.42 ANOVA/ANCOVA Model Comparisons: DV = $SQRT\_T_{MEAN}$

Factor	Effect Size (η^2) & significance Model 1	Model 2	Model 3
P	0.039	0.039	0.053
	(<0.000)	**(<0.000)**	**(<0.000)**
D	0.044	0.044	0.058
	(<0.000)	**(<0.000)**	**(<0.000)**
B	0.154	0.154	0.182
	(<0.000)	**(<0.000)**	**(<0.000)**
CC	0.000	0.000	0.000
	(0.014)	(0.009)	(0.629)
PMR	0.011	0.011	0.016
	(<0.000)	**(<0.000)**	**(<0.000)**
OPS	0.000	0.000	0.004
	(0.939)	(0.935)	**(<0.000)**
WC	0.281	0.281	0.161
	(<0.000)	**(<0.000)**	**(<0.000)**
RC	0.001	0.001	0.001
	(0.001)	**(0.001)**	**(0.002)**
k	-	0.045	0.051
	-	**(<0.000)**	**(<0.000)**
k * P	-	0.003	0.003
	-	**(<0.000)**	**(<0.000)**
k * D	-	0.002	0.002
	-	**(<0.000)**	**(<0.000)**
k * B	-	0.000	0.000
	-	(0.113)	(0.109)
k * CC	-	0.000	0.000
	-	(0.700)	(0.697)
k * PMR	-	0.001	0.001
	-	(<0.000)	(<0.000)
k * OPS	-	0.000	0.000
	-	(0.623)	(0.619)
k * WC	-	0.000	0.000
	-	(0.188)	(0.184)
k * RC	-	0.000	0.000
	-	(0.964)	(0.964)
Mean_PC	-	-	N/A
	-	-	**(<0.000)**
Adjusted R^2	0.529	0.579	0.588
Increase to R^2	-	0.050	0.009
F statistic	-	22.53	1.70
p-value of F statistic	-	**0.000**	0.032

Table 4.43 ANOVA/ANCOVA Model Comparisons: DV = SQRT_s_T

Factor	Effect Size (η^2) & significance Model 1	Model 2	Model 3
P	0.008	0.008	0.021
	(<0.000)	**(<0.000)**	**(<0.000)**
D	0.091	0.091	0.114
	(<0.000)	**(<0.000)**	**(<0.000)**
B	0.157	0.157	0.188
	(<0.000)	**(<0.000)**	**(<0.000)**
CC	0.000	0.000	0.000
	(0.014)	(0.012)	(0.292)
PMR	0.004	0.004	0.008
	(<0.000)	**(<0.000)**	**(<0.000)**
OPS	0.000	0.000	0.004
	(0.087)	(0.078)	**(<0.000)**
WC	0.289	0.289	0.174
	(<0.000)	**(<0.000)**	**(<0.000)**
RC	0.001	0.001	0.001
	(0.001)	**(0.001)**	**(0.003)**
k	-	0.018	0.020
	-	**(<0.000)**	**(<0.000)**
k * P	-	0.004	0.005
	-	**(<0.000)**	**(<0.000)**
k * D	-	0.001	0.001
	-	**(<0.000)**	**(<0.000)**
k * B	-	0.001	0.001
	-	(<0.000)	(<0.000)
k * CC	-	0.000	0.000
	-	(0.585)	(0.580)
k * PMR	-	0.001	0.001
	-	(<0.000)	(<0.000)
k * OPS	-	0.000	0.000
	-	(0.570)	(0.565)
k * WC	-	0.001	0.001
	-	(<0.000)	(<0.000)
k * RC	-	0.000	0.000
	-	(0.735)	(0.731)
Mean_PC	-	-	N/A
	-	-	**(<0.000)**
Adjusted R^2	0.550	0.575	0.586
Increase to R^2	-	0.025	0.011
F statistic	-	10.76	2.10
p-value of F statistic	-	**0.000**	**0.004**

Table 4.44 Adjusted Marginal Means

Complexity Factor	Level*	k	S_{FT}	L_{MEAN}	S_L	T_{MEAN}	S_T
P	0		773.01	849.20	566.22	362.09	487.40
	1		712.15	1,154.27	647.00	596.38	625.00
D	0		539.11	908.03	468.87	372.08	423.53
	1		977.85	1,087.82	760.55	583.71	702.09
B	0		589.80	801.58	445.43	298.59	385.12
	1		912.25	1,211.27	791.09	684.86	753.63
PMR	0		774.67	971.74	551.07	418.92	518.88
	1		710.56	1,020.34	663.41	528.17	590.39
OPS	0		703.55	966.76	568.23	439.04	523.96
	1		782.03	1,025.45	644.85	506.07	585.00
WC	0		1,028.49	1,338.33	927.92	820.44	885.45
	1		502.63	703.96	352.30	219.22	300.00
RC	0		N.S.	986.18	N.S.	461.53	545.01
	1			1,005.65		482.51	563.18
k	0		N.S.	874.97	573.93	381.32	499.52
	1			1,124.64	638.81	572.26	611.42
Significant Interactions		k					
P	0	0	N.S.	701.54	522.65	265.07	412.98
		1		1,010.94	611.53	474.20	567.97
	1	0	N.S.	1,067.53	627.61	518.65	594.29
		1		1,244.39	666.69	679.52	656.47
D	0	0	N.S.	819.66	451.32	307.93	386.09
		1		1,000.91	486.77	442.29	462.71
	1	0	N.S.	932.08	711.26	462.55	627.55
		1		1,255.58	811.49	718.95	780.83

* Low setting = 0; High setting = 1

Further analysis of the PC revealed that there was a difference in the amount of protective capacity in systems with four work centers compared to systems with ten work centers. The average PC for systems with four work centers was 15.5%. This is 17.6% lower than the average of systems with ten work centers – 33.1%. (Refer to Appendix C for work center protective capacity and utilization statistics.) This likely contributed to the high effect size for the WC factor. Additionally, it helps, in part, to explain the "reverse prediction" of performance by WC. Because the PC tended to be much larger for experiments with many work centers (ten) than for those with few work centers (four), it is logical that performance would improve. The opportunity for a "moving" bottleneck or simultaneous bottleneck work centers is reduced when the mean protective capacity in a system is higher.

Although the inclusion of PC did help explain part of the large effect due to the number of work centers, WC, the relationship between WC and performance has not changed. As the number of work centers increased, performance improved for all five measures of performance. This was the case for RC as well. However, when controlling for mean protective capacity, RC was not statistically significant for the performance measures s_{FT} and s_L.

Lastly, one additional factor became statistically significant when the covariate was considered - the number of routing steps, OPS. Although statistically significant, OPS explained less than 1% of the variation of any measure of performance. The marginal means for OPS show that for every measure of performance, systems with lower complexity due to having fewer routing steps (four) had better performance than systems with more routing steps (ten). This was as anticipated.

Summarized results for Hypothesis 2

The results of the ANOVAs for the eight internal manufacturing static complexity factors revealed that six of these factors appeared to be statistically related to manufacturing performance. These were P, D, B, PMR, WC, and RC. The models consisting of these factors explained a large portion of the variation in each of the five performance measures. The adjusted R^2 ranged from 0.503 to 0.621.

Two factors, B and WC, consistently explained a sizeable portion of variation in performance on their own. The factor D, depth of the product structure, individually explained more variation for performance measures that measured the standard deviations (s_{FT}, s_L, and s_T), than it did for those measuring the mean of a statistic (L_{MEAN} and T_{MEAN}). The number of end-products manufactured in a system, P, played a smaller role in explaining changes to performance. It appeared to contribute more to performance measures involving the means for lateness and tardiness and less to those measures of the variation, i.e. s_{FT}, s_L, and s_T. The remaining two factors, PMR and RC, although statistically significant, their effect sizes were very small.

The six significant factors did not always affect performance as expected. The results for all five performance measures indicated that systems with WC at the high complexity setting performed better than those set to the low complexity setting for WC. The same occurred for factor RC across all five measures of performance. With the exception of s_{FT}, the complexity factors, P, D, B, and PMR all predicted performance as was anticipated - when complexity increased, performance decreased. Only for s_{FT} did P and PMR have results that were opposite of what was expected. For both of these factors, system at the high complexity setting for that factor, on average, outperformed those at the low complexity setting.

In the post hoc analysis, the effects of due date tightness and mean protective capacity were studied. The tightness of due date setting did not affect performance as measured by s_{FT}. Due date tightness did moderate the effect of two factors, P and D, for the other four measures of manufacturing performance. In all cases, as due dates were set tighter, performance worsened. The models including the due date tightness factor, k, with the predictable exception of s_{FT}, explained more variation in performance than the initial models.

Lastly, controlling for mean protective capacity in a system, to a small extent, helped to explain overall variation in the performance measures involving the variability in flow time, lateness, and tardiness. The inclusion of PC helped to remove some of the "noise" in the variation in performance and provided a clearer idea of the effects of the complexity factors. The effect of the factors P, D, and B almost universally was larger when PC was included. More importantly, the effect size of WC decreased substantially for all performance measures. Further investigation revealed that the average amount of protective capacity in the experiments with higher number of work centers was much larger than the experiments with fewer work centers. This helped to explain part of the counterintuitive results from changes in WC. However, including PC did not change the way factors predicted performance. WC and RC continued to show improved performance at the higher complexity setting for those factors across the five performance measures.

Tests of Hypothesis 3

The final concern of this research was to test the ability of ISMC to predict performance compared to the measure of internal manufacturing static complexity proposed by Frizelle and Woodcock (1995). They propose an entropy-based measure, H. The null hypothesis for H3 is “ISMC does not predict variation in performance better than H”.

Regression Analysis

In order to compare ISMC to H, a regression analysis was performed similar to that done for the first hypothesis regarding ISMC. The omnibus regression model checked to see if H appeared to be related to overall manufacturing performance using the factor score of the transformed dependent variables. Table X shows the results of the regression. Since the p-value of the model is less than 1%, it was concluded that H helps to predict manufacturing performance.

Follow-up regression tests were performed for each of the individual performance measures. The results of these tests are found in Tables 4.46 through 4.50. H showed statistical significance for all performance measures. The most important finding from these regression results is that, for all five measures of performance, the estimated coefficients for H were negative. This indicates that for systems with greater complexity as measured by H, performance tended to improve. This is not what is expected from any proposed measure of complexity.

Table 4.45 Omnibus Regression Results for H

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	140.21	1	140.21	142.80	0.000	0.018
Residual	7538.79	7678	0.98			
Total	7679.00	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	0.314	0.029	10.979	0.000
H	-0.015	0.001	-11.950	0.000

Table 4.46 Regression Results for H: DV = $SQRT\_s_{FT}$

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	12669.18	1	12669.18	229.548	0.000	0.029
Residual	423763.61	7678	55.19			
Total	436432.79	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	30.233	0.215	140.814	0.000
H	-0.138	0.009	-15.151	0.000

Table 4.47 Regression Results for H: DV = SQRT_ L_{MEAN}

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	4225.97	1	4225.97	68.801	0.000	0.009
Residual	471609.70	7678	61.42			
Total	475835.67	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	33.284	0.226	146.949	0.000
H	-0.080	0.010	-8.295	0.000

Table 4.48 Regression Results for H: DV = SQRT_ s_L

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	12767.95	1	12767.95	192.406	0.000	0.024
Residual	509506.87	7678	66.36			
Total	522274.82	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	27.616	0.235	117.303	0.000
H	-0.139	0.010	-13.871	0.000

Table 4.49 Regression Results for H: DV = SQRT_ T_{MEAN}

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	8215.12	1	8215.12	76.990	0.000	0.010
Residual	819275.97	7678	106.70			
Total	827491.09	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	24.131	0.299	80.833	0.000
H	-0.111	0.013	-8.774	0.000

Table 4.50 Regression Results for H: DV = SQRT_ s_T

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	10568.86	1	10568.86	134.629	0.000	0.017
Residual	602752.55	7678	78.50			
Total	613321.41	7679				

Variable	Coefficients b	Standard error	t	Significance
Constant	26.268	0.256	102.585	0.000
H	-0.126	0.011	-11.603	0.000

Comparison of ISMC to H

Although statistical analysis comparing the R^2 values in the regression models with ISMC and models with H is possible, a simple visual inspection of Table 4.51 provides the information necessary to draw a conclusion for H3. Both measures of internal manufacturing static complexity explain between approximately 1 to 3 % of the variation in performance for the five performance measures. It is obvious that they differ in their ability to predict the different measures of performance. ISMC appears to do better in explaining mean lateness and mean tardiness. H better explains the differences in s_{FT} and s_L.

Table 4.51 Comparison of Regression Results – ISMC vs. H

	Ajusted R^2				
	$SQRT\_S_{FT}$	$SQRT\_L_{Mean}$	$SQRT\_S_L$	$SQRT\_T_{Mean}$	$SQRT\_S_T$
ISMC	0.009	0.030	0.018	0.032	0.023
H	0.029	0.009	0.024	0.010	0.017
ISMC - H	-0.020	0.021	-0.006	0.022	0.006

Post hoc Analyses

As with the first two hypotheses, further analysis of the effect of H was conducted giving consideration to the tightness of due date and the amount of mean protective capacity. A set of hierarchical regressions were performed, the same as was done for the analysis of ISMC, that included the factors k and PC and the interactions k*H and H*PC.

An omnibus test was conducted first using the factor of the transformed DVs in order to prevent inflation of the probability of making a Type I error. The regression results for the omnibus test are provided in Table 4.52. The interaction k*H was not statistically significant so it was excluded from the subsequent follow-up regressions for each of the five performance measures.

Tables 4.53 through 4.57 show the results of the hierarchical regression for each of the five measures of manufacturing performance. As would be expected, k was not statistically significant for the performance measure associated with flow time, $SQRT\_s_{FT}$. For the remaining four performance measures, k was statistically significant. Including k in the regression model helps to explain the variation in each performance measure to nearly the same extent as when it was added to the corresponding regression model with ISMC. In both cases, the regression models are able to separate the unique variation explained by the due date tightness factor.

For all five performance measures, incorporating mean protective capacity, PC, caused a large increase to adjusted R^2. The increases are comparable to the regression models for ISMC. This means that the covariate, PC, is capturing the same variation in performance in the presence of the complexity measure H as it does for ISMC. There were small differences between the regression models with H and those with ISMC.

Table 4.52 Omnibus Regression Results for H - Revised Model

ANOVA

Source	Sum of Squares	df	Mean Square	F	Significance	Adjusted R-Square
Regression	1916.98	5	383.40	510.616	0.000	0.249
Residual	5762.02	7674	0.75			
Total	7679	7679				

Coefficients

Variable	b	Standard error	t	Significance
Constant	0.357	0.072	4.927	0.000
H*PC	0.022	0.004	5.940	0.000
k	0.307	0.050	6.133	0.000
k*H	-0.001	0.002	-0.624	0.533
PC	-0.989	0.271	-3.654	0.000
H*PC	-0.136	0.014	-9.723	0.000

Table 4.53 Hierarchical Regressions for H: DV = $SQRT\_S_{FT}$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
H	-0.170	-0.170	-0.150	0.058
	(<0.000)	(<0.000)	(<0.000)	(0.099)
k		-0.140	-	-
		(0.214)	-	-
PC			-0.326	-0.104
			(<0.000)	(0.005)
H*PC				-0.321
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.029	0.029	0.135	0.139
Increase to R^2	-	0.000	0.106	0.004
F statistic	-	0.00	394.93	8.85
p-value of F statistic	-	1.000	0.000	0.000

Table 4.54 Hierarchical Regressions for H: DV = $SQRT\_L_{MEAN}$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
H	-0.094	-0.093	-0.064	0.292
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.251	0.251	0.251
		(<0.000)	(<0.000)	(<0.000)
PC			-0.481	-0.100
			(<0.000)	(0.003)
H*PC				-0.548
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.009	0.072	0.302	0.315
Increase to R^2	-	0.063	0.230	0.013
F statistic	-	479.24	818.97	23.21
p-value of F statistic	-	0.000	0.000	0.000

Table 4.55 Hierarchical Regressions for H: DV = $SQRT\_S_L$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
H	-0.156	-0.156	-0.130	0.153
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.079	0.079	0.080
		(<0.000)	(<0.000)	(<0.000)
PC			-0.423	-0.121
			(<0.000)	(0.001)
H*PC				-0.436
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.024	0.031	0.209	0.217
Increase to R^2	-	0.007	0.178	0.008
F statistic	-	52.44	661.81	16.18
p-value of F statistic	-	0.000	0.000	0.000

Table 4.56 Hierarchical Regressions for H: DV = $SQRT\_T_{MEAN}$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
H	-0.100	-0.099	-0.069	0.257
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.211	0.211	0.212
		(<0.000)	(<0.000)	(<0.000)
PC			-0.483	-0.134
			(<0.000)	(<0.000)
H*PC				-0.502
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.010	0.054	0.286	0.297
Increase to R^2	-	0.044	0.232	0.011
F statistic	-	334.37	842.11	20.09
p-value of F statistic	-	0.000	0.000	0.000

Table 4.57 Hierarchical Regressions for H: DV = $SQRT\_s_T$

	Standardized β Coefficient			
	Model 1	Model 2	Model 3	Model 4
H	-0.131	-0.131	-0.103	0.179
	(<0.000)	(<0.000)	(<0.000)	(<0.000)
k		0.132	0.132	0.133
		(<0.000)	(<0.000)	(<0.000)
PC			-0.450	-0.149
			(<0.000)	(<0.000)
H*PC				-0.434
				(<0.000)
p-value of Model	<0.000	<0.000	<0.000	<0.000
Adjusted R^2	0.017	0.035	0.236	0.244
Increase to R^2	-	0.018	0.201	0.008
F statistic	-	135.82	744.24	15.63
p-value of F statistic	-	0.000	0.000	0.000

The interaction H*PC was also statistically significant for all performance measures. The changes in adjusted R^2 between the model including this interaction (Model 4) and Model 3 was relatively small, ranging between .004 and .013. This was universally smaller in all similar models that included ISMC. This indicates that how H predicts performance is affected less by the amount of protective capacity than ISMC. This is an important consideration for any measure of complexity. The ability of both H and ISMC to predict changes in manufacturing performance depends upon the amount of protective capacity in a system.

Two other observations resulted from the hierarchical regression analysis. First, for all five performance measures, the signs of the coefficients for PC and H*PC are negative. This signifies that as mean protective capacity increased, performance improved. This is supported by Lawrence and Buss (1994), but differs from the prior analysis of ISMC.

Finally, when including the mediating affect of PC, the way H predicts performance is not always counterintuitive, i.e. as complexity increases, performance improves. The coefficients of H were all negative in Models 1 -3. When the interaction H*PC was included in Model 4, the coefficients of H were positive. However, since the interaction was statistically significant, the level of PC must also be considered when interpreting these coefficients. Since the coefficients of the H*PC interaction are negative, there is a point at which the amount of protective capacity in a system may dominate and changes in H may have counterintuitive results.

Table 4.58 summarizes for each of the measures of manufacturing performance the “turning point” values for PC where H begins to “reverse predict” performance and the percentage of experiments in which the PC was greater than the turning point value. The proportion of experiments for which H increased and predicted improved performance is much greater than for ISMC across all performance measures. This supports ISMC having greater predictive reliability than H.

Table 4.58 Evaluation of H*PC Interaction - Turning Points Values for PC

	$SQRT\_S_{FT}$	$SQRT\_L_{Mean}$	$SQRT\_S_{L}$	$SQRT\_T_{Mean}$	$SQRT\_S_{T}$
Turning Point for PC *	0.067	0.196	0.129	0.188	0.148
% Above **	93.0	59.8	76.2	61.7	72.3

* The value for PC **above** which H predicts improved performance with increased complexity

** The percentage of experiments with a mean PC greater than the turning point value

Summarized Results for Hypothesis 3

The conclusion to the third hypothesis is that ISMC does not predict performance better than H. Even when considering the tightness of due dates and the mean protective capacity in systems, neither H nor ISMC is clearly superior. Frizelle and Woodcock's (1995) H is less affected by differences in protective capacity. However, H tends to predict performance more frequently in a manner that is inconsistent with the intent of a measure of manufacturing complexity.

However, neither does much to explain any one performance measure. To then suggest that ISMC is better or worse than H would not mean much. It is better to say that both explain little about changes in performance.

Alternative formulations for ISMC

The individual factors that comprise ISMC explained a large proportion of the differences in system performance. In the ANOVA models, the adjusted R^2 always exceeded 0.50, i.e. they explained over 50% of the variation in any performance measure. The inference from analysis of the second research hypothesis is that these individual elements are highly related to manufacturing performance. However the composite measure of complexity, ISMC, as currently formulated, did not explain much of the variation in manufacturing performance (adjusted R^2 of 0.032 or less).

There are a few possible reasons for the poor performance of ISMC. One of the reasons is that ISMC assumed that systems having more work centers (WC) would have greater complexity and, thus, worse performance. The effect size of WC was relatively large (i.e., it explained between 15 to 18% of the variation in performance), but its effect was the opposite of the predicted direction. So, systems with more work centers had a higher ISMC than systems with fewer work centers. But, the ANOVA results showed improved performance for systems with more work centers, instead of decreased performance. An explanation of how the research design failed to control for the effect of the number of work centers on protective capacity was given earlier.

ISMC performance may have been hurt by including factors that had no statistical or practical significance, e.g. CC and OPS. Changes in any of these factors resulted in a change in the value of ISMC, but there was little, if any, corresponding change in manufacturing performance. This further reduced the reliability of ISMC.

Another possible cause of poor predictive reliability of ISMC was the method used to measure some of the individual elements of complexity. For example, the method used to incorporate the routing commonality factor (RC) was one of many possible methods. This researcher chose to evaluate routing commonality by calculating the proportion of identical routings in a system and then create a factor based on that proportion ranging between one (i.e. least complex) to two (i.e. most complex).

A post hoc analysis was conducted to examine whether different formulations of ISMC would improve its validity. Four of the eight complexity factors were highly correlated with manufacturing performance – D, B, WC, and P. But as stated earlier, WC cannot be considered to be a reliable metric. Therefore, it was excluded from post hoc analysis. Revised formulations for ISMC that incorporate D, B and P were examined, because each of these factors explained a proportion of performance that was practically significant. The breadth of the product structures had a consistently large effect on all five measure of manufacturing performance, explaining from 15% to 18% of the variation in performance. The number of levels in the product structures (D) was not as consistent over all the performance measures, but was substantially more correlated to those measuring the predictability of orders, e.g. the standard deviation of flow time. The number of end-products (P) was shown not to have much effect on the predictability measures, but it had higher correlations with the measure of *mean* performance, e.g. mean lateness. Including these practically significant complexity factors in the revised ISMC should result in a measure that recognizes the impact to both mean performance and predictability.

Two possible formulations for the revised ISMC are suggested in the following equations.

$$ISMC = |\mathrm{E}| \times \left(\frac{\sum_{i=1}^{e} (Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} + \frac{\sum_{i=1}^{e} (Q_i \times b_i)}{\sum_{i=1}^{e} Q_i} \right) \tag{17}$$

$$ISMC = |\mathrm{E}| \times \frac{\sum_{i=1}^{e} (Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} \times \frac{\sum_{i=1}^{e} (Q_i \times b_i)}{\sum_{i=1}^{e} Q_i}, \tag{18}$$

where |E| is the number of distinct end-items, Q_i represents the total requirements (e.g. annual) for the i^{th} end-item, d_i is the number of levels in the product structure for the i^{th} end item, and b_i is the breadth of the product structure of the i^{th} end item. The number of end-products is reflected by e. The weighted average number of levels in the products structures for all end-products, the second term, measures the depth of the product structures in a manufacturing system. Similarly, the weighted average breadth of the product structures for all end-products, the last term in both formulae, measures the depth of the product structures in a manufacturing system.

In both equations (17) and (18), the number of end-products geometrically increases the value of ISMC. This was meant to imply that by adding one more end-product to a system's portfolio, the complexity of the system increases drastically due to the additional components and the added complexity of having to complete a new set of manufactured components in sequences specified in the bill of materials.

In both equations, the effect of three complexity factors is equally weighted. Given the exploratory nature of this research and the limited environment that was tested, establishing weights for these factors was not justified.

The difference between equations (17) and (18) is that changes in either the depth or the breadth of the system's product structures would result in a increase in ISMC.

Equation (18) implies that increases in the depth or breadth results in a more dramatic increase in system complexity than equation (17). The formulation proposed in equation (17) adds the total depth of all product structures (number of end-products*weighted average depth of the product structures) to the total breadth of all product structures (number of end-products*weighted average depth of the product structures). In this proposed version of ISMC, all three factors have an effect, but no interaction between the depth and breadth of product structures is presumed.

In equation (18) a change in either the product structure depth or the breadth results in a larger change ISMC that is equation (17). Here, an interaction between the depth and breadth of the product structures is considered. It may be that the breadth of a system's product structures adds more complexity when there are more levels in that system's product structures, i.e. it has a greater effect on manufacturing performance when there is greater depth in the product structures.

At the same time, it may be that a combination of these factors will not predict performance better than using one of the three factors. The factor measuring the breadth of the product structures, B, consistently explained a large amount of variation in each of the five measures of manufacturing performance. Perhaps, it could be as good of a measure of internal static manufacturing complexity as either of the two proposed versions of ISMC.

In order to initially evaluate these possibilities, a set of statistical tests were conducted using the existing simulation results. First, a set of ANCOVAs was performed to measure the effects of the three factors individually. Then another set of ANCOVAs was conducted to gauge to effect of a model containing all three factors with and without the interactions between the factors. Lastly, two further ANCOVAs were conducted to evaluate the two proposed revised formulations of ISMC. The dependent variable used was the factor created from the five transformed measures of manufacturing performance. This was considered to be a measure of the overall manufacturing performance.

Table 4.59 summarizes the results for the first two sets of ANCOVAs that investigated the three complexity factors. When looking at the three factors individually, as expected, B explained more of the variation in overall performance. It explained approximately 10% more of the variation in performance than the base model containing only the due date tightness factor, k, and the covariate PC, which measured the mean protective capacity.

An additional 5% of the variation in manufacturing performance was explained when all three factors were included in the model. When the possible interaction between the factors was considered, these interactions explained an additional 3.2% of the variation in performance. The best possible model had an adjusted R^2 of 0.429 compared to an adjusted R^2 of 0.229 for the base model and 0.329 for the single factor model (B).

Table 4.60 summarizes the results from ANCOVAs for three possible revised formulations for ISMC. The first two ANCOVA models evaluated the formulations proposed in equations (17) and (18). The adjusted R^2 for these was 0.332 and 0.331, respectively. Neither one appeared to be superior to the other. Also, these forms of ISMC were not better than using the single factor, B. The results must be considered with caution. Recall, ISMC was intended to be a ratio-type measure. However, the design of the experiment only had two levels for each factor. For these three measures, the levels were the same, i.e. two and five end-products, two and five levels of depth in the product structure, and a product structure breadth of two and five. So, the calculation for ISMC using these formulation and the factors levels permitted a very limited range of values for ISMC. There were, at most, five different values for ISMC for each measure, despite there being 256 different systems. Using the current experiment provided a limited evaluation for these formulations for ISMC.

The third model is based upon the significant interactions observed in the ANCOVA that included the interactions between the three components. Since the interactions P*D and D*B were significant, another alternative for ISMC was created as shown in the following equation:

$$ISMC = \left[|\mathrm{E}| \times \frac{\sum_{i=1}^{e} (Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} \right] + \left[\frac{\sum_{i=1}^{e} (Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} \times \frac{\sum_{i=1}^{e} (Q_i \times b_i)}{\sum_{i=1}^{e} Q_i} \right] \tag{19}$$

There are many other ways to mathematically combine these three components of complexity. The three proposed versions of ISMC were simple combinations of these factors created to explore their interactions. Proposing a measure of internal static manufacturing complexity in which the effect of a change is one factor would be easily understood was one of the objectives of this study. More complex formulations are possible, however as the complexity of the formulation increases, the ability to intuitively understand ISMC decreases.

Table 4.59 Summary of the results of the ANCOVAs for Factors P, B and D

Factor	Base Model		"P" only		"D" Only		"B" Only		P, D, and B - No Interactions		P, D, and B - With Interactions	
	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared	Sig.	Eta Squared
P			0.000	0.004					0.002	0.001	0.000	0.001
D					0.000	0.079			0.000	0.083	0.000	0.082
B							0.000	0.127	0.000	0.130	0.000	0.128
P*D											0.000	0.004
P*B											0.588	0.000
D*B											0.000	0.038
P*D*B											0.511	0.000
k	0.000	0.025	0.000	0.025	0.000	0.025	0.000	0.025	0.000	0.025	0.000	0.025
Mean PC	0.000		0.000		0.000		0.000		0.000		0.000	
Adjusted R^2	0.229		0.232		0.292		0.329		0.397		0.429	

Table 4.60 Summarized results of ANCOVAs for three alternatives for ISMC

Factor	Revised ISMC - Additive Equation (17) Sig.	Revised ISMC - Additive Equation (17) Eta Squared	Revised ISMC - Multiplicative Equation (18) Sig.	Revised ISMC - Multiplicative Equation (18) Eta Squared	Revised ISMC - A Third Alternative Equation (19) Sig.	Revised ISMC - A Third Alternative Equation (19) Eta Squared
ISMC = Px(D+B)	0.000	0.163				
ISMC = PxDxB			0.000	0.130		
ISMC = (PxD)+(DxB)					0.000	0.141
k	0.000	0.024	0.000	0.025	0.000	0.025
Mean PC	0.000		0.000		0.000	
Adjusted R^2	0.332		0.331		0.340	

The final results of the ANCOVA show that this version of ISMC explained 34% of the variation in overall manufacturing performance. This is marginally more that either of the other formulations and the single factor, B.

Plots of the adjusted marginal means for each formulation for ISMC are presented in Figure 4.1. Note that the calculations of ISMC from two levels of P, B, and D resulted in only four values of ISMC using equation (18) and five values for the other two versions of ISMC. This chart shows that the additive model specified in equation (17) did not predict performance reliably. There are occurrences where higher complexity systems, according to ISMC, tended to have better performance than lower complexity systems. Both of the other alternatives logically predicted performance, that is, as complexity increased, performance worsened.

The adjusted marginal means for the individual factors were also plotted and are presented in Figure 4.2. The factor P, when none of the other complexity factors are present, predicted performance counterintuitively. As the number of products increased, the measure for overall manufacturing performance decreased meaning performance improved. This may, in part, explain why equation (17) did not perform reliably. As was shown in the ANCOVA results, the effect size of P was very small ($\eta^2 = .004$). So, although P explained more substantial proportions of variation for some of the individual measures of performance, it did not explain much in the overall manufacturing performance.

The plots for the factors D and B show that their correlation with overall performance was as expected. As either the depth or breadth of the product structures increased, measures of overall manufacturing performance increased, meaning performance worsened. The charts also confirm that the effect of B is greater than the effect of D.

Summary

Although demonstrated to be a statistically significant predictor of manufacturing performance, ISMC was shown to have little practical predictive ability. The degree to which it helps to explain changes to manufacturing performance is relatively low. When consideration is given the amount of protective capacity in a system, ISMC was not a consistently valid predictor of manufacturing performance.

Six of the eight components that make up ISMC were shown to be related to manufacturing performance. Three of these factors, breadth of the product structure (B), depth of the products structures (D), and the number of work centers (WC), individually explained a substantial amount of performance. The number of work centers predicted performance opposite as expected, in that as the number of work centers in a system

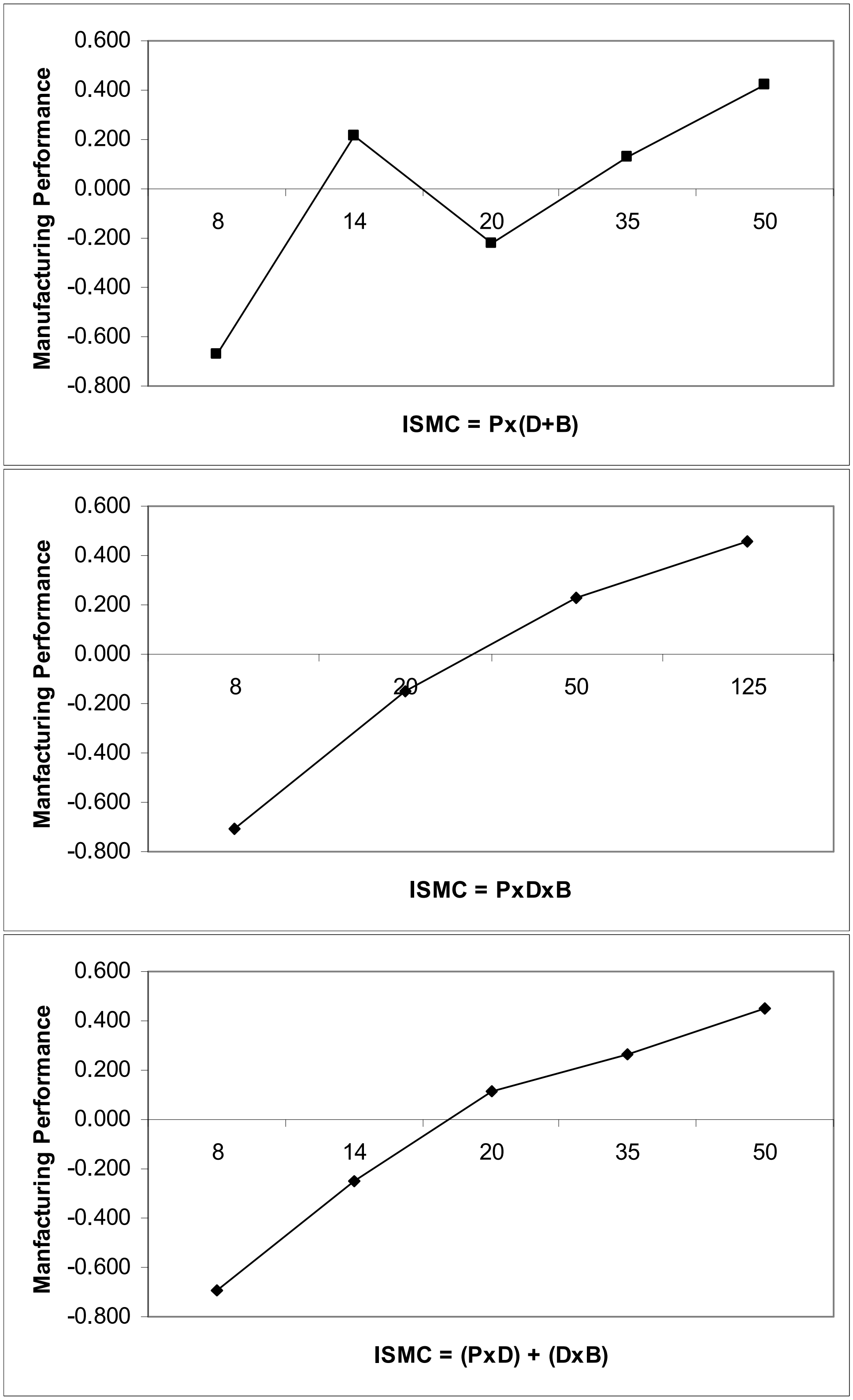


Figure 4.1 Plots of the Adjusted Marginal Means for the Three Alternatives for ISMC

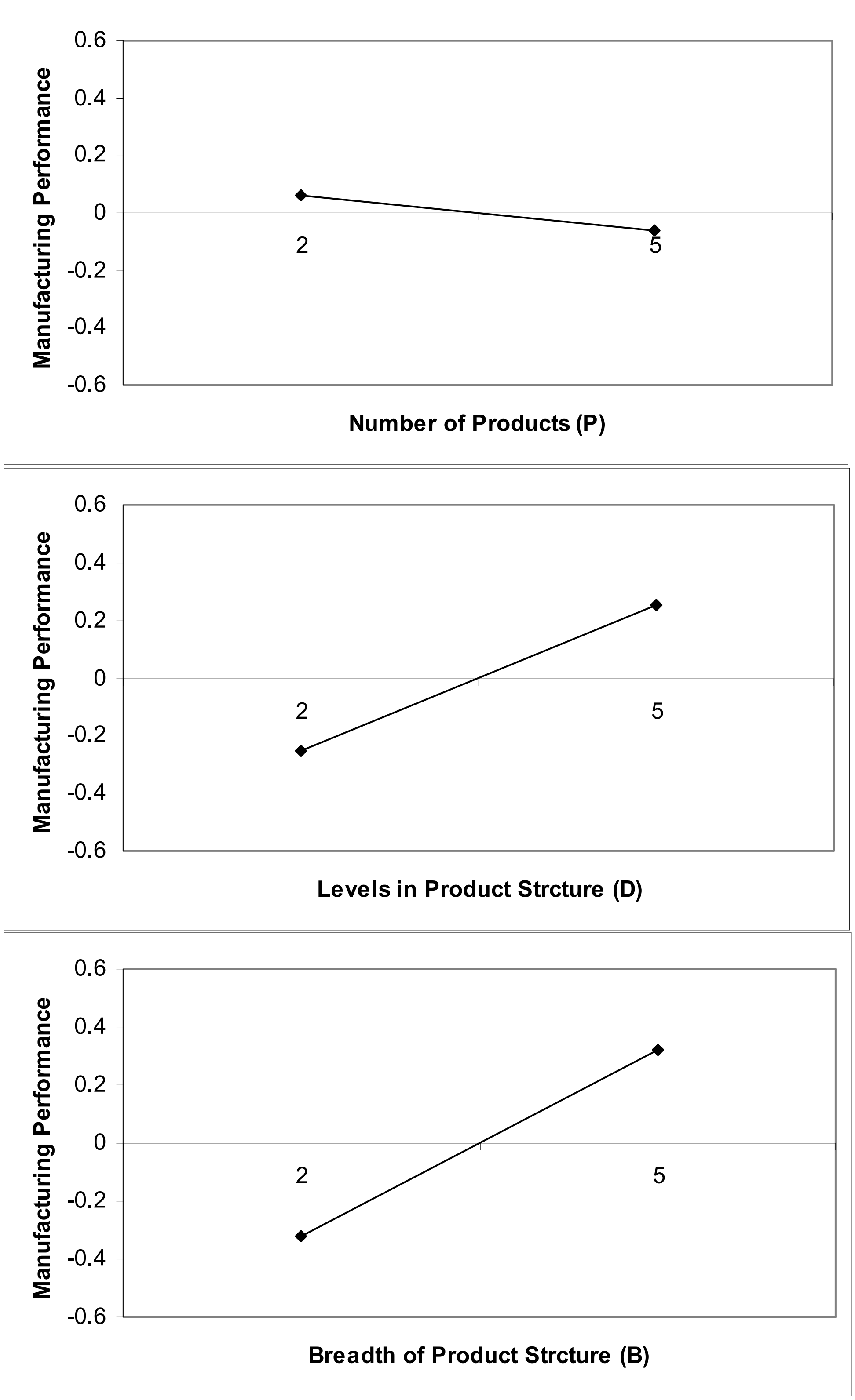


Figure 4.2 Plots of the Adjusted Marginal Means for the Complexity Factors P, B, and D

increased, the performance improved. The relevance of these factors was clarified by considering the amount of protective capacity in a manufacturing system.

The comparison of the proposed complexity measure, ISMC, was not superior to a previous measure put forth by Frizelle and Woodcock (1995). However, neither proposed complexity measures were very good predictors of manufacturing performance. For both H and ISMC, how they predicted performance was affected by the amount of protective capacity in a system. Also, both frequently “reverse” predicted performance.

Although ISMC was not a valid predictor of performance, many of the individual complexity factors were. Three revised formulations for ISMC were suggested and then tested. Although a limited range of values for ISMC results, these versions appeared to explain more variation in performance than the originally proposed formulation. At the same time, they did not explain much more than using a single complexity factor, B.

CHAPTER V

CONCLUSIONS

The purpose of this study was to examine two research questions. These were (1) do systems with lower levels of internal static manufacturing complexity have better manufacturing performance, and (2) which elements of internal static manufacturing complexity have a greater impact on manufacturing performance? To answer these questions, a measure of internal static manufacturing complexity, ISMC, was developed. ISMC incorporated eight complexity elements identified from the literature. Two hypotheses were proposed to test the two research questions. A third hypothesis compared the predictive validity of ISMC to H, another existing measure of internal static manufacturing complexity. Data was obtained from a simulation in which each element of ISMC was tested at both a high and low level. Post-hoc analyses of the influence of the due date tightness factor, the amount of protective capacity and alternative formulations for ISMC were also conducted.

The meaning of these findings is presented first. Then, the implications for both theory and practice are discussed followed by the limitations of the study follows the summary of findings. Finally, opportunities for future research suggested by these findings are offered.

Summary of Findings

The conclusions to the three primary research hypotheses are presented in Table 5.1. The first hypothesis investigated the relationship between internal static manufacturing complexity and manufacturing performance. It was not supported in the statistical analysis. The second hypothesis explored the effects of the eight individual elements that comprise ISMC. Seven of these elements were shown to be related to manufacturing performance. Lastly, the predictive validity of ISMC was compared to another existing measure of internal static manufacturing complexity, H, proposed by Frizelle and Woodcock (1995). The hypothesis that ISMC was superior to H was not supported. Following is a summary of the findings from the statistical analysis.

The Effect of Internal Static Manufacturing Complexity on Performance (H1)

As internal static manufacturing complexity (measured by ISMC) increased, performance decreased. This was true for all five performance measures – the standard deviation of flow time, the mean order lateness, the standard deviation of order lateness, the mean order tardiness, and the standard deviation of order tardiness. Although ISMC was statistically significant for each performance measure, the amount of variation explained was very small, meaning ISMC is not practically significant. This suggests that the current formulation of ISMC is not a valid predictor of performance, and thus is not a good measure of internal static manufacturing complexity, so hypothesis 1 is shown as not supported in Table 5.1

Table 5.1. Summary of the Research Hypotheses

		Conclusion				
Hypothesis	Description	S_{FT}	L_{MEAN}	S_L	T_{MEAN}	S_T
H1	Changes in internal static manufacturing complexity affect manufacturing performance.	Not Supported	Not Supported	Not Supported	Not Supported	Not Supported
H2	The eight elements of ISMC are related to manufacturing performance.					
	Number of End-products (P)	Supported	Supported	Not Supported	Supported	Supported
	Depth of Product Structures (D)	Supported	Supported	Supported	Supported	Supported
	Breadth of Product Structures (B)	Supported	Supported	Supported	Supported	Supported
	Component Commonality (CC)	Not Supported	Not Supported	Not Supported	Not Supported	Not Supported
	Product Mix Ratio (PMR)	Supported	Supported	Supported	Supported	Supported
	Number of Routing Steps (OPS)	Not Supported	Not Supported	Not Supported	Not Supported	Not Supported
	Number of Work Centers (WC)	Supported	Supported	Supported	Supported	Supported
	Routing Commonality (RC)	Supported	Supported	Supported	Supported	Supported
H3	ISMC is a better predictor of performance than H (Frizelle and Woodcock, 1995).	Not Supported	Not Supported	Not Supported	Not Supported	Not Supported

A post hoc analysis was conducted to determine if the results were influenced by the due date tightness, or the mean protective capacity. The post-hoc analysis indicated, with one exception, that performance worsened in systems where due dates were set tighter. The only performance measure not affected was the standard deviation of flow time. This result is intuitive because flow time is not associated with an order's due date. The initial design of the experiments controlled for differences in utilization between systems by setting the average utilization for the bottleneck work center in each system to 85%. However, the random generation of routings (as planned) and the inherent differences due to the dynamic nature of a stochastic environment allowed some settings to have more protective capacity. The results of the post hoc analysis suggested that the amount of protective capacity does affect performance. In general, systems with greater amounts of protective capacity performed better than those with less protective capacity. However, the tests of ISMC when PC was the covariate demonstrated that ISMC was not a reliable measure, because at higher amounts of protective capacity, greater values of ISMC predicted improved performance. This suggests that the environment simulated added a confounding variable that prevented a final conclusion about the value of a composite measure of complexity.

The Effects of the Eight Elements of ISMC on Performance

ISMC was made up of eight individual complexity factors, based on previous research and this researcher's manufacturing experience. A description of these factors is given in Table 5.2.

Table 5.2 Individual Internal Manufacturing Static Complexity Factors

Factor	Description
P	Number of end-products produced
D	Levels in product structure
B	Breadth of product structure
CC	Component commonality index
PMR	Product mix ratio
OPS	Number of routing steps (operations)
WC	Number of work centers in the system
RC	Routing commonality index

In the past, these factors have been primarily used as environmental factors, (e.g. Veral and LaForge, 1985; Benton and Srivastava, 1985; Fry et al, 1989; and Collier, 1982). The second research hypothesis sought to determine if the eight factors were each related to system performance. This hypothesis was supported in that six of the eight elements of internal static manufacturing complexity were shown to be related to manufacturing performance. Table 5.3 summarizes how each of experimental factors, representing the elements of ISMC, affected the individual performance measures in the study.

Notice that, as the level of complexity increased for WC and RC, every performance measure decreased, which means performance improved (see Table 5.3). Also, the standard deviation of flow time performance improved (i.e., the measure decreased) at the high complexity setting of P and PMR. For the other four performance measures, performance worsened (i.e., the measure increased) at high complexity for P and PMR. Only for D and B, did performance always worsen at their high complexity level.

The individual factors that comprise ISMC explained a large proportion of the differences in system performance. In the ANOVA models, the adjusted R^2 always exceeded 0.50, i.e. they explained over 50% of the variation in any performance measure. The inference from the set of tests for the second research hypothesis is that these individual elements are highly related to manufacturing performance. Recall that ISMC did not explain much of the variation in manufacturing performance (adjusted R^2 of 0.032 or less). The simulation results showing that ISMC was a poor predictor of manufacturing performance while some of its components, particularly D and B, were good predictors, suggest that ISMC's combination of the individual elements was flawed.

There are four possible reasons for the poor performance of ISMC. One of the reasons is that ISMC assumed that systems having more work centers (WC) would have greater complexity and, thus, worse performance. As discussed earlier, the high level of WC was correlated with increased PC. Because of this inadvertent confounding it is not clear from this experiment how the number of work center affects complexity and performance.

The second reason for the poor reliability of ISMC is that it included factors that did not have either a statistically significant or practically significant effect on manufacturing performance. Changes in any of these factors (i.e., CC, PMR, OPS and RC) changed ISMC, but there was little, if any, corresponding change in manufacturing performance. This further reduced ISMC's performance.

A third possible cause of the poor predictive ability of ISMC was the method used to measure some of the individual elements of complexity. For example, the method used to incorporate the routing commonality factor (RC) was one of many possible methods. This researcher chose to evaluate routing commonality by calculating the proportion of identical routings in a system and then create a factor based on that proportion ranging from one (i.e. least complex) to two (i.e. most complex). This factor was incorporated into the process structure subcomponent of ISMC by multiplying it by the combination of measures for the number of operations and the number of work centers. So, the method of calculating these factors, like RC and CC, could have made a large difference to the value of ISMC, perhaps "overstating" of "understating" the relative amount of internal static manufacturing complexity.

The design of the simulated manufacturing systems is the last possible reason for explaining ISMC's performance. In the creation of the routings, work centers were randomly assigned to each step of the process. Processing times were randomly established for each product step. This was done to avoid influencing the effect of the routing design or the processing times. Additionally, the arrival rate of orders and the order quantity for each end-product was random. As such, the workload in each work center could not be controlled. To attempt to fairly compare production systems in the set of experiments, the mean arrival rate of orders was set so that the bottleneck work center had an average utilization rate of 85%. But, there was no consideration given to the differences between non-bottleneck work centers. The post hoc analysis accounted for some of these differences by using the average utilization difference between each work center and the bottleneck. But these differences were estimated, since the experiment was not designed to evaluate work center utilization, and the actual data was not collected in the simulation runs. The mean protective capacity used in the post-hoc ANCOVAs was based upon the utilization from the preliminary simulation runs. So, the

PC for a replication was not based upon the work center utilizations observed in that specific replication. The differences between work centers could have been small or large. In systems where the work center utilization rates varied greatly, there might have been more opportunity for orders to flow quickly through work centers with low utilization, reducing both the mean flow time and variance of order flow times. Lower mean flow times would also affect mean lateness and mean tardiness. Similarly, reducing the standard deviation in order flow time could reduce the standard deviation in both order lateness and order tardiness. This would account for part of the effect size of the WC factor, which, as previously discussed, likely confounded the relationship between manufacturing performance and ISMC.

Additionally, in the simulated systems the interrarival time between orders was determined randomly using the exponential distribution. The random arrival rates represented dynamic complexity. While the exponential distribution is normally used for queuing studies, it probably has a much larger coefficient of variation (CV) than is found in practice. For example, Lawrence and Buss (1994), who based their simulation on observed arrival rates at a facility, used distributions whose CV ranged from 0.5 to 0.832. The CV of one used here may have been a dominant factor in affecting shop performance and may have hidden some effects of static complexity. To fully investigate these issues would require a new set of experiments.

Table 5.3. Summary of the Relationship of Complexity Factors to Performance

		Effect on Performance				
	Increased Complexity from	S_{FT}	L_{MEAN}	S_L	T_{MEAN}	S_T
P	Number of End-products (P)	Decreased	Increased	Increased	Increased	Increased
D	Depth of Product Structures (D)	Increased	Increased	Increased	Increased	Increased
B	Breadth of Product Structures (B)	Increased	Increased	Increased	Increased	Increased
CC	Component Commonality (CC)	N.S.	N.S.	N.S.	N.S.	N.S.
PMR	Product Mix Ratio (PMR)	Decreased	Increased	Increased	Increased	Increased
OPS	Number of Routing Steps (OPS)	N.S.	N.S.	N.S.	N.S.	N.S.
WC	Number of Work Centers (WC)	Decreased	Decreased	Decreased	Decreased	Decreased
RC	Routing Commonality (RC)	Decreased	Decreased	Decreased	Decreased	Decreased

N.S. – not statistically significant

These findings regarding the individual factors also lend support to the empirical results of Bozarth and Edwards (1997), Anderson (1995), and Foster and Gupta (1990), that a larger product mix negatively affects manufacturing performance. With one exception, as the number of end-products (P) in a system increased, performance decreased. The lone exception was the standard deviation of flow time. In this case, as the number of end-products in a system increased, the standard deviation of flow time also increased, meaning the predictability of order flow times was worse.

For the next two factors, the results showed that as the depth of product structures (D) or the breadth of product structures (B) increased, manufacturing performance universally worsened. The conclusions regarding depth and breadth of the product structure confirms implicit findings from Benton and Srivastava (1985; 1993) and Sum et al. (1993).

The complexity factor measuring component commonality (CC) was not statistically significant. Past research has indicated that commonality of components should positively affect performance. However, prior research tended to focus on the effect of component commonality on inventory, e.g. Collier (1981; 1982) and Baker (1985; 1986). No study investigated the impact of component commonality on performance using any of the five performance measure in this study. Although, one of the conclusions from Baker (1985) is that service level may be negatively affected by commonality of parts shared among end-products.

Although this study did not show an effect of component commonality on performance, component commonality may affect performance in other ways. For example, manufacturing operations employing a make-to-stock strategy often seek to utilize resources more efficiently by implementing a manufacturing planning system like MRP (materials requirements planning). An MRP system is used to reduce the complexity due to many of the issues previously identified, e.g. customer orders, number of end –products, and number of components. Component commonality may help to reduce the number of manufacturing orders required to be processed, and, thus, reduce the time consumed by changeovers. Or, a firm may desire to reduce the inventory of manufactured components as a tactic to reduce cost. In this case, having increased amounts of component commonality may help decrease inventory.

The results for the next factor, the product mix ratio (PMR), are similar to those for the number of products. With the exception of the standard deviation of flow time, systems having one dominant end product tended to perform better than systems not having a single dominant product. This supports the untested proposition of Kotha and Orne (1989).

Contrary to the suppositions of Frizelle and Woodcock (1995) and Deshmukh et al. (1998), systems with more work centers had better performance than systems with fewer work centers. If the work center results from this research are valid, they may explain in part the failure of Frizelle and Woodcock's measure, H, to reliably predict performance. H is an entropic measure that incorporated the number of resources, which, was represented by the number of work centers in this study. Increases in the number or work centers would increase H, yet in the experiments conducted in this study, system performance improved.

In the initial analysis, this researcher's supposition that the number of routing steps (OPS) in the routings of all manufactured items would affect performance was not supported. Another finding regarding routings was that systems that had some degree of routing commonality performed worse than systems with no routing commonality. This is contrary to the past research of Monahan and Smunt (1999). They found that systems with higher degrees of routing commonality outperformed systems with no routing commonality. The difference between this study and that of Monahan and Smunt is that a smaller proportion of routings were common in the current research than in the former. It is interesting to note that Monahan and Smunt did find a situation where systems having random routings had lower mean flow times than systems with high routing commonality. So, the results of both studies support for the need for more research into the effect of routing commonality under a variety of environmental conditions.

The post-hoc tests sought to evaluate the effect of due date tightness and the amount of protective capacity. As anticipated, systems with tight due dates performed worse than those with loose due dates. This was demonstrated for the performance measures involving the performance to order due date. The only exception was the standard deviation of flow time, which is a measure that is not based on the due date.

Controlling for differences in the amount of protective capacity between systems helped to eliminate some of the "noise" in the analysis. The results show that, for the five performance measures, protective capacity does explain a small portion of the changes in performance.

Additionally, the results show that the number of routing steps (OPS) was related to performance. Systems in which manufactured items encountered a greater number of routing steps tended to have worse performance than system with fewer routing steps.

More importantly, accounting for differences in protective capacity helped to clearly establish the relative importance of each factor. Table 5.4 presents the ranking of the importance of each of the significant factors for the five performance measures based upon the post-hoc tests. The rankings are based upon the effect size obtained in the statistical analysis (reported parenthetically).

Table 5.4 Ranking of Factors by Performance Measure and Effect Sizes

	Performance Measure				
Rank	S_{FT}	L_{Mean}	S_L	T_{Mean}	S_T
1	D (0.291)	B (0.171)	WC (0.177)	B (0.182)	B (0.188)
2	B (0.147)	WC (0.150)	B (0.174)	WC (0.161)	WC (0.174)
3	WC (0.144)	P (0.075)	D (0.132)	D (0.058)	D (0.114)
4	PMR (0.006)	D (0.035)	PMR (0.020)	P (0.053)	P (0.021)
5	OPS (0.006)	PMR (0.003)	P (0.008)	PMR (0.016)	PMR (0.008)
6	P (0.004)	OPS (0.002)	OPS (0.006)	OPS (0.004)	OPS (0.004)
7	-	RC (0.000)	-	RC (0.001)	RC (0.001)

Eta squared shown in parentheses

Predictability of Order Flow Time

The depth of the bill of materials for the end-products in a system has the greatest effect on the predictability of order flow times. Systems with deep product structures exhibited more variability than those with shallow product structures. This indicates the difficulty of having the required components simultaneously available to either start the parent item in production or to have all end-products completed for shipment of the full order to the customer. Each level in the product structure adds variability to the overall flow time for an end product. In these experiments, an order could not be shipped until all end-products were completed. So, the variability in order flow time was compounded by the variability in the end product flow times.

The breadth of product structure had the second largest impact on variability in flow times. More unpredictability was observed in systems with broad product structures than in those with narrow products structures. This also points out the difficulty of having the required components available simultaneously. The variability of the flow times for manufactured components at each level, combined with the variability in the flow time of end-products, created the overall variability in the flow time for an order. As the number items that must be synchronized increased, each having its own variability, the overall order variability increased. This means that order completion dates were less predictable.

The number of work centers had the third largest impact on the predictability of flow times. As with all of the performance measures, as the number of work centers increased, performance tended to improve. In this instance, improved performance means that flow times became more predictable. Implicit in the formulation of ISMC was the notion that systems with more work centers were more complex. It was hypothesized that system with more complexity would have poorer performance than those with less complexity. So, this result was not anticipated. After controlling for the differences in protective capacity, there is no clear reason to explain this unexpected relationship. Further, future investigation is necessary.

The other three elements, although statistically significant, did not appear to have a practical effect on the variability in order flow time. The number or end-products and the balance of the product mix (PMR) had little effect on the predictability of order flow times. Neither did the number of production steps in the routing for manufactured items exhibit much influence on variability of order flow times.

<u>Order Lateness</u>

Both mean order lateness and the predictability of order lateness were strongly influenced by the breadth of the product structures of a system's end-products. Systems with broad structures tended to have orders completing farther past their due date than systems with narrow product structures. This finding indicates, similar to that for flow times, that the greater the need to having simultaneous arrivals of items, either for the release of the parent item or the completion of an order for shipment, the greater the opportunity was for the entire order to be delayed past its due date. At the same time the variability in order lateness increased for systems with broad product structures compared to those with narrow structures. This implies that the delay of the completion of manufacturing orders and, thus, customer orders, became less consistent when a greater number of manufacturing orders was being processed simultaneously in order to fulfill another customer order. There was likely a large, sudden demand of system capacity from all the components and subcomponents required by the end-products, which increases the opportunity for bottlenecking and longer queue times that, in turn, affected both the overall system order lateness and the variability in the amount of order lateness. This appears to have been a byproduct of the variability observed in order flow time.

The number of work centers in a system highly influenced both lateness performance measures. As shown in Table 5.2, the mean order lateness and the variability in order lateness improved for systems with more work centers. Even after adjusting for the effect of protective capacity. This may indicate that the "flood" of work required to complete a customer order was spread among the many work centers, reducing the opportunity for long queues, thus giving manufacturing orders more opportunity to finish early than when system have fewer work centers. Not only that, since having more work centers also reduced variability in flow times, it also reduced the variability in order lateness as was observed in the results from the experiments.

The depth of the bill of materials also had an impact on the two performance measures pertaining to order lateness. For both, systems with deep product structures performed poorer than systems with shallow structures. However, the depth of the product structure had a much larger effect on the predictability of order lateness, than mean order lateness. This seems to indicate that the length of the "chain of dependencies" affected the variability in the flow time for end-products, and thus customer orders, which, in turn, affected the variability in order lateness. The greater the sequence of dependent items in a product structure, the greater the variability in order flow time. This led to greater variability in order lateness.

The depth of the product structures in a system, however, had less affect on mean order lateness. This indicates that a greater number of dependencies increased variability, but, to a much lesser extent, increased order lateness. Perhaps, when the product structures were deep, there was more opportunity for components to "catch up" and recover from being delayed. The use of the earliest due date priority rule in the simulation may have enabled this "catching up" to occur.

The product variety offered by a system also had a sizeable effect on mean order lateness. It had no practical effect on the variability in order lateness. The results showed that systems with more end-products tended to be completed longer after their due date than systems with fewer end-products. This seems to indicate that the “flood” of manufacturing orders released to support the increased number of products added a *consistent* additional load to the shop, resulting in longer completion times, thus, increased mean order lateness. Because the additional load is consistent, the product variety had little effect on the variability in order lateness.

<u>Order Tardiness</u>

The breadth of a system’s product structures had the largest impact on order tardiness, both mean tardiness and variability in tardiness. Systems with broad product structures had greater tardiness and less predictability in tardiness. This is consistent with the findings regarding order flow times and order lateness. Since mean order lateness was always positive, this indicates that orders were generally completed longer after their due dates than before. Since tardiness is only concerned with orders past their due date, an increase in mean order tardiness corresponded to the increase in mean order lateness. This is supported by the high degree of correlation observed between these two performance measures reported in Chapter IV. So the same conclusion regarding the effect that the breadth of products structures had on order lateness applies to order tardiness. It appears that the greater the need to having simultaneous arrivals of items either to begin a manufacturing order for the parent item or to complete a customer order for shipment, the greater the opportunity was for the entire order to be delayed past its due date. The likely “flood” of manufacturing orders demanding system capacity increased with a broader set of product structures, so that there is a greater opportunity for bottlenecking. This affected both the overall system order lateness and the variability in the amount of order lateness. Again, this is mostly likely a byproduct of the variability observed in order flow time.

The number of work centers in a system had a similar influence on the measures of order tardiness. The mean order tardiness and the variability in order tardiness tended to be less for systems with more work centers than for those with fewer. That was the reverse of what was expected. It appears that, after controlling for the affect of protective capacity, the "flood" of work required to complete a customer order was distributed among a greater number work centers, thus reducing the opportunity for delays due to long queues. This, in turn, permitted the manufacturing orders more opportunity to finish earlier than in systems having fewer work centers. This helped to reduce order tardiness. Also, since having more work centers reduced variability in flow times, it thereby reduced the variability in order tardiness as observed in the results from the experiments.

Based upon the previous discussion, it is not surprising that the influence that the depth of a system's product structures had on the tardiness measures is similar to that observed for the measures of lateness. Systems with deeper product structures tended to have greater mean order tardiness and greater variability in order tardiness. Again, the logic will be the same as for lateness. This suggests that the longer the "chains of dependencies" the greater the variability in the flow time for end-products which, in turn, also affects the variability in order tardiness. Because the depth of the product structures in a system had less affect on mean order tardiness, although it a greater number of dependencies increased variability, it increased order tardiness to a much lesser extent. As previously suggested when the product structures were deep, there might have been more opportunity for components to recover from being delayed. This was especially likely as a result of using of the earliest due date priority sequencing rule.

The product variety offered by a system had a sizeable, but smaller effect on the tardiness measures than the three previous factors. Systems with more end-products were apt to have higher mean order tardiness and greater order variability. This is consistent with what was observed for the measures order lateness. The results showed that orders in systems with more end-products tended to be completed longer after their due date than systems with fewer end-products. This seems to indicate that there the "flood" of manufacturing orders released to support the increased number of end-products, which increased the capacity load to the shop. This resulted in longer completion times, thus, increased mean order tardiness.

The amount of product variety had a much smaller influence on the variability in order tardiness than it had on mean order lateness. This is similar to what was observed with mean order lateness. Its observed affect, although statistically significant, has marginal practical significance. The effect of the "flood" of work released to support a greater number of end-products, i.e. more component manufacturing orders, was fairly consistent. This extra load increased variation in order tardiness marginally.

In the discussion of the effect of the complexity factors on performance, there were cases where the factors did not have the anticipated effect on performance. When PMR and P were at their high complexity setting, the order flow time became more predictable, meaning performance improved when complexity increased. Although statistically significant differences were found, the effect size of each factor was marginal. As shown in Table 5.4, PMR and P explained less than 1% of the variation in the standard deviation of flow time, which means that they do not have a practically significant effect on the standard deviation of flow times.

As previously noted, the findings regarding the complexity factor measuring routing commonality (RC) consistently indicated that systems with no routing commonality, hence more complexity, resulted in better performance for three of five measures of manufacturing performance. This was the opposite of what was expected. For the other two performance measures, RC was not statistically significant. Even though the findings were opposite of what was anticipated, the effect sizes were minute, explaining less than 0.2% of the variation in performance. Therefore RC cannot be considered to be a practically significant element for measuring internal static manufacturing complexity.

The factor having the most surprising results was WC, which accounted for the complexity due to the number of work centers in a manufacturing system. For all five measures of manufacturing performance, those systems with more work centers had better performance than systems with fewer work centers. Systems with more work centers were expected to be more complex, and correspondingly have worse performance.

There are three possible reasons (at least) for the unanticipated results for this factor. The first is due to the design of the simulated systems. The planned creation of routings for all manufactured items in a system could not control for the variation in the utilization rates of work centers. Large differences in work center utilization could lead to improved performance. The details of the potential impact of the differences in work loads between work centers have previously been discussed. This effect of the utilization differences could be reflected in the results observed for WC.

The second possible explanation for the unexpected outcome that having more work centers led to improved performance was how set-up time was modeled in the simulation. When two manufacturing orders for the same items requiring the same routing step were processed consecutively, no machine set-up was required for the second order. This models real systems. This was also the basis for believing component commonality would affect performance. Because work centers were randomly assigned to routing steps, systems with more work centers had a narrower set of items assigned to them. This may have permitted a greater opportunity for processing orders for the same item sequentially, thus reducing order flow times for some orders, which in turn reduce mean order lateness and tardiness.

The third possible reason for the observed effect of WC is due to the dispatch rule used in the simulation experiments. When prioritizing manufacturing orders that were waiting to be processed at a work center, priority was given to the manufacturing order having the earliest order due date. Systems with fewer work centers might have longer queues. Fewer work centers also meant that there was greater opportunity for a routing to require an item to have multiple, non-sequential routing steps assigned to that same work center. This may have increased the opportunity for reprioritization of manufacturing orders which increased the queue time of more manufacturing orders, thus increasing mean and variability of order flow times, lateness, and tardiness.

Some reasons supporting the negative impact of greater number of work centers may have to do with factors not included in the simulation model. For example, more work centers increases the amount of internal transportation required to move manufacturing orders for one work center to the next. This could cause delays in the overall flow of products.

Based upon this researcher's personal experience, the number of work centers may affect dynamic complexity more than static complexity. In actual shops, the operations that had more work centers employed more supervisors or work center coordinators (lead persons) to manage the increased complexity. With more work centers there is more opportunity for human error. This can mean more quality rejects, transporting materials to the wrong work center, or other issues associated with having to make a greater number of decision. All of these would result in decreased performance. It may be more appropriate to model WC as part of dynamic complexity, which was not part of this study.

Comparison of ISMC to H

The third research hypothesis compared the predictive validity of ISMC to that of H, the static manufacturing measure proposed by Frizelle and Woodcock (1995). To date, their measure has not been tested. Frizelle and Woodcock (1995) and Calinescu et al. (1998) only present examples of calculations along with anecdotal evidence to support the validity of H. The hypothesis was not formally tested, however the conclusion was that ISMC was not superior to H, nor was H superior to ISMC. The findings were that, like ISMC, H is not a good measure of internal static manufacturing complexity. It was not a reliable predictor of manufacturing performance. In fact, it tended to predict performance opposite of how Frizelle and Woodcock (1995) supposed. They purported that systems with greater static complexity, H, would not perform better than systems with lower static complexity.

Alternative formulations for ISMC

Three alternative revised formulations for ISMC were proposed and tested in Chapter IV. These formulations were developed utilizing the three of the four complexity factors with the greatest correlations to the five performance measures. These were P, the number of end-products, D, the depth of products structures, and B, the breath of products structures. The factor, WC, was excluded at this time. A post hoc examination of WC was not possible using the data from these experiments.

The three alternative formulations for ISMC that were proposed were simple combinations of the three factors that explained sizeable proportions of the variation in performance for the five individual performance measures. The combinations were designed to (1) explore the interactions between the three factors and (2) to be easy to understand intuitively.

Of these three alternatives, the two proposed in equations (18) and (18) demonstrated reliability. For these formulations, as ISMC increased, overall manufacturing performance worsened. Even given the limited set of values for each, they explained over 10% of the variation in overall manufacturing performance. Equation (18) performed marginally better than equation (18). Both suggest that there are interaction effects between the three factors. In fact, equation (18) resulted from the observed significant interactions between (1) the number of products and the product structure depth and (2) the product structure depth and breadth.

However neither performed much better than simply using a single factor, the product structure breadth, B. It explained the same amount of variation in manufacturing performance.

These results should be viewed cautiously. The intent of this study was not to find a single factor to use to describe complexity. This was exploratory research. More levels of each factor would be necessary to better measure the performance of each as a measure of complexity. The same must be said for the alternatives proposed in equations (18) and (18). The values for ISMC should make it a continuous variable. This study's experiments were not designed to test these alternate formulations for ISMC. Less than five different values for the revised formulations of ISMC resulted using the existing experimental design. Because the set of values was so limited, the post hoc analysis conducted considered ISMC a categorical variable, not a continuous variable. A larger range of continuous values is needed to fully test these versions. So, at this point, the results are positive, but not conclusive regarding their performance as measures of internal static manufacturing complexity.

A composite measure of complexity, even if only marginally better than using a single factor, may still be preferable to use. Managers may like to see the relevant factors that increase or decrease system complexity combined into one measure. Using a simple composite measure utilizing these factors will help them evaluate how their decisions change the internal static complexity in their facility.

Implications for Practice

Although six of eight of the individual complexity factors were statistically significant, not all six appear to be important to practicing operations managers. There are three factors to consider when evaluating decisions involving design of a manufacturing system. These are the number of end-products manufactured (i.e. product mix), the depth of product structures, and the breadth of product structures.

When making decisions regarding expanding product offerings, managers should consider the consequential impact on performance. If no supplementary effort is added to manage the increased complexity, performance will likely worsen. The additional management effort required to maintain current performance levels while expanding the product line will increase manufacturing costs.

The level of vertical integration should also be carefully considered. The findings of this study show that the depth of the products structure affects the predictability of outcomes in a manufacturing system. Even when the in-house cost to make components is lower than the cost to purchase the components, managers must account for the overall impact to performance. This study's findings suggest that systems with deeper product structures have less predictability in performance than systems with shallow product structures, i.e. having less vertical integration. When increasing the amount of vertical integration, additional process management will be necessary to counter the unpredictability that would result, resulting in increased operating costs.

Lastly, understanding the breadth of the product structures in a manufacturing system is important. Product design efforts to combine individual purchased components into a single module would benefit a firm. The breadth of product structures was the factor having the largest affect on every measure of manufacturing performance in this study. Reducing the breadth of product structures would help to improve performance to customer deliveries, reduce finished goods inventories and make completion dates more predictable.

Limitations of this Study

This study was designed to explore a possible method of quantifying internal static manufacturing complexity. In an effort construct such a measure, several individual factors were identified. The anticipated relationship that each complexity factor had with manufacturing performance was tested by employing a set of simulation experiments. The range of manufacturing environments was limited to what could be practically evaluated in a single study. Caution should be used when interpreting the results, because they are not readily generalizable to all manufacturing environments.

These simulation environments used the exponential distribution for the arrival rate of orders. This is typical for such simulations (e.g. Fry et al., 1989; Russell and Taylor, 1985) because it is a simple distribution that was used in simple theoretical queuing systems (Law and Kelton, 2000). However, the exponential distribution used in the 1980's may no longer be appropriate in current production literature. Successful companies have moved far away from the extremely random environments represented by the exponential. Future studies should consider using distributions with much lower variability and no infinite tails. Having used the exponential distribution to generate the time between order arrivals in this study may have created such a large variation hat the effects of static complexity could not be detected. This could mean one of two things.

First, the complexity factors identified could have a larger effect than resulted from these experiments. Alternatively, the results suggest that it may be the external dynamic complexity arising from the unpredictability in demand that affects performance more than the static complexity.

One specific limitation was that the type of manufacturing system in the experiments was confined to batch-type systems where random routing of products and components was feasible. There are many other types of systems ranging from job shop to assembly line production and all possible hybrids.

Another limitation was that only two levels of each factor were included in the study. This study was considered exploratory, so the minimum levels of a broad range of factors was incorporated. Many existing systems handle far more than five end-products, which was the high level in this study. At the same time, it might be equally questionable that many systems would have five levels of depth in their product structures.

Future Research

This was an exploratory study of elements considered a part of internal static manufacturing complexity. As such, there are many possible areas for further research. This study limited its scope to static complexity. A likely step would be to extend it by investigating dynamic complexity factors, e.g. control systems, decision-making of managers, equipment breakdown, and maintenance plans.

Before attempting to reformulate ISMC, an investigation is needed into the effect observed for the factor WC, the number of work centers. Others, beside this author, have purported that systems with more work centers are more complex, thus they should have experienced decreased performance. The opposite was observed in this study. This may have been due to the type of system simulated or some combination of system parameters. This factor should be investigated in other experimental environments to better understand its effects before deciding how to include it in ISMC.

Suggestions for investigating WC would include a new set of simulation experiments that have a greater range in the number of work centers between low and high settings. Additionally, more factor levels should be included. This research showed that the difference in work center utilization is important, so these differences must be carefully controlled. One method to control these is to run preliminary simulations to observe the utilization differences. Item processing times could be adjusted proportionally to increase or decrease work center utilizations so differences are no so extreme.

These experiments could be conducted in a manufacturing system similar to the design considered in this research – a batch system with random (predetermined) routings. However, additional types of systems should also be examined in the future. Batch system with less "random" routings may better reflect real systems. Or hybrid systems that have both a job shop and assembly shop set of operations (Fry et al., 1988) or ones that have a gateway and finishing work center (Barman and LaForge, 1998).

The proposed measure of internal static manufacturing complexity contained a combination of eight individual complexity factors identified from previous research. (These eight factors were used to operationalize the three components of internal static manufacturing complexity – product line complexity, product structure complexity and process complexity.) The proposed measured, ISMC, did not demonstrate predictive validity. ISMC explained little variation in manufacturing performance. Additionally, there were situations where ISMC predicted performance opposite of what was expected. The reasons for the unreliability of ISMC have only partially been explained.

The analysis of the eight individual complexity factors revealed that these factors, after accounting for due date tightness and mean protective capacity, explained approximately 35% of the variation in manufacturing performance. However, four of these factors were either not statistically or practically significant. One of the factors that explained a sizeable portion of the variation in performance was the number of work centers. However, this factor's effects were counterintuitive. Further study is suggested to better understand this factor.

The remaining three factors, in the ANCOVA model, explained approximately 17% of the variation in performance when the interactions were not considered, and 20% when the interactions effects were included. Based upon these results, three alternative reformulations for ISMC were proposed and tested. Although, due to the limited range of the values for ISMC, the results cannot be considered conclusive, any one of the three alternative measures only explained approximately 10% of the variation in performance. This was no better than utilizing a single complexity factor – the breadth of the product structures.

Over 40% of the variation in manufacturing performance was left unexplained. There are either other elements of internal static manufacturing complexity that have not been identified in past literature, or the dynamic complexity elements of this simulation explain the difference. But, it is not likely that a complexity element explaining such a large portion of performance has been missed.

However, the dynamic attributes of the simulations could have had a large effect. Recall, the interarrival time between orders occurred randomly based upon the exponential distribution. Additionally, the order quantity for each end-product was also varied to better model a real system. These two dynamic variables might have confounded the observed effects of the complexity factors. Recall, past literature did purport that environmental dynamicism due to demand variation was part of manufacturing complexity (Kotha and Orne, 1989; Calinescu et al., 1998; and Khurana, 1999). If this was the case, further research should remove these dynamic factors in order to better study the static complexity factors. In this case, a mathematical analytic approach would be needed instead of simulation research since there would no longer be a stochastic element in the systems studied.

However, if these two dynamic factors did mask the effects of the static complexity factors, this indicates that dynamic complexity may play a substantially larger role in determining system performance. Or, by eliminating most of the internal dynamic complexity from the simulation, the effects of these factors were reduced. It may be that internal static and dynamic manufacturing complexity cannot be analyzed separately. The elements of internal manufacturing complexity, both static and dynamic, may be interrelated, e.g. the effect of the depth of product structures depends upon the amount of quality defects that are scrapped or reworked. The effects due to the interrelationships that occur within a system follows Casti's (1979) thought that complex systems have a complicated structure and unpredictable behavior. This suggests that manufacturing complexity research should include both sets of elements in future research.

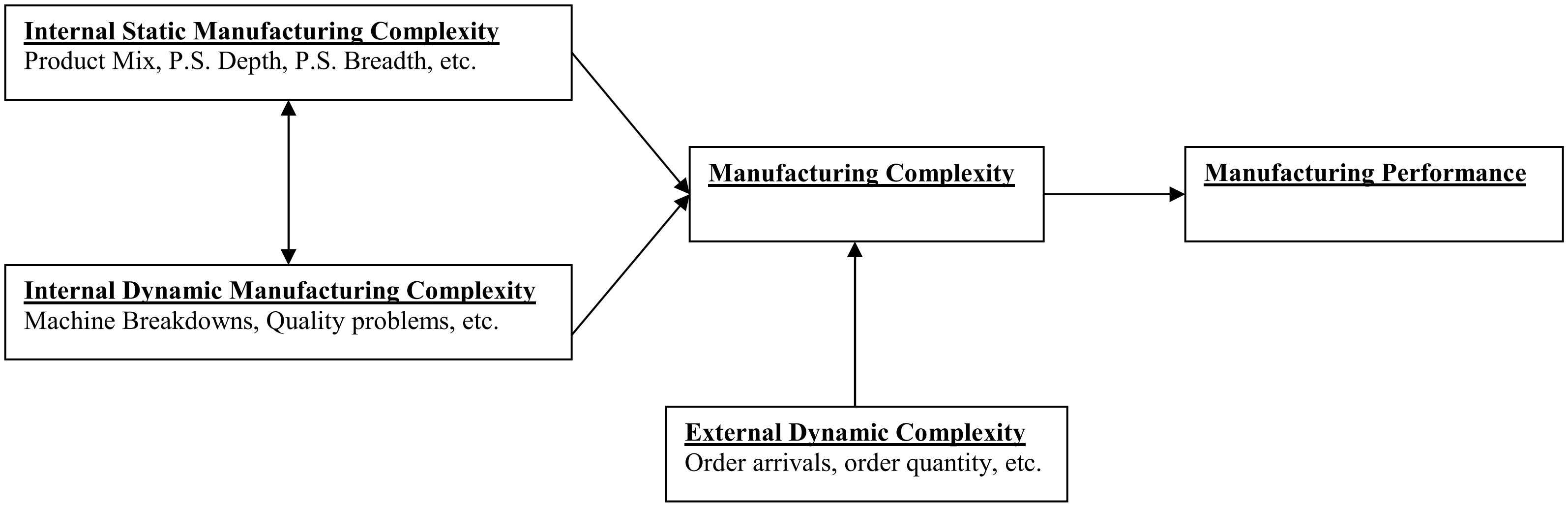


Figure 5.1 The Revised Theoretical Model for Measuring the Effects of Manufacturing Complexity on Manufacturing Performance

Figure 5.1 presents a revised theoretical model for manufacturing complexity. Static and dynamic complexity elements are now presumed to interact, so they should be studied simultaneously. Managers make decisions regarding static system design elements as well as dynamic system design. For example, managers can implement programs that reduce quality defects, reduce machine breakdowns, etc. External events also affect a manufacturing system and add complexity to it. The resulting total manufacturing complexity affects manufacturing performance.

Further research using this model would first require identification of the elements of dynamic manufacturing complexity. Then, testing of the static and dynamic elements can be performed using simulation research to explore the effects of these elements. Lastly, empirical research should be conducted to verify findings from the simulation research.

As far as quantifying manufacturing complexity, it may not be possible to formulate a measure of manufacturing complexity. The purposes of such a measure are (1) to help study other theories of management by being able to control for the effects of differences in complexity between systems, and (2) to provide a tool for managers to understand the effects that their decisions have on business performance. Further research can identify complexity elements and examine their effects. A single complexity measure, although attractive, may not adequately capture the true complexity of a system. According to Ashby (1972), the complexity of a system cannot be quantified simply by the components that make up the complex system. The "richness" of the interactions makes it too difficult to understand the complexity. As demonstrated in this research, a simple combination of static complexity factors did not explain much of the variation in manufacturing performance. Further attempts should be made for the previously identified reasons. However, it is recognized that even if a measure can be developed, it may not be practically deployable, that is, it may not be intuitive to users nor the data easily accessible.

APPENDICES

Appendix A

An Example of the ISMC Calculation

Two product structures from a fictitious manufacturing system are presented in Figure A.1. Using these product structures, the method of calculating the proposed measure for product structure complexity is demonstrated. The product structures presented in Figure A.1 have no component commonality. There are two end items and 15 manufactured components. The purchased items are also shown, but they are not considered in the calculations as discussed previously. For simplicity, assume the demand for each end product is 50 units. The product line complexity according to equation (9) is:

$$\text{Product Line Complexity} = \left(|E| + |C|\right) \times \left\{ 2 - \left[\frac{MAX(Q_i)}{\sum_1^e Q_i} - \left(\frac{1 - \frac{MAX(Q_i)}{\sum_1^e Q_i}}{|E| - 1} \right) \right] \right\}$$

$$= (2 + 15) \times \left\{ 2 - \left[\frac{50}{100} - \left(\frac{1 - \frac{50}{100}}{2 - 1} \right) \right] \right\}$$

$= 17 \text{ x } 2$

Product Line Complexity $= 34$

End-products E-1 and E-2 have four levels and three levels of manufactured items, respectively, representing the amount of vertical integration. E-1 has a product structure breadth of four, which is determined by counting the number of manufactured components at the lowest level of each branch of the product structure (C-31, C-22, C-23, and C-24). The breath of the product structure for E-2 is five (C-25, C-26, C-15, C-27, and C-17). There are no common components within or between the end-products; therefore, according to equation (11), the CCI is zero. Applying equation (10), the product structure (P.S.) complexity is:

$$\text{P.S. Complexity} = \frac{\sum_{i=1}^{e}(Q_i \times d_i)}{\sum_{i=1}^{e} Q_i} \times \frac{\sum_{i=1}^{e}(Q_i \times b_i)}{\sum_{i=1}^{e} Q_i} \times (2 - CCI)$$

= {[(50 x 4) + (50 x 3)]/100} x {[(50 x 4) + (50 x 5)]/100} x (2 - 0)

= 3.5 x 4.5 x 2

= 31.5

In order to demonstrate the calculation of the process complexity component of the proposed complexity measure, some additional information about the fictitious manufacturing system is required. Using the product structure in Figure A.1 and the previous end product demand of 50 units each, assume that the end-products have two routing steps, the level 1 items have five routing steps each, the level 2 items have six routing steps, and the level three item has four steps. Also, assume that there are 10 work centers in the manufacturing system. Lastly, assume that no two routings have an identical sequence of steps, i.e. no routing commonality. The resulting process complexity using equation (12) is:

$$\text{Process Complexity} = \frac{\sum_{i=1}^{e}\left[Q_i \times \frac{Steps(E_i) + \sum_{j}^{|C_i|} Steps(C_{ij})}{|C_i| + 1}\right]}{\sum_{i=1}^{e} Q_i} \times |WC| \times (2 - RC)$$

= {50 x (2 + 5 + 5 + 5 + 6 + 6 + 6 + 6 + 4)/(8 + 1)]

+ 50 x (2 + 5 + 5 + 5 + 5 + 6 + 6 + 6)/(7 + 1)]}/100

x 10 x (2 – 0)

= {[50 x (45/9)] + [50 x (40/8)]}/100 x 10 x 2

= 5 x 10 x 2

Process Complexity = 100

The total ISMC for this scenario is the combination of the three components:

ISMC = Product Line Complexity x (P.S. Complexity + Process Complexity)

= 34 x (31.5 + 100)

ISMC = 4,471

Now, let's examine the impact of component commonality on the calculation. Figure A.2 shows the revised product structures for the two fictitious end-products. E-2 has been redesigned, replacing manufactured component C-16 with component C-21. In this scenario manufactured component C-31 also becomes "common" to E-2.

The CCI is calculated first using equation (11).

CCI = 1- [(13-1)/(16-1)] = 1 – 0.857 = 0.143

Now the product structure complexity component is calculated as follows:

P.S. Complexity = {[(50 x 4) + (50 x 3)]/100} x {[(50 x 4) + (50 x 6)]/100} x (2 - **0.143**)

= 3.5 x 4.5 x **1.857**

= 29.25

The product line complexity component is also affected by component commonality. There are two less manufactured components is the system. Therefore, the product line complexity component is now:

$$= (2+13) \times \left\{ 2 - \left[\frac{50}{100} - \left(\frac{1 - \frac{50}{100}}{2-1} \right) \right] \right\}$$

=15 x 2

Product Line Complexity = 30

The total ISMC is now:

ISMC = 30 x (29.5 + 100)

ISMC = 3,885

This is 586 points lower than the scenario where there was no component commonality.

Another example occurs where management has decided to outsource all manufactured components. Figure A.3 represents the product structures for this final scenario. The manufacturing system is redesigned to strictly to assembly end-products E-1 and E-2. The number of levels and the breadth of the products structure are reduced to one for both E-1 and E-2, meaning that the system is only assembling the end-products. The new value of Product Structure complexity is:

P.S. Complexity = {[(50 x **1**) + (50 x **1**)]/100} x {[(50 x **1**) + (50 x **1**)]/100} x (2 - 0)

= 1 x 1 x 2

P.S. Complexity = 2

The product line complexity component is now:

$$= (2+0)\times\left\{2-\left[\frac{50}{100}-\left(\frac{1-\frac{50}{100}}{2-1}\right)\right]\right\}$$

=2 x 2

Product Line Complexity = 4

The process complexity component is:

= {50 x (2)/(0 + 1)] + 50 x (2)/(0 + 1)]}/100 x 10 x (2 – 0)

= {[50 x (2/1)] + [50 x (2/1)]}/100 x 10 x 2

= 2 x 10 x 2

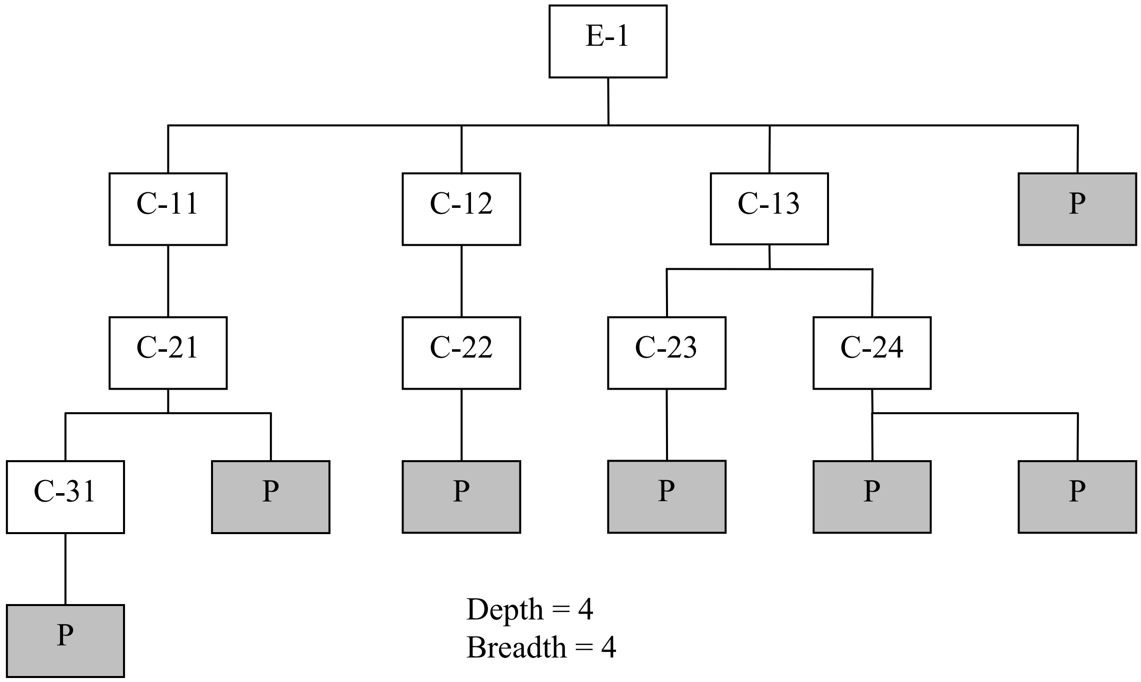
Process Complexity = 40

The total ISMC is now:

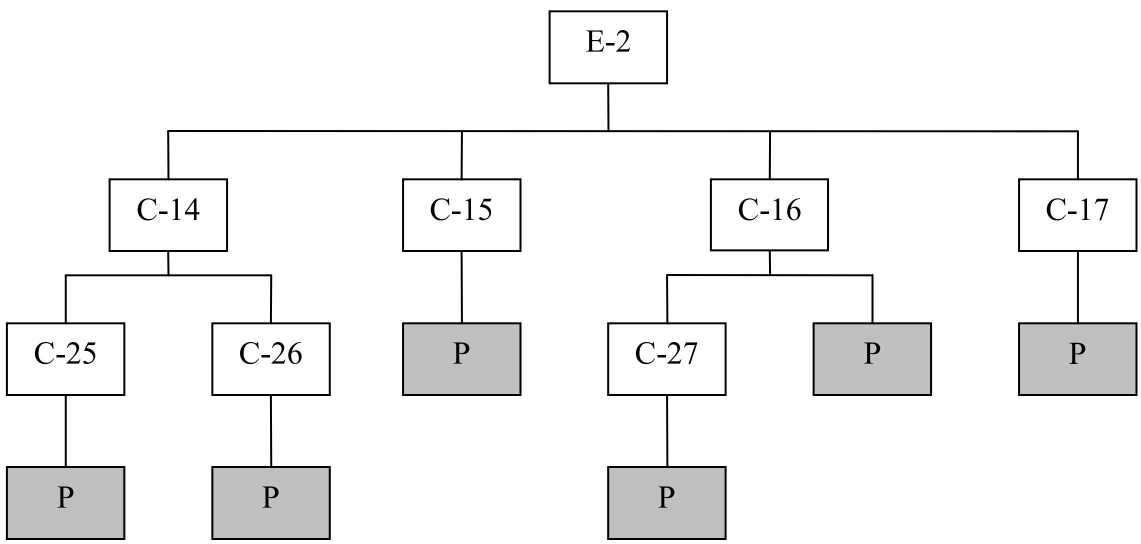
ISMC = 4 x (2 + 40)

ISMC = 84

This is drastically lower than either of the two previous scenarios where vertical integration was present. Here, the proposed measure is indicating that there is much less complexity due to no longer being required to coordinate system resources to manufacture the internally supplied components.

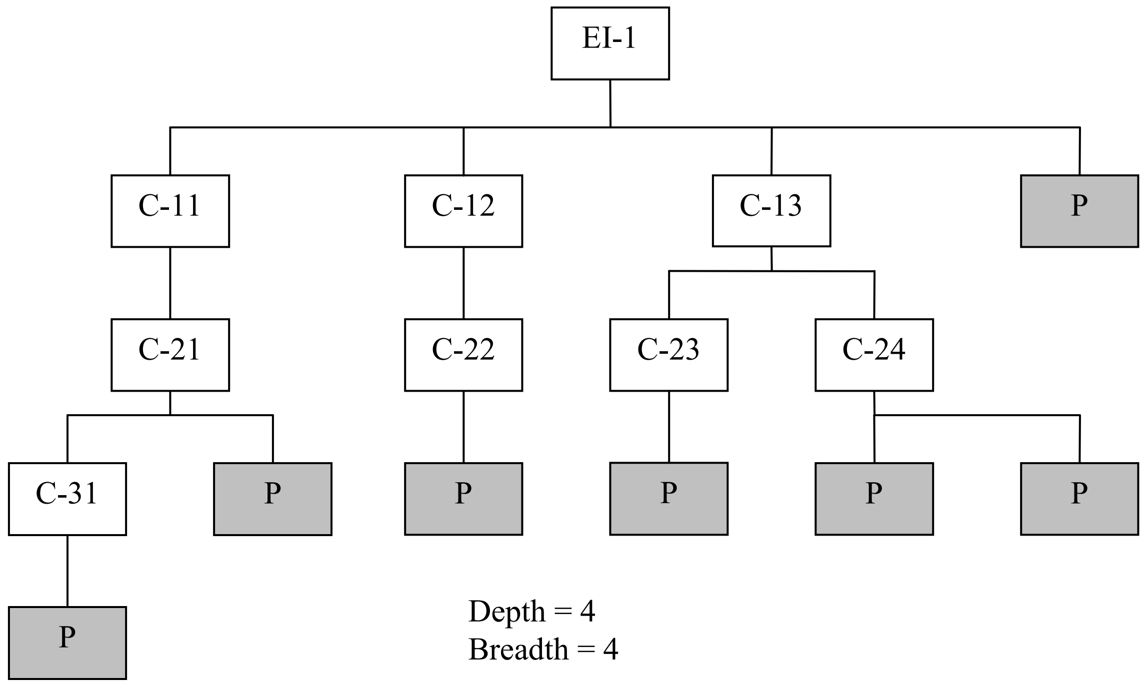


Depth = 4
Breadth = 4

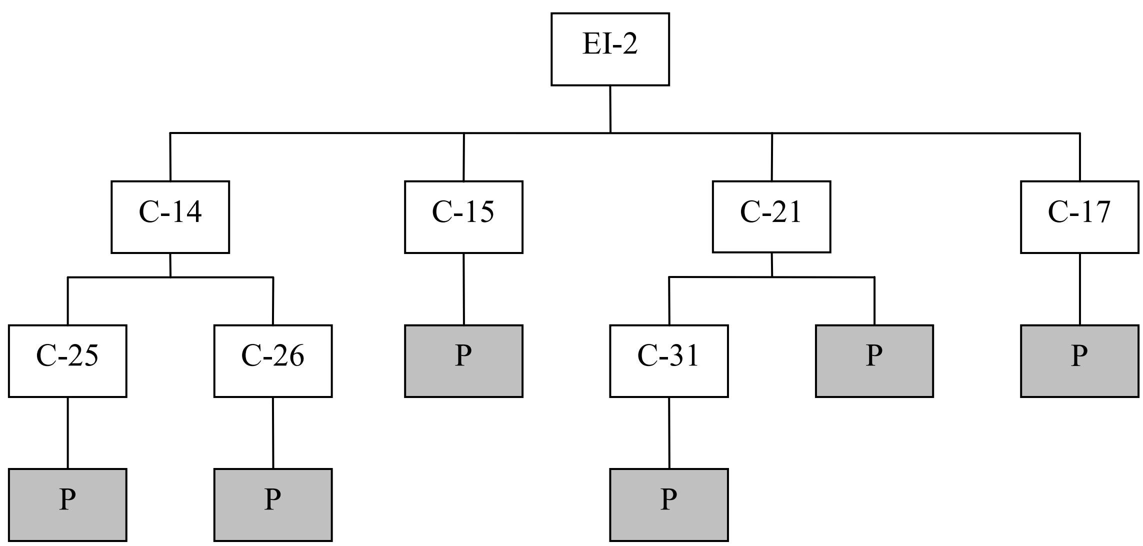


Depth = 3
Breadth = 5

Figure A.1 Product Structures – No Component Commonality

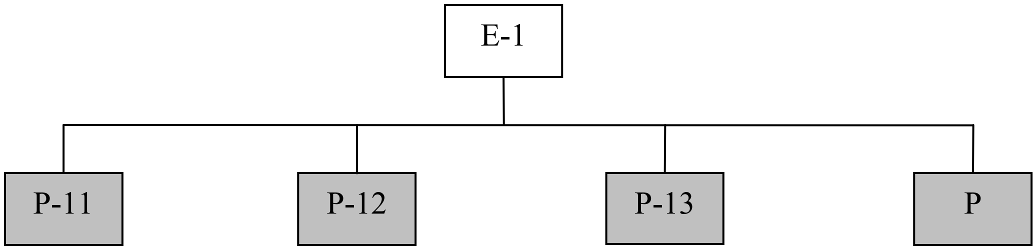


Depth = 4
Breadth = 4

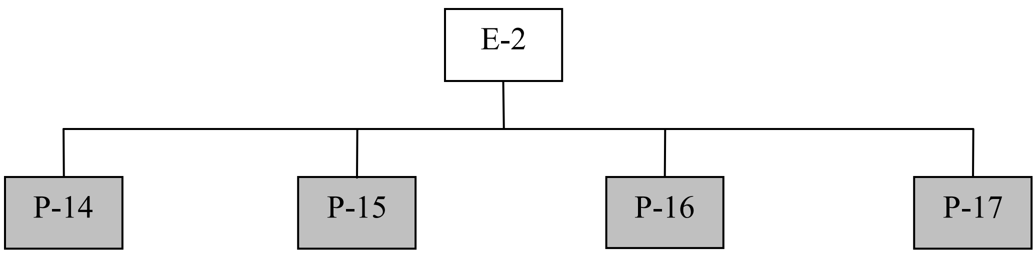


Depth = 4
Breadth = 5

Figure A.2 Product Structures with Component Commonality



Depth = 1
Breadth = 1



Depth = 1
Breadth = 1

Figure A.3 Product Structures with Outsourced Components

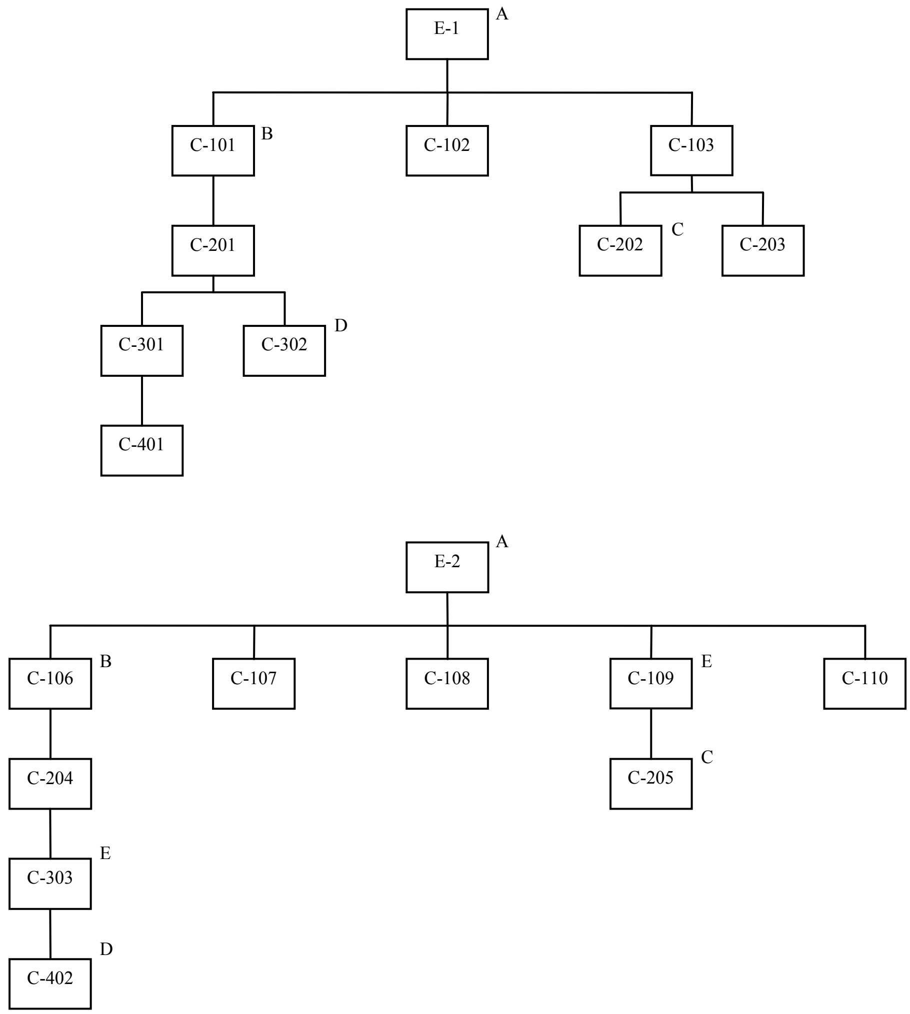
Appendix B

Product Structures used in the Experiment

Found in this appendix are eight sets of product structures used in the research experiments. All items are "manufactured items", meaning they are items that are fabricated or assembled. No purchased items appear on the product structures. Items containing the prefix of "E" are the end-products. The prefix "C" denotes items that are the manufactured components.

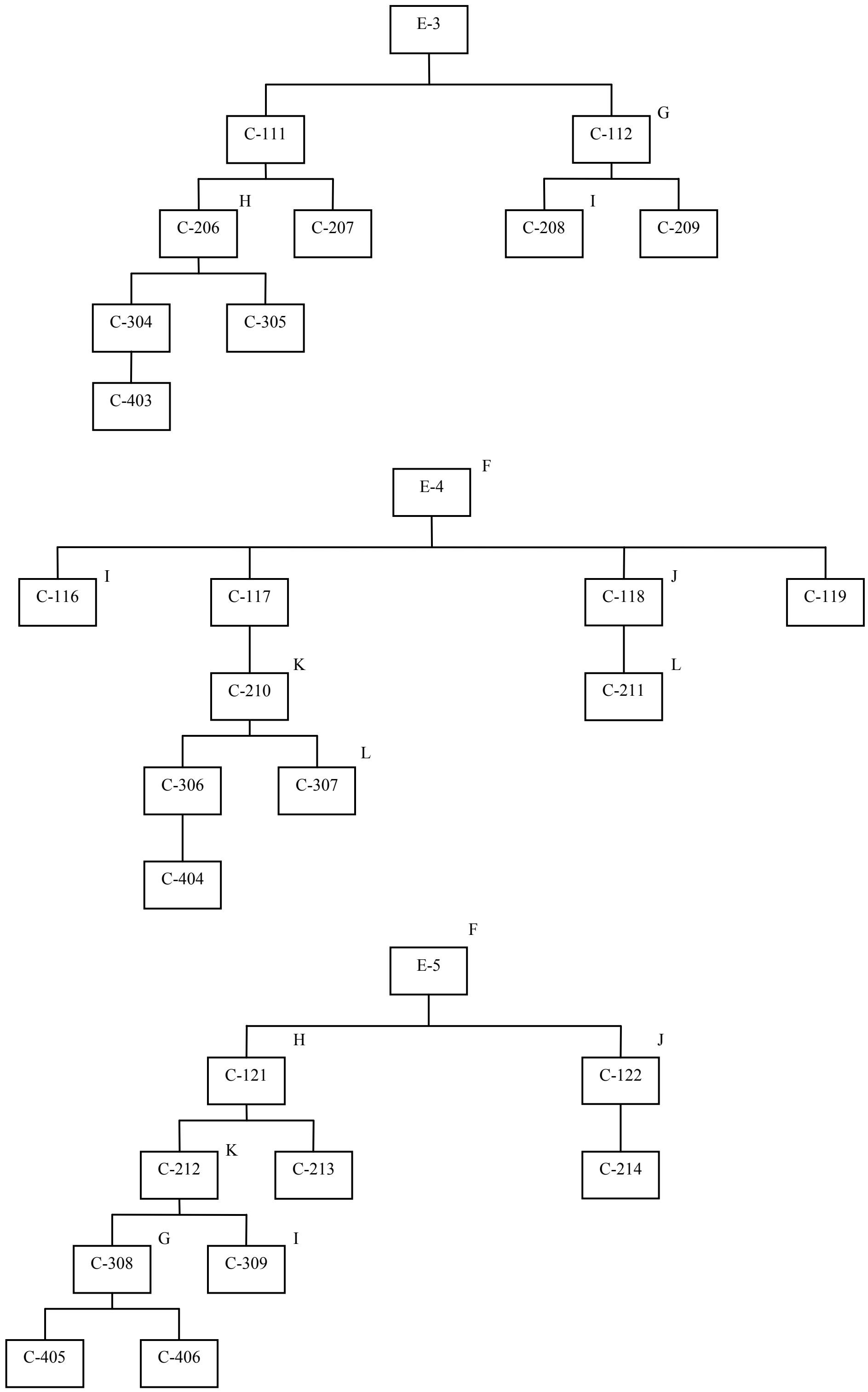
The first four figures, B.1 through B.4, are product structures in which there is no component commonality. Figures B.5 through B.8 are the revised product structures that include component commonality within and between end-products.

In all eight figures, the superscript capital letter indicates items with routing commonality when the experiment was designated to have routing commonality. When the experiment was to not have routing commonality, then not routings were made identical and these superscripts have no meaning.



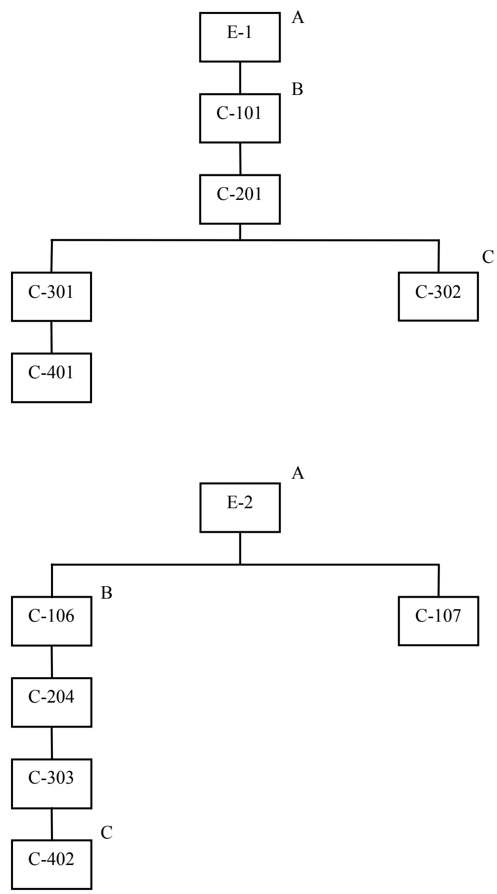
Letters denote items with “common” routings when Routing Commonality=High

Figure B.1 Product Structures with experimental settings of Depth=High, Breadth=High, Component Commonality = Low



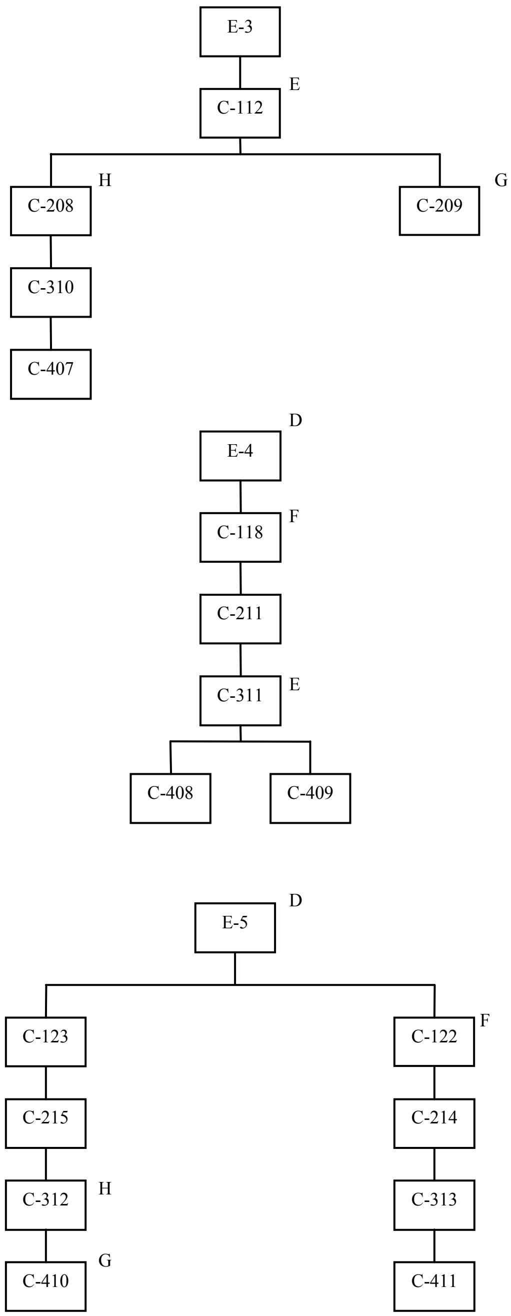
Letters denote items with “common” routings when Routing Commonality=High

Figure B.1 Product Structures with experimental settings of Depth =High, Breadth =High, Component Commonality = Low (Continued)



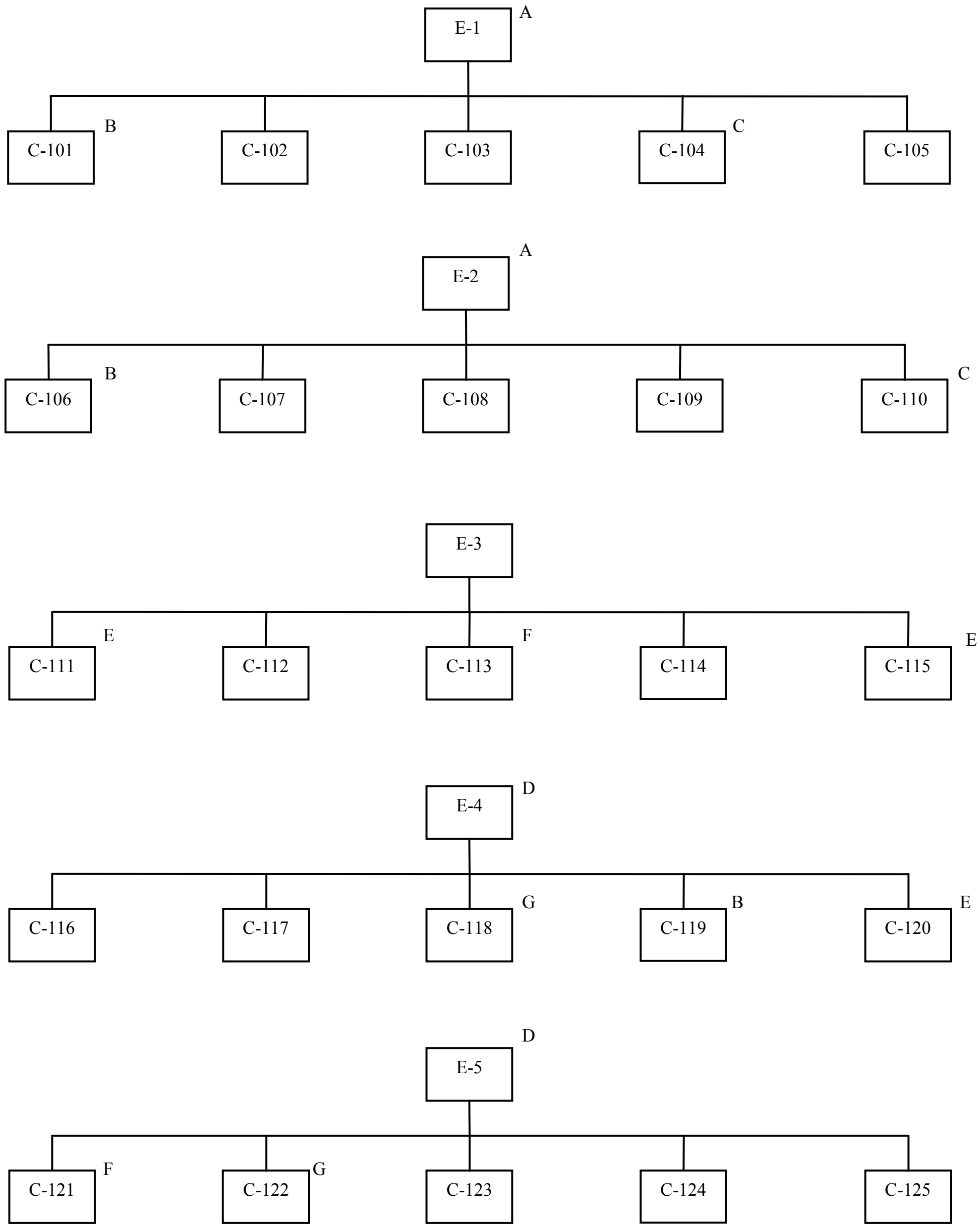
Letters denote items with “common” routings when Routing Commonality=High

Figure B.2 Product Structures with experimental settings of Depth =High, Breadth =Low, Component Commonality = Low



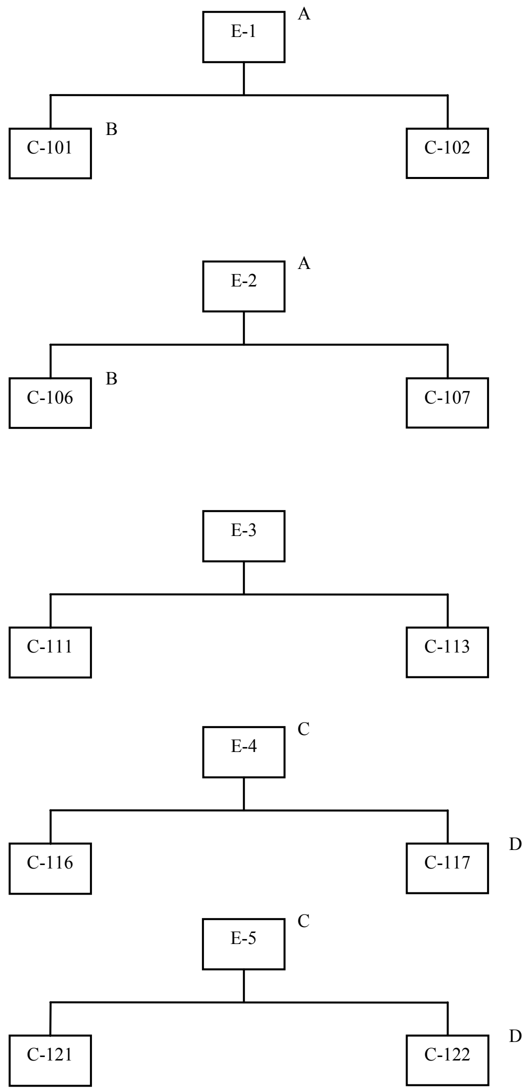
Letters denote items with “common” routings when Routing Commonality=High

Figure B.2 Product Structures with experimental settings of Depth =High, Breadth =Low, Component Commonality = Low (Continued)



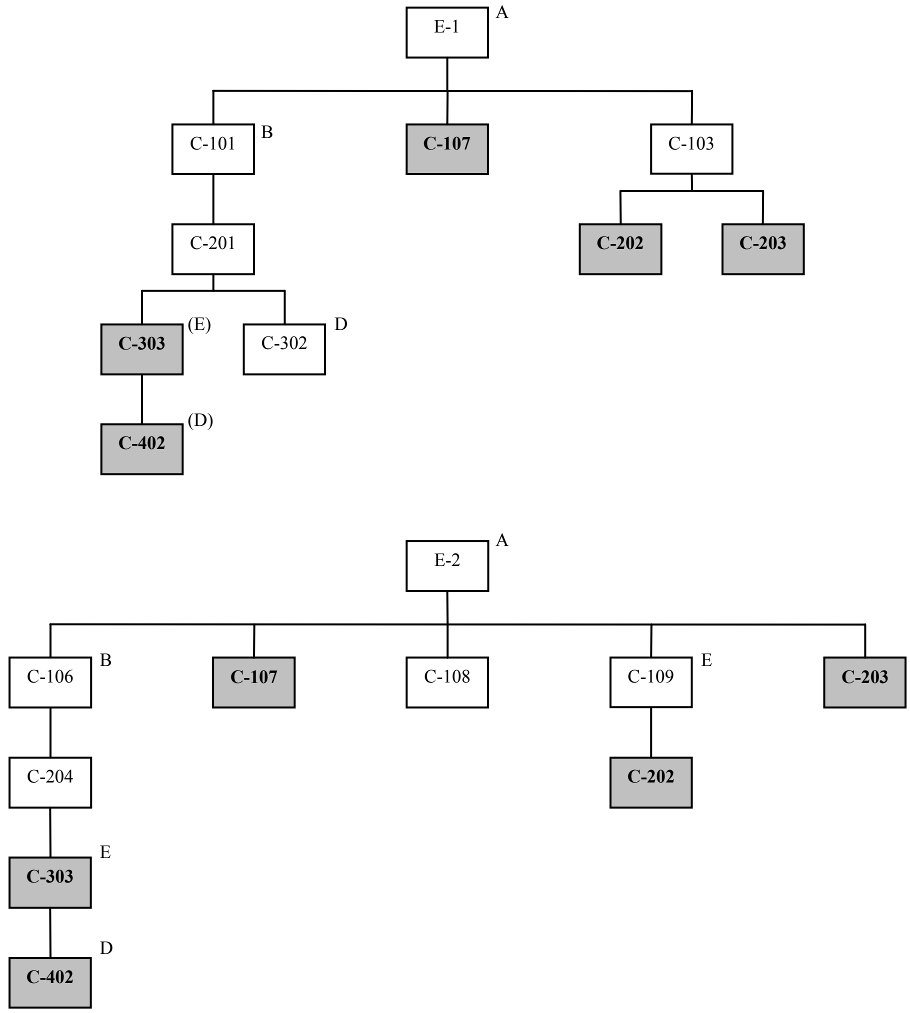
Letters denote items with “common” routings when Routing Commonality=High

Figure B.3 Product Structures with experimental settings of Depth =Low, Breadth =High, Component Commonality = Low



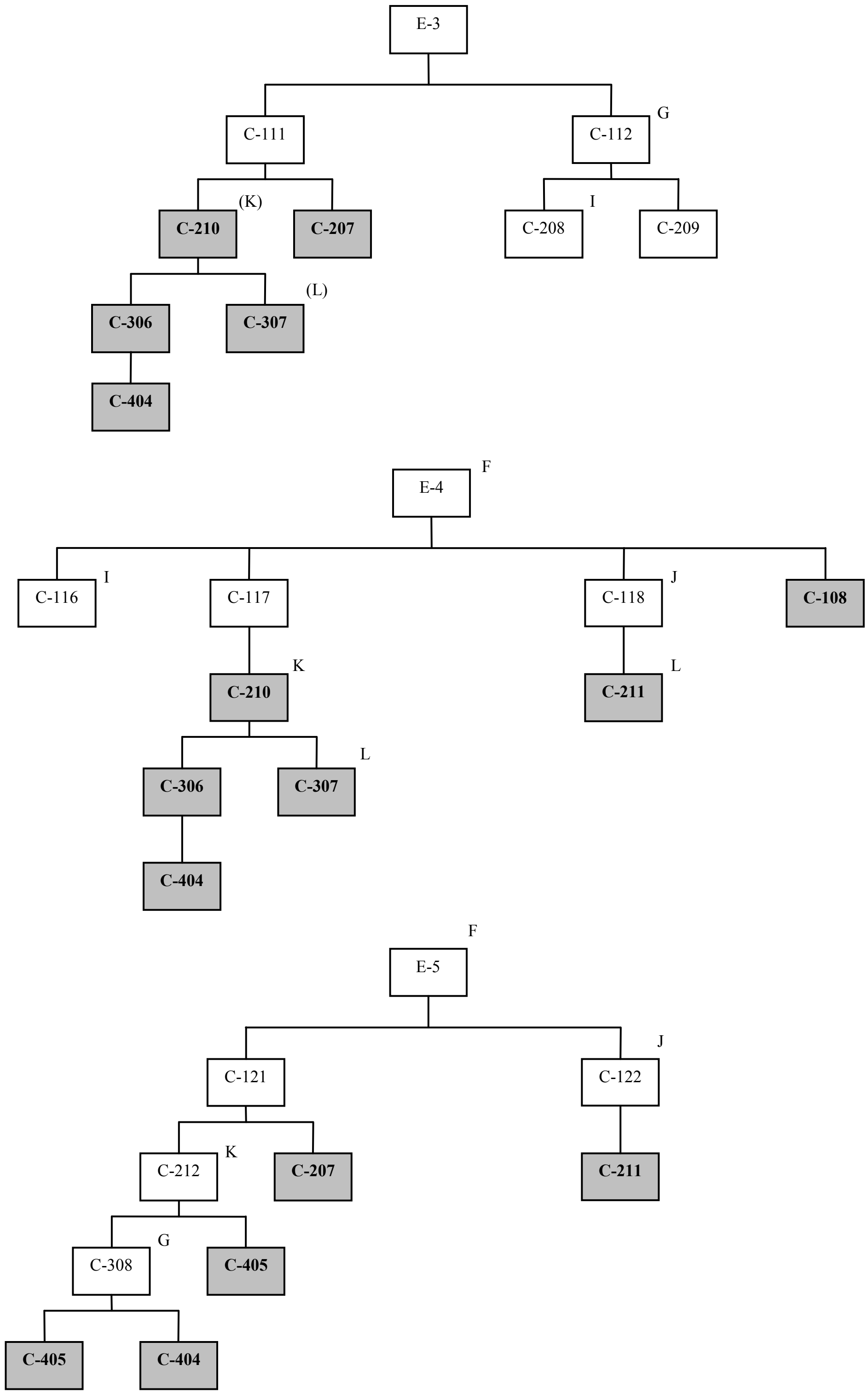
Letters denote items with “common” routings when Routing Commonality=High

Figure B.4 Product Structures with experimental settings of Depth =Low, Breadth =Low, Component Commonality = Low



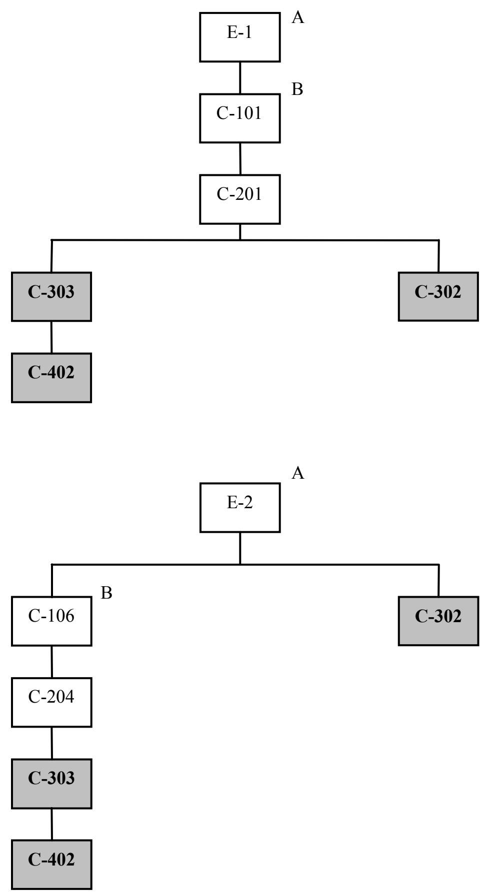
Letters denote items with "common" routings when Routing Commonality=High
Bold, shaded items are "common" components.

Figure B.5 Product Structures with experimental settings of Depth =High, Breadth =High, Component Commonality = High



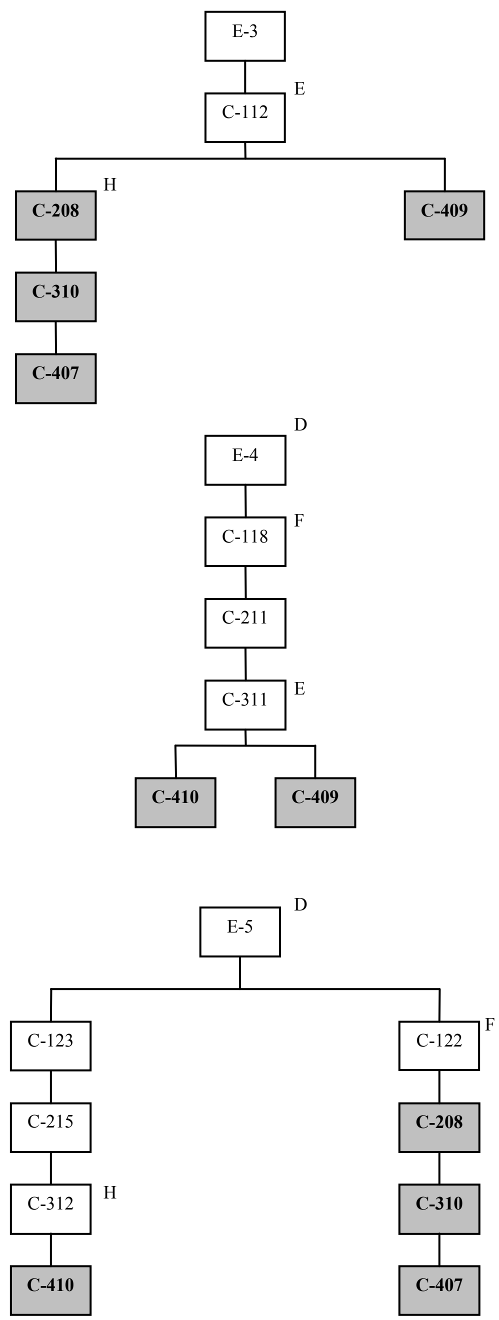
Letters denote items with “common” routings when Routing Commonality=High
Bold, shaded items are “common” components.

Figure B.5 Product Structures with experimental settings of Depth =High, Breadth =High, Component Commonality = High (Continued)



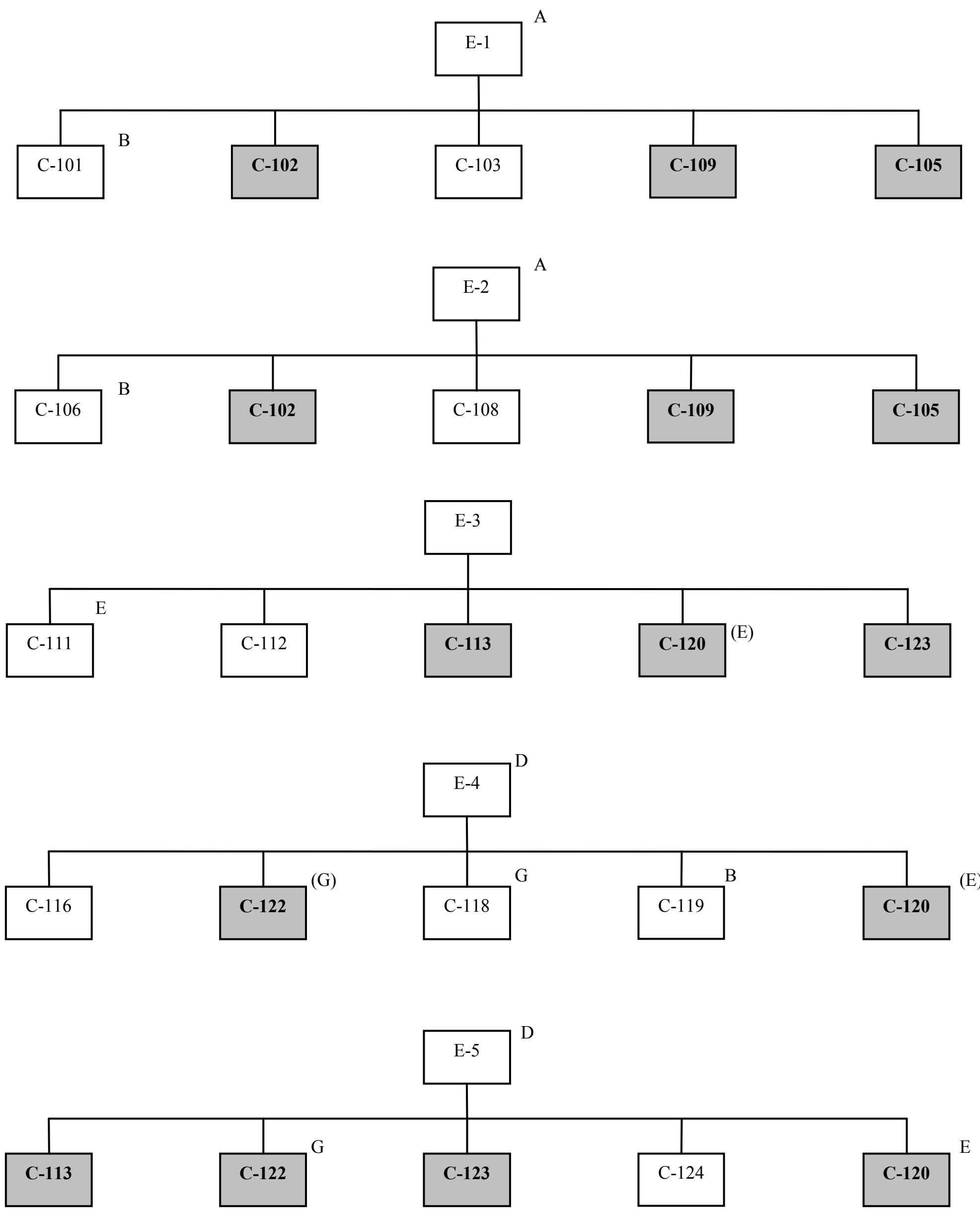
Letters denote items with “common” routings when Routing Commonality=High
Bold, shaded items are “common” components.

Figure B.6 Product Structures with experimental settings of Depth =High, Breadth =Low, Component Commonality = High



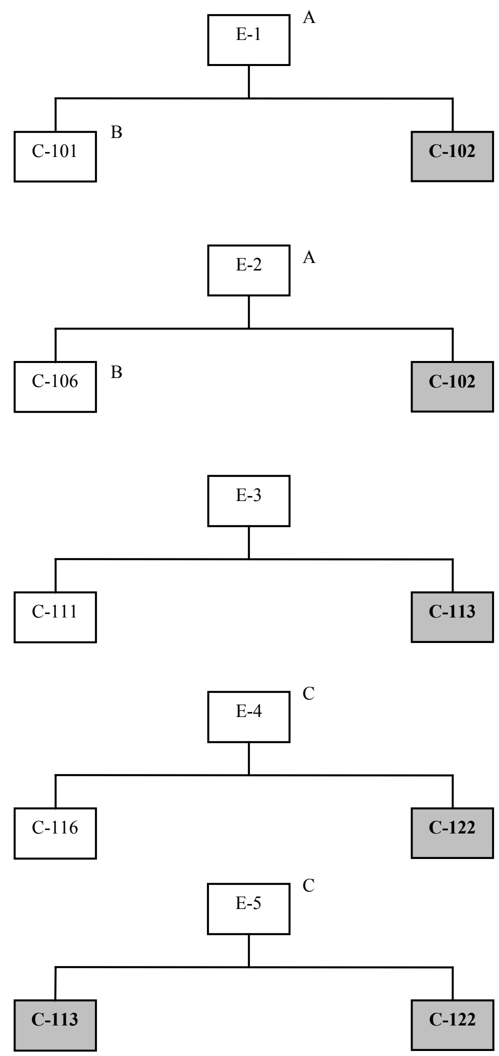
Letters denote items with “common” routings when Routing Commonality=High
Bold, shaded items are “common” components.

Figure B.6 Product Structures with experimental settings of Depth =High, Breadth =Low, Component Commonality = High (Continued)



Letters denote items with "common" routings when Routing Commonality=High
Bold, shaded items are "common" components.

Figure B.7 Product Structures with experimental settings of Depth =Low, Breadth =High, Component Commonality = High



Letters denote items with “common” routings when Routing Commonality=High
Bold, shaded items are “common” components.

Figure B.8 Product Structures with experimental settings of Depth =Low, Breadth =Low, Component Commonality = High

Appendix C

Work Center Mean Utilization and Mean Protective Capacity

Table C.1 summarizes the observed mean utilization of work centers for the 256 simulated systems. These mean utilizations were obtained from each system during a long-run steady state period of 500,000 simulated hours. The utilization statistic from AWESIM was reported at 100 hour time increments during the simulation run. The mean of these utilizations is reported in table C.1 along with the mean protective capacity for each experiment. The mean protective capacity is the mean difference in utilization between the bottleneck work center and the mean utilization of all of the other work centers.

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
1	0.9059	0.4474	0.5122	0.6616	-	-	-	-	-	-	0.6318	0.3655
2	0.8939	0.6273	0.7876	0.8228	-	-	-	-	-	-	0.7829	0.1480
3	0.6984	0.9407	0.5533	0.5506	-	-	-	-	-	-	0.6858	0.3399
4	0.8024	0.9294	0.7245	0.7264	-	-	-	-	-	-	0.7956	0.1783
5	0.9137	0.5539	0.4802	0.5068	-	-	-	-	-	-	0.6136	0.4001
6	0.9362	0.6718	0.7195	0.6524	-	-	-	-	-	-	0.7450	0.2549
7	0.6233	0.8468	0.6046	0.5459	-	-	-	-	-	-	0.6552	0.2556
8	0.6304	0.8380	0.7024	0.6131	-	-	-	-	-	-	0.6960	0.1894
9	0.9032	0.3979	0.6011	0.7735	-	-	-	-	-	-	0.6689	0.3123
10	0.8009	0.5746	0.9039	0.8373	-	-	-	-	-	-	0.7791	0.1663
11	0.9403	0.9167	0.3369	0.9002	-	-	-	-	-	-	0.7735	0.2224
12	0.9001	0.8437	0.5292	0.9243	-	-	-	-	-	-	0.7993	0.1666
13	0.9377	0.4660	0.4950	0.6830	-	-	-	-	-	-	0.6454	0.3897
14	0.9256	0.6082	0.8662	0.7685	-	-	-	-	-	-	0.7921	0.1780
15	0.7559	0.8627	0.3687	0.5663	-	-	-	-	-	-	0.6384	0.2990
16	0.7870	0.8561	0.5822	0.6718	-	-	-	-	-	-	0.7243	0.1758
17	0.9114	0.7226	0.5624	0.6592	-	-	-	-	-	-	0.7139	0.2634
18	0.7376	0.7739	0.8833	0.8015	-	-	-	-	-	-	0.7991	0.1124
19	0.6922	0.9444	0.5012	0.6309	-	-	-	-	-	-	0.6922	0.3362
20	0.8767	0.9351	0.8181	0.8812	-	-	-	-	-	-	0.8778	0.0765
21	0.9449	0.7133	0.6523	0.5494	-	-	-	-	-	-	0.7150	0.3066
22	0.8923	0.7819	0.9329	0.7320	-	-	-	-	-	-	0.8348	0.1308
23	0.6655	0.8726	0.6599	0.6446	-	-	-	-	-	-	0.7107	0.2159
24	0.6714	0.8718	0.8099	0.7147	-	-	-	-	-	-	0.7670	0.1398
25	0.8132	0.5638	0.7530	0.8913	-	-	-	-	-	-	0.7553	0.1813
26	0.5038	0.5863	0.8998	0.6976	-	-	-	-	-	-	0.6719	0.3039

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
27	0.7478	0.9460	0.3610	0.8995	-	-	-	-	-	-	0.7386	0.2766
28	0.8131	0.8204	0.6345	0.9394	-	-	-	-	-	-	0.8019	0.1834
29	0.9360	0.5866	0.6508	0.8063	-	-	-	-	-	-	0.7449	0.2548
30	0.6764	0.5898	0.9369	0.6698	-	-	-	-	-	-	0.7182	0.2916
31	0.6599	0.8599	0.4273	0.5768	-	-	-	-	-	-	0.6310	0.3053
32	0.7609	0.8539	0.7415	0.7453	-	-	-	-	-	-	0.7754	0.1047
33	0.9134	0.7738	0.5510	0.6995	-	-	-	-	-	-	0.7344	0.2386
34	0.9110	0.7773	0.7838	0.8339	-	-	-	-	-	-	0.8265	0.1126
35	0.9240	0.9395	0.8092	0.7023	-	-	-	-	-	-	0.8437	0.1276
36	0.9408	0.8908	0.8811	0.8975	-	-	-	-	-	-	0.9025	0.0510
37	0.9387	0.8597	0.8136	0.7416	-	-	-	-	-	-	0.8384	0.1338
38	0.9083	0.8499	0.9226	0.8529	-	-	-	-	-	-	0.8834	0.0522
39	0.7797	0.8710	0.7911	0.7345	-	-	-	-	-	-	0.7941	0.1026
40	0.7555	0.8358	0.8055	0.7696	-	-	-	-	-	-	0.7916	0.0589
41	0.9074	0.7665	0.5459	0.7368	-	-	-	-	-	-	0.7391	0.2244
42	0.8914	0.8627	0.8485	0.9000	-	-	-	-	-	-	0.8757	0.0325
43	0.9374	0.7002	0.7505	0.7981	-	-	-	-	-	-	0.7966	0.1878
44	0.9339	0.7295	0.8267	0.9289	-	-	-	-	-	-	0.8548	0.1056
45	0.9429	0.9061	0.6720	0.7699	-	-	-	-	-	-	0.8227	0.1603
46	0.9191	0.9267	0.9027	0.9114	-	-	-	-	-	-	0.9150	0.0157
47	0.8589	0.7862	0.7869	0.7625	-	-	-	-	-	-	0.7986	0.0804
48	0.8361	0.7900	0.8601	0.8591	-	-	-	-	-	-	0.8363	0.0317
49	0.8990	0.8559	0.6559	0.7461	-	-	-	-	-	-	0.7893	0.1464
50	0.8507	0.7698	0.9091	0.8790	-	-	-	-	-	-	0.8521	0.0759
51	0.9212	0.9399	0.8535	0.8222	-	-	-	-	-	-	0.8842	0.0743
52	0.8656	0.7913	0.8459	0.9390	-	-	-	-	-	-	0.8604	0.1048

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
53	0.9413	0.9248	0.9142	0.7269	-	-	-	-	-	-	0.8768	0.0860
54	0.8272	0.8085	0.9432	0.8373	-	-	-	-	-	-	0.8541	0.1189
55	0.7616	0.8538	0.8427	0.7621	-	-	-	-	-	-	0.8050	0.0650
56	0.7569	0.8356	0.8529	0.8152	-	-	-	-	-	-	0.8151	0.0503
57	0.8870	0.8489	0.6532	0.8572	-	-	-	-	-	-	0.8116	0.1006
58	0.7196	0.8006	0.9079	0.8763	-	-	-	-	-	-	0.8261	0.1091
59	0.9345	0.7984	0.8451	0.9400	-	-	-	-	-	-	0.8795	0.0807
60	0.8289	0.6890	0.7920	0.9235	-	-	-	-	-	-	0.8083	0.1535
61	0.9119	0.9414	0.7520	0.8205	-	-	-	-	-	-	0.8565	0.1132
62	0.7814	0.8385	0.9297	0.8817	-	-	-	-	-	-	0.8578	0.0959
63	0.8390	0.8337	0.8436	0.7906	-	-	-	-	-	-	0.8267	0.0226
64	0.7766	0.7684	0.8704	0.8702	-	-	-	-	-	-	0.8214	0.0653
65	0.3961	0.6916	0.1473	0.2904	0.5185	0.3250	0.8612	0.2352	0.2061	-	0.4079	0.5099
66	0.3433	0.7587	0.3468	0.3729	0.5781	0.4938	0.8360	0.3166	0.3022	0.1560	0.4504	0.4284
67	0.7564	0.8826	0.3482	0.6388	0.6763	0.6794	0.8195	0.5011	0.6188	0.3655	0.6287	0.2822
68	0.6743	0.8263	0.5929	0.7615	0.7241	0.5894	0.8940	0.4753	0.6088	0.4169	0.6564	0.2641
69	0.5696	0.9091	0.3225	0.7203	0.8903	0.2541	0.7779	0.7263	0.3820	0.3080	0.5860	0.3590
70	0.6130	0.8508	0.6521	0.6570	0.8809	0.4554	0.7697	0.7280	0.6230	0.4350	0.6665	0.2382
71	0.6670	0.9133	0.4914	0.8821	0.7673	0.5845	0.7472	0.7361	0.5576	0.3012	0.6648	0.2761
72	0.7553	0.8353	0.7540	0.9097	0.8294	0.7263	0.7764	0.7322	0.6388	0.5079	0.7465	0.1813
73	0.3606	0.6969	0.0657	0.2911	0.5779	0.3242	0.8614	0.2359	0.2467	-	0.4067	0.5116
74	0.4078	0.6883	0.2531	0.2590	0.5426	0.3407	0.8380	0.2467	0.4413	0.1835	0.4201	0.4643
75	0.8199	0.6514	0.0408	0.1794	0.1808	0.9143	0.6475	0.3443	0.5208	0.2505	0.4550	0.5104
76	0.7327	0.7324	0.2977	0.5760	0.4054	0.8374	0.9005	0.3437	0.5877	0.3975	0.5811	0.3549
77	0.5749	0.9266	0.2189	0.4782	0.6799	0.2146	0.8129	0.3268	0.1628	0.3717	0.4767	0.4998
78	0.7633	0.9057	0.5226	0.4829	0.7353	0.3745	0.8534	0.5035	0.4601	0.5182	0.6120	0.3263

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
79	0.8713	0.8213	0.5008	0.6518	0.3049	0.9160	0.7634	0.6858	0.3652	0.2041	0.6084	0.3418
80	0.8632	0.7421	0.7742	0.8036	0.3889	0.8748	0.9021	0.7257	0.4193	0.3336	0.6827	0.2437
81	0.4507	0.5899	0.3735	0.1910	0.5794	0.4754	0.8386	0.1547	0.2384	-	0.4324	0.4570
82	0.3467	0.7944	0.6501	0.4015	0.6845	0.7399	0.8403	0.3517	0.4134	0.3027	0.5525	0.3198
83	0.8852	0.7145	0.4205	0.3793	0.5832	0.8618	0.9027	0.4671	0.4454	0.2696	0.5929	0.3442
84	0.6453	0.6874	0.6973	0.6744	0.6675	0.5776	0.9055	0.4197	0.4989	0.3796	0.6153	0.3224
85	0.7255	0.7658	0.4222	0.5813	0.8680	0.3662	0.8995	0.7113	0.3276	0.3674	0.6035	0.3289
86	0.6776	0.7034	0.8736	0.5195	0.8170	0.6080	0.7733	0.6832	0.7191	0.5200	0.6895	0.2046
87	0.8988	0.7897	0.4764	0.7077	0.7690	0.7119	0.9213	0.7773	0.5647	0.3565	0.6973	0.2488
88	0.9172	0.7297	0.9183	0.8502	0.8720	0.8743	0.8716	0.7487	0.6969	0.6707	0.8150	0.1148
89	0.3714	0.6123	0.1735	0.1919	0.7323	0.4788	0.8456	0.1554	0.3410	-	0.4336	0.4636
90	0.4608	0.6548	0.4492	0.1974	0.6026	0.4324	0.8334	0.2255	0.6449	0.3306	0.4832	0.3891
91	0.8085	0.5754	0.1006	0.1110	0.2501	0.9172	0.6428	0.3432	0.5155	0.2477	0.4512	0.5178
92	0.5512	0.6239	0.4298	0.6873	0.5055	0.6498	0.9040	0.2831	0.5194	0.4155	0.5570	0.3856
93	0.5562	0.8285	0.2323	0.5068	0.8008	0.3181	0.8880	0.3476	0.2262	0.3928	0.5097	0.4203
94	0.8690	0.7887	0.7515	0.4774	0.8064	0.5380	0.8816	0.6347	0.7124	0.6200	0.7080	0.1929
95	0.8768	0.6765	0.4985	0.6483	0.3612	0.9203	0.8504	0.7291	0.2768	0.2004	0.6038	0.3517
96	0.7585	0.5487	0.8292	0.7888	0.4106	0.7441	0.9060	0.6757	0.3607	0.3666	0.6389	0.2968
97	0.8299	0.6402	0.3083	0.4543	0.4178	0.4016	0.5249	0.2612	0.4951	0.2458	0.4579	0.4133
98	0.8440	0.7442	0.5306	0.6669	0.6190	0.5541	0.5958	0.2946	0.5353	0.5088	0.5893	0.2830
99	0.9104	0.6606	0.3441	0.6779	0.5880	0.5305	0.5845	0.6251	0.6889	0.4663	0.6076	0.3364
100	0.9128	0.8018	0.6462	0.9020	0.7307	0.5928	0.7173	0.6661	0.6813	0.6246	0.7276	0.2058
101	0.8707	0.8930	0.5178	0.8382	0.7981	0.3936	0.5583	0.5843	0.5438	0.3683	0.6366	0.2849
102	0.8673	0.8278	0.7847	0.8643	0.8889	0.5868	0.6696	0.5688	0.6114	0.6204	0.7290	0.1777
103	0.8462	0.6964	0.4849	0.9146	0.6411	0.6138	0.5176	0.6561	0.5173	0.4985	0.6386	0.3066
104	0.7758	0.7010	0.6746	0.9062	0.7021	0.6743	0.5964	0.6197	0.5891	0.5876	0.6827	0.2484

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
105	0.8349	0.6412	0.2526	0.4513	0.4497	0.3621	0.5133	0.2288	0.5145	0.2762	0.4525	0.4249
106	0.8322	0.6919	0.4311	0.4602	0.5546	0.4205	0.5734	0.2133	0.5005	0.4652	0.5143	0.3532
107	0.9163	0.6131	0.1505	0.3069	0.4533	0.6000	0.5781	0.4103	0.4161	0.2973	0.4742	0.4912
108	0.9166	0.8164	0.4025	0.5920	0.6334	0.6469	0.7259	0.4590	0.5035	0.4823	0.6178	0.3320
109	0.8773	0.8423	0.4707	0.8679	0.8604	0.4859	0.5960	0.4636	0.5091	0.6494	0.6623	0.2389
110	0.8977	0.7388	0.6518	0.7518	0.8915	0.6206	0.6778	0.4550	0.4958	0.7706	0.6951	0.2250
111	0.9123	0.7392	0.5010	0.7277	0.5619	0.8401	0.5864	0.6407	0.3019	0.3484	0.6160	0.3292
112	0.8856	0.7832	0.7536	0.8991	0.6217	0.9068	0.7568	0.6709	0.3911	0.5191	0.7188	0.2089
113	0.8391	0.6951	0.6604	0.4956	0.5450	0.6224	0.7447	0.2624	0.5295	0.2412	0.5635	0.3062
114	0.8096	0.8087	0.8282	0.8131	0.7961	0.7460	0.7188	0.3061	0.5531	0.6899	0.7070	0.1347
115	0.9100	0.6232	0.4691	0.5277	0.6643	0.5957	0.6623	0.5809	0.5026	0.3618	0.5898	0.3558
116	0.8893	0.8282	0.8249	0.9098	0.8105	0.6304	0.7932	0.6430	0.5719	0.6351	0.7536	0.1735
117	0.8664	0.7798	0.6350	0.8818	0.8065	0.4763	0.6951	0.6221	0.5001	0.4796	0.6743	0.2305
118	0.7720	0.6622	0.8873	0.8031	0.8416	0.6579	0.7095	0.5133	0.5643	0.7319	0.7143	0.1922
119	0.9158	0.6358	0.5273	0.8502	0.7288	0.6267	0.6338	0.6791	0.4744	0.5190	0.6591	0.2852
120	0.7935	0.7009	0.8096	0.9062	0.7933	0.7323	0.7033	0.6315	0.6264	0.6608	0.7358	0.1894
121	0.8399	0.6872	0.4913	0.4718	0.6151	0.4983	0.6876	0.1714	0.5585	0.3170	0.5338	0.3401
122	0.8427	0.7515	0.6478	0.4797	0.6903	0.5226	0.6928	0.1899	0.5202	0.6148	0.5952	0.2749
123	0.9243	0.6174	0.2556	0.3065	0.5577	0.6597	0.6856	0.4262	0.4115	0.3200	0.5165	0.4531
124	0.8732	0.9025	0.5887	0.7315	0.7584	0.6653	0.8287	0.4691	0.5250	0.5787	0.6921	0.2338
125	0.7329	0.7192	0.5008	0.8025	0.8710	0.5065	0.6583	0.4353	0.4572	0.6484	0.6332	0.2642
126	0.8446	0.6412	0.7403	0.6708	0.9011	0.6883	0.7368	0.4391	0.4678	0.8147	0.6945	0.2296
127	0.9137	0.7066	0.5920	0.7902	0.6860	0.9011	0.6834	0.7120	0.2607	0.4185	0.6664	0.2747
128	0.7715	0.7046	0.8353	0.9106	0.6266	0.8593	0.8045	0.6372	0.3741	0.5792	0.7103	0.2226
129	0.6380	0.7790	0.8850	0.7730	-	-	-	-	-	-	0.7688	0.1550
130	0.7402	0.7903	0.8823	0.8677	-	-	-	-	-	-	0.8201	0.0829

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
131	0.6362	0.9380	0.9363	0.5385	-	-	-	-	-	-	0.7622	0.2343
132	0.8236	0.9267	0.9181	0.7571	-	-	-	-	-	-	0.8564	0.0937
133	0.9443	0.5910	0.7981	0.5865	-	-	-	-	-	-	0.7300	0.2858
134	0.9223	0.6060	0.8985	0.6687	-	-	-	-	-	-	0.7739	0.1979
135	0.3812	0.4852	0.5680	0.3786	-	-	-	-	-	-	0.4532	0.1530
136	0.6894	0.7756	0.8579	0.6456	-	-	-	-	-	-	0.7421	0.1543
137	0.5461	0.6579	0.9076	0.8153	-	-	-	-	-	-	0.7317	0.2345
138	0.4710	0.6205	0.9049	0.7650	-	-	-	-	-	-	0.6903	0.2861
139	0.6470	0.9444	0.4286	0.8072	-	-	-	-	-	-	0.7068	0.3168
140	0.7964	0.9208	0.5695	0.9200	-	-	-	-	-	-	0.8017	0.1588
141	0.9352	0.7130	0.7655	0.8442	-	-	-	-	-	-	0.8145	0.1609
142	0.9015	0.7097	0.9266	0.7949	-	-	-	-	-	-	0.8332	0.1246
143	0.7983	0.8749	0.6844	0.6178	-	-	-	-	-	-	0.7439	0.1748
144	0.8587	0.7987	0.7012	0.6547	-	-	-	-	-	-	0.7533	0.1406
145	0.6739	0.9022	0.7501	0.6721	-	-	-	-	-	-	0.7496	0.2035
146	0.8116	0.8471	0.8209	0.8731	-	-	-	-	-	-	0.8382	0.0466
147	0.6514	0.9423	0.7305	0.6290	-	-	-	-	-	-	0.7383	0.2720
148	0.9327	0.9149	0.8139	0.9131	-	-	-	-	-	-	0.8937	0.0521
149	0.9427	0.7337	0.8685	0.5910	-	-	-	-	-	-	0.7840	0.2116
150	0.8437	0.6289	0.9269	0.6756	-	-	-	-	-	-	0.7688	0.2109
151	0.6464	0.7898	0.8754	0.6812	-	-	-	-	-	-	0.7482	0.1696
152	0.7775	0.8154	0.8496	0.7259	-	-	-	-	-	-	0.7921	0.0767
153	0.5234	0.6996	0.9055	0.8629	-	-	-	-	-	-	0.7479	0.2102
154	0.4199	0.6110	0.8974	0.7483	-	-	-	-	-	-	0.6691	0.3043
155	0.5670	0.9454	0.4097	0.8282	-	-	-	-	-	-	0.6876	0.3438
156	0.8052	0.8559	0.6068	0.9399	-	-	-	-	-	-	0.8020	0.1840

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
157	0.9098	0.7601	0.8423	0.9143	-	-	-	-	-	-	0.8566	0.0769
158	0.7674	0.6402	0.9288	0.7015	-	-	-	-	-	-	0.7595	0.2258
159	0.6979	0.8711	0.6602	0.6293	-	-	-	-	-	-	0.7146	0.2086
160	0.8694	0.7798	0.7179	0.6951	-	-	-	-	-	-	0.7656	0.1384
161	0.6771	0.9068	0.6734	0.8261	-	-	-	-	-	-	0.7709	0.1813
162	0.8265	0.8705	0.8668	0.9112	-	-	-	-	-	-	0.8687	0.0566
163	0.9121	0.9385	0.9213	0.7044	-	-	-	-	-	-	0.8691	0.0926
164	0.9372	0.8752	0.8699	0.8435	-	-	-	-	-	-	0.8814	0.0743
165	0.8680	0.9378	0.9143	0.8374	-	-	-	-	-	-	0.8894	0.0646
166	0.8785	0.8355	0.9246	0.8592	-	-	-	-	-	-	0.8745	0.0669
167	0.7298	0.8659	0.8563	0.7401	-	-	-	-	-	-	0.7980	0.0905
168	0.7447	0.8266	0.8374	0.7466	-	-	-	-	-	-	0.7888	0.0647
169	0.6648	0.8968	0.6663	0.8633	-	-	-	-	-	-	0.7728	0.1653
170	0.6782	0.8610	0.8514	0.9078	-	-	-	-	-	-	0.8246	0.1109
171	0.8734	0.8252	0.8821	0.9334	-	-	-	-	-	-	0.8785	0.0732
172	0.8578	0.7747	0.8318	0.9337	-	-	-	-	-	-	0.8495	0.1123
173	0.7719	0.9382	0.7108	0.8024	-	-	-	-	-	-	0.8058	0.1765
174	0.8209	0.9190	0.8478	0.8636	-	-	-	-	-	-	0.8628	0.0749
175	0.8412	0.7999	0.8546	0.7148	-	-	-	-	-	-	0.8026	0.0693
176	0.7853	0.7509	0.8368	0.7415	-	-	-	-	-	-	0.7786	0.0776
177	0.7119	0.9071	0.7100	0.7977	-	-	-	-	-	-	0.7817	0.1672
178	0.8471	0.7846	0.9086	0.8668	-	-	-	-	-	-	0.8518	0.0758
179	0.9062	0.9300	0.9212	0.8210	-	-	-	-	-	-	0.8946	0.0472
180	0.9355	0.8354	0.8340	0.9287	-	-	-	-	-	-	0.8834	0.0695
181	0.8575	0.9336	0.9419	0.7562	-	-	-	-	-	-	0.8723	0.0928
182	0.8723	0.7891	0.9361	0.8363	-	-	-	-	-	-	0.8585	0.1036

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
183	0.7142	0.8413	0.8726	0.7380	-	-	-	-	-	-	0.7915	0.1081
184	0.7585	0.8165	0.8494	0.7615	-	-	-	-	-	-	0.7965	0.0706
185	0.6792	0.8847	0.6965	0.8940	-	-	-	-	-	-	0.7886	0.1405
186	0.6484	0.7920	0.9034	0.8844	-	-	-	-	-	-	0.8070	0.1284
187	0.8060	0.8035	0.8511	0.9420	-	-	-	-	-	-	0.8506	0.1218
188	0.8236	0.7414	0.7913	0.9259	-	-	-	-	-	-	0.8205	0.1405
189	0.7856	0.9437	0.7614	0.8253	-	-	-	-	-	-	0.8290	0.1530
190	0.8427	0.9081	0.9327	0.8962	-	-	-	-	-	-	0.8949	0.0504
191	0.7916	0.8159	0.8557	0.7141	-	-	-	-	-	-	0.7943	0.0818
192	0.7614	0.7491	0.8477	0.7675	-	-	-	-	-	-	0.7814	0.0884
193	0.2645	0.3433	0.3439	-	0.8832	0.5022	0.6477	-	0.3933	-	0.4826	0.4674
194	0.2490	0.4627	0.4513	0.1431	0.8289	0.6707	0.6809	0.1582	0.5010	0.1031	0.4249	0.4489
195	0.8329	0.2651	0.4661	0.3316	0.9052	0.8515	0.7255	0.2534	0.3531	0.4167	0.5401	0.4056
196	0.7920	0.4881	0.5631	0.5405	0.8061	0.7314	0.9054	0.3654	0.4857	0.4584	0.6136	0.3243
197	0.5375	0.4616	0.3482	0.1925	0.9116	0.2982	0.4574	0.3197	0.2333	0.3158	0.4076	0.5600
198	0.6403	0.5740	0.6682	0.2923	0.9053	0.5858	0.5734	0.5297	0.4402	0.3479	0.5557	0.3885
199	0.7542	0.5420	0.5800	0.4977	0.9105	0.6645	0.7444	0.4474	0.7060	0.3992	0.6246	0.3177
200	0.8871	0.6736	0.7395	0.6577	0.9094	0.8288	0.7939	0.5232	0.7895	0.4959	0.7299	0.1995
201	0.2172	0.3242	0.2528	-	0.8785	0.4707	0.6061	-	0.4039	-	0.4505	0.4994
202	0.3405	0.4767	0.3827	-	0.8387	0.5120	0.8058	0.0771	0.6699	0.1879	0.4768	0.4072
203	0.6547	0.3972	0.1585	-	0.3950	0.9147	0.4794	0.1693	0.5724	0.2175	0.4399	0.5342
204	0.7853	0.6144	0.3004	0.3927	0.4723	0.9010	0.8442	0.2254	0.6981	0.3051	0.5539	0.3857
205	0.4763	0.6790	0.3501	0.2665	0.9187	0.3422	0.6719	0.1562	0.2937	0.3527	0.4507	0.5199
206	0.7341	0.6976	0.6303	0.3721	0.9127	0.5331	0.7592	0.4181	0.6565	0.3724	0.6086	0.3379
207	0.9121	0.5650	0.5633	0.4594	0.4820	0.6971	0.8296	0.3995	0.2218	0.4389	0.5569	0.3947
208	0.9021	0.5870	0.6566	0.6326	0.5032	0.7072	0.8649	0.4107	0.3404	0.3638	0.5968	0.3392

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
209	0.3705	0.3698	0.5132	-	0.8520	0.6096	0.7169	-	0.3780	-	0.5443	0.3590
210	0.2812	0.5627	0.6131	0.2639	0.7257	0.8442	0.7153	0.2882	0.5659	0.1984	0.5059	0.3760
211	0.8740	0.3220	0.4626	0.1980	0.6960	0.9064	0.7912	0.2969	0.2798	0.2939	0.5121	0.4382
212	0.6872	0.5581	0.5358	0.5190	0.5697	0.5972	0.9052	0.3869	0.4567	0.3685	0.5584	0.3853
213	0.6976	0.4928	0.4389	0.2376	0.9272	0.3904	0.6660	0.4382	0.2418	0.3772	0.4908	0.4849
214	0.6946	0.5865	0.8842	0.3524	0.7389	0.7888	0.6763	0.6858	0.5532	0.3422	0.6303	0.2822
215	0.9034	0.5695	0.5106	0.4333	0.8236	0.5951	0.9175	0.5032	0.6319	0.4777	0.6366	0.3122
216	0.9064	0.6705	0.7036	0.6363	0.7472	0.7824	0.7863	0.5192	0.6991	0.5182	0.6969	0.2327
217	0.2569	0.3407	0.2798	-	0.8803	0.5382	0.6336	-	0.4212	-	0.4787	0.4686
218	0.3994	0.5139	0.4324	-	0.6512	0.4850	0.8312	0.1302	0.7720	0.3092	0.5027	0.3695
219	0.7031	0.4158	0.1744	-	0.3861	0.9206	0.5335	0.2279	0.5525	0.2269	0.4601	0.5181
220	0.7133	0.6278	0.3351	0.5761	0.4069	0.6736	0.9215	0.2355	0.6056	0.2956	0.5391	0.4249
221	0.4752	0.6442	0.3129	0.3510	0.9290	0.3890	0.7631	0.2239	0.3045	0.3684	0.4761	0.5032
222	0.8493	0.6067	0.7592	0.4576	0.7950	0.6449	0.7806	0.6127	0.8683	0.3492	0.6723	0.2178
223	0.8847	0.5532	0.5276	0.5121	0.4621	0.6497	0.9137	0.4860	0.1863	0.4142	0.5590	0.3941
224	0.8818	0.5908	0.6916	0.7542	0.5057	0.6877	0.9163	0.4515	0.3915	0.3081	0.6179	0.3316
225	0.4588	0.4867	0.8305	0.2188	0.7417	0.5129	0.6230	0.0245	0.3678	0.3122	0.4577	0.4142
226	0.4679	0.5606	0.8403	0.4888	0.7789	0.6623	0.5556	0.1274	0.4483	0.4752	0.5405	0.3331
227	0.6834	0.5364	0.6342	0.4832	0.9038	0.4995	0.5634	0.4322	0.4198	0.4449	0.5601	0.3819
228	0.7184	0.7557	0.7424	0.7004	0.9030	0.5793	0.6487	0.5612	0.4882	0.5629	0.6660	0.2633
229	0.5525	0.7032	0.7755	0.6070	0.9061	0.4180	0.5563	0.3779	0.4066	0.3679	0.5671	0.3766
230	0.5819	0.6348	0.8922	0.6809	0.9038	0.6264	0.6018	0.4192	0.4922	0.5076	0.6341	0.2997
231	0.7862	0.6187	0.8026	0.8188	0.9164	0.5752	0.6182	0.4609	0.5024	0.5645	0.6664	0.2778
232	0.7595	0.7093	0.8740	0.8954	0.9093	0.7211	0.6469	0.5171	0.5935	0.6231	0.7249	0.2049
233	0.5067	0.5311	0.8427	0.2377	0.8415	0.5154	0.6660	-	0.4224	0.3732	0.5485	0.3310
234	0.6090	0.6419	0.8047	0.3119	0.8411	0.5694	0.6954	0.0582	0.4805	0.5497	0.5562	0.3166

Table C.1. Work Center Mean Utilization and Mean Protective Capacity for each Simulation Experiment (Continued)

Experiment	WC1	WC2	WC3	WC4	WC5	WC6	WC7	WC8	WC9	WC10	Average	Mean Protective Capacity
235	0.9101	0.6714	0.5285	0.2342	0.7800	0.8270	0.7895	0.3612	0.4387	0.4174	0.5958	0.3492
236	0.9020	0.8627	0.6031	0.5389	0.7939	0.7600	0.7807	0.4353	0.4869	0.4891	0.6653	0.2631
237	0.4997	0.6019	0.7028	0.5753	0.9038	0.4682	0.5516	0.2383	0.3422	0.5757	0.5460	0.3976
238	0.5771	0.5652	0.7955	0.6161	0.9004	0.6711	0.5846	0.3226	0.4020	0.5991	0.6034	0.3300
239	0.8237	0.8470	0.8557	0.7060	0.9101	0.8814	0.6951	0.4980	0.1822	0.5638	0.6963	0.2376
240	0.7753	0.8365	0.9066	0.8585	0.8107	0.8943	0.7365	0.4896	0.3012	0.5939	0.7203	0.2070
241	0.4274	0.4502	0.8390	0.2448	0.6247	0.5559	0.6447	0.0583	0.3392	0.2280	0.4412	0.4420
242	0.4575	0.5831	0.8444	0.6452	0.7376	0.7629	0.5301	0.1955	0.4769	0.5268	0.5760	0.2982
243	0.8045	0.5742	0.6842	0.4329	0.9100	0.6048	0.6809	0.4832	0.3581	0.3709	0.5904	0.3552
244	0.8016	0.9044	0.8298	0.7989	0.9132	0.6756	0.7520	0.6571	0.4991	0.6016	0.7433	0.1887
245	0.6542	0.6682	0.8249	0.7299	0.9000	0.4976	0.6974	0.4820	0.4166	0.4791	0.6350	0.2945
246	0.5896	0.5331	0.9028	0.7145	0.8242	0.7228	0.6311	0.4459	0.5022	0.5857	0.6452	0.2862
247	0.8484	0.6071	0.7531	0.7841	0.9120	0.5770	0.7090	0.5119	0.4649	0.6180	0.6785	0.2594
248	0.7664	0.7435	0.8813	0.9127	0.8973	0.7908	0.6942	0.5601	0.6183	0.6685	0.7533	0.1771
249	0.5345	0.5483	0.8464	0.2858	0.8229	0.5581	0.7320	-	0.4465	0.3498	0.5694	0.3117
250	0.6915	0.7235	0.8028	0.3775	0.8405	0.6369	0.7605	0.1026	0.5391	0.6545	0.6129	0.2529
251	0.9117	0.6488	0.5129	0.2577	0.7782	0.8085	0.8323	0.3915	0.4221	0.3960	0.5960	0.3508
252	0.8583	0.8999	0.6035	0.6530	0.7595	0.6864	0.7529	0.4520	0.4737	0.4843	0.6624	0.2640
253	0.5057	0.5812	0.6554	0.6251	0.9078	0.4973	0.6279	0.2925	0.3585	0.6037	0.5655	0.3803
254	0.6309	0.5503	0.8406	0.6724	0.9081	0.8092	0.6459	0.3956	0.4482	0.6325	0.6534	0.2830
255	0.8126	0.7920	0.8442	0.7681	0.9178	0.8959	0.7618	0.5716	0.1770	0.6189	0.7160	0.2242
256	0.7138	0.7724	0.8840	0.9135	0.7292	0.8640	0.7519	0.4890	0.3380	0.5997	0.7055	0.2310

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