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Distributed Control Synthesis for Manufacturing Systems using Customers' Decision Behaviour for Mass Customisation

Thesis Supervisor: Glen Bright

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Signed: ____________________

Declaration by Supervisor

As the candidate's Supervisor I agree/do not agree to the submission of this thesis.

Signed: ____________________ Date: ____________________

Professor Glen Bright

Declaration

The author hereby declares that he has produced this work without the prohibited assistance of third parties and without making use of aids other than those specified; notions taken over directly or indirectly from other sources have been identified as such. This work has not previously been submitted in identical or similar form to any other University examination board.

The work was completed by the author at the School of Engineering, University of KwaZulu-Natal from January 2010 to March 2013.

Signed: ____________________ Date: ____________________
Anthony John Walker

To my wife Angela

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Abstract

The mass customisation manufacturing (MCM) paradigm has created a problem in manufacturing control implementation, as each individual customer has the potential to disrupt the operations of production. The aim of this study was to characterise the manufacturing effects of customers' decisions in product configuration, in order to research steady state control requirements and work-in-process distributions for effective MCM operations. A research method involving both analytic and empirical reasoning was used in characterising the distributed control environment of manufacturing systems involved in MCM.

Sequences of job arrivals into each manufacturing system, due to customers' decisions in product configuration, were analysed as Bernoulli processes. A customer model based on this analysis captured the correlation in product configuration decisions over time. Closed form analytic models were developed from first principles, which described the steady state behaviour of flow controlled manufacturing systems under generalised clearing policy and uncorrelated job arrival sequences. Empirical analysis of data sets achieved through discrete event simulation was used in adjusting the models to account for more complex cases involving multiple job types and varying correlation. Characteristic response surfaces were shown to exist over the domains of manufacturing system load and job arrival sequence correlation.

A novel manufacturing flow control method, termed biased minimum feedback (BMF) was developed. BMF was shown to posses the capability to distribute work-in-process within the entire manufacturing facility through work-in-process regulation at each manufacturing system, so as to increase the performance of downstream assembly stations fed from parallel upstream processing stations. A case study in the production of a configurable product was used in presenting an application for the models and methods developed during this research. The models were shown to be useful in predicting steady state control requirements to increase manufacturing performance.

Keywords:
Distributed Flow Control, Biased Minimum Feedback, Configure-to-Order, Customer Decision Behaviour

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CHAPTER 1

Introduction

There is in my opinion a great similarity between the problems provided by the mysterious behaviour of the atom and those provided by the present economic paradoxes confronting the world

Paul Dirac

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This introductory chapter presents an overview of the problem space considered and method used in conducting this research. Also, a summary of research outputs obtained during this study is provided, along with the layout and content of each chapter.

1.1 Motivation

In the past, formal manufacturing engineering practice, established during and after the industrial revolution (circa. 1850), became an important economic mechanism for industrialised nations. The development of machine-tools, division of labour, and times of scarcity after World War II, prescribed the need for and facilitation of mass scale manufacturing systems. These systems, along with their inherent economy of scale, created prosperous economies and increased the standard of living in developed and developing nations. With increased wealth, standard of living and economic growth, consumerism developed more complex characteristics, which in turn resulted in segmented markets and the need for increased product variety. To facilitate these developments, more suitable manufacturing technologies and system organisations were required. Many technological developments ensued in order to facilitate increased product variety. The concept of group technology

(GT), developments in flexible manufacturing systems (FMS), cellular manufacturing, and the establishment of more complex supply chains and operations management, initiated a manufacturing paradigm of high variety batch production. Within this paradigm, increasing competition allowed manufacturing firms to facilitate highly segmented markets through large product portfolio's, thus stabilising prices and increasing the quality of products.

Market segmentation has since continued to the point of the individual customer, requiring a paradigm shift in manufacturing operations, which has lead to the concept of mass customisation, Pine [55]. When constrained to operate within feasible pricing points, mass customisation manufacturing (MCM) is in conflict with well established inverse relationships between product variety and production quantity. Research into MCM implementation has predominantly addressed the variety management problem from planning and design domains, such as product platform design, process and assembly system design and supply chain design. Since it is the customers who instantiate unique production requirements, an understanding of the effects of customers' decisions in product configuration, on manufacturing control requirements and steady state performance bounds, would be beneficial in implementing MCM. The development of closed form models describing the steady state behaviour of manufacturing systems due to customers' decision processes in product configuration, would be useful in both the design and active control of manufacturing systems for MCM. The positive impact with which these models would have on an understanding of the effects of customer manufacturer interaction in the manufacturing control environment of MCM motivated this research.

1.2 Research Overview

This study researched distributed control of manufacturing systems involved in the implementation of MCM operations. Customers decisions in product configuration were treated as stochastic processes. These stochastic processes were considered to generate unique product orders through time, resulting in customer generated sequences of job arrivals into each manufacturing system. Of particular interest was the determination of work-in-process distributions that increase assembly system performance, when job arrival sequences into parallel upstream processing stations, which feed assembly stations, are generated through customers decision processes in product configuration.

1.2.1 Aims and Objectives

The aim of this study was to:

- Research and interpret the current state of the art in MCM production system design and control implementation.

- Develop closed form analytic models that describe the effect of customer decision processes in product configuration, on steady state manufacturing control requirements.

- Determine whether new system properties exist under MCM, that can be measured and used in increasing the performance of distributed control implementation, specifically for those operations which supply unique components into assembly stations.

1.2.2 Method

The research method used in this study consisted of both constructive and exploratory components. Customer decision behaviour in product configuration was considered and treated through the use of probabilistic models. Analysis of associated limiting distributions was used in characterising the effects of customers' decision behaviour in product configuration, on steady state distributed manufacturing system control performance. Concepts developed from variety management research formed the basis for assumptions regarding product and process structure, supply chain implementation and manufacturing system design.

Analysis was performed through the development of manufacturing models from first principles, under simplifying assumptions, which were then adjusted through approximate methods to include the effects of more complex behaviour via empirical reasoning from data sets generated through discrete event simulation. Data sets achieved through discrete event simulation were in turn validated for internal consistency by testing them against well known laws governing the steady state behaviour of queuing systems. This method allowed for a circular validation path in which the applicability of models derived from first principles were tested against valid data sets, describing the behaviour of real manufacturing systems.

1.2.3 Research Contribution

This research study made the following contributions:

- For stable flow controlled manufacturing systems with non-negligible setup times, characteristic response surfaces were determined over the domains of system load and job type arrival sequence correlation. These response surfaces were shown to be useful in determining steady state resource and control requirements at each manufacturing system.

- For flexible manufacturing systems operating under stable flow control policy, steady state setup frequency was shown to be independent of the number of job types assigned to the manufacturing system, when system load is above a critical system load. Furthermore, a critical system load was shown to exist if and only if the product of setup time and production capacity is greater than $n_v - 1$, where n_v is the number of job types entering the system.

- A distributed flow control law termed biased minimum feedback (BMF). It was shown that BMF is capable of adjusting work-in-process distributions to suit changing correlation in job arrival sequences into distributed manufacturing systems, which was shown to increase downstream assembly performance.

1.2.4 List of Publications

- Walker, A. J., and Bright, G. Stabilisation and control of configurable product manufacturing through biased decision feedback decoupling. *Journal of Manufacturing Systems 32*, 1 (2013), 271 – 280.

- Walker, A. J., and Bright, G. Discrete event modelling and control of multi-stage batch-of-one production systems. *Proceedings of the* 1^{st} *international conference on sustainable intelligent manufacturing*, Liera, Portugal, June 29 - July 1, 2011, IST Press.

- Walker, A. J., and Bright, G. Manufacturing flow control using biased minimum feedback. *Proceedings of the IFAC conference on manufacturing modelling, management and control*, Saint Petersburg, Russia, June 19 - June 21, 2013 (Accepted paper.)

- Walker, A. J., and Bright, G. Production flow control using biased minimum feedback. *Proceedings of the international conference on competitive manufacturing (COMA)*, Stellenbosch University, South Africa, January 30 - February 1, 2013.

1.3 Layout

Chapter two presents a literature review of past research outputs regarding MCM implementation. Within the literature review process, a holistic view of MCM production planning and product design is taken, such that treatment of the distributed control problem occurs under valid assumptions. An overview of MCM research is presented with reference to a control theoretic construct in order to expose the cause and effect relationships present in the implementation of MCM. Since the majority of operations complexity results from increased product variety, much of the background literature is related to planning requirements for effective variety management. The fundamental objective of chapter two is to determine how research into the planning phase of MCM production implementation has imposed on the resulting distributed control environment and requirements thereof.

Chapter three forms the main research component of this work and presents the method and approach taken in working towards and achieving the research objectives. Research contributions made are presented through rigorous analysis and quantitative reasoning on customer-manufacturer interaction and steady state response characteristics of stable flow controlled manufacturing systems. Manufacturing control requirements, as a result of customers decision behaviour in product configuration, are formally characterised and used in the synthesis of a distributed control system for MCM implementation. Closed form models are presented which are shown to be applicable in determining steady state control requirements under customer induced process disturbances brought on by decisions in product configuration. The closed form models are validated through discrete event simulation.

Chapter four presents a case study construction of a configurable product, well suited to mass customisation. Included is an overview of the market characteristics surrounding the product platform considered. A full product specification is developed in both the functional and physical design domains. Based on concepts exposed through the literature review in chapter two, as well as current trends within the industry, a process plan is developed and used in discrete event simulation of a produce-to-order production system. The models and methods developed in chapter three are applied in resolving steady state requirements for the implementation of effective distributed control. It is shown that the models developed in chapter three are useful in determining steady state manufacturing control requirements. Some of the inherent drawbacks associated with resolving distributed control requirements based on steady state analysis are also presented.

Chapter five presents a discussion of the models, metrics and methods presented in this research. Results achieved and contributions made are put into context with respect to the MCM research field as a whole. Significant aspects of the results and models presented are discussed and their impact in other fields on MCM research highlighted.

Chapter six concludes this research, presents a summary of contributions made and presents open questions for future research in production control for MCM implementation.

1.4 Summary

This chapter provided motivation for this research study by highlighting the need for closed form models which can accurately predict the steady state control requirements due to customers' decision behaviour in product configuration in MCM. The aims and objectives of this research study were presented as well as the method used in conducting this research. Research outputs, such as analytic response surfaces for the description of steady state behaviour in flow controlled manufacturing systems were listed as research contributions. A summary of each chapter's content and context was presented in order to describe the formal layout with which this work is presented.

Chapter 2

MCM Implementation: A Literature Review

Just as the largest library, badly arranged, is not so useful as a very moderate one that is well arranged, so the greatest amount of knowledge, if not elaborated by our own thoughts, is worth much less than a far smaller volume that has been abundantly and repeatedly thought over

Arthur Schopenhauer

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The variety management problem in MCM implementation has required research into production system design, under formal consideration of both product and process variety due to customer-manufacturer interaction.

This chapter reviews and interprets past developments made in researching the variety management problem in MCM implementation. Since requirements in manufacturing control depend on production system design, the review includes literature on proposed solutions in product design, process planning and supply chain design, facility layout and customer-manufacturer interaction.

2.1 Overview of MCM and Research Inquiry

The concept of mass customisation first appeared in Alvin Toffler's *Future Shock* [65]. Toffler, much appreciated for his propositions and explanations of modern sociological phenomena, described mass customisation as a method of catering to niche markets. The term *Mass Customisation* was formally introduced by Stan Davis. In his book, *Future Perfect* [18], Davis projected trends encompassing micro-segmentation of consumer markets and unique product development for customers.

Due to the hard inverse relationship between production quantity and product variety, proposed strategies for the implementation of MCM have revolved around delayed product differentiation (DPD). The majority of concepts derived through research within the fields of product and process design, supply chain implementation and assembly system design have been in alignment with the overall DPD strategy. DPD based production takes advantage of scale economy through produce-to-stock operations, which provide input for scope economy through produce-to-order operations. Many researchers have investigated the applicability of DPD strategy in the implementation of MCM. In He *et al.* [22], the authors investigated the impact of DPD on the performance of high variety manufacturing systems, within the context of product design and resulting manufacturing complexity. The output of their research was a method of selecting designs so as to minimise the cost of differentiation and manufacturing.

Produce-to-order production delivers unique product instances derived from a customer induced functional design perturbation of a configurable product platform. In effect, where custom job-shop deliverables are bounded by a firm's technological processing capability and manufacturing capacity, MCM based produce-to-order deliverables are artificially bounded, so as to create feasible variety bandwidths within design and production. This can be considered as the principle of MCM implementation. Research inquiry into the variety management problem in MCM, and results thereof, support this general principle.

2.1.1 A Control Theoretic Perspective on MCM Research

The principle research objective in MCM implementation has been to resolve an optimal external variety for an associated internal complexity. In Tseng *et al.* [66], product design formalisms were proposed which explicitly considered the properties and characteristics of modern supply chain implementations, highly segmented markets, as well as principles from design for manufacture (DMF), in order to design products for mass customisation. Wang *et al.* [69] applied constrained optimisation methods in the multi-objective optimisation of products, processes, business operations and manufacturing systems in order to determine the best product variety for an associated manufacturing complexity.

Viewpoints taken in MCM research have been centered around the consensus that successful implementation relies on holistic constructions of the problem space induced by increased variety, McCarthy [45]. In keeping with canonical perspectives, a brief overview of the main areas of research into MCM implementation follows with reference to Figure 2.1. The presentation of literature is centered around a control theoretic construct in order to expose the cause and effect relationships provided by manufacturing support systems, such as product design and process planning, which contribute to requirements in MCM control implementation.

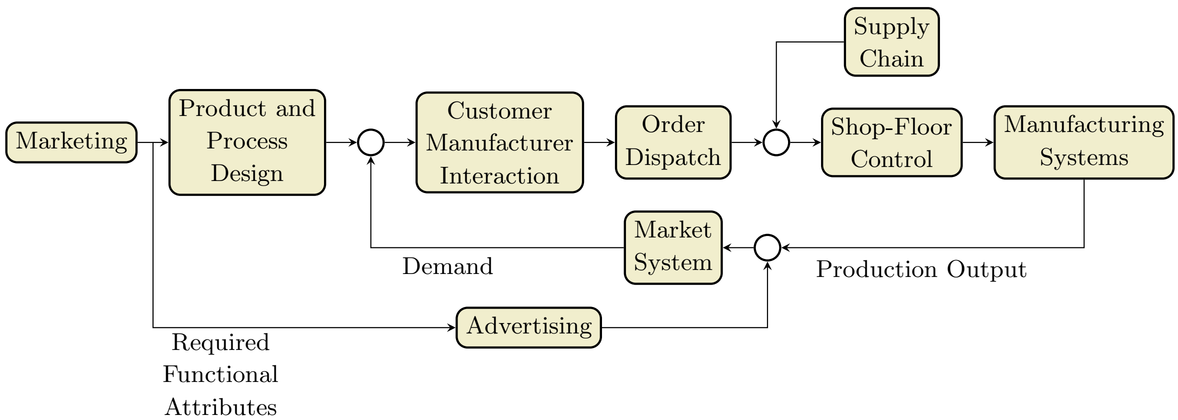


Figure 2.1: Authors view of a simplified control theoretic construct of MCM production operations and systematic relationships

Within an operational context of MCM, marketing acts to understand a market system's characteristics and extract functional product attributes which prospective customers find attractive in facilitating their life sequences of value. Marketing research has focused on understanding an individualised consumer market and determining the effects of mass customisation on competition. Syam *et al.* [63], investigated the competitive mass customisation market in order to characterise economic equilibrium points associated with multiple manufacturers involved in the production of configurable products. One of the most valuable outputs from their research was the realisation that each firm should limit the range of customised offerings in order to prevent decreasing product differentiation between firms from resulting in an effective oversupply and price deflation. Similar aspects of mass customisation market competition were researched in Cavusoglu and Raghunathan [15], and Syam and Kumar [62]. In Mendelson *et al.* [46, 47], it was determined that MC firms should avoid competing with mass producers in large markets, due to the mass producers advantage in economy of scale. Research outputs such as these suggest that the trends towards DPD strategies are a natural consequence of increased product variety.

In the construct shown, demand is initiated through advertising campaigns, which propagate attributes into the market population. Demand also results from word-of-mouth effects, when customers receive production outputs, thus establishing consumer imitation behaviour. Demand generation, as depicted here in a control theoretic context, resembles concepts in product diffusion proposed by Frank Bass [6]. Research into understanding demand for customised products has been based on characterising functional utility, which a market population would consider as value deliverables. In Valenzuela *et al.* [67], the configuration methods used by customers were analysed. They determined that configuration on a per attribute basis results in greater satisfaction and willingness to purchase a customised option. Merle *et al.* [48], developed metrics that measure perceived value and the effectiveness of the co-design process. A large portion of research into demand generation and sustainability has been through empirical surveys. For example, Bharadwaj *et al.* [9] concluded that customised product repurchasing behaviour was a characteristic of customers who have greater confidence in their individual preferences.

In the planning phase of MCM operations, functional product attributes are transferred through product and process design systems, in order to create a configurable product platform, which customers configure to suit their needs, at a customer-manufacturer interaction system. This operational aspect is the single differentiator between MCM and high variety production, and has absorbed substantial research inquiry. The survey paper by Jiao *et al.* [27] presented a substantial overview of platform based product development and the implications for mass customisation. Huang *et al.* [25] recognised and established effective product and process platform design as a key MCM enabler. Product design, process planning, facility layout and supply chain design have been major focus areas as many of the operations and control difficulties in MCM are due to requirements in produce-to-order product variety. Research into planning has been the main focus in resolving the variety management problem in MCM. In the survey paper by Fogliatto *et al.* [20], the authors highlighted the need for research into control requirements for MCM, as the requirements for effective distributed control have received less attention than other aspects of MCM implementation.

Following from customer-manufacturer interaction, orders are dispatched to manufacturing, where shop-floor control operates over manufacturing systems, under supply from both internal operations and external sources, in order to produce a customer's product. Although shop-floor control, specifically distributed control of manufacturing systems, was the main concern in this research, systems shown in the forward loop such as product and process design and customer-manufacturer interaction, play large roles in establishing control requirements. Therefore, in this research it was necessary to characterise the properties of these systems as suggested by past and current research developments into MCM implementation.

Product and process design plays a particularly strong role in determining required active control structures. Developments made in researching product and process design for MCM implementation are presented in the following section.

2.2 Product Family Design

The need to implement MCM has imposed additional requirements in the design and development of products, as well as the informational constructs used in their production management and manufacturing execution. The problem space addressed in researching product platform design and implementation has been encapsulated by the author in the system shown in Figure 2.2.

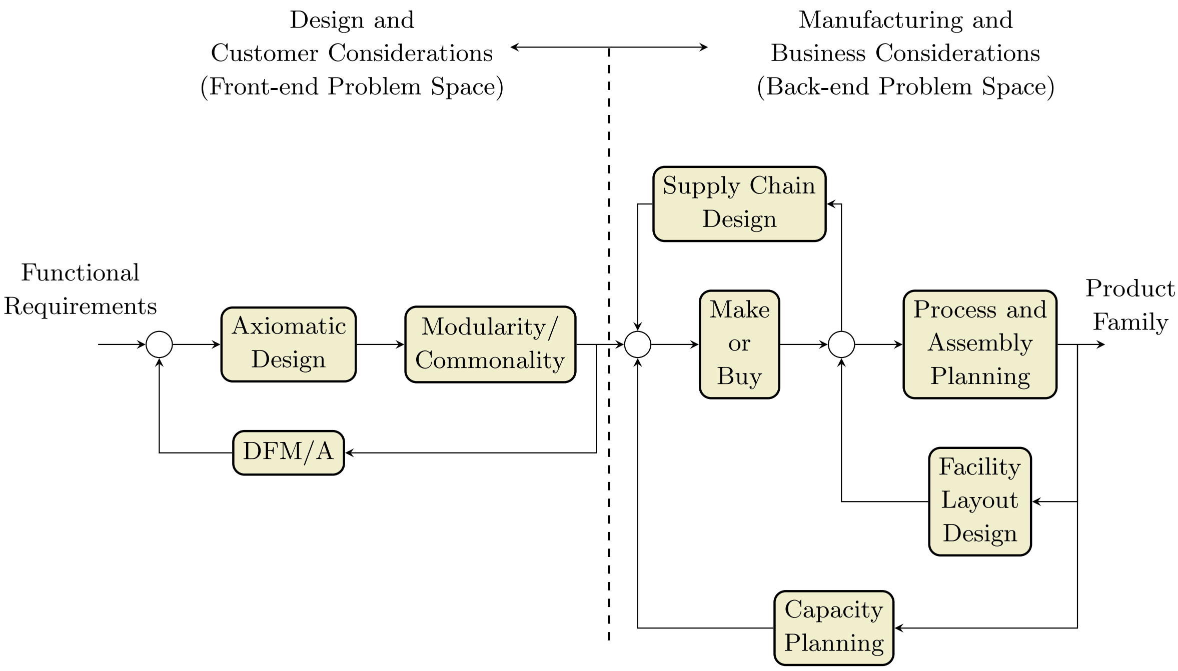


Figure 2.2: Product platform design environment for MCM implementation

Research objectives have been to resolve suitable product platforms from functional requirements, while considering the effects of all contributing subsystems within the context of design and production. Systematic constraints in the design process have resulted in the need for concurrent analysis in the design of products, processes, supply chains and facility layouts. The inherent combinatorial problem spaces that arise in resolving suitable product platforms have been addressed using methods involving heuristic search, mathematical programming and integer programming procedures. Simpson, Maier and Mistree [58], systematically resolved methods in the design, analysis and modelling of product platforms and their resulting product families. Their product platform concept exploration method (PPCEM) serves as a benchmark for other research efforts and uses multi-objective optimisation within a mathematical programming framework in order to extract solutions. Tseng and Jiao [32] proposed a case based evolutionary design (CBED) approach in achieving the requirements for effective MCM. With reference to Figure 2.2, make or buy decisions coupled with modular design methods have resulted in a trend towards assemble-to-order operations, which have had the largest impact in determining control requirements. Literature related to these developments is covered in section 2.3.1.

Research into product family design has exposed two fundamental viewpoints, the first being from a functional perspective and the other from a purely technical perspective. Progress made in researching product design and modelling within these viewpoints is presented in the following section.

2.2.1 Functional and Technical Viewpoints

Traditional product design does not include the objective to facilitate customers decisions in configuring a product according to their needs. Research into configurable product design has established the concept of design for mass customisation (DFMC). The concept of DFMC involves two fundamental requirements, the first being customer orientated and based on functional decompositions, Jiao and Tseng [33], the second related to production efficiency, Daaboul *et al.* [17]. DFMC prescribes the need to design a product platform such that customers can configure the products functional attributes with maximum utility. According to Simpson *et al.* [27], this is termed front-end design. Since the front-end design space establishes the characteristics of customers decision behaviour in product instantiation, research outputs in this field of study have contributed to a qualitative and quantitative understanding of customers in MCM.

Conceptually, the facilitation of requirements in the front-end problem space has relied on axiomatic design principles, in which functional product attributes FR are resolved as linear combinations of design parameters DP, i.e. $[FR] = [DM][DP]$, where DM represents a design structure matrix. Modular product platform design principles, such as those considered by Kusiak [38], try to diagonalise the design matrix such that each functional attribute maps onto one design parameter, which could exist as a component subset of a product platform. Also proposed is the axiomatic design of processes and resources in order to create manufacturing agility. Modular product design and component commonality among variants has long been regarded as a preliminary necessity in enabling MCM. Many techniques have been developed based on the use of design structure matrices. In research by

Blackenfelt [10], two functional design structures namely design structure matrices (DSM) and module indication matrices (MIM) were combined in an effort to efficiently integrate the methods of axiomatic design. In regard to these forms of research, inquiry tends to result in the development of measures to describe and analyse the degree of bijective mapping within a product family.

The second requirement prescribed by DFMC relates to the imposed complexity at the production level. This is considered the back-end design process. A substantial amount of research has addressed the effects of modular product design on production complexity, specifically in the case of assembly system design, analysis and implementation. In the literature, combinatorial optimisation has been the main method of solution, with genetic algorithms forming the main heuristic search procedure. In Suh *et al.* [61], the authors presented a platform design process in response to increased functional and physical bandwidth in product platforms. Using a case study of an automotive body-in-white, where 10 out of 21 components were identified as possible flexibility points, it was shown that their method can systematically pin point and value flexible elements. It was noted however that there is an average increase of 34% in initial investment in manufacturing equipment and tooling. Their research also focused on collapsing the marketing and management requirements in product design onto engineering levels, where commonality metrics were developed and used in combinatorial optimisation of a product platform. Rahul and Allada [56], used agent-based optimisation to handle the multi-objective environment of the product platform design problem. Zhang *et al.* [73] proposed a method in which the configuration of product platforms and supply chains occurs in tandem in order to increase the effectiveness of both product design and manufacturing operations.

Jiao *et al.* [29] proposed that product family design and data organisation faces three fundamental challenges. Firstly, the organisation of product data must be explicit in the relationships between product variants. Secondly, a formal product variant must result from a parameterised instance of its parent product platform. Lastly, both functional and technical viewpoints must be available to completely describe a product platform. Subsequently, a major research area in MCM focuses on determining product models that can accurately describe both the functional and technical domains of a product family, such that customers can configure products with maximum utility, while associated technical data remains well organised and platformed. Many product platform models have been developed over the course of research into understanding variety management in MCM. Bei and MacCallum [7], proposed a product family classification tree (PFCT), which was used in representing configuration knowledge in the classification of end-products from a functional viewpoint. Jiao and Tseng [28] introduced a generic structure, termed a functional requirement decomposition/classification tree (FR/DCT), to represent product instance variety, as viewed by a customer. The author feels that all structural concepts developed in this regard can be represented as the instance is shown in Figure 2.3. Each functional constituency, represented with a c prefix, specifies a products functional structure, i.e. those functional attributes exposed to customers configuration decisions. Each functional constituent contains configurable parameters p, upon which customers make selection decisions among variants v, in order to instantiate a product which satisfies their requirements. It is this aspect of MCM which is considered in this research, more specifically, the effects of temporal correlation in decisions made in p from consecutive customers, on manufacturing control requirements and steady state characteristics.

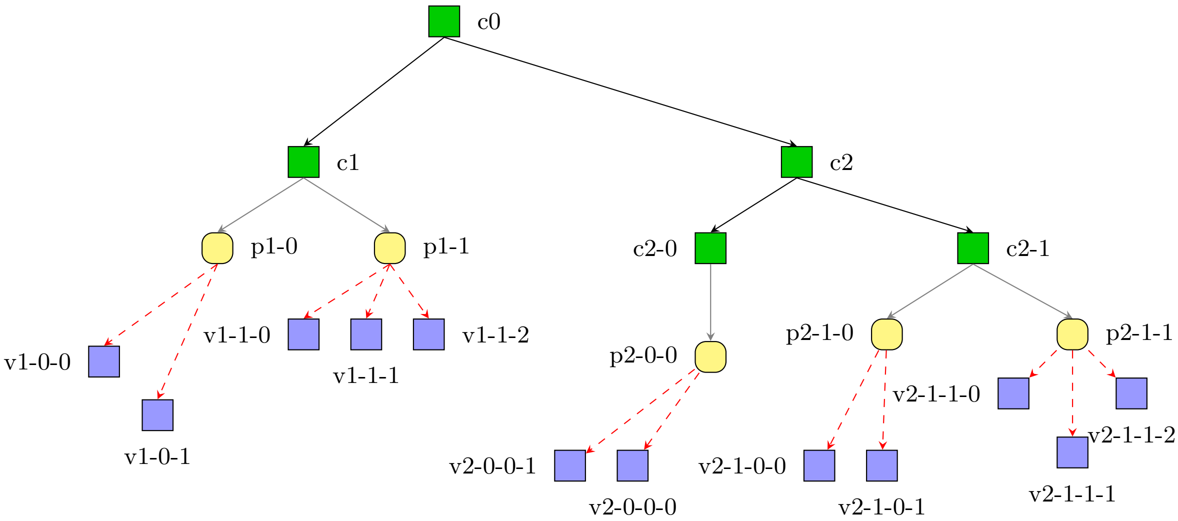


Figure 2.3: Author's understanding of a functional requirement decomposition classification tree structure representing the functional architecture of a configurable product

In order to effectively address increased variety in the back-end problem space, process platforms have been researched. Literature related to developments made in process platforms is presented in the following section.

2.2.2 Coupled Product and Process Structures

Regarding technical aspects of product modelling, the industrial standard method in complete and organised description of a product's physical structure is a bill-of-materials (BOM). A BOM is generally constructed through the decomposition of fully specified engineering drawings at sub-assembly and component levels. This decomposition results in tree like structures, resembling assembly sequences in a step by step manner. Although a BOM may not necessarily map bijectively to assembly procedures and precedence of the actual physical product, constituent component collectives forming functional attributes of the product stem from distinct nodes in many instances. Material requirements planning (MRP) systems use BOM's in establishing production control procedures and therefore

BOM's are a fundamental requirement in manufacturing control operations. Under high variety manufacturing, the standard construct of a BOM fails to provide such functions, as each product model requires its own BOM and a data explosion problem results, Olsen and Stre [51]

In order to prevent the data explosion problem, Veen [68] established the concept of a generic bill of materials (GBOM), that represented a basis composition of multiple BOM into a flexible generic instance. Where a BOM describes a single product structure, a GBOM describes a family of related products without data redundancy, hence formed upon a basis description. The GBOM concept deals with engineering orientated product structure, in terms of physical components and interfaces, and lacks formal consideration of functional relationships or the transfer of product configuration variations onto the production management and manufacturing system levels. In order to include the mapping from product to process, Jiao *et al.* [30] developed a generic bill-of-materials and operations (BOMO) concept to encapsulate a product model in structure, function and required process variation.

The BOMO concept indicates the need to combine both material requirements planning and manufacturing operations into a single organised data model in the implementation of high variety production and MCM. By having a generic information model that considers both material requirements, as well as processing operations, parameterisations in the functional domains, which are exposed to customers' decisions, can be related to process variations and manufacturing control requirements. Concepts in the generic representation of product and process structures were further researched in Jiao *at al.* [31], where a generic product and process structure was developed and used in a case study of custom vibration motors for cellular phones. Their representation is shown in Figure 2.4.

The research outputs presented have shown that the trend in product design and modelling for MCM is to establish generic process structures and material flow routings. This can be considered as the principle driver in economy of scale under large product and process variety. Required manufacturing system layout and design, based on these generic structures, has also received extensive research interest as manufacturing system layout and design determines the effects of translation from process variation to manufacturing control requirements. Developments made in researching this problem space is presented in the following section.

2.3 Developments in Production System Design

Delayed product differentiation structures have been researched in the implementation of high variety production and MCM. As variety increases, the time horizons associated with planning initiatives decrease, and as such, planning emphasis is focused at the product and production system design phase. DPD operates on the strategy that produce-to-order operations are supplied by produce-to-stock items, often imported through supply chains, so

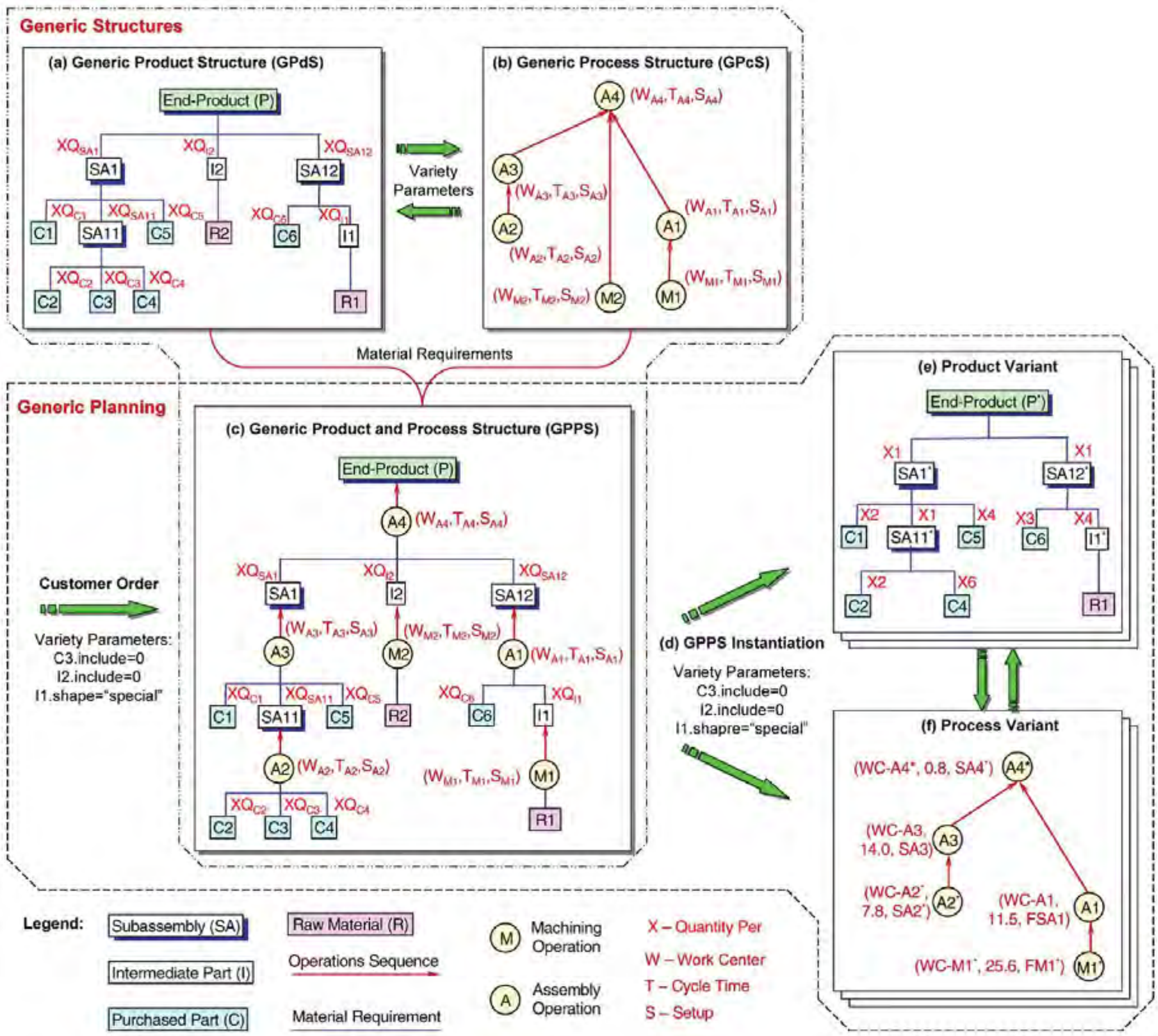


Figure 2.4: Implications of process platform development. (Figure adapted from Jiao *et al.* [31])

as to maintain economy of scale while achieving the agility required by MCM. It has been a natural consequence of DPD implementation that resulting production systems for MCM operate on an assemble-to-order basis. Developments made in researching assembly system design under high product variety follows.

2.3.1 Assembly System Design and Implementation

Assemble-to-order systems have been identified as one of the most cost effective approaches in implementing MCM. Hu *et al.* [23], reviewed the state of the art in assembly system design under high product variety and modularity. Topics in sequence generation, line balancing and assembly modelling were considered. AlGeddawy and ElMaraghy [2] used a case study in the design of an assembly line for customisable belt tensioners. They used a biological classification tool (Cladistics) to analyse product variants that are candidates for delayed differentiation. Wang *et al.* [69] used multi-objective optimisation in the design of products and required assembly lines. They used a metric of relative complexity to find an optimal solution in line with the objectives of optimising variety for minimum complexity. Hu *et el.* [24] defined entropy measures and used functions thereof in describing complexity propagation in multi-stage assembly systems with multi-echelon supply chains. The applicability of delayed product differentiation and modular product architectures in assemble-to-order operations was researched in Blecker and Abdelkafi [11]. An interesting result of their research was the demonstration that the principle of delayed product differentiation through assemble-to-order operations is only reliable when the selection probabilities of module variants at each assembly stage are equal. In their research, this outcome was resolved through the use of entropy measures, which described the proliferation of complexity throughout the entire assembly process.

The mixed model line balancing problem has received considerable attention. In the survey paper by Hu *et al.* [23], the authors considered new challenges which are posed through the implementation of mixed model assembly lines, such as those which result form the implementation of MCM through delayed differentiation strategies. The authors highlighted that under the implementation of mixed model assembly lines, new problems such as drift, i.e. cycle time variance, and part sequencing play large roles in analysis and performance evaluation. Also, where in the case of a single model assembly system, in which true balance can be achieved through preliminary design and workload assignment, mixed model assembly systems seldom achieve a true balanced state and are more sensitive to demand fluctuations. This highlights a need for active control, specifically in the sequencing problem in MCM assembly systems.

2.3.2 Manufacturing System Layout Design

Manufacturing system layouts have evolved in accordance with two principle measures, production volume and product variety. Traditionally, the design objective regarding manufacturing systems themselves, layout, and material handling systems, has been to accommodate either production volume or product variety, but not both. This is due to a strong inverse relationship between the two measures. Layouts associated with job-shop operations accommodate variety and are implemented with groupings of machines by function. Differing process requirements for each job type are achieved through routing and sequence variations. Due to this operational mode, job-shops are characterised by substantial material handling and control complexity, along with a need for occasional changes in manufacturing system setup and have limited production capacity. When product variety is limited, specifically in the case of only one product type, flow line layouts accommodate manufacture through a single sequence flow between each processing station. Single sequence flow, along with automated materials handling and processing stations, results in less control complexity and tighter bounds on required material handling capacity. Flow lines are capable of large scale production, but have limited scope for variety. Automated flow line and job-shop layouts can be considered to accommodate the extremum of production quantity and product variety respectively.

With the introduction of group technology (GT) out of the Soviet Union, many different manufacturing system configurations and layouts have resulted. The principle goal of GT was the establishment of manufacturing cells, in which design objectives regarding machine groupings changed from those of similar function to those of part family. Advanced manufacturing technologies, such as flexible manufacturing systems, are physical derivatives from these concepts in GT. Today, the range of manufacturing systems and facility layouts varies between job-shop and flow line, each inheriting a subset of the flexibility associated with job-shop layouts, and scale production capability from flow line formalisms. Accordingly, the control requirements surrounding each manufacturing cell design and layout vary as well.

Traditional cellular layouts based on GT do not adequately support the production requirements of customer perturbed product platform instances. Cellular layouts came into practice to facilitate high variety production, within produce-to-stock operations. Application of these layouts is only feasible when product mix and volume are deterministic and stable over a long time period. In Benjaafar *et al.* [8], the authors outlined the needs and challenges of designing manufacturing system layouts in highly volatile environments with large product variety. They interpreted developments in four streams of research, namely modular layouts, reconfigurable layouts, agile layouts and distributed layouts. The authors determined through a literature survey that layouts for high product variety are formed upon two separate viewpoints. One viewpoint considers that the implementation of sub-optimal yet robust layouts, are best suited to frequent changes in production requirements and demand variations. For instance, in plants with automated manufacturing and materials handling systems, where reconfiguration costs are high, this view can be considered ideal. Another viewpoint considers that the implementation of reconfigurable layouts are best suited to instances of frequent changes in production requirements and demand. Reconfigurable layouts are those which change configuration at a low frequency, although are more efficient during production operations, Koren and Shpitalni [36]. An interesting approach to the implementation of manufacturing cells and layouts for MCM was introduced in Barudeen and Masel [4]. The authors proposed the implementation of minicells, in which each minicell produces option families. This implementation concept can be considered as the most direct projection of generic product and process platforms, such as the BOMO concept covered in section 2.2.2, onto robust layout structures.

Figure 2.5 is the author's depiction of the concept behind the implementation of minicells, which is a modified version of Figure 2.3. The implementation of minicells aids in the

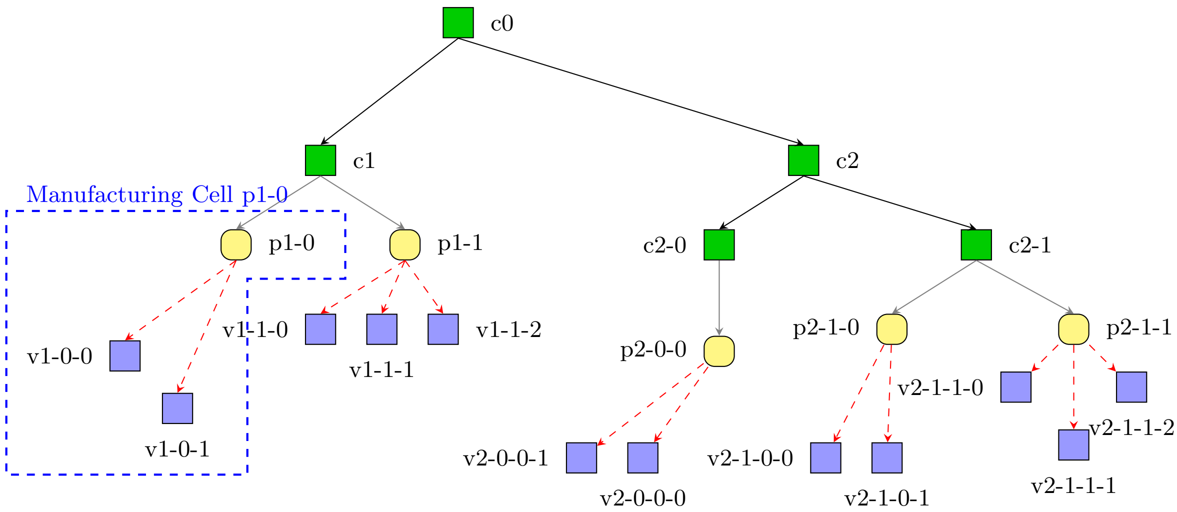


Figure 2.5: Graph node grouping representation for the concept of minicells

direct characterisation of customers decisions in product instantiation at the manufacturing system level, since processing requirements are dependent on selections made in the variety parameter p.

The author feels that minicells are a valuable system construct in the design of manufacturing systems for MCM, and can be considered as GT applied to produce-to-order MCM. This is especially true if one considers that, when viewed at the manufacturing system level, customers are no more than bounded stochastic input disturbances to an otherwise deterministic set of required production operations. With this view, it is then feasible to localise variations to each minicell based manufacturing system, as opposed to requirements in complex routing and control. This however, can create the need for increased manufacturing infrastructure, such as jigs and tooling, although this has already been established as a necessary requirement for effective variety management in MCM implementation, Suh *et al.* [61].

With the implementation of minicells and concepts such as BOMO, requirements in manufacturing control under production variations, imposed by customers decisions in product configuration, results in the need for distributed setup scheduling and flow control. Customers decisions in p, and the effects thereof on manufacturing requirements, are represented diagramatically in Figure 2.6. With reference to Figure 2.6, each decision made in p translates into different infrastructure requirements, which constitute processing and/or assembly stations. Literature related to developments made in setup scheduling and manufacturing control is reviewed in the following section.

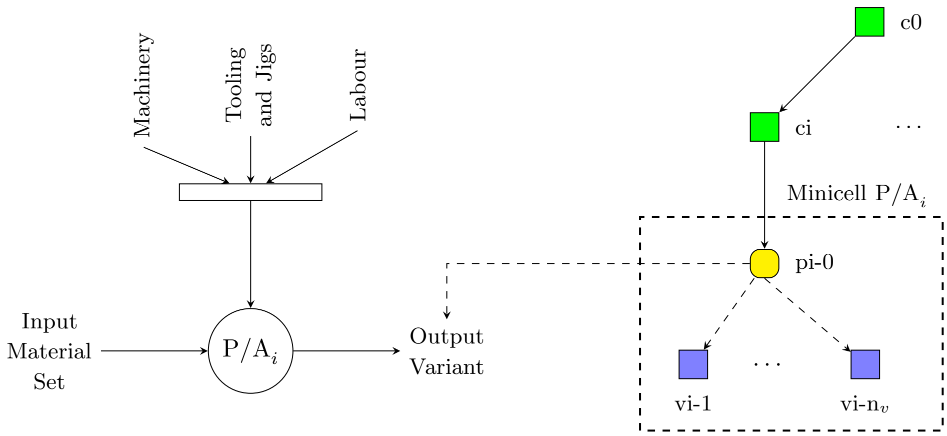


Figure 2.6: Implications in manufacturing requirements due to customers selection decisions in p

2.4 Methods in Manufacturing Control

Many control architectures have been researched and implemented in advanced manufacturing systems. Control objectives include the coordination of material supply into processing and assembly stations, the determination of task assignment through scheduling, and the maintenance of performance and stability bounds when uncertainty is a characteristic of system operation. It is the case that control systems operate over finite capacity systems, both in production and storage. Due to these capacity and capability constraints, many methods in the development of optimal schedules and resource allocation systems incorporate mathematical programming techniques implementing constrained optimisation.

Control requirements change according to the variety of product types produced, and plant layout. As layout distribution increases, along with routing variation, so the complexity associated with assigning tasks to processing stations increases, specifically when redundancy exists in the capabilities of manufacturing infrastructure. For example, in a flow line layout, producing a single product type, formal active control in maintaining stability and utilisation collapses onto a problem of determining sufficient inter-process buffer storage. Required buffer capacities are determined according to the failure and repair distributions of upstream and downstream processing stations, such that the flow line remains free of blocking while maintaining high levels of utilisation. Control in this regard falls under planning initiatives, such as flow line design and line balancing.

Figure 2.7, which is a modification of Figure 2.1, explicitly isolates those subsystems which contribute to manufacturing control implementation in MCM. The order dispatch subsystem, depicted in the forward loop, has received extensive research inquiry whereby the problem of optimal scheduling in high variety production systems has been addressed. Dynamic

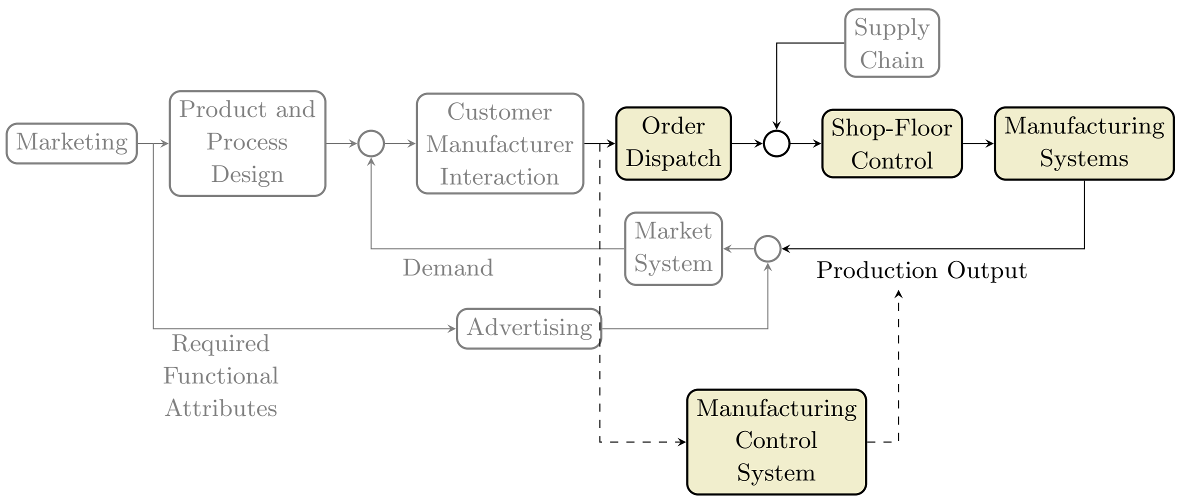


Figure 2.7: Manufacturing control subsystems within MCM implementation

job-shop scheduling is the canonical term used to describe the process of resolving an optimal assignment of tasks, i.e. production processes, to finite capacity resources over time, under random job arrivals. Optimality in this regard is considered to be the minimisation of an objective function, which in many cases is a linear combination of measures such as work-in-process, average tardiness, utilisation and makespan. Panwalkar and Iskander [52] provided a comprehensive survey of various techniques used in developing optimal or near optimal schedules within these environments. A survey of scheduling problems in high variety production environments under the consideration of setup times or costs is provided in Allahverdi *et al.* [3]. Solutions to the dynamic job-shop scheduling problem have involved constrained optimisation through the use of exhaustive search techniques, and refinements thereof such as genetic algorithms, branch and bound, tabu search, simulated annealing and other search heuristics. The principle drawback in the implementation of control through scheduling at this level of production is the NP-hard nature of the resulting problem space. This property of the problem space limits practical application of these methods to small or medium sized production systems and resource/job sets, with predictable production resources.

The dynamic job-shop scheduling problem can be considered as a centralised control approach, whereby decisions are made at the order dispatch level. In order to overcome the inherently combinatorial problem surrounding scheduling efforts at this level, control is often implemented locally at each manufacturing system, in a decentralised control approach. This is considered with reference to Figure 2.7 as distributed shop floor control. Distributed shop floor control is more suitable in the context of MCM implementations, as the scheduling workload is distributed over many resource collectives, allowing for less complex decision making procedures which are tractable in real-time.

It is a natural consequence of production system structure that various levels of control exist. As one varies scope from the physical equipment level up to market forecast driven master production schedules, control requirements change according to various reference requirements and informational feedback. Figure 2.8 represents a generic feedback loop in manufacturing control implementation. Each loop in the control theoretic construct represents a different level in the manufacturing control hierarchy. Time horizons within each loop vary between seconds at the process level, minutes at the workstation level, up to hours, days and weeks at the higher levels of control scope.

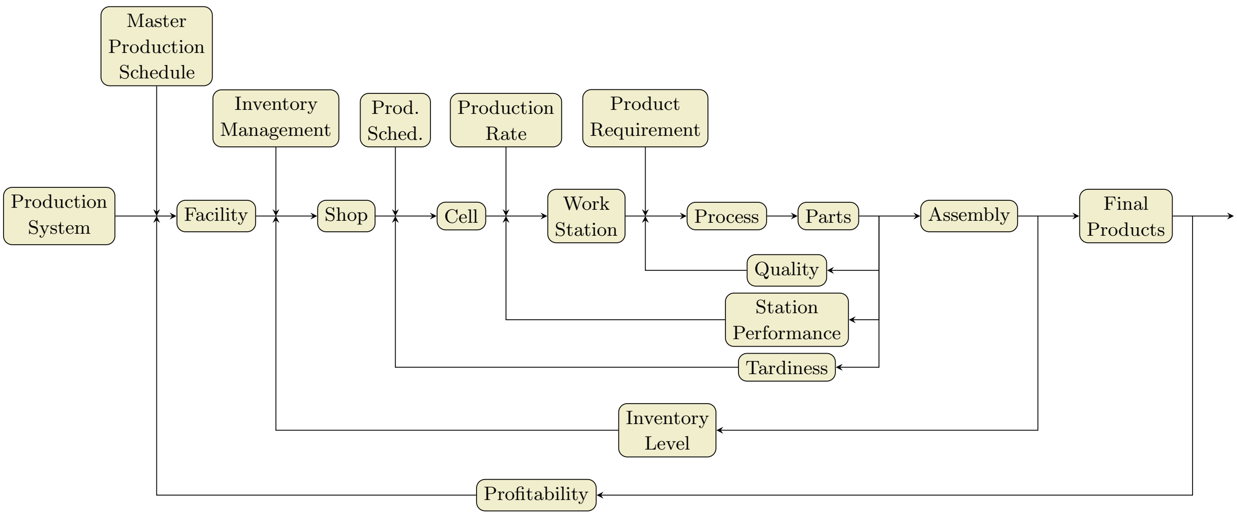


Figure 2.8: Generic multi-level manufacturing control loop

Different approaches have been taken by both researchers and practitioners in designing control systems which implement the multiple loops in Figure 2.8. Three forms of control architectures, namely hierarchical, heterarchial and hybrid have resulted. Hierarchical architectures are those which are most intrinsic to the informational flows and time horizons associated with the various levels of production, from physical machines through work-station levels up to system scoped control requirements, such as demand tracking. Hierarchical architectures are centralised in operation, where control decisions originate from the system scoped level and propagate towards the control of physical infrastructures. The informational feedback follows the converse path from physical infrastructure back towards system scoped reference requirements. It is for this reason that hierarchical control architectures suffer the disadvantage of being slow to react to changes which occur at relatively high frequencies, although perform well when reference requirements are stable and uncertainty is minimal.

Heterarchial control architectures do not subscribe to the natural hierarchies present in production system implementation. Control operates in a distributed fashion under various levels of autonomy. Due to the distributed implementation of heterarchial control structures, agility and responsiveness are inherent properties, making these control architectures favourable under high product variety and performance uncertainty. Heterarchial control architectures rely on communication between distributed control implementations in order to perform and maintain global performance objectives. For this reason, absolute certainty on performance bounds is difficult to characterise and the tracking of global objectives is sub-optimal in many cases. Hybrid control architectures try to combine the favourable characteristics of both hierarchical and heterarchial architectures. Hybrid control allows for distributed decision making within regions bounded by higher level supervisory control.

A substantial amount of research has been dedicated to the control and coordination problem underlying flexible manufacturing systems and manufacturing systems with non-negligible setup times, as well as manufacturing cells producing multiple part or product types. Control objectives have been to resolve optimal machine loading and utilisation, task assignment and part sequencing, as well as optimal demand tracking. A review of related literature is presented in the following sections.

2.4.1 Mathematical Programming

Methods used in this approach have been based upon constrained optimisation models. A comprehensive review of the analytic models developed for the design and control of flexible manufacturing systems is provided by Buzacott and Yao [14]. The authors highlighted the need for analytic methods over simulation based approaches, in developing greater insight into system performance. Typical solution synthesis has been through decomposition of the problem space. Stecke [59] divided the flexible manufacturing system operation problem space into two sub-problems, setup determination and control operation. Setup determination forms the planning problem prior to execution of part production, and it was determined that this prior planning phase in the control of flexible manufacturing systems is crucial in the overall performance of task assignments and execution. Problem formulations in the approach taken by Stecke [59] resulted in large nonlinear mixed integer problems which required extensive computation thus diminishing the effectiveness of industrial application.

The machine loading problem was addressed in Lashkari *et al.* [40], where the authors considered refixturing and constrained the problem through limited tool availability. They considered objectives consisting of the minimisation of transportation requirements within flexible manufacturing systems, as well as refixturing requirements. Their solution applied a linear programming technique, although the authors showed that for even relatively small number of parts, jigs, tools, and machines, the computational problem loses practicality. Kimemia and Gershwin [35], addressed a problem involving the optimal routing of parts through a flexible manufacturing system. They considered an objective of maximising flow while keeping work-in-process bounded. The authors applied a network of queue's method in modelling the problem and analysing the problem space.

Due to large computational requirements, the real-time application of mathematical programming techniques to practical industrial problems is not ideal. Many simplifying assumptions are necessary in order to create tractable solution paths. In order to counteract these difficulties, many researchers have investigated the application of heuristic rule based control systems.

2.4.2 Heuristics and Dispatching Rules

In many cases, heuristic methods take the form of dispatching rules, where jobs are assigned to machines under predefined rules. Stecke and Solberg [60] investigated the application of heuristics in the control and operation of flexible manufacturing systems. Their analysis included loading problems involving the assignment of tooling and operations to machines, as well as real-time flow control. Results achieved are different to the usual job-shop characteristics and they found that the application of a heuristic involving the ratio of shortest processing time and total operation time to be particularly useful. Their analysis also presented an interesting insight in that unbalanced loading achieved consistently better performance. Scheduling rules through dispatching heuristics were investigated by Co *et al.* [16]. The authors found that a jobs mean flow time through a FMS is independent of the dispatching rule used when machine loading is minimal. In the context of research presented in chapter three, the author feels that this result is a control property of all manufacturing systems in high variety production operations. In this regard, it tends to be the case that decisions made during control application only effect steady state performance if there exists the potential to do so, either as a result of system loading, or a sensitivity to system load that results due to the inflexible nature of the manufacturing system. This aspect of control implementation is formally addressed in chapter three.

Heuristics are applicable to dynamic flexible manufacturing system problems as their computational overhead is minimal. Simple dispatching rules have found extensive application as their performance is adequate, even in scenarios involving uncertainty. Research into the operations problem surrounding flexible manufacturing systems has also been based on control theoretic constructs. Literature related to this field is reviewed in the following section.

2.4.3 Control Theoretic Constructs

Manufacturing flow control can be generalised to the construct shown in Figure 2.9. Jobs of each type enter a buffer according to a random arrival process. In the context of this research, each job's type on arrival would be determined by a customer's decision process in product configuration, due to a selection of product module variants. Each job type requires a different manufacturing system setup. If setups consume a considerable amount of time, the scheduling of setups is important and both the frequency of setups and setup trajectories within the configuration set of a manufacturing system must be controlled in order to maintain manufacturing performance.

Although represented as multiple buffers in Figure 2.9, for clarity, a single buffer could exist in reality. A distributed real-time controller observes the buffer's state and operates to stabilise work-in-process, $\sum_{\mathcal{S}} x_s$. The flow controller, F_c, drives a manufacturing systems setup according to $\sigma(t)$, where $\sigma(t)$ is a piece-wise, continuous from the right, setup selection signal. The control signal σ latches each job type and associated buffer to the machines capacity set C_s.

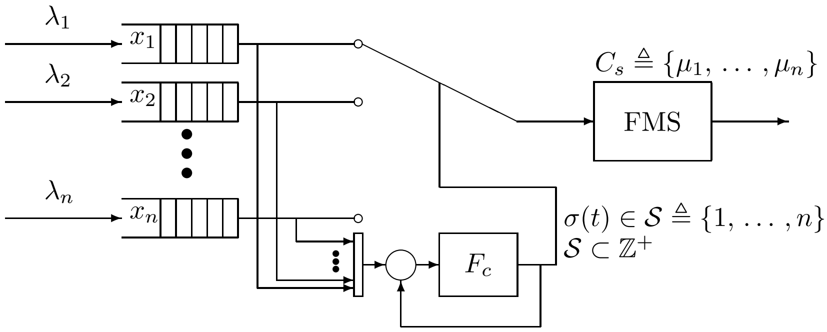


Figure 2.9: Author's representation of the manufacturing flow control construct

When flow control is implemented, the effective capacity of a flexible manufacturing system is a function of setup frequency. Determining feasible setup frequencies and/or setup trajectories is important in order to keep work-in-process bounded. Traditionally, the stability of flow control operation has been measured on work-in-process alone, however stable distributed instances of flow control does not ensure stability of the entire manufacturing facility. The majority of research into flow control implementation has been based on continuous models, which exclude effects of part sequencing on downstream assembly stations. The change in part sequencing from arrivals to departures through a manufacturing system can degrade downstream assembly performance, independently of capacity constraints. Specific inquiry into this detrimental system variable was considered in this research study. Analysis in this regard is formally presented in chapter three.

In much of the literature, the availability of the machine is modelled according to a Markov process, in which the transition rate matrix is parameterised according to mean time between failure (MTBF) and mean time to repair (MTTR) for the machine. It can be the case that when failure rates are substantially slower and/or recovery rates much faster than the operating rate of the process, the Markov modeling is disregarded and instead the machines maximum capacity for each job type is adjusted to a lesser value than its maximum.

In Sharifnia, Caramanis and Gershwin [57], the flow control problem was investigated in terms of a multi-level hierarchy of discrete events, each with a distinct frequency of occurrence. The authors suggested that provided each event frequency is sufficiently distinct, the problem can be decomposed into multiple sub-problems, on which analysis can be focused. This can be thought of as a cascading analysis method. In their control implementation, setups are controlled with state feedback and hypercone corridors in the surplus space of each part type, where surplus space is the cumulative difference between demand and production rate. They showed that by the proper selection of corridor, a stable limit cycle persists in steady state. Perkins and Kumar [54] and Kumar and Seidman [37], addressed the setup scheduling problem with non negligible setup times. They developed distributed control strategies in which setup decisions are made based on the state of the input buffer/s. Also addressed is the stability of the distributed control strategy. In their work, Lyapunov functions formed the basis for determining the stability of each control policy.

Lou *et al.* [43], characterised the capacity for a single machine with random breakdowns in order to find conditions upon which work-in-process remains bounded. Their research was valuable in that it determined the effects of non unity availability on the effectiveness and stability of flow control implementation. Boccadoro and Valigi [12] considered the setup scheduling problem for an unreliable manufacturing system with finite buffers. They considered a single machine two part type system and used dynamic programming to minimise a cost function under transient and steady state conditions. Elhafsi and Bai [19] presented work on the optimal control of a single machine, two product type, flexible manufacturing system with significant setup changes. Their system was modelled in the context of a continuous time dynamic environment. Lan *et al.* [39] considered a multi-product, single server system in which there is a cost incurred whenever a setup occurs. Their system modelled a produce-to-order environment in which a backlogging cost was also considered. They found local and global heuristics which minimise the long-run average cost per unit.

The majority of flow control implementations can be classified as clear a generalised fraction (CGF) methods, Perkins and Kumar [54]. With reference to Figure 2.9, CGF implementations are clearing policies in which σ is chosen on the condition that $x_\sigma(t) \geq f(\sum_S x_s(t))$, at which time all jobs of type p_σ are cleared from the buffer before selecting another job type. One such F_c, which is a specific instance of CGF is clear a fraction (CAF) where σ is selected upon the condition that $x_\sigma(t) \geq \varepsilon \sum_{\mathcal{S}} x_s$, for $\varepsilon \in (0, 1)$. As long as $\sum_{\mathcal{S}} \frac{\lambda_s}{\mu_s} < 1$, all CAF type policies are stable. The reader is referred to Perkins and Kumar [54] for a Lyapunov function based proof of stability for CAF policies.

2.4.4 Simulation Based Approaches

Simulation methods have been researched in the context of online model reference control. In this approach, back-end simulation is used to evaluate dispatching rules online, where the simulations are parameterised and built upon real data from a physical system. Concurrent simulation, as a method to carry out production scheduling, was proposed by Davis and Jones [34]. They used multiple simulators of a production system, initialised with the latest state of each FMS, to determine the best dispatching rules based on terminating simulation data. A multi-pass expert control system (MPECS) was proposed by Wu and Wysk [70]. Their method used discrete event simulation for on-line control and scheduling of flexible manufacturing systems, under various dispatching rules. Through simulation, a dispatching rule was determined during each short period prior to implementation time. The long term behaviour of their approach was that various dispatching rules are combined in response to the dynamic environment.

In determining adequate and optimal simulation windows, Ishii and Talavage [26], used a transient based algorithm where the scheduling interval was defined based upon system transients determined through discrete event simulation. A filtering type method was also used in predicting the performance of candidate dispatching rules for the next scheduling period.

Simulation based methods have the advantage that very few simplifying assumptions, if any, are necessary to achieve valid solutions. Simulation models can be designed to represent reality as close as possible, however in doing so, simulation run times can become the bottleneck in successful control implementation, specifically when many candidate rules exist.

2.4.5 Artificial Intelligence and Holonic Control Implementations

Artificial intelligence techniques have found application in the control and coordination of material flow through flexible manufacturing systems, as well as in the higher levels of shop floor control. Lin and Solberg [41] applied a heterarchial intelligent agent system at a shop floor level. Each job and resource was modelled according to an intelligent agent module, in which interaction between the agents takes place over a bidding protocol. The objective of their implementation was to optimise a weighted objective function over the due date, price and other factors.

Parunak *et al.* [53], and Baker *et al.* [5] proposed an intelligent agent architecture for shop floor control and scheduling. The authors attempted to provide a system which allowed direct communication between customers and distributed manufacturing systems for the implementation of MCM. Their system followed a particular operation path where a customer placed a preliminary order, upon which the agent architecture determined possible delivery dates and cost. The customer then finalised the order prior to production execution. This aspect of operation, in which customers are directly involved in the order placement and dispatching process is of particular interest. The ability to predict costs and delivery dates is important in the implementation of MCM. The development of control systems which stabilise average manufacturing lead time through a manufacturing facility would greatly benefit customer-manufacturer interaction and customer satisfaction. Stabilising manufacturing lead time per product through a manufacturing facility is analogous to increasing the determisms with which costs can be predicted and presented to prospective customers.

2.5 Constraint Induced MCM Control Environment

From research outputs and concepts presented in previous sections, the main implementation requirements for MCM control can be rationalised. Many developments made in researching the variety management problem have established particular properties in the manufacturing environment upon which MCM control operates. Concepts such as generic product and process structures, and minicells, have allowed for flow line formalisms to be integrated into high variety production environments. This single aspect is perhaps the most influential of all concepts highlighted through research inquiry into the variety management problem, in determining the type of distributed control necessary for MCM implementation.

With this view, it can be considered that the mode of control required by MCM implementation, in order to achieve efficient manufacture while effectively managing variety, is tending towards switched flow line control in an assemble-to-order operation, where each manufacturing station or cell produces a set of module variants associated with each variety parameter of a product family. An important realisation in researching delayed differentiation in assemble-to-order implementation was made in Blecker and Abdelkafi [11], where it was determined through analysis of complexity propagation, that the principle of delayed differentiation is only reliable when the selection probabilities of module variants are equal at each assembly stage. Given that deterministic or reliable behaviour is governed by this requirement, then this single aspect allows for an assumption to be made in that the long term decision behaviour in product variant selection by customers can be assumed to manifest as uniform demand for each variant type. This viewpoint forms the basis in assumptions made regarding the analysis presented in the following chapter.

2.6 Summary

This chapter presented a literature review of research outputs in requirements for effective variety management in MCM implementation. A holistic overview of MCM research was provided with product and production system design being highlighted as having formal contribution to the manufacturing control problem in MCM implementation. It was noted that research into requirements for MCM implementation has resulted in particular manufacturing system layouts and operations, the control of which can be handled through distributed control constructs, such as manufacturing flow control. The various approaches in controlling advanced manufacturing systems such as flexible manufacturing systems were reviewed and interpreted. Mathematical programming approaches, although applicable to less complex manufacturing scenarios, were characterised as being too computationally demanding for industrial application, specifically in the case of MCM. Dispatching rules based on heuristics were reviewed and determined to be more applicable to complex manufacturing systems, where the dynamic environment required real-time scheduling and control operation. Many control theoretic approaches were reviewed and results from these investigations were reported as achieving good performance. Research carried out in the investigation of simulation back-ends in augmenting the application of heuristics was also reviewed. These systems were reported as showing great promise in the control and coordination of flexible manufacturing systems, as well as being able to characterise the performance of the entire production system as a whole.

Consideration of developments made in various fields of MCM implementation research, specifically the variety management problem, allowed for the interpretation of control operations necessary to facilitate the properties of production systems designed to manage increased variety in MCM implementation. The concept of minicells was interpreted as a trend to localise variations to each manufacturing system, as opposed to complex routing and coordination. Reasoning on these research outputs in product design, process planning, and manufacturing system design and layout exposed the critical aspects of MCM control implementation.

Chapter 3

Analytic Models for Distributed Control Synthesis

When a truth is necessary, the reason for it can be found through analysis, that is, by resolving it into simpler ideas and truths until the primary ones are reached

Gottfried Leibniz

Contents

This chapter presents the methods and analysis used in researching distributed control requirements, due to customers decision processes in product configuration. Firstly, the fundamental ways in which customers' instantiate product instances from a parent product family are presented, and the process variations thereof determined. A probability model is applied to characterise these effects for use in determining the steady state response of stable flow controlled manufacturing systems. Closed form analytic models are developed, that describe the effects of customer decision processes through time, on the steady state performance and control requirements of manufacturing systems involved in MCM operations. Finally, a new method of distributed flow control is presented which has the capability to regulate work-in-process at each manufacturing system so as to favourably distribute work-in-process throughout the manufacturing facility in order to increase downstream assembly performance.

3.1 Modelling Time Sequences of Job Arrivals

To a large extent, it is the temporal correlation in decisions made by consecutive customers rather than explicit decisions in product configuration, which determines manufacturing control requirements and steady state performance. Each customers decision in module selection results in varying material inputs, processing and assembly operations, and routing through each manufacturing system. These explicit decisions in product configuration export tasks to production control systems, which operate on supply chain, inventory, and manufacturing systems, in order to maintain and coordinate the supply of material inputs and processing operations at each manufacturing system. Increasing product variety is analogous to increasing the size of the sample space over which random variables, i.e. customers' decisions in product configuration, take values. Within the market population, if customers' collective decision behaviour has sufficient variance, then it is expected that correlation in consecutive order arrivals into the production system would be decreasing with increasing product variety. Characterising this variance was considered valuable in synthesising manufacturing control requirements during this research.

Mathematical description of the manufacturing control effects of customer decision processes required an understanding of the mechanisms with which customers instantiate product variants, and the methods by which product platforms expose these mechanisms to the customer. This is covered in the following section.

3.1.1 Properties of a Configurable Product Family

The principle ways in which product variants are instantiated by customers' was considered, in order to develop a probabilistic model describing the manufacturing effects of customer decision behaviour in the time domain. Of particular interest was the characterisation of steady state control requirements due to customers' decision processes in product configuration, and subsequent job arrivals at each manufacturing system. Figure 3.1 shows the context of the customer model. From this point on the term job refers to a full specification on materials, tooling, fixtures, manufacturing operations, and process sequence required to produce a component subset of a product variant.

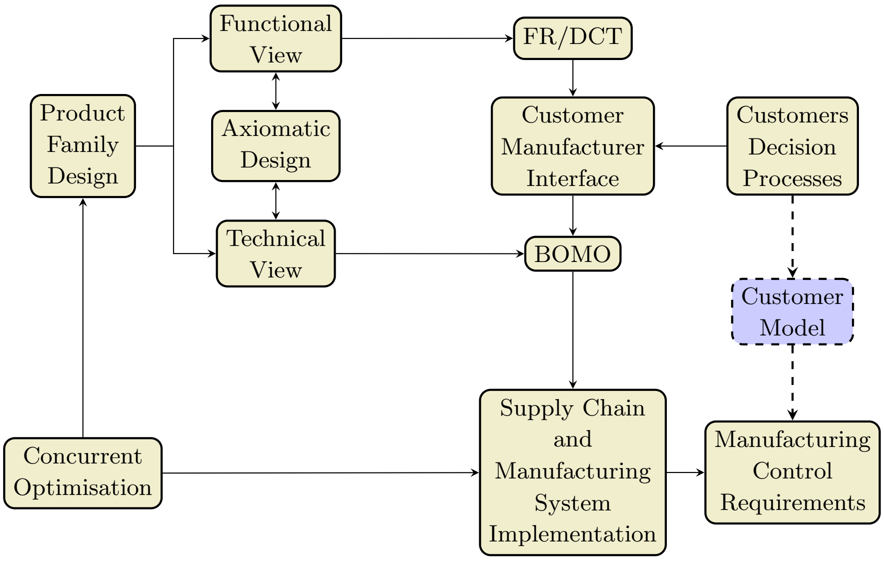


Figure 3.1: Context and position of customer model relative to product and process family design formalisms

Research by Zamirowski and Otto [71] suggested that product platforms occur in three principle forms, namely modular, scalable and generational. A variant instance of a modular platform results from selections made between existing, fully specified product modules, Meyer and Lehnerd [49]. Scalable platforms are those which are configured through continuous scaling of module parameters, to achieve required functional capacity, Simpson *et al.* [58]. Generational platforms are considered in the literature as being instantiated through leveraging product life cycles for rapid next generation products. Martin and Ishii [44] developed a product platform architecture using this approach with the aid of a variety of indices related to redesign efforts. This third type of product platform is associated with engineer-to-order (ETO) operations, and as such was not considered to represent the characteristics of those product platforms used in MCM.

Given the above mentioned principle product platform types, a product platform can be functionally configured through the variation of two ordinates. These ordinates consist of continuous variables, which act as scalars in capacity and dimension, and discrete variables that map to mutually exclusive product module variants in a finite set. The way in which customers' decisions in continuous and discrete ordinates map to process variations is considered in the following section.

3.1.2 Continuous Parameter Induced Process Variations

Continuous parameters are those which scale the functional capacity of a particular module variant, an instance of which is shown in Figure 3.2 within the abstract manufacturing cell p2-1-1.

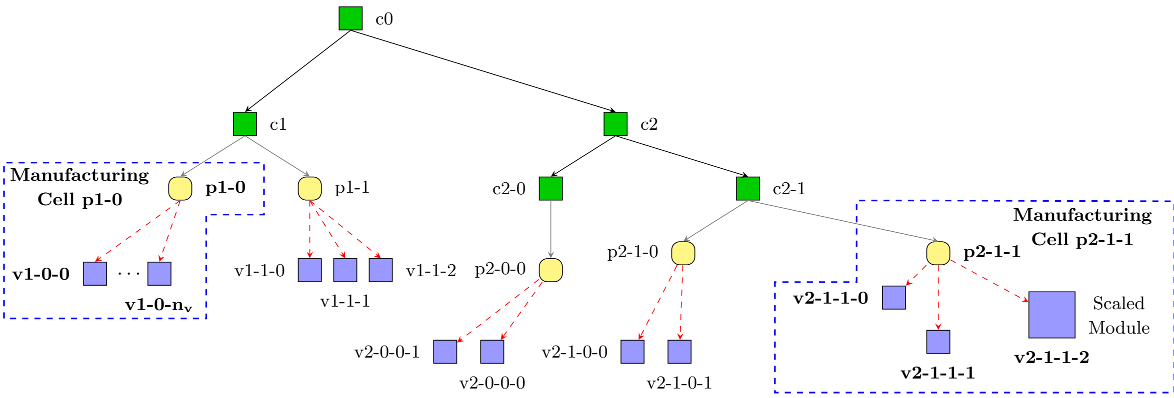


Figure 3.2: Functional requirement decomposition/classification tree structure depicting discrete and continuous parameter variations

The applicability of exposing continuous parameterisations in product platforms is dependent on manufacturing process capabilities, customer characteristics within the market, and whether or not such continuous scalability exists inherently in a product's design. To clarify this statement, consider the case of a configurable bicycle, in which customers select between seat module variants. If the market niche consists of professional cyclists, they may select a non-adjustable seat module, so as to integrate the seat into the frame of the bike, making it lighter and more rigid. This would require a continuous variable parameter in order to adjust seat height to suit the customers leg length. On the other hand, if customers select an adjustable seat module, then product configuration, in terms of seat height, occurs during product use. The principle of MCM is to move away from a *one size fits all* design paradigm, therefore in developing a model of customer-manufacturer interaction, customers were considered to instantiate product variants which do not allow for adjustable components during product use.

In the case of discrete parameters, customers' decisions can be considered to select physical component subsets, i.e. functional modules, that are fully specified prior to customer interaction with a product platform. However, selections associated with continuous parameters can be considered as continuous random variables, which take values over a sample space prescribed by the manufacturer. As an example, consider a shaft with configurable turned length, Figure 3.3, which could represent the scaled module variant produced at station p2-1-1 as depicted in Figure 3.2.

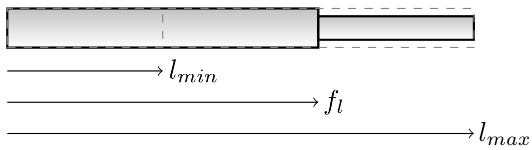


Figure 3.3: Example of a shaft of configurable turned length

The function, $f_l = l_{max}p + (1-p)l_{min}$, $p \in [0,1]$, represents a variation range function defining the manufacturers bounds on a sample space of shaft length. Customers decisions in this context are random variables over a subset of the reals $[0,1]$. The range between lower and upper bounds l_{min} and l_{max} is physically constrained by manufacturing capability and artificially constrained by the depth at which the market is understood, as well as feasible product design. An artificial constraint can be interpreted under the condition that physical ranges determine expected distributions over the interval $[0,1]$. If customers preferences in product configuration are such that their collective selections in shaft length result in a uniform distribution over the interval $[0,1]$, then it is expected that the bounds imposed on product configuration do not adequately capture a market populations preferences. If customers' collective decision behaviour is such that a minimally variant Gaussian distribution over $[0,1]$ results, then decreasing the range $[l_{min}, l_{max}]$ decreases the probability of large manufacturing variations, although does not exclude a large proportion of customers' requirements. This construct relates back to concepts in optimal product configuration space, in which the manufacturer establishes maximum external variety for an associated internal manufacturing complexity, Wang *et al.* [69]. As an aside, given the concept of an artificial constraint, if one was to monitor customers' requirements in l over time and adjust the interval $[l_{min}, l_{max}]$ according to a preferred reference statistical distribution over $[0,1]$, then an optimal configuration space could be resolved online. A reference distribution over $[0,1]$ could be determined through capacity planning of the manufacturing system in question, i.e. manufacturing cell p2-1-1, such that customers decisions in f_l do not adversely affect steady state performance.

For the case of a shaft with configurable turned length, distributions over the interval $[0,1]$ are equivalent to cycle time variations, when the shaft is turned under a constant feed rate. Under continuous parameter perturbations, customers can be considered as shifts in the mean of Gaussian distributions over cycle time, Figure 3.4.

If the cycle time variance associated with a manufacturing process's natural behaviour is greater than the variance imposed by the selections made over $[l_{min}, l_{max}]$, then the effects of customers' decisions in continuous product parameters can be disregarded, and instead the natural behaviour can be adjusted to include customer decision processes during modelling

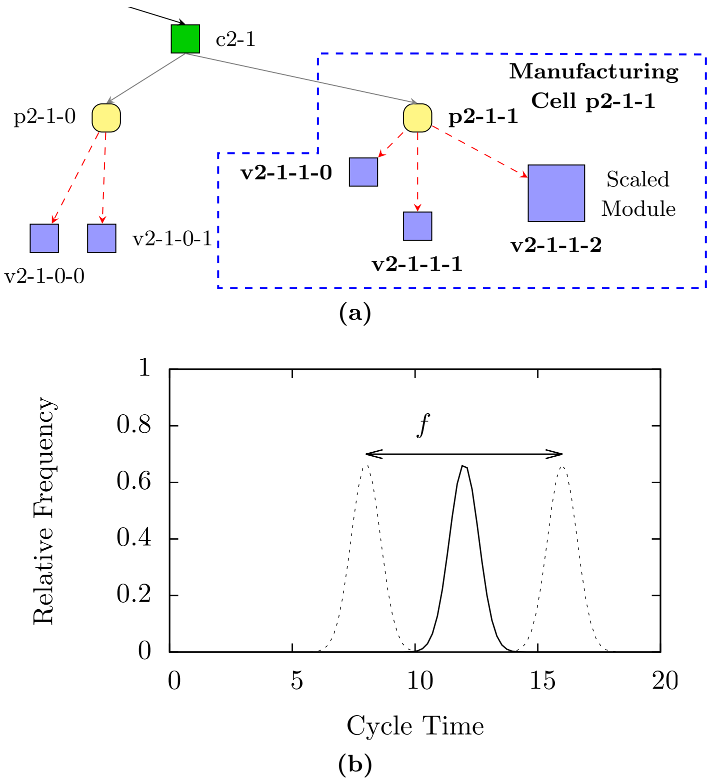


Figure 3.4: Effects of customer decision behaviour as shifts in the mean of distributions over cycle time

and process planning. Considering the research outputs reviewed in section 2.4.2, where in Co *et al.* [16], the authors found that mean flow time through a flexible manufacturing system is independent of the dispatching rule when system load is minimal, then this view on the effects of variations is applicable.

Through effective planning, if one localises the effects of continuous parameter perturbations to each manufacturing system, then provided the expected variance in f is sufficiently small due to product design decisions in $[l_{min}, l_{max}]$, changes in control requirements due to customers' decisions in f can be considered negligible. In cases where the variance is not negligible, then well utilised job scheduling policies such as shortest processing time first (SPT) can provide the necessary control to bound work-in-process levels and maintain stability. Process variations due to selections made in discrete parameters have the potential to be more detrimental to manufacturing system performance. Analysis in this regard is covered in the following section.

3.1.3 Discrete Parameter Induced Process Variations

Parameterisations associated with discrete variant selections are those depicted as dashed lines in an isolated branch of the FR/DCT shown in Figure 3.5.

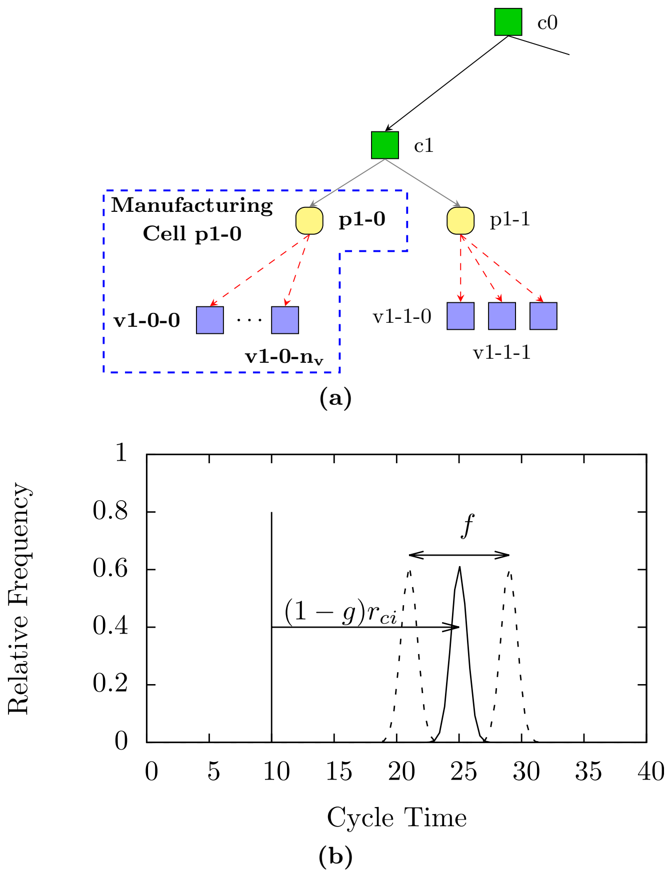


Figure 3.5: Machine grouping associated with the production requirements of product variants v1-0-0 through v1-0-n_v, and associated cycle time variations due to discrete variant selections

By considering the cases in which a different manufacturing system setup is required for each module variant, discrete selections made between product module variants map to setup time inclusive shifts in the mean of Gaussian distributions over cycle time. If no active control is applied in the scheduling of jobs into a manufacturing system, i.e. FIFO policy, then the variable g is a binary random variable based on whether consecutive customers decisions in product module variants are identical.

The effects of correlation in consecutive customer decision behaviour is best described through an example. Consider the following two cases with reference to Figure 3.5, in which the number of module variants v for a single parameter space p is $n_v \geq 2$, with a FIFO buffer discipline at the manufacturing system producing the two module variants. For the two cases considered, associated with each module variant are a set of jigs, tools and fixtures, which have to be set up and calibrated before processing can begin. In the first instance, the order arrival sequence is such that there are n_v different job types awaiting processing resources from the manufacturing system. This will result in the need for, at least $n_v - 1$ setup changes. This scenario indicates an upper bound in customers' decision induced setup frequency at a manufacturing system. In another instance, the order arrival sequence is such that there are n_v of the same job type awaiting processing. This would result in at most 1 setup change, where the single change in setup is dependent on the manufacturing systems initial setup condition. This can be considered as the lower bound in customer induced setup frequency. In order to measure the effect of correlation in job arrival sequences, a metric termed average cumulative correlation was developed. The rationale behind and derivation of average cumulative correlation follows.

Since customers' decisions regarding the selection of product module variants, are random variables, average cumulative correlation is also a random variable. Assuming that customers' do not influence each others product configuration decisions, one can regard customers decision processes through time as sequences of independent Bernoulli trials, with a successful outcome ($g = 1$) representing two consecutive customers selecting the same module and ($g = 0$) otherwise, where g represents a binary random variable. If the probability of two consecutive customers selecting the same module variant is p, then the probability of counting k instances in which two consecutive customers select the same module variant in a sequence of n customers is given by;

$$P(k,n) = \binom{n}{k} p^k \left(1-p\right)^{n-k}$$

which is the well known Binomial distribution. According to the weak law of large numbers (WLLN), the expected number of instances in which two consecutive customers select the same module variant as $n \to \infty$ is np. Furthermore, one would expect that $\lim_{n\to\infty} E\left[\frac{k}{n}\right] = p$. If one could determine the value of p in the characterisation of customers decision behaviour in product configuration, then steady state control requirements could be resolved in terms of expected average cumulative correlation. For this reason, average cumulative correlation was defined according to Equation 3.1;

$$C_c = \lim_{n\to\infty} \frac{1}{n} \sum_{j=1}^{n} X, \quad P(X=1) = \frac{1}{n_v} \tag{3.1}$$

where n represents the number of orders placed, i.e. dispatched for manufacturing, and n_v represents the number of product module variants assigned to a discrete decision parameter p of a product family's FR/DCT.

Average cumulative correlation diminishes with increasing n_v. For $n_v = 1$, correlation would be independently 1, and approaches 0 as $n_v \to \infty$. Larger work-in-process levels, although detrimental to lead-times, can be beneficial in batching minimally correlated arrival sequences, thus increasing manufacturing system utilisation. A description of steady state behaviour in flow controlled distributed manufacturing systems, in response to changes in C_c, was considered to be beneficial in determining control requirements in produce-to-order MCM. This is covered in the following section.

3.2 Steady State Behaviour in Stable Flow Control

Markovian constructs, queuing theory and discrete stochastic process theory are applicable in the steady state analysis of generalised discrete part manufacturing systems, Buzacott and Shanthikumar [13]. In this research, continuous analytic models were developed and used in approximating the steady state characteristics of stable flow controlled manufacturing systems, under variations in average cumulative correlation. Using continuous models to characterise steady state behaviour was considered feasible under the assumption of stable operations. The assumption of stability means that over a long time period, any stochastic variations, provided they are sufficiently bounded, would converge onto associated statistical means of the underlying random variables.

The objective of this analysis was to answer the following questions:

1 - In what manner does average cumulative correlation in consecutive customer decision processes, effect the fundamental steady state characteristics of a stable flow controlled manufacturing system?

2 - How do upstream response characteristics of stable independently controlled manufacturing systems effect the performance of downstream produce-to-order assembly operations?

3 - How should work-in-process be distributed within the entire manufacturing facility in order to decrease downstream performance volatility under variations in job arrival sequences into upstream processing stations?

Setup frequency, i.e. the rate of setup changes through time, is an important decision variable in flow control implementation. Increasing setup frequency decreases the effective capacity of the manufacturing system. In order to maintain work-in-process stability, increasing demand must result in a lower average setup frequency. However, lowering setup frequency results in increased work-in-process. Description of this behaviour was handled first and is presented in the following section.

3.2.1 Characteristic Setup Frequency Response

Analytic development of a model to characterise steady state setup frequency in response to variations in C_c over the interval $[0, 1)$ followed a particular path. In order to simplify derivation, a uniform demand for each job type was assumed, along with a setup selection policy of clear largest buffer first (CLBF), which is known to be stable under sub unity loads, see Perkins and Kumar [54]. To further simplify derivation, it was also assumed that $C_c = 0$, and that production occurred at its maximum value instantaneously after a setup change. It may be argued that this assumption weakens the validity of the model, as in reality a manufacturing system would ramp up to its maximum production rate after a setup change. However, by increasing the setup time to include ramp up, provided it occurs over a small time period, allows the effects of ramp up to be disregarded.

Model development and analysis occurred via first principles under consideration of the manufacturing flow control case depicted in Figure 3.6. In this regard, Equation 3.2 represents a piece-wise continuous dynamic model describing work-in-process dynamics associated with the flow control operations in Figure 3.6.

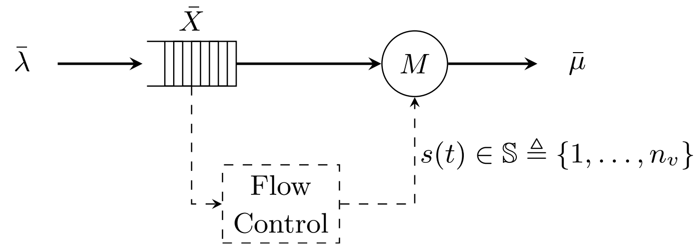


Figure 3.6: For clarity, this figure has been drawn using a single buffer, the thick lines represent multiple job types entering the system

$$\frac{d}{dt}x_i = \begin{cases} \lambda_i & ,\text{if } s(t) \neq i, \\ \\ \lambda_i - \mu_i \sigma(t - [t^- + r_{ji}]) & ,\text{if } s(t) = i, s(t^-) = j \end{cases} \tag{3.2}$$

In the dynamic model, $x_i \in \bar{X} = [x_1, \ldots, x_{n_v}]^T$ represents the buffer level of job type i, $\lambda_i \in \bar{\lambda} = [\lambda_1, \ldots, \lambda_{n_v}]^T$ represents the arrival rate of job type i, and $\mu_i \in \bar{\mu} = [\mu_1, \ldots, \mu_{n_v}]^T$ represents the machines production capacity for job type i. Also, $s(t)$ is a piece-wise continuous from the right setup selection signal and r_{ij} is the time required to change setup from i to j. The function $\sigma(t - \tau)$ is the unit step function at $t = \tau$. The dynamics associated with Equation 3.2 are typical of hybrid automata and switched systems with time delays. If one is to imagine the trajectory of work-in-process, $\bar{X}(t)$, within a cartesian coordinate system, it would evolve according to a linear trajectory which changes direction upon arrival at each consecutive coordinate axis. Furthermore, under a constant demand, these coordinate intersection events would evolve in a round-robin sequence.

Under uniform demand, i.e. $\lambda_i = \lambda_j, \forall i, j \in [1, \ldots, n_v]$ with a clear largest buffer first (CLBF) setup selection policy, the state trajectory of each job type, for a two job type system, would follow that shown in Figure 3.7. Consecutive customer decision behaviour in product configuration for such a situation would be a sequential round robin selection process among module variants. Under this decision behaviour, average cumulative correlation would be identically zero.

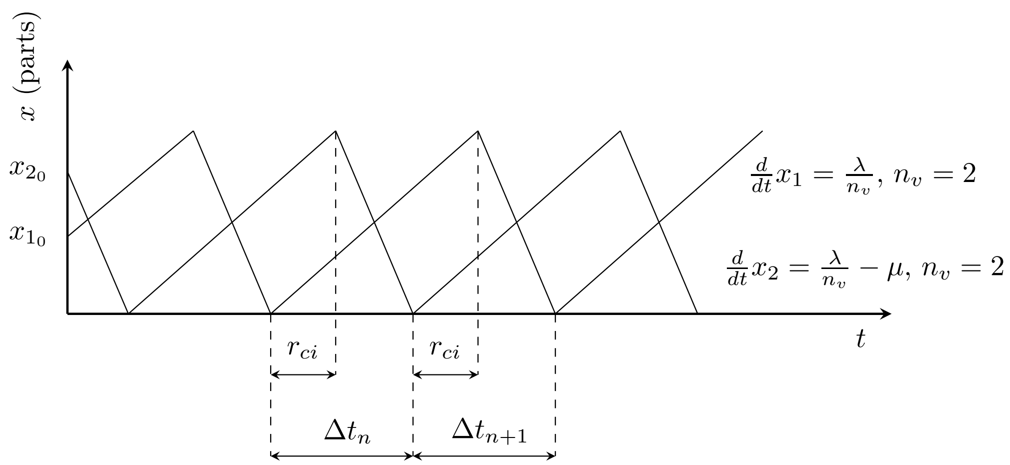


Figure 3.7: State trajectory for a two job type system under a cumulative correlation of zero

An interesting property of steady state average setup frequency was discovered through analysis of the dynamic model described by Equation 3.2. Theorem 1 formally presents the result.

Theorem 1 (Job Type Set Independence)**.** *Let $\mathbb{T}$, $|\mathbb{T}| \geq 2$ be a countable set of job types processed at a manufacturing system with clear largest buffer first (CLBF) flow control policy. Let r_{ci} be the setup period, λ, the average job arrival rate, and μ, the average service rate. If system load $\phi \triangleq \sum_{k=1}^{n} \frac{\lambda_k}{\mu_k}$, $n = |\mathbb{T}|$ is greater than $\phi^* \triangleq \frac{n_v}{\mu r_{ci}+1}$, then steady state setup frequency is independent of $|\mathbb{T}|$.*

Proof. See Appendix A.1.1.

Corollary 1.1. *For a stable flow controlled manufacturing system, a critical system load exists if and only if $\mu r_{ci} > n_v - 1$.*

Proof. Let $\mathbb{A} \subset \mathbb{R}^+$ be an open proper subset of the reals over the interval (0,1), let $\mathbb{B} \subseteq \mathbb{A}$ be a subset of $\mathbb{A}$, and let ϕ^* be a critical system load.

Since for stable systems, $\phi \in \mathbb{A}$, $\forall r_{ci} < \infty$, then $\forall \mu r_{ci} \leq n_v - 1$, it is the case that under the definition of a critical system load $\phi^* = \frac{n_v}{\mu r_{ci}+1}$, $\{\nexists\, \phi^* \in \mathbb{B} \mid \phi \in \mathbb{A}\}$. Therefore $\exists\, \phi^* \iff \mu r_{ci} > n_v - 1$. $\square$

Using the dynamics represented by Equation 3.2, a model was developed to determine a closed form description of steady state average setup frequency for stable flow controlled manufacturing systems. This model helped to determine whether controllable system parameters exist, which can aid in adjusting operating conditions under customer decision induced variations in the cumulative correlation of job arrival sequences. As a consequence of Theorem 1, i.e. job type set independence, Equation 3.3 is an analytic approximation of average steady state setup frequency, in setups per day, as a function of demand, capacity, setup time and the number of job types facilitated at a manufacturing system. Note that the relationship described in Equation 3.3 is centered around an average cumulative correlation of zero and uniform demand for each job type.

$$S_{f_\infty} = 60H_d \frac{1-(n_v-1)\frac{\frac{\lambda}{n_v}}{\mu-\frac{\lambda}{n_v}}}{r_{ci}\left[1+\frac{\frac{\lambda}{n_v}}{\mu-\frac{\lambda}{n_v}}\right]} \tag{3.3}$$

In Equation 3.3, n_v is the number of module variants produced at the associated manufacturing system, λ is the total demand in jobs per minute, μ is the manufacturing systems production rate in jobs per minute, considered equal for all job types in this model, and r_{ci} is the time required to change setup in minutes per setup, considered constant. The parameter H_d is the number of hours in each working day.

Although an approximation, this closed form relationship describes the characteristic response of stable flow controlled manufacturing systems. In order to maintain stability, increasing demand results in decreased setup frequency. If setups are more time consuming, the resulting average setup frequency is lower. A plot of Equation 3.3 over a normalised domain of system load $\phi = \sum_{k=1}^{n_v} \frac{\lambda_k}{\mu_k}$ is shown in Figure 3.8. The normalised metric ϕ can also be regarded as a measure of manufacturing system utilisation as higher loads result in decreased idle time as a result of lower setup frequency.

The characteristic response curve of Equation 3.3 was used as a starting point for analysis into the effects of varying average cumulative correlation on limiting average setup frequency. Analytic tractability of a closed form relationship diminishes with an increasing number of orders n. This is due to the Binomial coefficient which forms part of the description of average cumulative correlation. For example, any particular value of average cumulative correlation $C_c = \frac{k}{n}$, for $k \in \mathbb{Z}^+, k \leq n$, results in $\frac{n!}{k!(n-k)!}$ possible arrival sequences that would form such a limit in C_c. Each sequence instance would generate a different setup frequency convergence response. Given uniform demand for each job type and assuming that customers decision processes are independent, the long term cumulative demand for each job type would converge to $\frac{n(t)}{n_v}$, where $n(t)$ is the cumulative demand up until time t. However, average cumulative correlation may vary between $[0, 1)$. An average cumulative correlation of identically 1 is excluded from the range as this would break the requirements

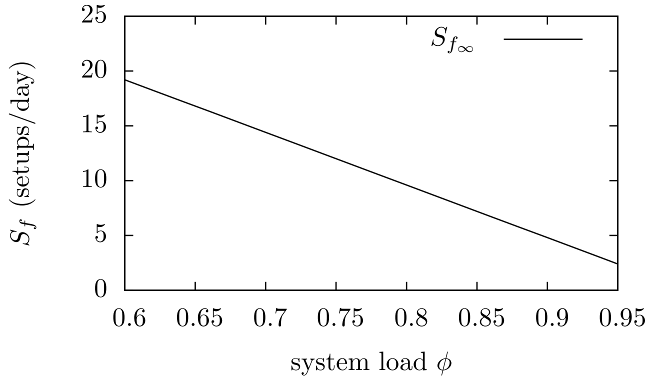


Figure 3.8: Plot of steady state average setup frequency as a function of system load

in uniform demand.

Highly correlated uniform demand results in a customer induced batching of part types into the manufacturing system. It is rational to propose that the effects of temporal correlation in job type arrival sequences into a manufacturing system varies with system load ϕ. Highly loaded systems, with inherently low setup frequencies and large work-in-process levels are less sensitive to variations in the correlation of part type arrivals. A method of polynomial curve fitting was used in adjusting Equation 3.3 for varying values of C_c in the interval $[0, 1)$. It was expected that increasing average cumulative correlation would decrease average setup frequency for a particular system load. To this effect, Equation 3.3 was adjusted to include the effect of average cumulative correlation according to the function $f(C_c)$, Equation 3.4.

$$S_{f\infty} = 60H_d f(C_c) \frac{1 - (n_v - 1)\frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}}{r_{ci}\left[1 + \frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}\right]} \tag{3.4}$$

The function $f(C_c)$, for a constant system load ϕ, takes the form of a polynomial in C_c, i.e. $f(C_c) = \sum_{k=0}^{n} a_k C_c^k$. Formal resolution of the coefficients a_k is deferred to section 3.3.1, where discrete event simulation outputs were used in a polynomial curve fitting procedure.

The synthesis of control requirements in assemble-to-order production operations requires particular consideration of job sequencing into assembly stations. Consideration of the literature on assembly system design and line balancing reviewed in section 2.3.1, this aspect of high variety production and indeed MCM is of particular concern. The job sequencing problem in controlling the flow of jobs through assemble-to-order manufacturing facilities was analysed during this research. The following section presents analysis carried out in determining the properties of the job sequencing problem in MCM.

3.2.2 Characteristic Sequence Entropy Response

Assembly is fundamentally a multi-input single output process. Furthermore, it is governed by precedence constraints. An assembly operation is also constrained to start only when all requisite components, sub-assemblies, or upstream process outputs have arrived at the assembly site. It is the case that although each distributed manufacturing system may indeed be operating effectively in terms of controlled regulation of work-in-process levels and utilisation of production capacity, however downstream assembly performance may still be sub-optimal. Poor scheduling in the arrival of constituent elements can quickly degrade the efficiency of an assembly operation, regardless of other complications. Uncorrelated job type arrival sequences creates the need to decouple from FIFO scheduling disciplines and therefore sequence entropy, i.e. the growth in sequence disorder between a parts arrival and departure from a manufacturing system, is a natural consequence of stable manufacturing flow control implementation. The author feels that the use of the term Entropy is valid as it is in accordance with a natural systematic growth in disorder, due to unavoidable characteristics associated with systems driven by random processes. Note that sequence entropy is to be understood in the thermodynamic context as the growth of disorder in a closed system.

Consider the assembly line depicted in Figure 3.9, where E_s represents average sequence entropy per processed job, defined according to Equation 3.5.

$$E_s = \frac{1}{n}\sum_{k=1}^{n} |S_i - S_o|_k \tag{3.5}$$

where n represents the number of jobs which have been processed through a manufacturing system, S_i, a set of sequence position values associated with job arrivals, and S_o, a set of output sequence position values associated with processed jobs.

Given stable operations, where work-in-process for each job type remains bounded over time, downstream work-in-process at the assembly station A_1 may grow uncontrollably. This behaviour in downstream work-in-process, although natural, is unfavourable and a result of poor synchronisation in the arrival of constituent components into an assembly station. Many sources governing the behaviour of upstream stations contribute to this uncontrollable growth in work-in-process. For example, referring to Figure 3.9, even if $\bar{\lambda}_1$ and $\bar{\lambda}_2$ are identical, along with identical performance in M_1 and M_2, differing average cumulative correlation in job arrival sequences would create different setup selection trajectories. This in turn would separate constituent components of product variants between the input and output of a manufacturing system. Average sequence entropy is a measure of this separation and should be balanced between competing upstream manufacturing systems in order to

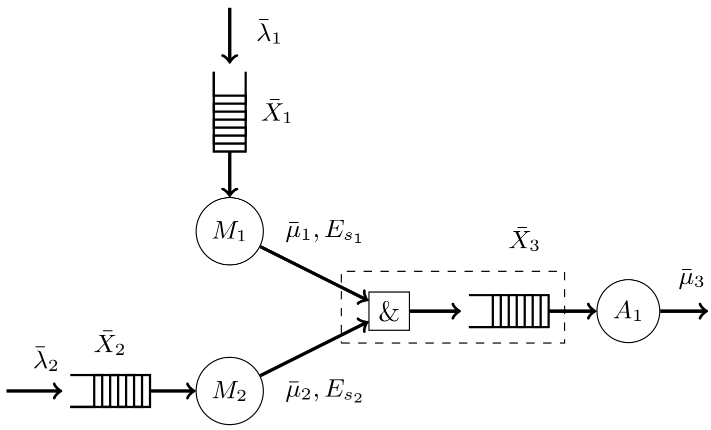


Figure 3.9: Example of competing upstream processing stations in an assembly line

bound work-in-process at downstream assembly stations.

Consider again the piece-wise continuous dynamic model described by Equation 3.2. It was determined through analysis in Appendix A.2.1, that steady state average sequence entropy, $E_{s_\infty} = \lim_{n\to\infty} \frac{1}{n}\sum_{k=1}^{n} |S_i - S_o|_k$, can be described by Equation 3.6.

$$E_{s_\infty} = \frac{n_v \lambda r_{ci}\Big[1+\beta\Big]}{4\Big[1-(n_v-1)\beta\Big]}, \quad \beta = \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}} \tag{3.6}$$

Steady state average sequence entropy is an important system variable in produce-to-order production within the context of MCM. Each individual customer specifies a unique configuration, and as such, mating procedures at assembly stations must wait for a one to one match in constituent components from upstream sources. This is different to high variety operations, in which component level features of a product are generic among a larger set of product configurations.

From the plot in Figure 3.10, steady state average sequence entropy is proportional to the square in arrival rate and is therefore more sensitive to increasing demand, or load on the flow controlled manufacturing system. The curve in Figure 3.10 is in fact a plot of steady state average sequence entropy per production capacity, i.e. $E^*_{s_\infty} = \frac{E_{s_\infty}}{\mu}$, over normalised system load ϕ. This was done to as to represent a generic curve, for a particular r_{ci} and n_v.

As steady state average setup frequency is monotonically non-increasing with system load and steady state average sequence entropy is monotonically non-decreasing over the same system load range, it is natural to suggest that there exists a unique system load value, or bounded range in system load, in which S_{f_∞} and $E^*_{s_\infty}$ are balanced. Through discrete

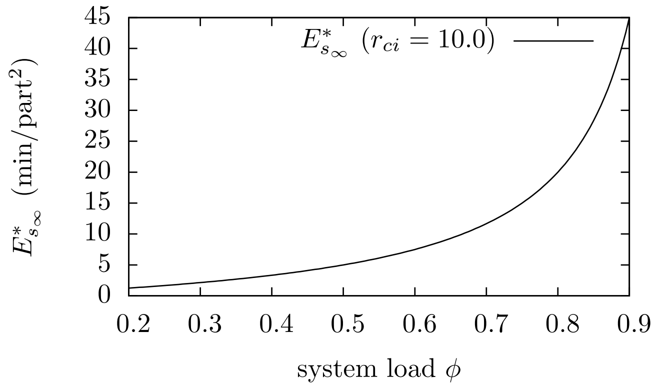


Figure 3.10: Generic curve representing steady state average sequence entropy per production capacity over a range of system load. (The curve represents that generic curve for $r_{ci} = 10.0$ minutes and $n_v = 2$ module variants)

event simulation, this hypothesis was shown to be true. Results are shown in section 3.3.3. Depending on the costs associated with implementing setups, and holding downstream work-in-process, planning a manufacturing systems capacity to run at this value of system load would be beneficial as one could optimise utilisation for a particular sensitivity to downstream work-in-process volatility. A plot of average setup frequency and average sequence entropy over the same system load range in shown in Figure 3.11.

Although the balanced load value is not simply resolved through algebraic manipulation of the relation $S_{f_\infty} = E^*_{s_\infty}$, a simple iterative procedure from either side of the balanced load could easily serve as a suitable method for determining the balanced load value.

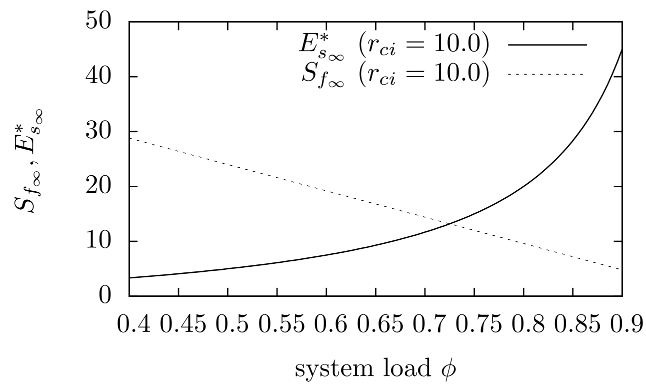


Figure 3.11: Plot showing a value of system load, upon which average sequence entropy per arrival rate and steady state setup frequency are balanced

The models presented in this section were validated through simulation of a single flow controlled manufacturing system. Simulation results are presented in the following section.

3.3 Model Validation through Simulation

Equation 3.3 and 3.6 were validated through discrete event simulation. Simulations were performed and compared with model predictions to determine the applicability of these models in describing the steady state behaviour of stable flow controlled manufacturing systems in produce-to-order production environments. All discrete event models used in simulation were based on the discrete event system specification (DEVS), described in Zeigler *et al.* [72]. The Adevs C++ based DEVS simulation engine developed and maintained by James Nutaro [50] was used in coding and executing simulation runs. Figure 3.12 shows the operational setup of the simulation.

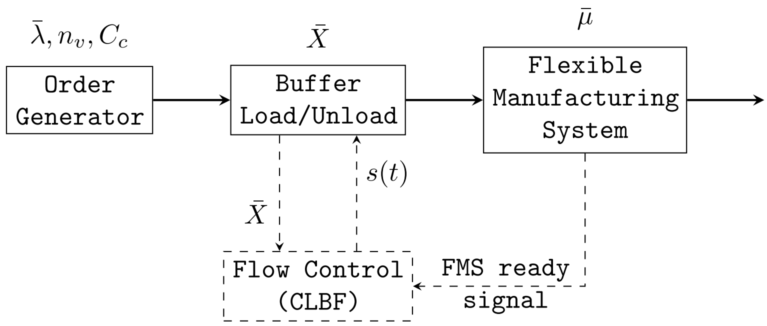


Figure 3.12: Simulation subsystems implementing flow control through a flexible manufacturing system

In preliminary simulation runs, the `Order Generator` in Figure 3.12 was configured to output n_v different job types with an exponentially distributed inter-dispatch time. The buffer model was designed to have a particular operating procedure under job arrival events from the `Order Generator`. An operating procedure was implemented such that when a job arrived, it was automatically loaded into a buffer associated with that job type and informed `Flow Control`, which maintained the buffers state space $\bar{X}$. Control action, driven off the setup selection policy of clear largest buffer first (CLBF), was sent to the buffer, which unloaded the appropriate job type into the flexible manufacturing system. The `Flexible Manufacturing System` was implemented such that a reconfiguration in setup would occur when it receives a job type instance which is different to that which resulted in its current configuration. A change in setup was simulated to take a deterministic amount of time, $\Delta t_s = r_{ci}$. During simulation, the `FMS Ready Signal` was used to inform `Flow Control` to operate on the state $\bar{X}$ and select the next part for unloading and processing. Figure 3.13 shows a simulation output of the work-in-process trajectories for each job type, which is the stochastic discrete event form of those trajectories used in deriving the closed form relationships in Equations 3.3 and 3.6.

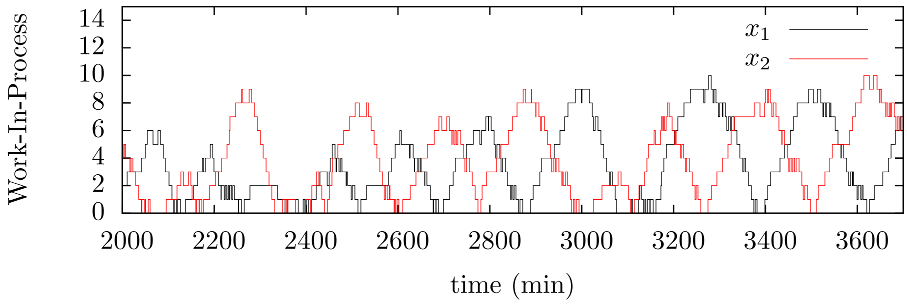


Figure 3.13: Example state trajectory for a two job type system under CLBF policy

In order to validate data sets achieved through discrete event simulation, a modification of Little's law, see Little [42], was used, Equation 3.7.

$$|X|_{ss} = \lambda(W_{ss} - S_{f_\infty} r_{ci}) \tag{3.7}$$

where $|X|_{ss}$ is the steady state average work-in-process, λ, the average arrival rate, W_{ss}, the average manufacturing lead time per job through the manufacturing system, S_{f_∞}, the steady state setup frequency and r_{ci} the time required to implement a change in setup. Little's law states that in steady state, the average work-in-process is proportional to the average manufacturing lead time, with the average arrival rate forming the proportional constant, i.e. $|X|_{ss} = \lambda W$. The modification to include setup periods was based on the premise that the increase in average manufacturing lead time per job would be proportional to r_{ci} and S_{f_∞}. It can be reasoned that the increase in manufacturing lead time is due to the increase in work-in-process during inter-setup periods when production capacity drops to zero for a time period of r_{ci}. In steady state, the average increase in work-in-process would be $\lambda S_{f_\infty} r_{ci}$. When this component in incorporated into Little's law, one resolves Equation 3.7.

$$\begin{aligned} |X|_{ss} + \lambda S_{f_\infty} r_{ci} &= \lambda W_{ss} \\ |X|_{ss} &= \lambda W_{ss} - \lambda S_{f_\infty} r_{ci} \\ |X|_{ss} &= \lambda(W_{ss} - S_{f_\infty} r_{ci}) \end{aligned}$$

As an example of data set validation, Figure 3.14 shows discrete event simulation results for a single manufacturing system controlled under clear largest buffer first flow control policy, with $r_{ci} = 25.0$ minutes, $n_v = 5$ job types, $\mu = 8.9$ jobs per hour and $\lambda = 6$ jobs per hour. An estimate of steady state work-in-process $|X|_{ss}$ and steady state average setup frequency S_{f_∞} is provided in the plot. According to the data, $|X|_{ss} \approx 16.0$ jobs, and $S_{f_\infty} = 5.95$ setups per day. The consistency and validity of this data is dependent on whether or not it can be

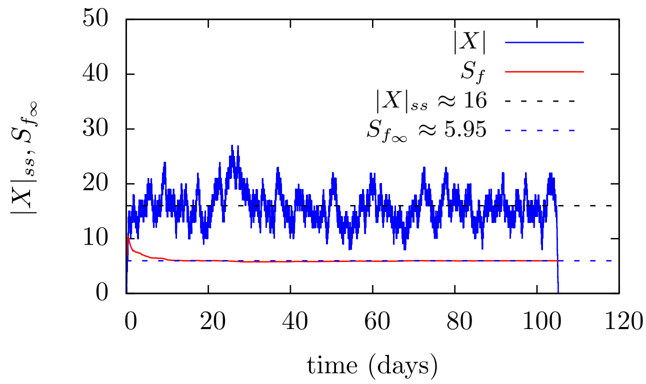


Figure 3.14: Plot of work-in-process and setup frequency through time for a manufacturing system with $r_{ci} = 25.0$ minutes, $n_v = 5$ job types and $\phi = 0.67$

used to predict steady state average manufacturing lead time per job. W_{ss} is calculated as follows;

$$\begin{aligned}
|X|_{ss} &= \lambda(W_{ss} - S_{f_\infty} r_{ci}) \\
16 &= 0.1(W_{ss} - \frac{5.95}{(60)(8)} 25.0) \\
W_{ss} &= \frac{16}{0.1} + 0.31 \\
W_{ss} &= 160.31\,\text{minutes.}\ \ (2.67\text{ hours})
\end{aligned}$$

The plot in Figure 3.15 shows that this prediction is accurate and as such, the data set achieved through discrete event simulation is valid and internally consistent according to Little's law.

Testing the internal consistency of data sets achieved through discrete event simulation in this way provides a circular validation path, in which the applicability of closed form mathematical models are tested against discrete event simulation output, which is in turn valid with respect to well known laws governing the steady state behaviour of queuing systems. This method was considered to be vital in ensuring that empirical reasoning based on the data sets achieved through discrete event simulation could be used to further develop the closed form models developed in the previous section.

3.3.1 Validation of Limiting Setup Frequency Model

Table 3.1 displays simulation parameters that were used in validating the model of steady state average setup frequency, Equation 3.3. The table also includes numerical results

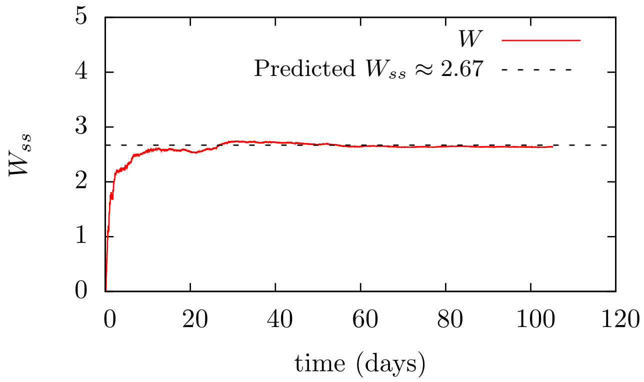


Figure 3.15: Plot of average manufacturing lead time, W, through time for a manufacturing system with $r_{ci} = 25.0$ minutes

achieved as well as the relative error between model prediction and simulation result. During simulation, a value of $r_{ij} = 10$ minutes, $\forall i, j,\ i \neq j$, was used as the setup time. Inter-arrival periods were simulated as being exponentially distributed and average production capacity was set to $\mu = 7$ jobs per hour.

Total Demand λ (parts/min)	Production Capacity μ (parts/min)	Load ϕ	Model Prediction $S_{f\infty}$ (setups/day)	Simulation Result $S_{f\infty}$ (setups/day)	|%Error|
0.093	0.155	0.6	9.6	9.7	1.03
0.1	0.155	0.65	8.4	8.6	2.33
0.108	0.155	0.7	7.2	7.4	2.7
0.116	0.155	0.75	6.0	6.25	4.0
0.124	0.155	0.8	4.8	5.05	4.95
0.132	0.155	0.85	3.6	3.8	5.26
0.140	0.155	0.9	2.88	2.99	3.67

Table 3.1: Table of parameters used in validating steady state average setup frequency, Equation 3.3, through discrete event simulation. (Note that for each simulation run, $C_c = 0$)

The plot of model prediction and simulation result, Figure 3.16, shows that this model is applicable over the system load range $[0.6, 0.9]$, and is most accurate at a load of approximately 0.7. Figure 3.17 shows two simulation results with model predictions. Both plots show convergence of average setup frequency S_f through time, onto the model predicted limiting value. A system load of $\phi = 0.89$ produced the result shown in the top plot. The bottom plot was a result of $\phi = 0.85$.

Equation 3.3 was adjusted to include the effects of varying average cumulative correlation over the interval $[0, 1)$, according to a polynomial approximation. A polynomial approxima-

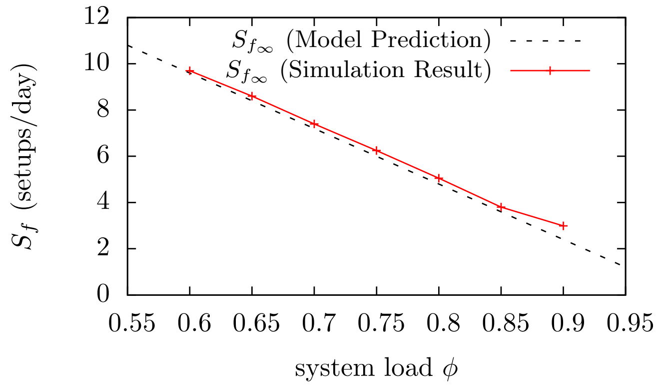


Figure 3.16: Plot of model predicted steady state average setup frequency and that result achieved through simulation

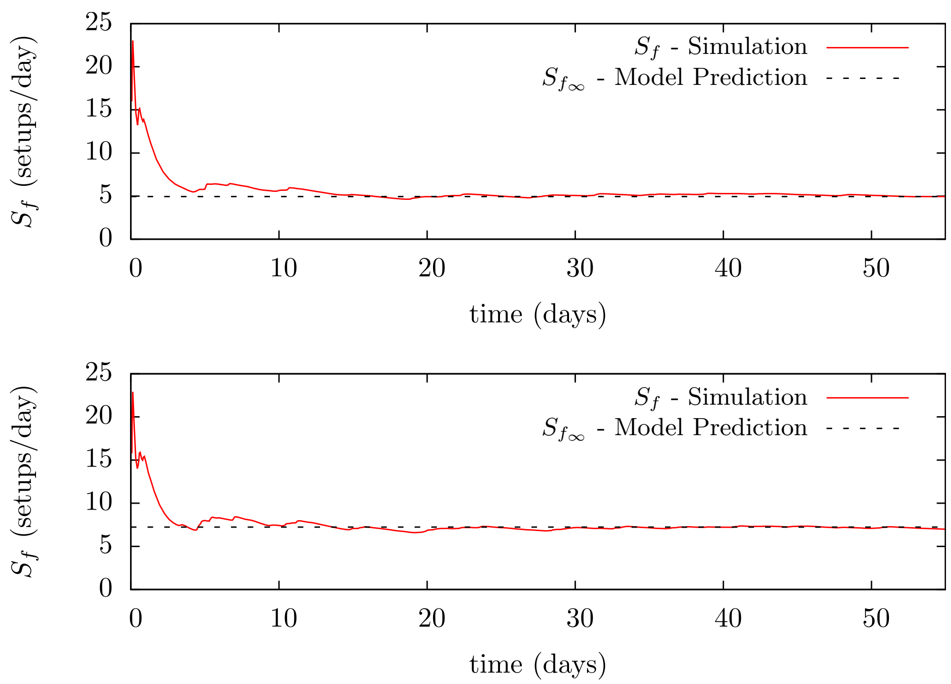


Figure 3.17: Two example simulation runs showing convergence to the model predicted values

tion was necessary as the analytic tractability of a closed form description is complicated by the combinatorial properties associated with the Binomial distribution.

Equation 3.4 represents this adjustment with the consideration of customers decision processes. Figure 3.18 shows a 4^{th} order polynomial approximation to steady state average setup frequency under variations in $C_c \in [0, 1)$. The plot shown was achieved at a system load of $\phi = 0.8$. At this load value, the function $f(C_c, 0.8)$ takes the form shown in Equation 3.8 with coefficients $[1, \frac{1}{5}, -1, 2, -2]$.

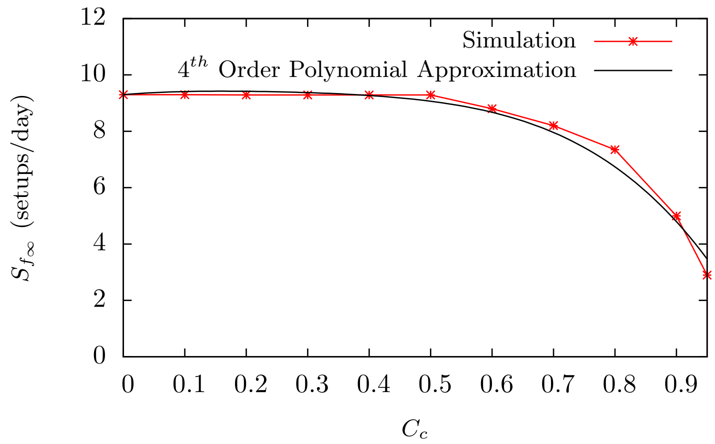


Figure 3.18: Fourth order polynomial approximation of the response achieved through discrete event simulation

It has been established that the effects of varying average cumulative correlation on control requirements depends on work-in-process levels and system load ϕ. Equation 3.8 is in fact a level curve of a response surface that specifies the effects of C_c over the full range of system load.

$$f(C_c) = 1 + \frac{1}{5}C_c - C_c^2 + 2C_c^3 - 2C_c^4 \tag{3.8}$$

With this knowledge, the original polynomial form $f(C_c) = \sum_{k=0}^{n} a_k C_c^k$ was adjusted to include the full range of system load, Equation 3.9.

$$f(C_c, \phi) = a_0 + g(\phi) \sum_{k=1}^{4} a_k C_c^k \tag{3.9}$$

From a qualitative viewpoint, the function $g(\phi)$ was considered as a linear function of system load. Figure 3.19 shows the response surface of steady state average setup frequency over the domain of system load ϕ and average cumulative correlation C_c, for a linear $g(\phi) = (c - \phi)$, where c is a constant such that at $\phi = 0.8$, the response curve is that represented in Figure 3.18.

Although partially qualitative, Equation 3.10 can be considered as a 4^{th} order description of steady state average setup frequency in stable flow controlled manufacturing systems under

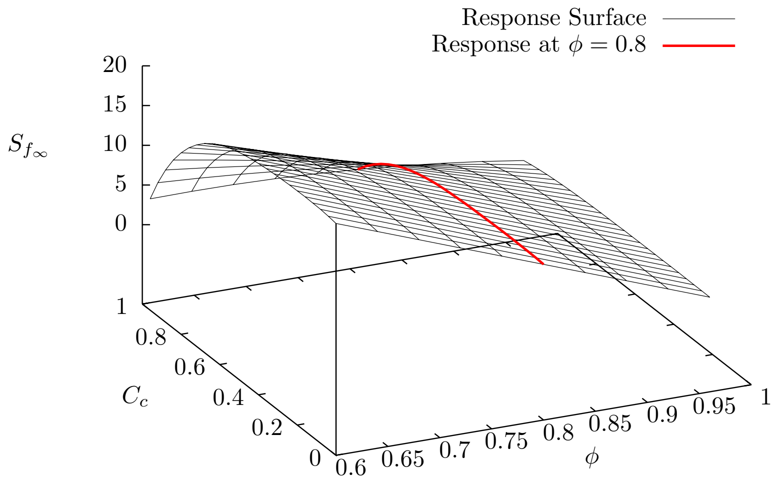


Figure 3.19: Steady state average setup frequency response surface showing the level curve at $\phi = 0.8$

varying correlation in job arrival sequences.

$$S_{f_\infty} = 60 H_d f(C_c, \phi) \frac{1 - (n_v - 1)\frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}}{r_{ci}\left[1 + \frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}\right]} \tag{3.10}$$

where $f(C_c, \phi)$ takes the form of Equation 3.9, i.e.

$$f(C_c, \phi) = 1 + (1.8 - \phi)\left[\frac{1}{5}C_c - C_c^2 + 2C_c^3 + 2C_c^4\right]$$

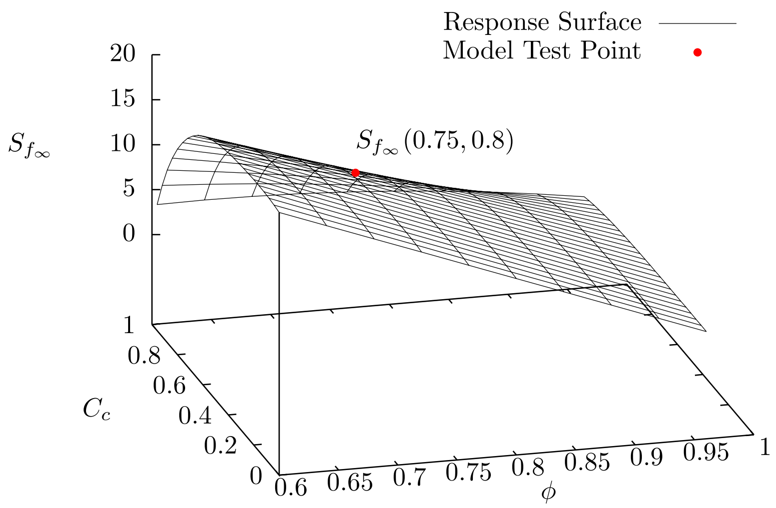
Figure 3.20 shows the simulation result for an arbitrary test point on the response surface model.

Validation of steady state average sequence entropy, Equation 3.6 occurred in a similar fashion to the analysis presented here. Results are presented in the following section.

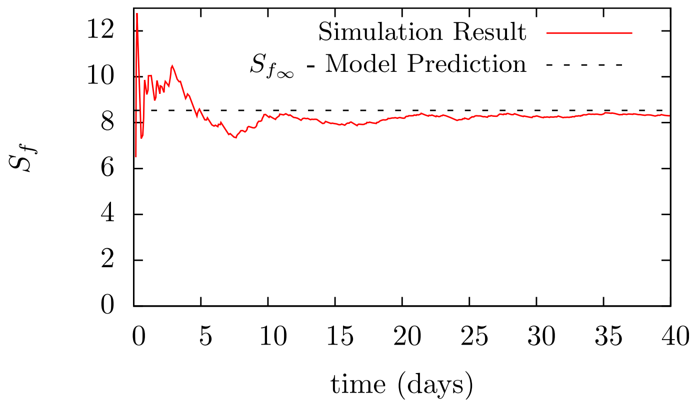
3.3.2 Validation of Limiting Sequence Entropy Model

Table 3.2 presents parameters used in validating the model of steady state average sequence entropy through stable flow controlled manufacturing systems. Included in the table are numerical results achieved, as well as the relative error between model prediction and simulation result.

The model of steady state average sequence entropy has a greater divergence from simulation results as system load exits the range $(0.4, 0.8)$. Within this load range, model predicted



(a)



(b)

Figure 3.20: Example model validation run with a test point taken from the response surface

values fall within 4% of results achieved through simulation. Figure 3.21 shows a plot of model prediction versus simulation result.

Figure 3.22 shows two example simulation results. The response in the top plot was achieved at a load of $\phi = 0.89$, and result in the bottom plot was achieved at a load of $\phi = 0.87$.

A similar polynomial curve fitting procedure to that in section 3.3.1 was used in adjusting Equation 3.6 to include the effects of varying $C_c \in [0, 1)$. The effects of varying C_c at a constant system load ϕ was characterised with a 2^{nd} order polynomial, $h(C_c) = \sum_{k=0}^{2} b_k C_c^k$, for constant ϕ, of which the coefficients were resolved through discrete event simulation.

Total Demand λ (parts/min)	Production Capacity μ (parts/min)	Load ϕ	Model Prediction $E^*_{s\infty}$ (min/part^2)	Simulation Result $E^*_{s\infty}$ (min/part^2)	|%Error|
0.031	0.155	0.2	1.25	0.8875	29
0.0465	0.155	0.3	2.14	1.8125	15
0.062	0.155	0.4	3.33	3.125	6.1
0.078	0.155	0.5	5.0	4.9	2
0.093	0.155	0.6	7.5	7.4	1.33
0.108	0.155	0.7	11.67	11.25	3.5
0.124	0.155	0.8	20.0	18.75	6.25
0.139	0.155	0.9	45.0	41.25	8.3

Table 3.2: Table of parameters used in validating steady state average sequence entropy, Equation 3.6, through discrete event simulation. (Note that for each simulation run, $C_c = 0$)

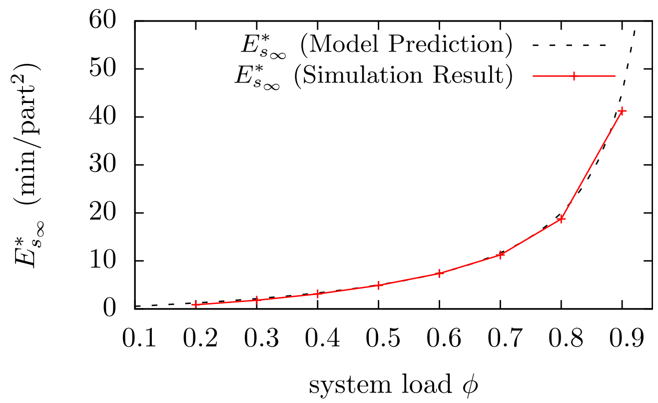


Figure 3.21: Plot of model predicted steady state average sequence entropy and that result achieved through simulation

In the case of steady state average setup frequency, it was a simple matter to rationalise that highly loaded systems with larger work-in-process are less sensitive to changes in C_c due to natural batching at the manufacturing system. In other words, for higher load values, the polynomial coefficients $a_k, k = \{1, 2, 3, 4\}$, decrease in absolute value. It was found that $g(\phi) = (c - \phi)$ was suitable in mapping each coefficient over the domain of $\phi \in [0, 1)$. In the case of steady state average sequence entropy, the change in coefficients b_k as system load varies is not as easily hypothesised. However, through simulation for varying load in the range $\phi \in [0.6, 0.9]$, it was determined that a linear function suffices to describe $b_k(\phi)$ for each coefficient, $b_k, k \geq 0$. At a system load value of $\phi = 0.85$, the polynomial curve $h(C_c) = 1 - \frac{1}{2}C_c - \frac{1}{2}C_c^2$ approximated simulation results in least square error. By incorporating a linear function to adjust the polynomial coefficients over the system load range $[0.6, 0.9]$,

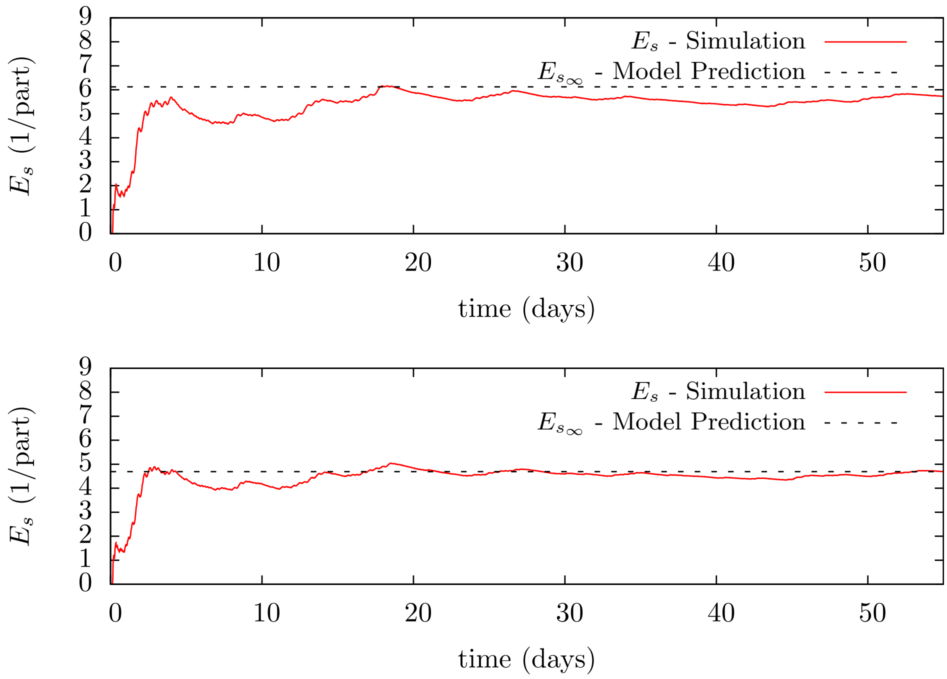


Figure 3.22: Two example simulation runs showing convergence to the model predicted values

the function

$$h(C_c, \phi) = 1 - (1.85 - \phi)\left[\frac{1}{2}C_c + \frac{1}{2}C_c^2\right]$$

provided the necessary adjustment to Equation 3.6, to include the effects of varying average cumulative correlation over a range in system load, Equation 3.11.

$$E_{s_\infty} = h(C_c, \phi)\frac{n_v \lambda r_{ci}\left[1 + \beta\right]}{4\left[1 - (n_v - 1)\beta\right]}, \quad \beta = \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}} \tag{3.11}$$

Figure 3.23a shows the steady state average sequence entropy response surface for varying C_c and $\phi \in [0.6, 0.9]$. The level curve shown in the plot is described by the polynomial $h(C_c, 0.85) = 1 - \frac{1}{2}C_c - \frac{1}{2}C_c^2$, which is shown in Figure 3.23b along with the simulation result.

Figure 3.24 shows a simulation result at a model test point of $\phi = 0.8$ and $C_c = 0.5$. The average sequence entropy response shown in the plot was for a production capacity of $\mu = 7$ jobs per hour and $n_v = 2$ module variants.

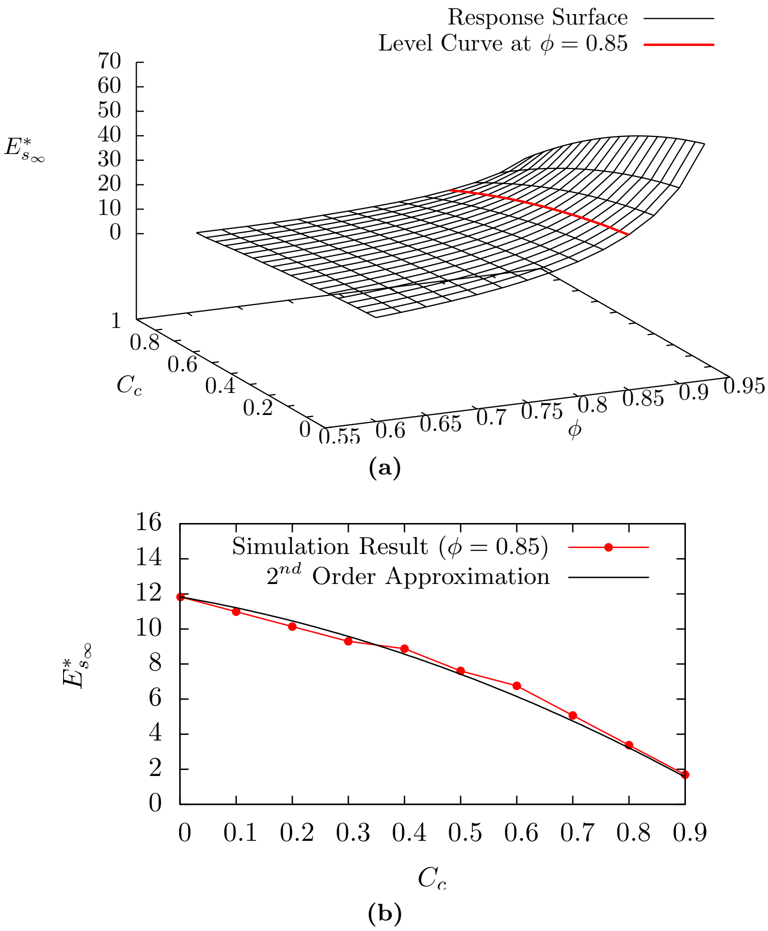


Figure 3.23: Steady state average sequence entropy response surface showing level curve at $\phi = 0.85$

3.3.3 Balanced Load Hypothesis

In section 3.2.2 it was hypothesised that due to the monotonically decreasing nature of S_{f_∞}, and monotonically increasing nature of E_{s_∞} over the domain of system load ϕ, then there must exist a unique system load in which $S_{f_\infty} = E_{s_\infty}$. In order to validate this hypothesis, consider the scenario of a single stable flow controlled manufacturing system operating under the conditions of $r_{ci} = 15$ minutes and $n_v = 4$ job types, with an average cumulative correlation of $C_c = \frac{1}{4}$ and production capacity of $\mu = 0.126$ jobs per minute (7.5 jobs per hour). For this system, the characteristic response curves are shown in Figure 3.25

Using a simple iterative procedure on system load ϕ, from an initial load of $\phi = 0$, consisting of a proportional controller which operates under the iterative procedure $\phi_{n+1} = \phi_n + P(S_{f_\infty} - E_{s_\infty})$, where ϕ_{n+1} is the next test value and P is a proportional constant, it was determined that $S_{f_\infty} = E_{s_\infty}$ at $\phi = 0.800649$ (0.8). Figure 3.26 shows the

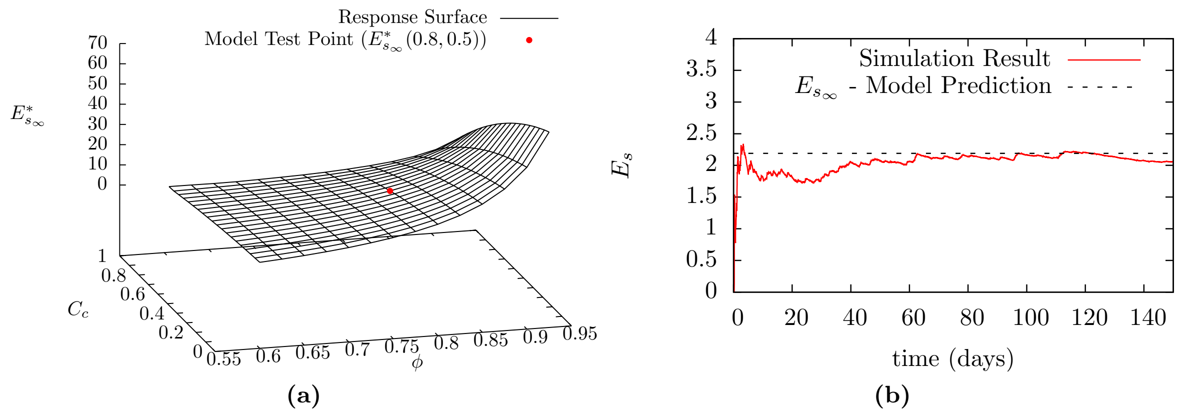


Figure 3.24: Example model validation run with a test point taken from the response surface

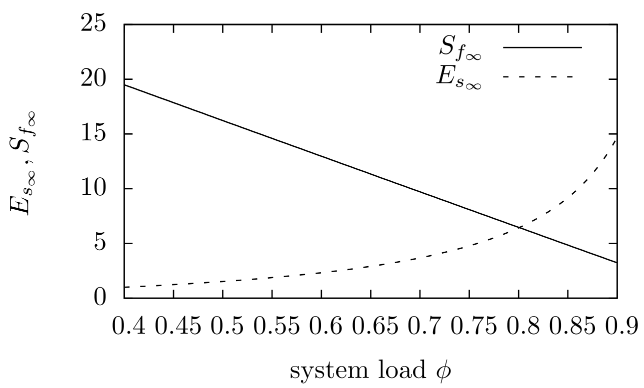


Figure 3.25: Plot of steady state average setup frequency and steady state average sequence entropy over a range in system load

response in average setup frequency and average sequence entropy at this balanced system load. Thus, for a reasonable number of job types processed at a stable flow controlled manufacturing system, a unique system load can be found such that average sequence entropy and average setup frequency balance in steady state.

The analytic models developed here have answered the first question posed in the beginning of this analysis. It was shown that for a single stable flow controlled manufacturing system, steady state average setup frequency and steady state average sequence entropy vary according to response surfaces, which are characterised by system load, the number of job types processes, and the cumulative correlation of job arrival sequences. These response surfaces can be considered as 4^{th} and 2^{nd} order polynomial approximations. The effect of average cumulative correlation on steady state response characteristics for stable flow controlled manufacturing systems is dependent on system load. Steady state average setup

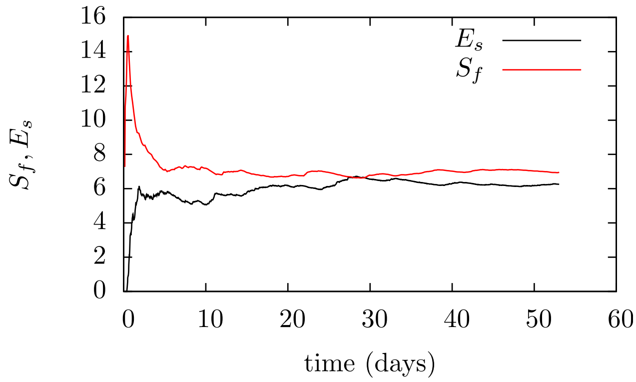


Figure 3.26: Convergence behaviour of average setup frequency and average sequence entropy at a balanced system load ϕ

frequency is less sensitive to changes in correlation as system load increases. Furthermore, steady state average setup frequency is independent of the number of job types processed at a manufacturing system when system load is above the critical system load $\phi^* = \frac{n_v}{\mu r_{ci}+1}$.

How these natural characteristics operate within a system context, with more than one manufacturing system, needed to be determined in order to answer the second question posed at the beginning of this analysis. This is covered in the following section.

3.4 Properties of Assembly System Performance

This section presents analysis that was aimed at answering the question of how competing upstream processing stations under stable flow control and varying C_c effects downstream assembly performance. The simulations presented were based on the production setup shown in Figure 3.27.

Processing station S_1 processes two job types, each job type instance being as a result of a customers decision during product configuration. Station S_2 processed six job types, also as a result of customers decisions regarding product configuration. Each station has identical production capacities $\mu_1 = \mu_2 = \mu$. Due to the varying number of job types requiring process mediation, the limiting value of average sequence entropy would be different across each station. The effects on downstream work-in-process due to differing steady state average sequence entropy across competing upstream stations is shown in Figure 3.28.

Even though work-in-process at stations S_1 and S_2 are bounded and stable due to the application of flow control under CLBF policy, downstream work-in-process grows uncontrollably until the production run ends, which was set at 500 orders in the simulation results presented here. Furthermore, this work-in-process is fundamentally uncontrollable,

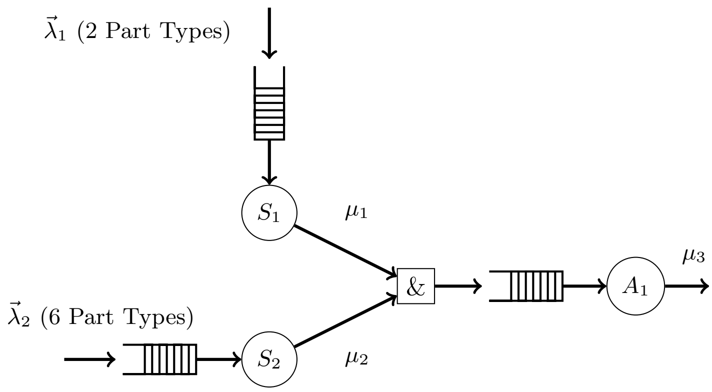


Figure 3.27: Assembly system setup used in simulation

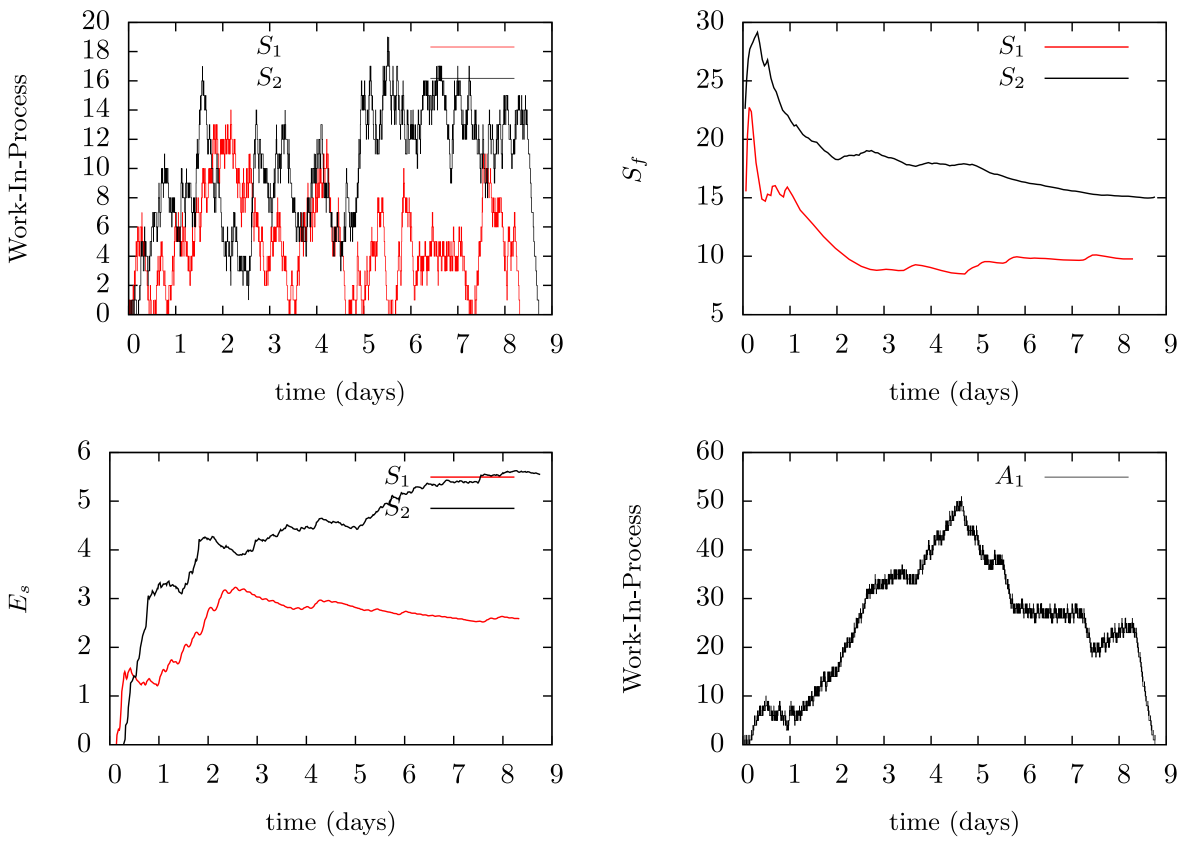


Figure 3.28: Downstream work-in-process response to unbalanced steady state average sequence entropy

in that it is a result of constraints imposed by produce-to-order production, in which part type instances are unique to each customers order. Increased assembly capacity would not increase performance in this case.

Figure 3.29 shows the same simulation run with station S_2 also processing two job types. As can be seen, downstream assembly performance is far greater due to balanced E_s across the two upstream processing stations.

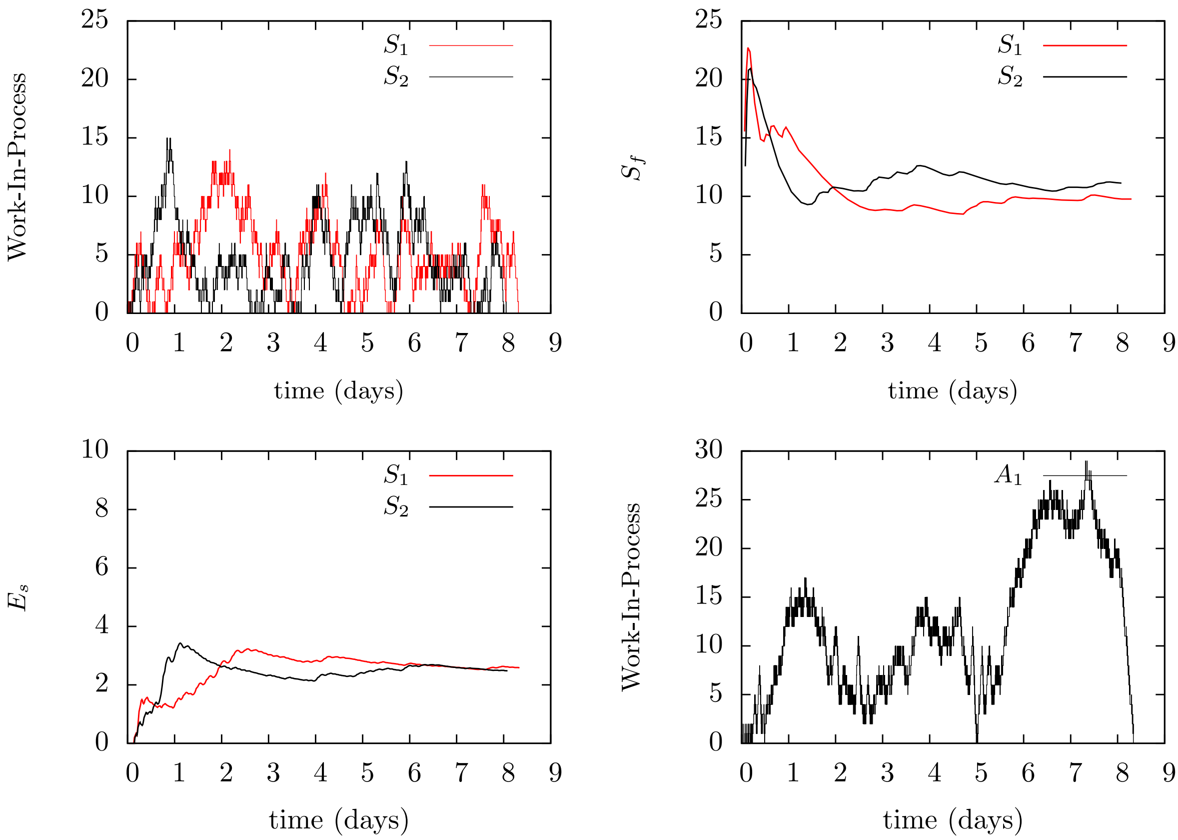


Figure 3.29: Downstream work-in-process response to balanced average sequence entropy

Figure 3.30 is a comparison of downstream work-in-process at assembly station A_1 from the two simulation runs. As can be seen from the comparison, steady state average sequence entropy is an important system variable and should be considered when implementing flow control in produce-to-order production operations. To answer the second question posed in the beginning of this analysis, parallel upstream processing stations under stable flow control cause an increase in downstream work-in-process if there exists a difference between their natural steady state average sequence entropy values due to differing response characteristics.

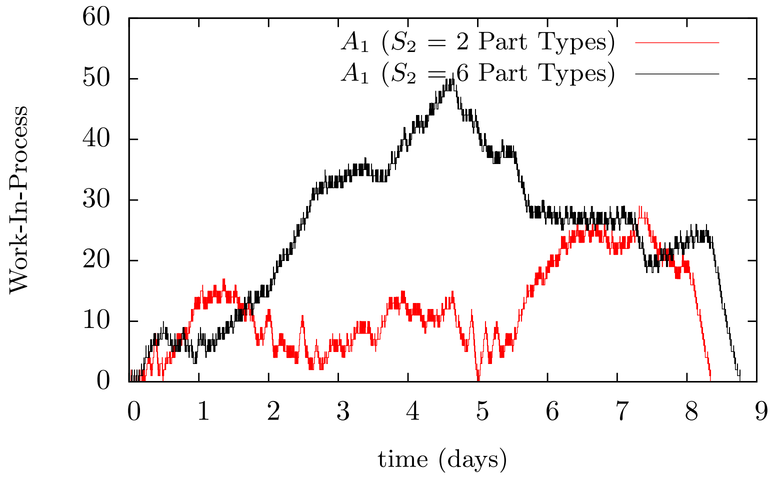


Figure 3.30: Comparison of downstream work-in-process response in balanced and unbalanced systems

3.5 Regulating Sequence Entropy in Flow Control

Although traditional flow control implementations provide stable work-in-process and setup frequency, their implementation does not allow for the active control of steady state average sequence entropy. This prevents distributed control from balancing E_{s_∞} across upstream parallel processing stations feeding assembly operations.

A new flow control method was developed in order to provide active control of steady state average sequence entropy across parallel upstream stations. Traditional flow control implementations treat workload at a manufacturing system in terms of the number of parts awaiting processing, without regard to other job properties, such as required cycle times. Since customers adjust required processing times according to product configuration decisions, bounded to exist within sets described by variation range functions f, metrics inclusive of processing time requirements were developed. The new flow control method relies on a particular form of workload metric, which saturates under increasing work-in-process per job type. An overview of the workload metric's properties is covered in the following section.

3.5.1 Configuration Influence as a Workload Metric

Configuration influence I_c performs the function of workload measure through the use of a functional description of the work-in-process per job type, Equations 3.12 to 3.14;

$$I_{c_i} = \frac{\tau x_i + r_{ci}}{\tau x_i} \frac{1}{T_{cav_i} T_{r_i}} \tag{3.12}$$

$$T_{cav_i} = \frac{1}{x_i} \sum_{k=1}^{x_i} T_{c_k} \tag{3.13}$$

$$T_{r_i} = \sum_{k=1}^{x_i} \left(t_k + \varepsilon - t_{in_k}\right) \tag{3.14}$$

where T_{cav_i} and T_{r_i} are the average cycle time, and accumulated resident time respectively, for all job types in the manufacturing systems input buffer requiring setup i. The parameter r_{ci} is the setup time to change configuration from the current to configuration i, and x_i is the number of jobs requiring manufacturing setup configuration i. The small offset time ε in T_r is to prevent singularities in the metric as jobs arrive at the manufacturing system's buffer from inventory or upstream sources.

The metric I_c exhibits a transition in workload measure as the number of jobs, for each job type, accumulate. This is noted by considering $\tau x_i \gg r_{ci}$, in which $\frac{\tau x_i + r_{ci}}{\tau x_i} \rightarrow 1$, and so arrival events of job type i only marginally effect I_{c_i}. Under these conditions, ΔI_c for each associated job type arrival event $\approx \frac{-1}{a(t)+\varepsilon}$, where $a(t) \gg 1$. The constant τ is used to adjust the rate of convergence to 1 for various reconfiguration times r_{ci}. Measuring workload in this way, as opposed to work-in-process per part type or $\sum_{\mathcal{S}} x_s$, decreases sensitivity of the switching signal σ to job arrival events or rapid changes in demand. This can aid in preventing closely competing queues of job types from causing a high rate of switching when the flow controller operates according to the policy that it selects the lowest I_{c_i} for access to a manufacturing system's resources and capacity set.

3.5.2 Biased Minimum Feedback Method

Biased minimum feedback (BMF) is a discrete event driven control law, which implements setup selection. The setup selection automata is governed by a biased feedback loop around a minimum argument function, Figure 3.31.

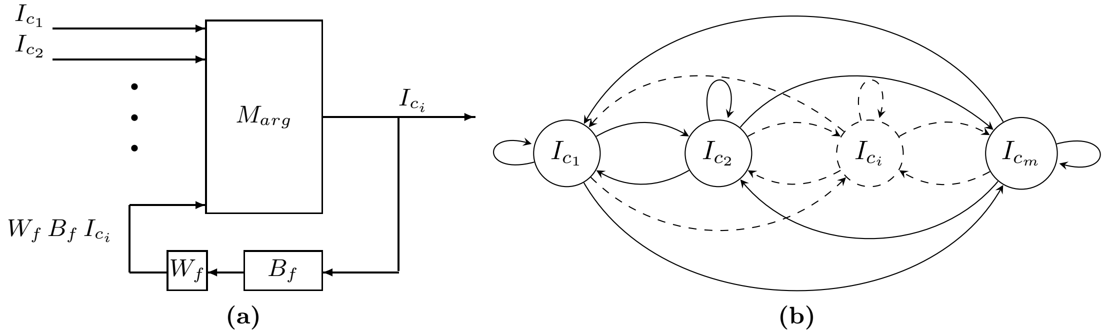


Figure 3.31: Control loop and finite state automata of biased minimum feedback

The biasing function takes on sub-unity values over the time interval between setup changes and is defined in Equation 3.15,

$$B_f = e^{-\alpha t_r} + 1 - e^{-\beta t_r} \tag{3.15}$$

where t_r is time since the last setup, and α and β are tuning parameters. The choice of biasing function in this method is arbitrary, although must maintain the following properties;

- $\lim_{t \to \infty} B_f = 1$
- B_f must have a positive global minimum at some point $g \in [0, \infty)$
- $\frac{d}{dt_r} B_f \leq 0$ for $t_r \in [0, g]$ and $\frac{d}{dt_r} B_f \geq 0$ for $t_r \in (g, \infty)$

Equation 3.15 meets these requirements and a plot for several values of α and β is shown in Figure 3.32.

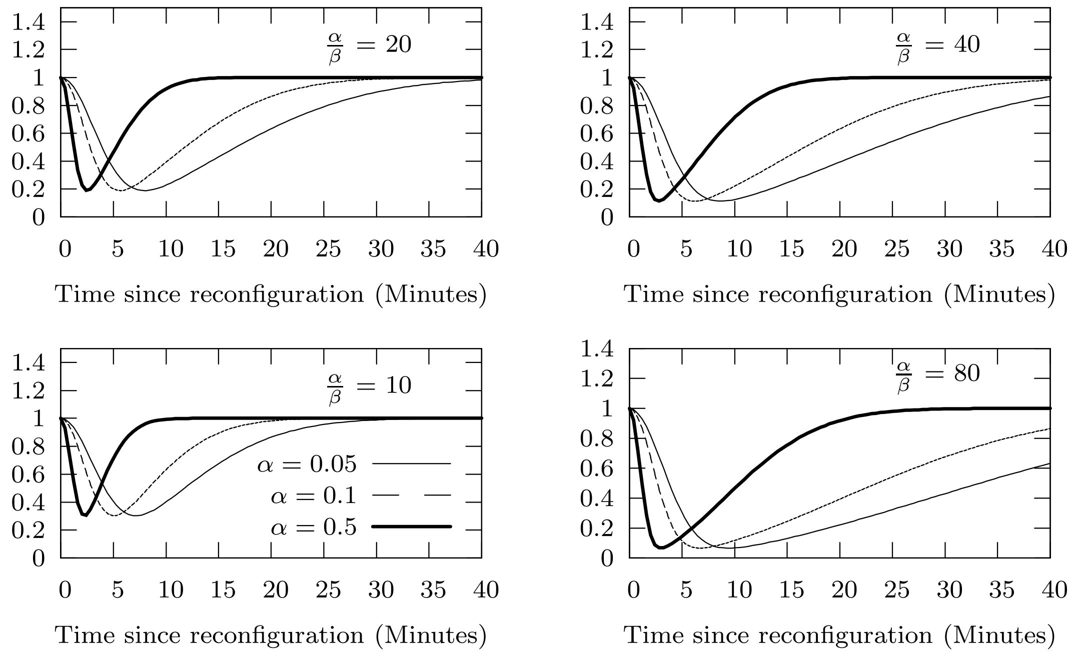


Figure 3.32: Biasing function for several α/β ratios and α values (In each plot, the range of α values is the same)

BMF includes a exponential weighting function that increases or decreases the probability of a setup in order to maintain a specified work-in-process level, Equation 3.16.

$$W_f = Ae^{-\zeta w}, \quad \zeta = \frac{ln(A)}{|X|_r} \tag{3.16}$$

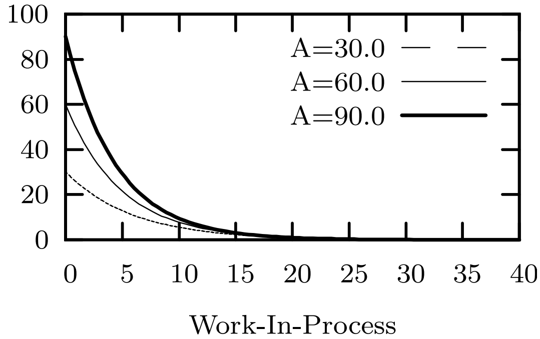


Figure 3.33: Variation in the shape of work-in-process regulation functions for various A values

A plot of several work-in-process regulation functions are shown in Figure 3.33. The parameter A in Equation 3.16 is chosen according to the rate in which work-in-process must reach required levels, i.e. rise time. The tuning of this regulator function is qualitative however, and the overall effect is that higher A values result in faster rise times to required work-in-process levels. The actual rise time is dependent on C_c and initial setup frequency, as well as the arrival rate. The parameter ζ is chosen such that the weight is unity on the required work-in-process level, $|X|_r$.

An important property of BMF separates its implementation from clearing type policies. This property can be understood by analysing I_c under decreasing setup time r_{ci}, and letting $\frac{\alpha}{\beta} \to 1$, and $A \to 1$. Under these conditions, i.e. $r_{ci} \to 0$, the metric $I_c = \frac{1}{T_{cav} T_r}$. In other words, the setup selection trajectory limits towards that trajectory resulting from first-in first-out buffer discipline. This can be interpreted as BMF favouring the minimisation of steady state average sequence entropy when manufacturing systems are highly flexible. This property of BMF is also in line with the fact that active scheduling at each distributed manufacturing system can only effect work-in-process dynamics, when there exists the potential to do so. The steady state work-in-process dynamics at infinitely flexible manufacturing systems, i.e. those systems with $r_{ci} = 0$, can not be adjusted through scheduling when each job type's required processing times are equal. Active flow control through setup scheduling is a necessity under variation in the processing requirements of job arrivals, however this variation is also necessary to implement flow control and so there exists a duality between variations and flow control implementation.

3.5.3 An Example BMF Application

BMF was implemented in order to resolve the steady state differential average sequence entropy problem. Simulation results for the case where station S_2 in Figure 3.27 produced six part types is shown in Figure 3.34.

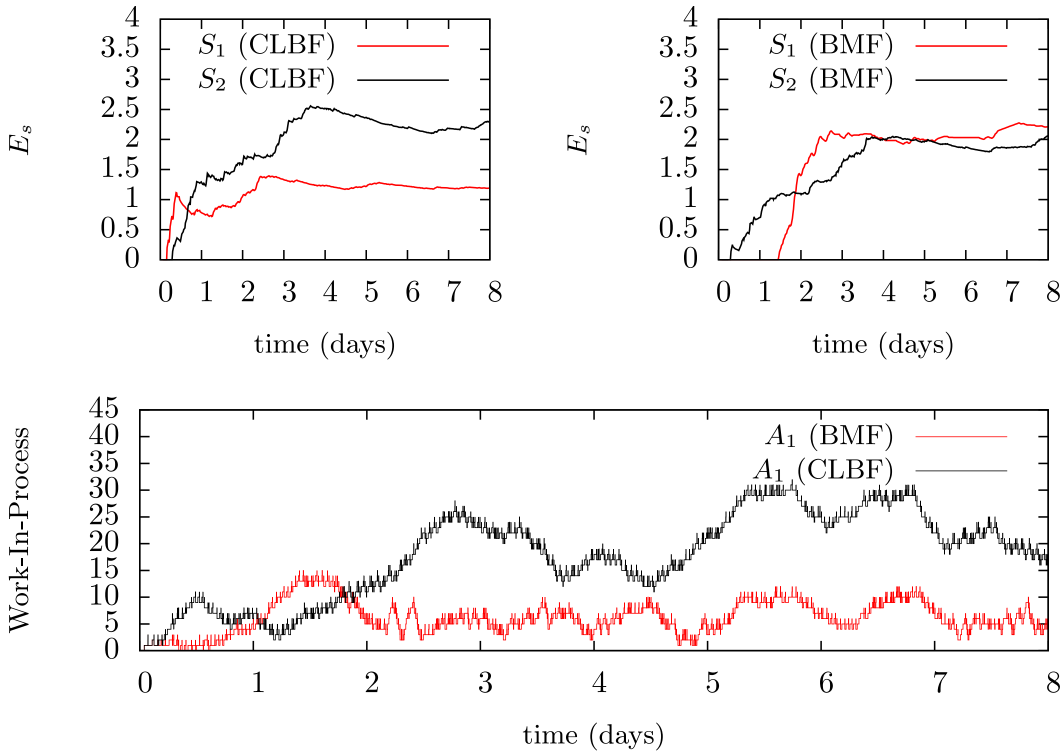


Figure 3.34: Application of BMF in balancing steady state average sequence entropy in an otherwise unbalanced system

In order to balance steady state average sequence entropy across stations S_1 and S_2, work-in-process reference, $|X|_r$ at station S_1 was increased until $E_{s_{\infty_1}} \approx E_{s_{\infty_2}}$. Although the BMF flow control method increases work-in-process at upstream stations in order to establish balance, overall manufacturing system performance is increased. Total work-in-process within the entire plant is conserved according to Little's Law, however lower work-in-process at assembly stations is beneficial as the costs associated with buffering sub-assembled or finished components is higher than those associated with buffering raw stock components. In order to determine required $|X|_r$, the following method was used.

3.5.4 A Method to Approximate Work-In-Process Reference Inputs

From analysis of steady state average sequence entropy, the level at which work-in-process is regulated effects the resulting steady state average sequence entropy. Since $E_{s_\infty} \propto \frac{\gamma}{4}$, $\gamma = \lambda \Delta t$, with Δt representing steady state inter-setup period, one can estimate required work-in-process levels to balance steady state average sequence entropy across parallel upstream processing stations.

Referring to Figure 3.35, work-in-process is at a maximum for all $t = t_1 + k\Delta t$, and at a minimum for all $t = t_0 + k\Delta t$, for $k \in \mathbb{Z}^+ \cup \{0\}$.

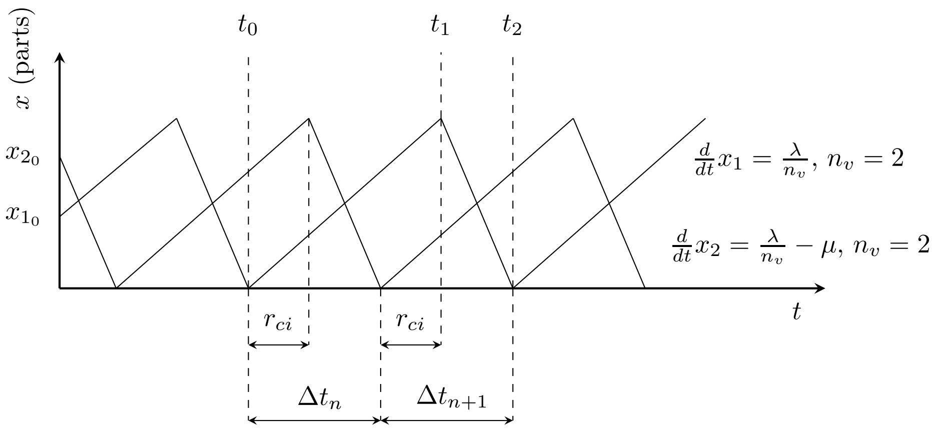


Figure 3.35: State trajectory for a two job type system

In steady state, work-in-process oscillates periodically between these maximum and minimum values, therefore average work-in-process is readily determined as the average between these two values. For the case where $n_v = 2$, maximum work-in-process is determined as;

$$\begin{aligned} |X|_{max} &= \sum_{k=1}^{n_v} X(t_1) \\ &= \frac{\lambda}{n_v}(\Delta t + 2r_{ci}) \end{aligned}$$

and minimum work-in-process is similarly determined as;

$$\begin{aligned} |X|_{min} &= \sum_{k=1}^{n_v} X(t_0) \\ &= \frac{\lambda}{n_v}(\Delta t) \end{aligned}$$

steady state average work-in-process can therefore be approximated as Equation 3.17.

$$|X|_{n_v=2} = \frac{1}{2}(|X|_{max} + |X|_{min}) = \frac{\lambda}{n_v}(r_{ci} + \Delta t) \tag{3.17}$$

Through analysis of trajectories for $n_v \geq 2$, Equation 3.18 is an approximation of steady state work-in-process levels under CLBF flow control policy.

$$|X|_{n_v \geq 2} = \frac{\lambda}{2n_v} \sum_{k=0}^{n_v-1} (k\Delta t + r_{ci}) + \frac{\lambda}{2n_v} \sum_{k=1}^{n_v-1} (k\Delta t) \tag{3.18}$$

In order to determine work-in-process reference requirements, for regulation under the application of BMF, the following method can be used in conjunction with the approximations derived for steady state work-in-process levels under CLBF flow control policy application.

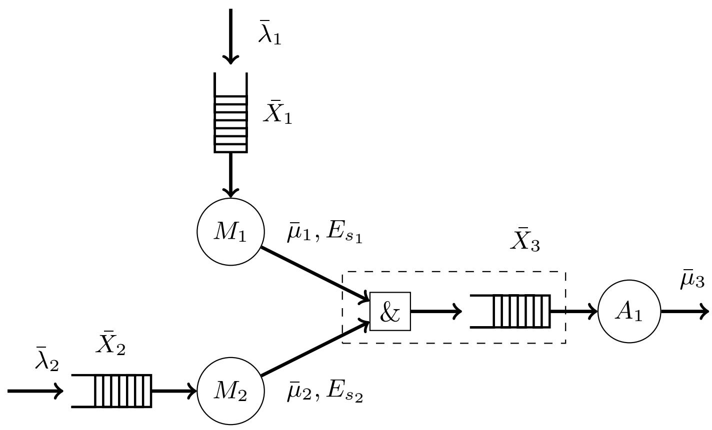


Figure 3.36: Competing upstream processing stations in an assembly line

Given the scenario depicted in Figure 3.36, with differing steady state average sequence entropy values $E_{s_{\infty_1}}$ and $E_{s_{\infty_2}}$, across stations $M1$ and $M2$, then $c = |E_{s_{\infty_1}} - E_{s_{\infty_2}}|$, for, $c > 1$, can be used to adjust the work-in-process level at which the station with lower E_{s_∞} is regulated. Qualitative reasoning would suggest that the required increase in work-in-process at the station with lower E_{s_∞}, would be a function of c, C_c, and the average work-in-process level associated with a clearing policy such as CLBF, i.e.

$$|X|_r \propto cf(C_c)|X|_{ss}$$

where $|X|_r$ represents the required work-in-process reference and $|X|_{ss}$ represents the steady state average work-in-process limit under CLBF. Furthermore, increasing C_c should result in increasing required work-in-process levels, such that under the condition that $C_c = 1$, such a reference does not exist i.e. is infinitely large. Many functions could be used to represent this qualitative property, the most simple being $\frac{1}{1-C_c}$, Equation 3.19.

$$|X|_r \approx \frac{|\Delta E_{s_\infty}||X|_{nv \geq 2}}{1 - C_c} \tag{3.19}$$

Note that since $c > 1$, the work-in-process at the station which limits towards a lower steady state average sequence entropy is increased in order to balance E_{s_∞} across the competing processing stations.

An example application of this method follows from the scenario depicted in Figure 3.37. Station S_1 processes 2 job types at a rate of $\mu_1 = 7$ jobs per hour, with a setup time $r_{ci} = 6.0$ minutes between job types and an average cumulative correlation $C_c = 0.5$. Station S_2 processes 6 job types at an average rate of $\mu_2 = 9$ jobs per hour with a setup time of $r_{ci} = 15.0$ minutes between job types and average cumulative correlation of $C_c = 0.17$. Jobs arrive at an average rate of $\lambda_1 = \lambda_2 = 6$ jobs per hour or 0.1 jobs per minute.

Figure 3.38a shows level curves associated with the response surfaces for each station. The particular steady state average sequence entropy values for each station are also shown, along with required ΔE_{s_∞} for balance. Figure 3.38b shows simulation results of E_s for each station along with the model predicted steady state value.

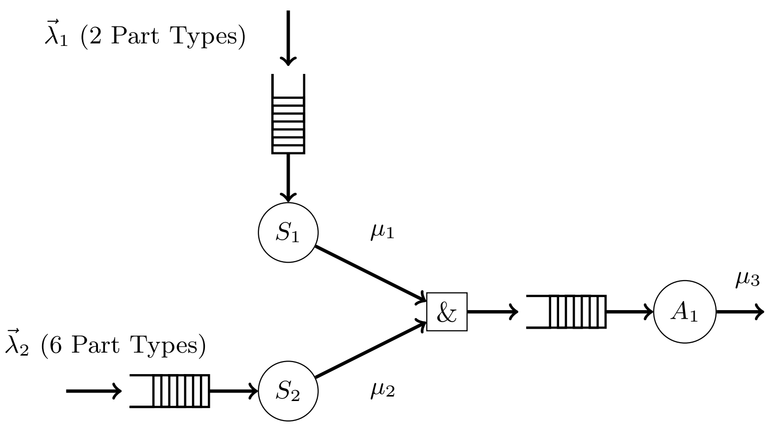
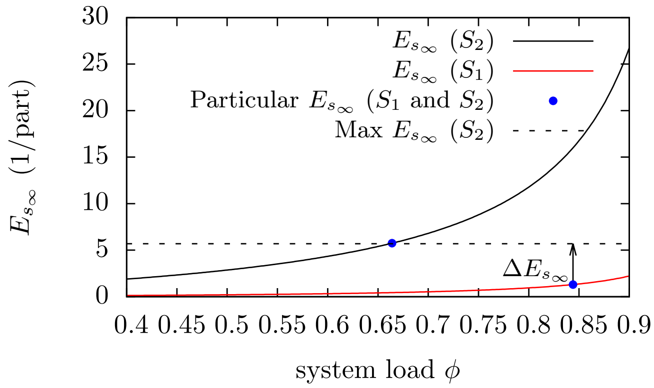
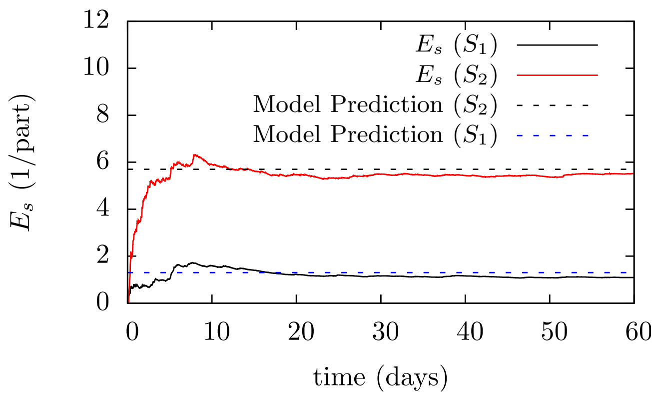


Figure 3.37: Parallel upstream processing stations with varying steady state average sequence entropy within an assembly line

Equation 3.19 can be used to estimate the required work-in-process level at station S_1 so as to balance steady state average sequence entropy. The required work-in-process level at station S_1, $|X|_{r_1}$, can be estimated by calculating the steady state work-in-process level achieved under CLBF using Equation 3.18. For station S_1, $|X|_{ss} = \frac{0.1}{2}(6.0 + 45.176) = 2.56$, (3 jobs), where the value of $\Delta t = 45.176$ was resolved from Equation 3.10. An approximation of the



(a)



(b)

Figure 3.38: Diagrammatic depiction of necessary requirements in order to balance steady state average sequence entropy through stations S_1 and S_2

required work-in-process level is;

$$\begin{aligned}|X|_{r_1} &= \frac{(E_{s\infty_2} - E_{s\infty_1})|X|_{ss}}{1 - C_c} \\ &= \frac{(5.7 - 1.3)(2.56)}{1 - 0.5} \\ &= 22.53 \quad (\approx 23 \text{ Jobs})\end{aligned}$$

Figure 3.39 shows the simulation results under CLBF with unregulated work-in-process and associated average sequence entropy, Figures 3.39a and 3.39b respectively, and those results achieved through regulating work-in-process at levels suggested by Equation 3.19, Figures 3.39c and 3.39d. Under the application of BMF, steady state average sequence entropy for each station limits towards a balanced value.

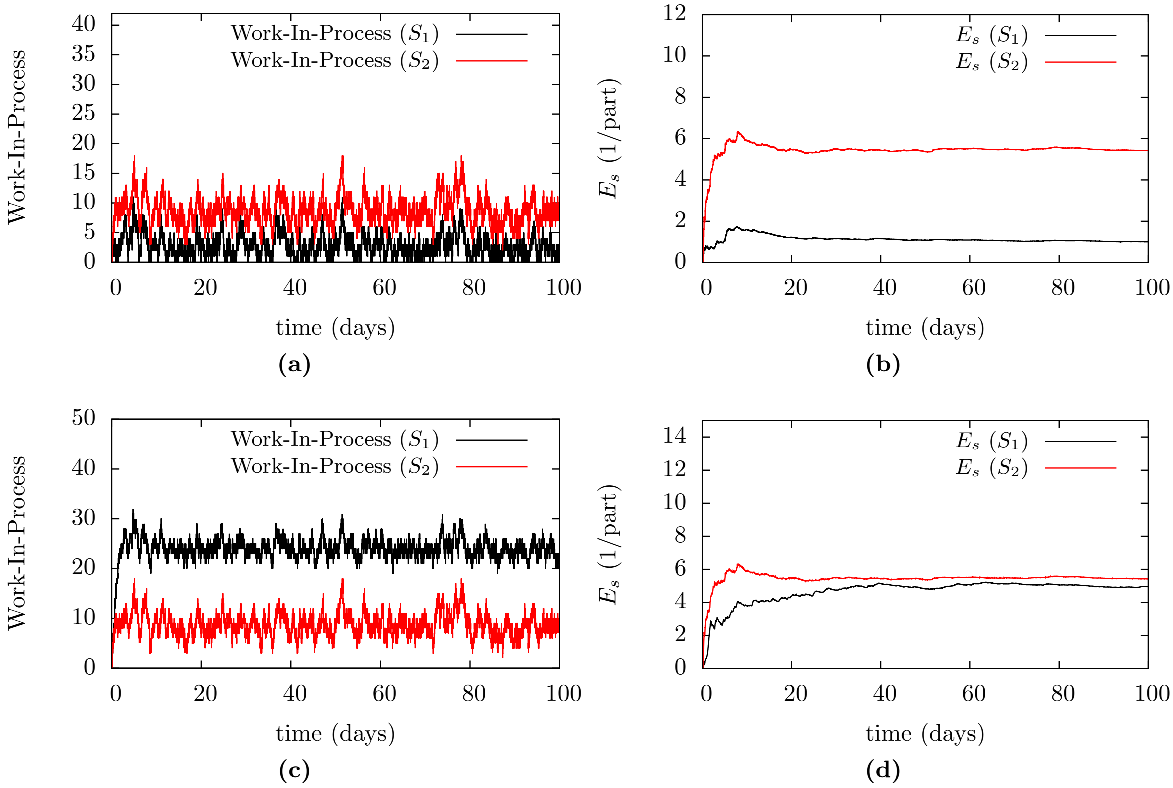


Figure 3.39: Change in work-in-process regulation level and associated balance in steady state average sequence entropy

3.6 Summary

In this chapter, customers product configuration decisions were characterised in the time domain. It was shown that the limiting distribution of a Bernoulli process can be used in characterising the correlation in consecutive customers decision behaviour in product configuration, and resulting job arrival sequences into manufacturing systems. By including the effects of customer decision behaviour in the time domain, analysis of steady state flow controlled manufacturing systems under a clearing policy produced two closed form relationships, Equation 3.3, describing the limiting behaviour in average setup frequency, and 3.6, describing the limiting behaviour in average sequence entropy.

Due to the definition of cumulative correlation, the effects of customers decisions in the time domain are analytically intractable in closed form. To provide an approximation of the effects of varying $C_c \in [0, 1)$, discrete event simulation results along with a polynomial curve fitting procedure was used in adjusting the closed form models in Equations 3.3 and 3.6 to account for varying cumulative correlation and system load.

The steady state differential average sequence entropy problem was shown to require flow controllers with the capability to explicitly regulate work-in-process at specified levels. A novel flow control method termed BMF was developed and shown to possess the capabilities to balance steady state average sequence entropy across competing upstream processing stations. Simulation results showed that BMF performs well and is easily tuned through the adjustment of only a few parameters. A method to approximate work-in-process reference requirements was presented, which would allow for the predetermination of work-in-process distributions to increase performance at downstream assembly stations.

Three questions were posed in the beginning of section 3.2 with specific inquiry into the effects of varying C_c on the steady state response characteristics of flow controlled manufacturing systems.

Q1 - In what manner does average cumulative correlation in consecutive customer decision processes, effect the fundamental steady state characteristics of a stable flow controlled manufacturing system with significant setup times?

A1 - The effect of varying average cumulative correlation in job arrival sequences on steady state response characteristics for stable flow controlled manufacturing systems was shown to be dependent on system load. Steady state average setup frequency was shown to be less sensitive to changes in correlation as system load increases. Furthermore, Theorem 1 showed that steady state average setup frequency is independent of the number of job types processed at a manufacturing system when system load is above the critical system load $\phi = \frac{n_v}{\mu r_{ci}+1}$.

Q2 - How do upstream response characteristics of independently controlled flexible manufacturing systems effect the performance of downstream produce-to-order assembly operations?

A2 - The performance of downstream assembly operations was shown to be dependent on the difference in steady state average sequence entropy between competing upstream processing stations. It was determined that downstream work-in-process increases uncontrollably if there exists a difference in steady state average sequence entropy between parallel upstream processing stations supplying components for assembly.

Q3 - How should work-in-process be distributed within the entire manufacturing facility in order to decrease downstream assembly performance volatility?

A3 - Work-in-process should be distributed according to the natural response characteristics of stable flow controlled manufacturing systems. Steady state average sequence entropy should be balanced by increasing work-in-process at those stations within competing station collectives, which have lower steady state average sequence entropy.

Chapter 4

Case Study Simulation of a MCM Facility

The logic of validation allows us to move between the two limits of dogmatism and scepticism

Paul Ricoeur

Contents

In this chapter, a case study construction of a MCM facility producing configurable fly reels is presented. The methods and models developed in chapter three are applied in determining distributed control requirements and work-in-process distributions for balanced steady state average sequence entropy.

In the preliminary sections, an overview of the product platform and production setup used during the case study is presented. A configurable product platform is formally constructed, on which a generic bill-of-materials and operations (BOMO) is developed, in order to provide comprehensive analysis of distributed control requirements under consideration of customer decision processes.

4.1 A Product Family: Configurable Fly Reel

There are a large number of fly fishing reel manufacturers around the world, particularly in the United States of America, where premium quality reels are in high demand. Many reel manufacturers in the USA, and other countries, have recently moved towards custom reel manufacture.

The fly fishing reel market is well suited to mass customisation as it is highly competitive. Customer requirements in reel function are largely dependent on personal preference, degree of skill, experience and intended application. For the case study considered, fly reels were used as the product basis in establishing process plans and material requirements. In order to validate the case study, simulated operations were derived from current manufacturing practices in fly reel production. Typical BOM's and operations used in the manufacture of fly reels are not unnecessarily complex, so as to make required process plan constructions tedious, although complex enough to validate the models presented in chapter three. A typical fly reel has 25 components on average, many of which can be made standard among a wide range of fly reel configurations, allowing for effective product platforming, and delayed product differentiation.

An overview of product form, process structure, and manufacturing technologies used in facilitating the fly reel market follows.

4.1.1 Fly Reel Components and Functional Operation

Fly reels consist of a frame, drag system and spool, Figure 4.1. The reel frame houses the main shaft and drag system, upon which the spool rotates under governance of drag pressure. The frame also includes a foot, which connects reel and rod. Some reel designs are such that the main shaft acts as a draw bar in order to lower component count and cost. The main shaft houses all rotary components making up the reel including the spool and drag subsystems.

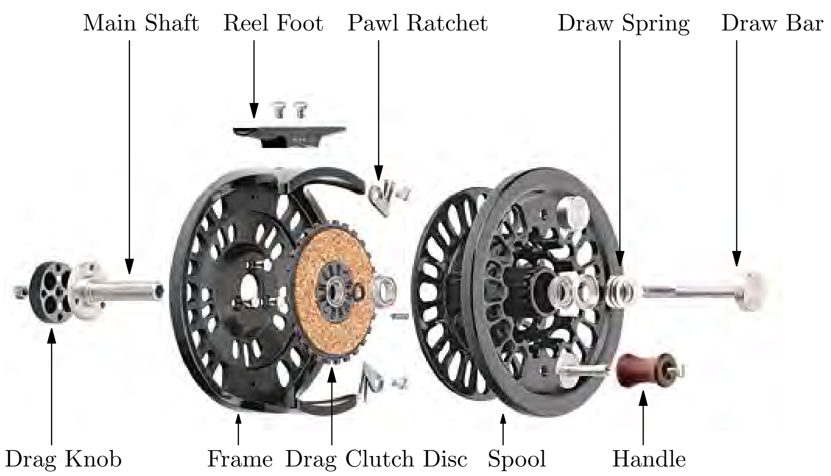


Figure 4.1: Main components of a modern fly fishing reel. (Image - © Abel Automatics Inc. [1])

The principle function of a drag system is to dissipate rotational energy in the form of friction heat, when line is removed from the spool under an engaged drag. Various drag configurations exist within the market's large product base, each with differing component level features, although all drag systems perform the same overall function. Drag pressure is varied through a draw bar and tension spring system which advances the spool towards the frame, causing increased friction between spool and drag disc. Drag is adjusted via a drag knob.

A drag system is engaged via two principle mechanisms, of which a pawl ratchet system is shown in the figure. In a right hand retrieve configuration, the drag disc rotates with the spool when turned clockwise, and remains fixed by the pawl ratchet when turned counter-clockwise, thus engaging the drag system. A clutch bearing can also serve as a drag engaging mechanism and has become popular among manufacturers. Clutch bearings only rotate freely in one direction and therefore perform the same function as pawl ratchets with fewer components, while providing increased load bearing. The function of a spool is to store and retrieve fly line. Spool capacities vary between 40 and 600 metres depending on spool width and diameter, as well as the line gauge used. Another component not explicitly labeled in Figure 4.1 is the spring loaded clicker and clicker plate. These components alert the angler when line is removed from the spool during drag engaged spool rotation.

Modern reels are modular in design, allowing for simple dis-assembly when maintenance is required. Although the purchasing behaviour of customers tends to be based on personal preference, there are key functional aspects on which customers base their purchasing decisions. These are discussed in the following section, and a functional requirement decomposition/classification tree (FR/DCT) structure is presented, which formed the basis for customer-manufacturer interaction in the case study.

4.1.2 Functional Classification Tree for a Fly Reel Product Family

In this section, product differentiators within the fly reel market are discussed in order to determine those functional attributes which provide application specific utility when customers purchase fly reels.

Drag technology and reel size are two major product differentiators within the fly reel market. Many companies have engineered specialised material compositions and mechanical designs in order to create, what they refer to as, superior drag systems. Since smooth stable drag systems are vital during product use, this aspect is closely considered by prospective customers. All drag system implementations have advantages and disadvantages associated with them. Personal preference and experience tend to be the main determinants of selected drag technology in purchasing behaviour. Maintenance is also considered by customers when making decisions regarding drag technology. High performance drags are associated with careful maintenance and therefore experience on the part of the customer is required. Different drag materials cause variations in the start up response of a drag. Startup inertia is the term used to describe a drags response under an impulsive drag engagement, i.e. when line is suddenly pulled off the spool, and can be considered as the difference between static and dynamic friction between spool assembly and drag disc. Drag materials used, as well as the placement and configuration of drag discs effect startup inertia and many disc drag configurations exist with varying startup inertia characteristics. Low startup inertia is favourable, especially when the customer intends on using lower line strengths and gauges, when targeting less powerful species or those species which are less inclined to attack a fly lure when higher strength and line gauges are used.

Another product differentiator is corrosion resistance, as it has been a growing trend for saltwater fisherman to target large fish species using fly fishing methods. Specifications in materials and reel function vary, based upon intended application, whether it be freshwater or saltwater. Freshwater applications seldom require large spool capacities and/or drag systems with high power dissipation capabilities. Customers consider the utility of large spool capacities for saltwater applications, and smaller spool capacities for freshwater applications. Ventilation through the frame and spool is an important consideration as high power drags create heat, which could damage those drags involved in high load saltwater applications. Highly ventilated frames allow for salt and other abrasive elements to enter the reels drag system, causing some customers to favour closed frame reels.

Modern drag systems come in two main forms of technology, namely click-pawl and compression disc. Click-pawl type drags do not utilise a friction disc and draw bar configuration. Instead, drag is adjusted by varying the tension of spring loaded pawls. These drag systems are less suitable under high load applications, when larger fish species and targeted. Disc drag systems are suitable over the entire range of load applications and can be configured for a wide variety of drag resolutions between high and low power dissipation. For this reason, this case study only considered the material and manufacturing requirements of compression disc fly reels. Three compression disc configurations were considered in developing a product family, namely offset multiplier, enclosed disc and peripheral disc. Figure 4.2 describes the applicability of each disc configuration in terms of startup inertia and drag range for a fixed draw bar stroke. Figure 4.3 shows each of the three disc drag configurations.

For the case study considered, a customer's functional configuration of a fly reel was decomposed into the functional requirement decomposition/classification tree represented in Figure 4.4. Customer-manufacturer interaction was considered to occur over seven variety parameters, [Ha.P, Sp.P, Spc.P, Fr.P, Frc.P, Drm.P, Drc.P]. Customers select between two handle types, one large and one small, in order to suit ergonomic requirements. Spool configuration occurs through two variety parameters, a continuous parameter that selects spool capacity over a predefined-defined range, and a discrete parameter which selects

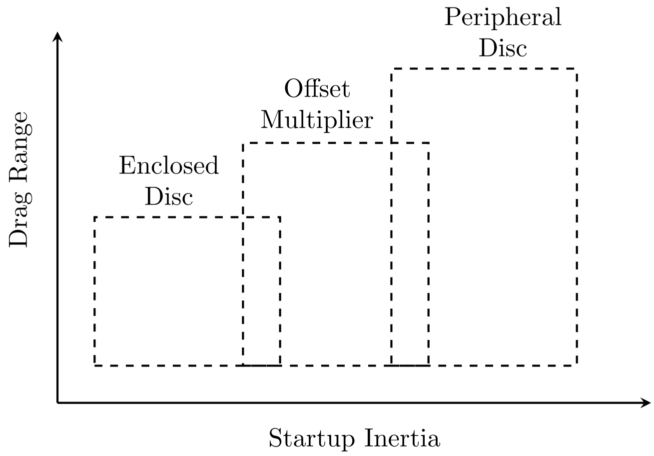


Figure 4.2: Application domain of the three drag disc configurations considered in the case study.

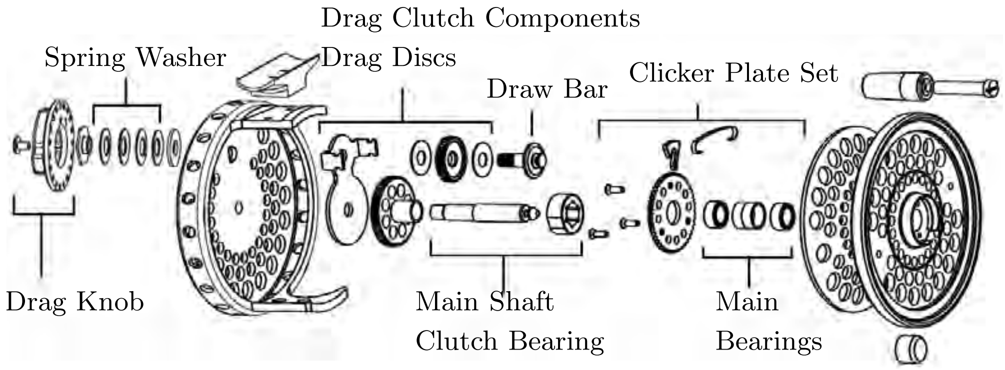
between five paint colours. The fly reel frame is configured through two discrete variety parameters, which select whether the frame is open and ventilated or closed, and between two paint colours. Customers select drag configuration according to two variety parameters which are both discrete. A choice between two drag materials may be selected and a discrete variety parameter selects between the three disc configurations shown in Figure 4.3.

Figure 4.4 formed the functional interface behind customer-manufacturer interaction, as depicted in chapter three Figure 3.1 as the FR/DCT system. In order to define a technical process flow which maps customer-manufacturer interaction into required manufacturing control requirements, a generic product and process structure in the form of a BOMO was developed. This is presented in the following section.

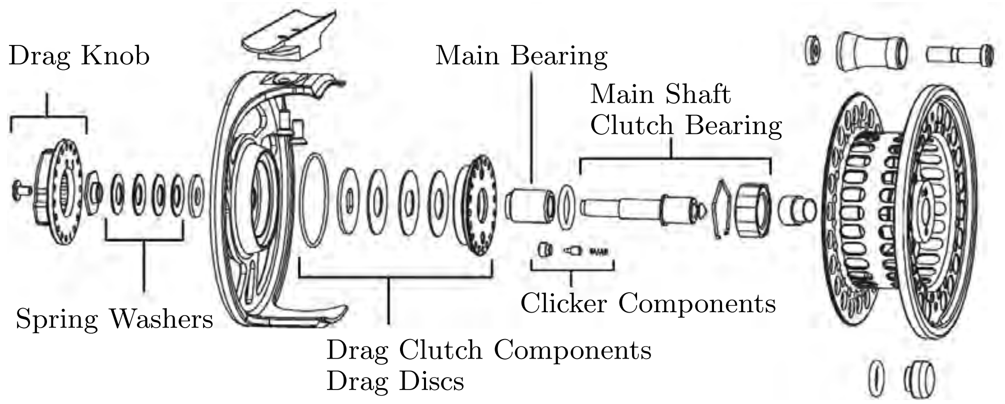
4.1.3 Generic Product and Process Structure: A Bill of Materials and Operations

Materials used in the manufacture of fly reels include aerospace grade aluminium 6082 T1, stainless steel, cork, various wood composites and plastics. Frames and spools are commonly machined from aluminium bar stock. Various drag materials are used such as carbon composites and cork composites. Drag washers are manufactured through stamping processes, although wire cutting processes are also used. Materials used for components such as the main shaft, and various bearings are commonly non-corrosive alloys for corrosion resistance in saltwater applications. Main shafts and drag clutch components are often machined from stainless steel bar stock.

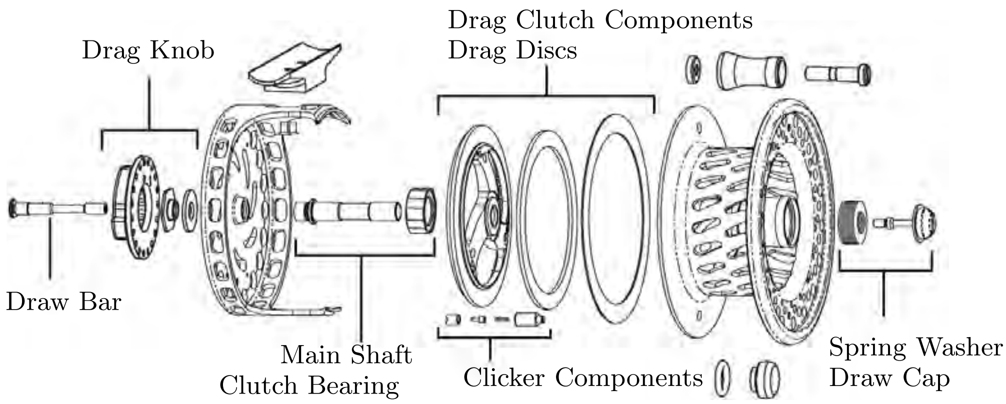
Considering the physical architecture of main component subsystems constituting fly



(a) Offset Multiplier



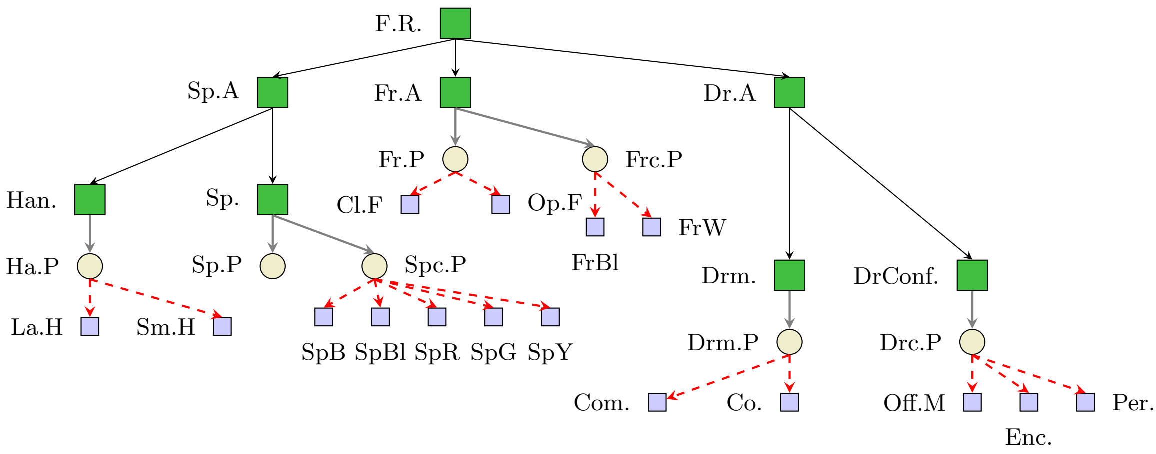
(b) Enclosed Disc



(c) Peripheral Disc

Figure 4.3: Three compression disc drag configurations with varying degrees of startup inertia and component count (Image's adapted from Orvis® Technical Manual [64])

reels, a generic product and process structure for the fly reel product family presented



Abv.	Description	Abv.	Description
F.R.	Fly Reel	Drm.P	Drag Material Parameter
Sp.A	Spool Assembly	Drc.P	Drag Disc Configuration Parameter
Fr.A	Frame Assembly	La.H	Large Handle
Dr.A	Drag Assembly	Sm.H	Small Handle
Han.	Handle	Cl.F	Closed Frame
Sp.	Spool	Op.F	Open Frame
Drm.	Drag Disc Material	Com.	Composite
Dr.Conf	Drag Disc Configuration	Co.	Cork
Ha.P	Handle Parameter	Off.M	Offset Multiplier Drag
Sp.P	Spool Capacity Parameter	Enc.	Enclosed Frame Drag
Fr.P	Frame Type Parameter	Per.	Peripheral Disc Drag
Frc.P	Frame Colour Parameter	Spc.P	Spool Colour Parameter
SpB	Spool Colour - Blue	FrBl	Frame Colour - Black
SpBl	Spool Colour - Black	FrW	Frame Colour - White
SpR	Spool Colour - Red	SpG	Spool Colour - Green
SpY	Spool Colour - Yellow		

Figure 4.4: FR/DCT structure for the fly reel family used as a case study.

in the previous section was constructed, Figure 4.5. A set of kitting stations denoted as [WC-K1,...,WC-K10] were included as preprocessing stations in which input materials are organised into the correct configuration for entry into processing and assembly station sets, denoted as [WC-M1,...,WC-M7] and [WC-A1,...,WC-A3] respectively. Included in the BOMO structure are the variety parameters exposed to customers decision processes. The variety parameters have been included in order to depict how customers decisions effect material and workstation setup requirements.

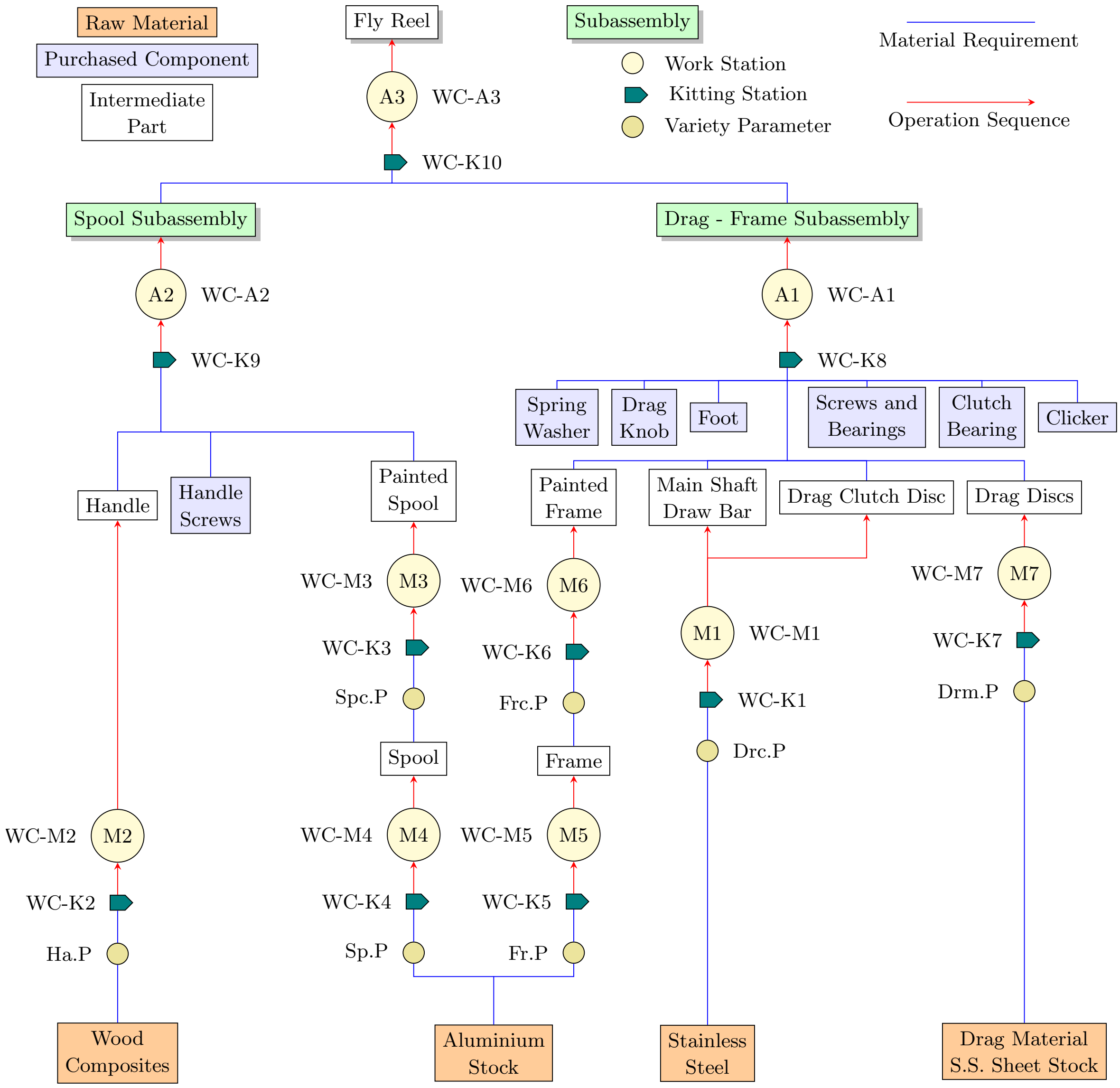


Figure 4.5: Generic Product and Process Structure for the Manufacture of Fly Reels

The data associated with the BOMO is summarised in Table 4.1.

4.2 Simulation Setup

4.2.1 Manufacturing Cell Model

In constructing a simulated environment, a manufacturing system, whether a processing or assembly station, was modelled according to the generic system shown in Figure 4.6.

Job No.	Seq. No.*	Operation based on Variety Parameter State	Work Station	Ave. T_c (Min)	Fixture Setups	Material Input	Parent Item
52	01	Machine Spool, Sp.P $\in [0,1]$	WC-M4	f(Sp.P) $\in [5,7]$	N/A	Aluminium Bar Stock	Spool
53	02	Paint Spool (Spc.P=SpB: Blue, Spc.P=SpBl: Black, Spc.P=SpR: Red, Spc.P=SpG: Green, Spc.P=SpY: Yellow)	WC-M3	4.5	M3-S1 M3-S2 M3-S3 M3-S4 M3-S5	Spool	Painted Spool
54	01	Machine Frame (Fr.P=Op.F: Open Frame, Fr.P=Cl.F: Closed Frame)	WC-M5	4.5(Fr.P=Op.F), 5(Fr.P=Cl.F)	N/A	Aluminium Bar Stock	Frame
55	02	Paint Frame (Frc.P=FrBl: Black, Frc.P=FrW: White)	WC-M6	4.9	M6-S1 M6-S2	Frame	Painted Frame
56	01	Machine Handle, Varnish coat Post Process(Ha.P=La.H: Large Handle, Ha.P=Sm.H: Small Handle)	WC-M2	6.2(Ha.P=La.H), 5.2(Ha.P=Sm.H)	N/A	Wood Bar Stock	Handle
57	01	Machine Main Shaft, Draw bar and Drag Clutch Discs (Drc.P=Off.M: Offset Multiplier Component Set, Drc.P=Enc.: Frame Enclosed Component Set, Drc.P=Per.: Peripheral Disc Component Set)	WC-M1	6.2(Drc.P=Off.M) 5.2(Drc.P=Enc.) 7.0(Drc.P=Per.)	N/A	Stainless Steel Bar Stock	Main Shaft, Draw Bar, Drag Clutch Discs
58	01	Stamp Drag Discs and Washers (Drc.P=Off.M: Offset Multiplier Component Set, Drc.P=Enc.: Frame Enclosed Component Set, Drc.P=Per.:Peripheral Disc Component Set)	WC-M7	1.5(Drc.P=Off.M) 1.4(Drc.P=Enc.) 1.0(Drc.P=Per.)	M7-S1 M7-S2 M7-S3	Cork Sheet if (Drm.P=Co.) Composite if (Drm.P=Com.) S.S. Sheet Stock	Drag Discs
59	03	Assemble Painted Frame and Drag. Frame-Drag Assembly Precedence varies According to Drag Type	WC-A1	5.9(Drc.P=Off.M) 8.5(Drc.P=Enc.) 4.5(Drc.P=Per.)	A1-S1 A1-S2 A1-S3	Painted Frame, Main Shaft, Drag Clutch Disc, Drag Disc, Purchased Parts	Drag-Frame Subassembly
60	03	Assemble Handle and Painted Spool. Assembly Precedence varies with Handle Type	WC-A2	2.1	A2-S1 A2-S2	Handle, Painted Spool, Purchased Screws	Spool-Handle Subassembly
61	04	Assemble Finished Frame-Drag and Spool-Handle Subassemblies, and Test Quality	WC-A3	4.7	A3-S1 A3-S2 A3-S3	Spool-Handle Subassembly, Frame-Drag Subassembly	Finished Fly Reel

Table 4.1: Data table for generic bill of materials and operations in the manufacture of a fly reel product family. (* Note that operations with the same sequence number occur in parallel)

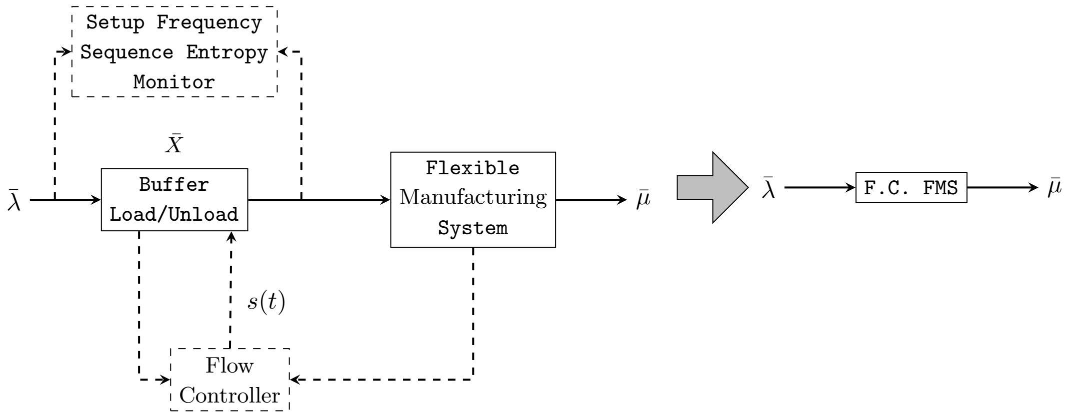


Figure 4.6: Component models used in creating a controlled manufacturing system DEVS atomic model

A manufacturing system was considered to contain a real-time flow controller, capable of implementing CLBF and BMF policies, which operated on an automated buffer system to load arrivals and dispatch control selected jobs into a manufacturing system. Within each generic manufacturing system model was an average setup frequency and average sequence entropy monitor that allowed data associated with the system to be exported for analysis. Each generic manufacturing system model was instantiated with parameters associated with each work stations capacity and setup time requirements.

4.2.2 System Layout

The simulated manufacturing facility consisted of seven processing stations, two sub-assembly stations, a final assembly station and a packaging station. Figure 4.7 shows the layout and connections associated with each processing and assembly station.

The simulated manufacturing facility also included an order generator and an inventory module which generated stochastic order arrivals and dispatched materials to the manufacturing system as needed. Order generation, inventory, processing stations and assembly stations were integrated as shown in order to simulate the production of fly reels.

With reference to Figure 4.7, 6082 T1 Aluminium bar stock is cut to length via circular saws and machined in CNC mill-turn centres to form frames and spools at stations WC-M4 and WC-M5 respectively. Bar stock wood composites are similarly cut to length and machined at station WC-M2 in order to produce handles. Also included within station WC-M2 is a post processing operation in which the handles pass through a varnishing bath. Stainless steel bar stock is machined at CNC mill-turn centres at station WC-M1 in order to produce

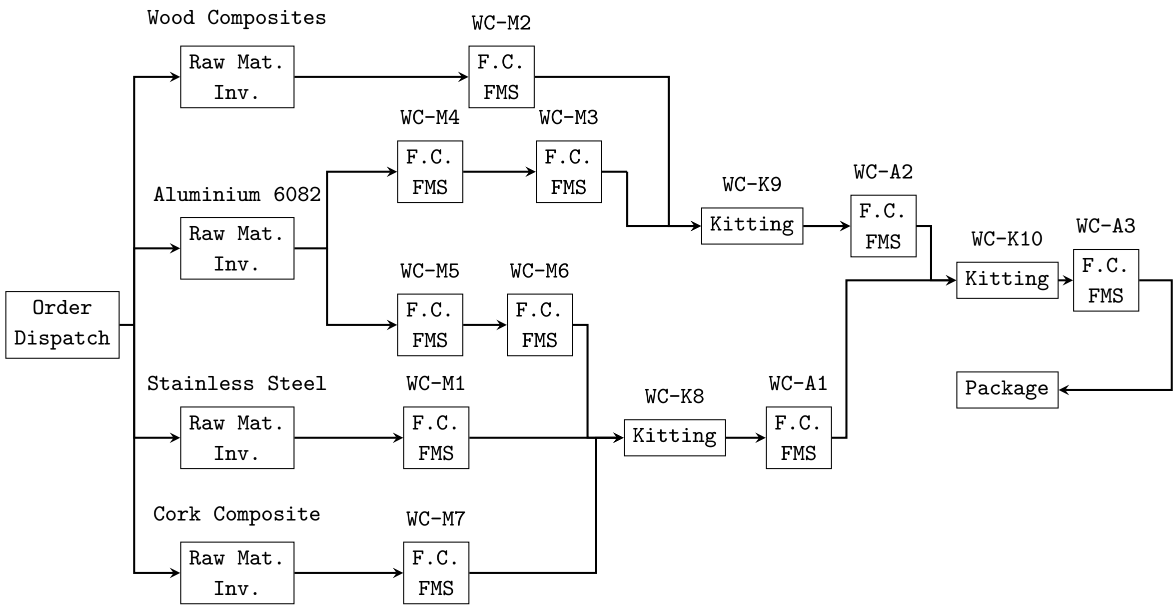


Figure 4.7: Fly reel manufacturing plant setup and layout

main shafts, draw bars and drag clutch discs according to drag type. Stainless steel sheet stock and cork composite drag material are stamped at station WC-M7 in order to produce drag discs and washers, also according to drag type. Finished frames and spools are painted at stations WC-M6 and WC-M3 respectively. Production outputs from stations WC-M6, WC-M7 and WC-M1 are assembled into drag-frame assemblies, post kitting, at assembly station WC-A1. Similarly, the production outputs from stations WC-M2 and WC-M3 are assembled into spool assemblies at station WC-A2. Finally, drag-frame and spool assemblies are assembled into completed fly reels at station WC-A3 for output to packaging.

Associated with each drag, handle, frame and spool colour, and drag disc variant are a set of tools and fixtures which require setup and calibration prior to assembly at stations WC-A1 and WC-A2. This dynamic of setups is in line with discrete variables causing assembly cell reconfigurations.

4.3 Model Predicted Steady State Control Requirements

Due to the natural response characteristics of stable flow controlled manufacturing systems, certain key upstream stations were selected for work-in-process regulation through the application of BMF flow control. The models developed in chapter three were used in predicting control requirements for balanced steady state average sequence entropy through upstream stations feeding assembly station WC-A1, which assembles drag components onto painted reel frames, and station WC-A2, which assembles handles onto painted spools, in order to achieve increased manufacturing performance.

Workstation WC	Simulation Parameters and Model Predicted Steady State Average Sequence Entropy				
	Total Demand λ (parts/min)	Production Capacity μ (parts/min)	Load ϕ	r_{ci} (min)	E_{s_∞} (1/part)	ΔE_{s_∞} (1/part)
WC-M2	0.1	0.1136	0.88	6.0	0.69	8.0
WC-M3	0.1	0.1439	0.7	25.0	8.69	
WC-M1	0.1	0.1134	0.88	12.25	6.29	4.09, 4.9
WC-M6	0.1	0.1399	0.72	25.0	2.204	
WC-M7	0.1	0.2817	0.4	20.0	1.39	

Table 4.2: Simulation parameters, model predicted results and simulation results

Table 4.2 lists the parameters used in simulation and the expected difference in steady state average sequence entropy, as predicted by Equation 3.11. Model predictions suggest that work-in-process at station WC-M2 should be increased with the application of BMF so as to balance steady state average sequence entropy, thus decreasing work-in-process at kitting station WC-K9. Figure 4.8 shows the steady state average sequence entropy for each station in simulation.

The approximate method of determining reference work-in-process levels for BMF application covered in section 3.5.4 provided the basis for determining required work-in-process levels at stations WC-M2, WC-M6, and WC-M7 using Equation 3.19.

As an example of method application, in the case of station WC-M2, the required reference work-in-process level, $|X|_{r_2}$, was determined by first calculating the expected steady state average work-in-process under clear largest buffer first policy, $|X|_{ss_2}$, as follows;

$$\begin{aligned}|X|_{ss_2} &= \frac{\lambda}{n_v}(r_{ci} + \Delta t)\\ &= \frac{0.1}{2}(6.0 + 38.0)\\ &= 2.2\,(3 \text{ jobs})\end{aligned}$$

where $\Delta t = 38.0$ minutes, was determined as $\frac{(60)(8)}{s_{f\infty}}$ through Equation 3.10 developed in chapter three, for $n_v = 2$ jobs, $\phi = 0.88$, $C_c = 0.5$, and $H_d = 8.0$ hours per day. Required reference work-in-process for station WC-M2, $|X|_{r_2}$ was then determined as;

$$\begin{aligned}|X|_{r_2} &= \frac{|\Delta E_{s_\infty}||X|_{ss_2}}{1 - C_c}\\ &= \frac{(8.0)(2.2)}{1 - 0.5}\\ &= 35.2\,(36 \text{ jobs})\end{aligned}$$

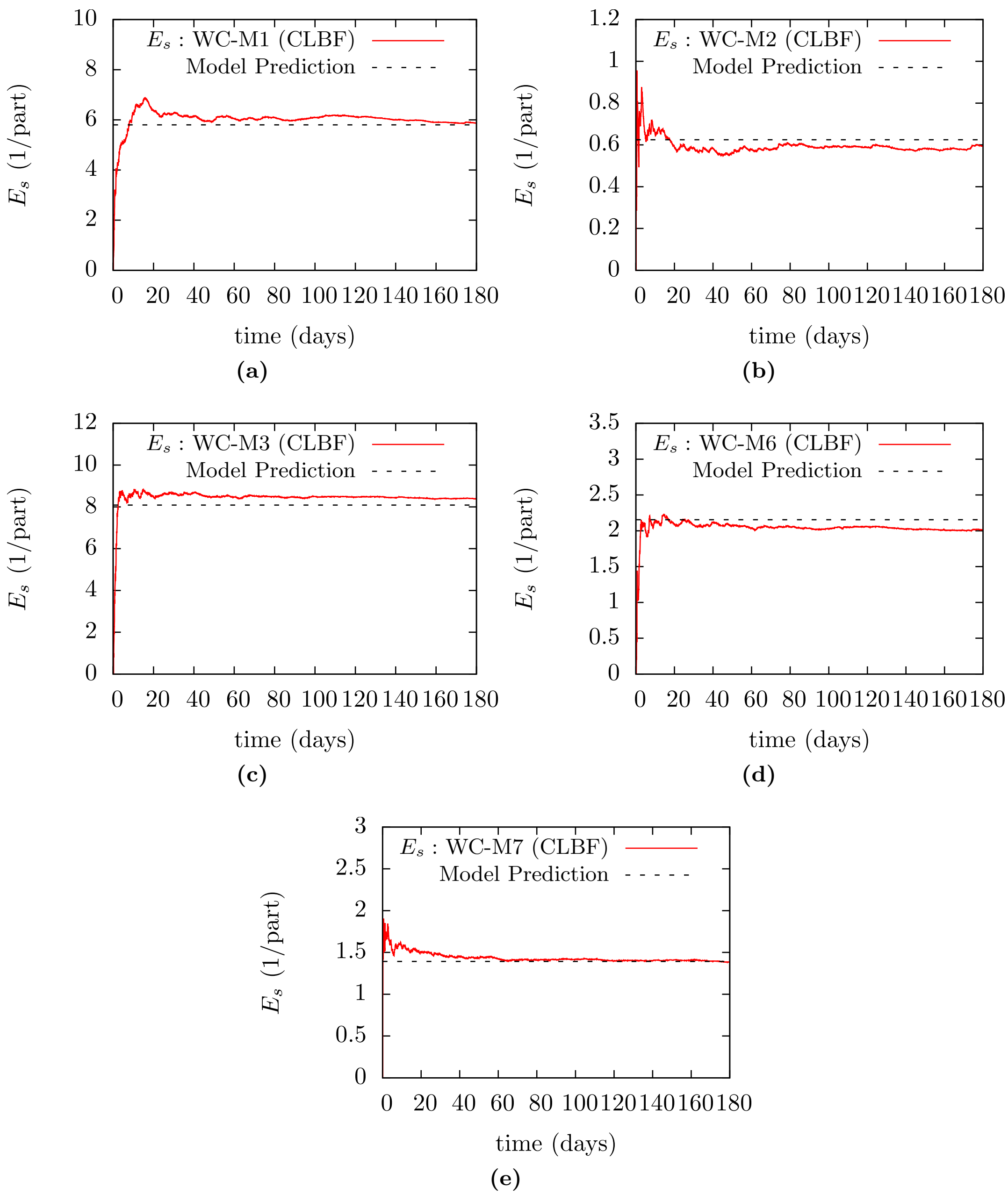


Figure 4.8: Plots showing convergence of simulation results towards model predicted value for each processing and assembly station

Table 4.3 lists the required work-in-process levels to balance steady state average sequence entropy for all key upstream stations. Note that stations WC-M2, WC-M6 and WC-M7 were selected for work-in-process regulation under BMF, as limiting average sequence entropy was lower than the associated competing station/s.

Workstation No.	Reference Workstation No.	Required ΔE_{s_∞} (1/part)	C_c	$\lvert X\rvert_{ss}$ (parts)	Anticipated $\lvert X\rvert_r$ Required (parts)
WC-M2	WC-M3	8.0	0.5	2.2	35.2
WC-M6	WC-M1	4.09	0.5	5.4	44.17
WC-M7	WC-M1	4.9	0.3	3.8	30.0

Table 4.3: Table of required work-in-process reference values for balanced steady state average sequence entropy

4.4 Simulation Results

Simulation results under the application of BMF are shown in Figures 4.9 and 4.10.

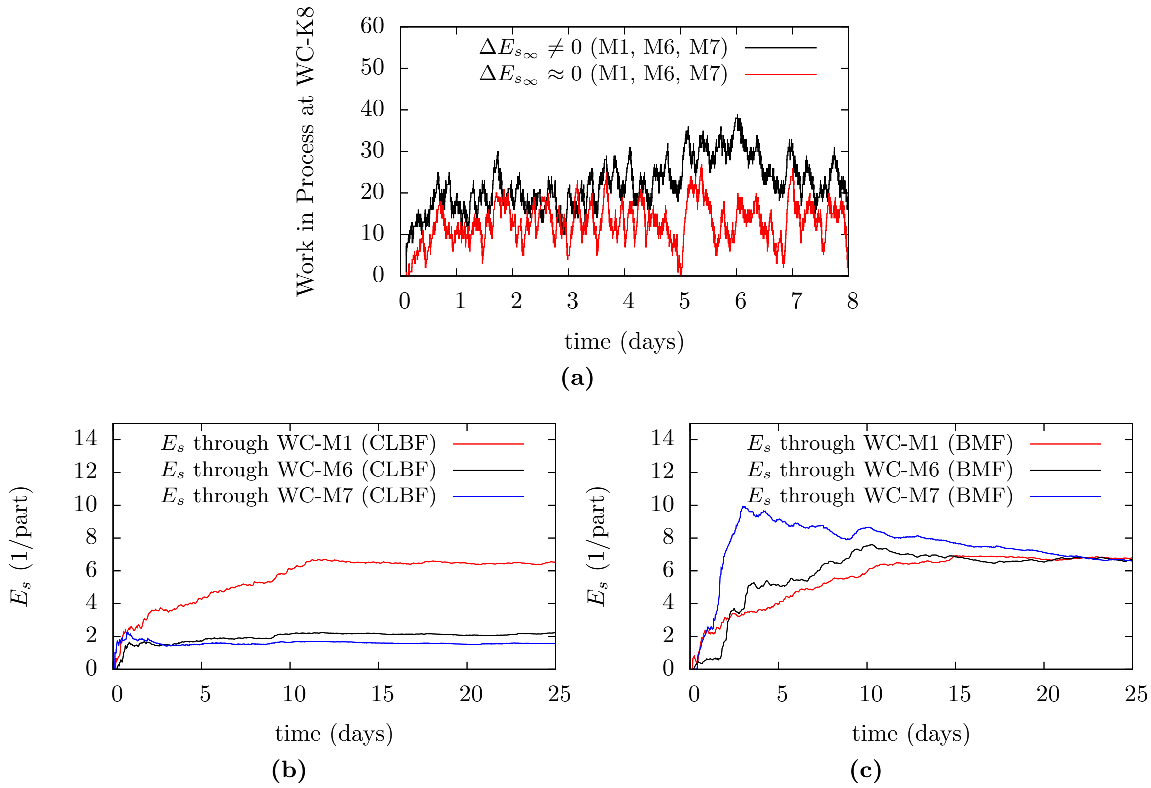


Figure 4.9: Effect of balanced average sequence entropy across stations WC-M1,WC-M6 and WC-M7

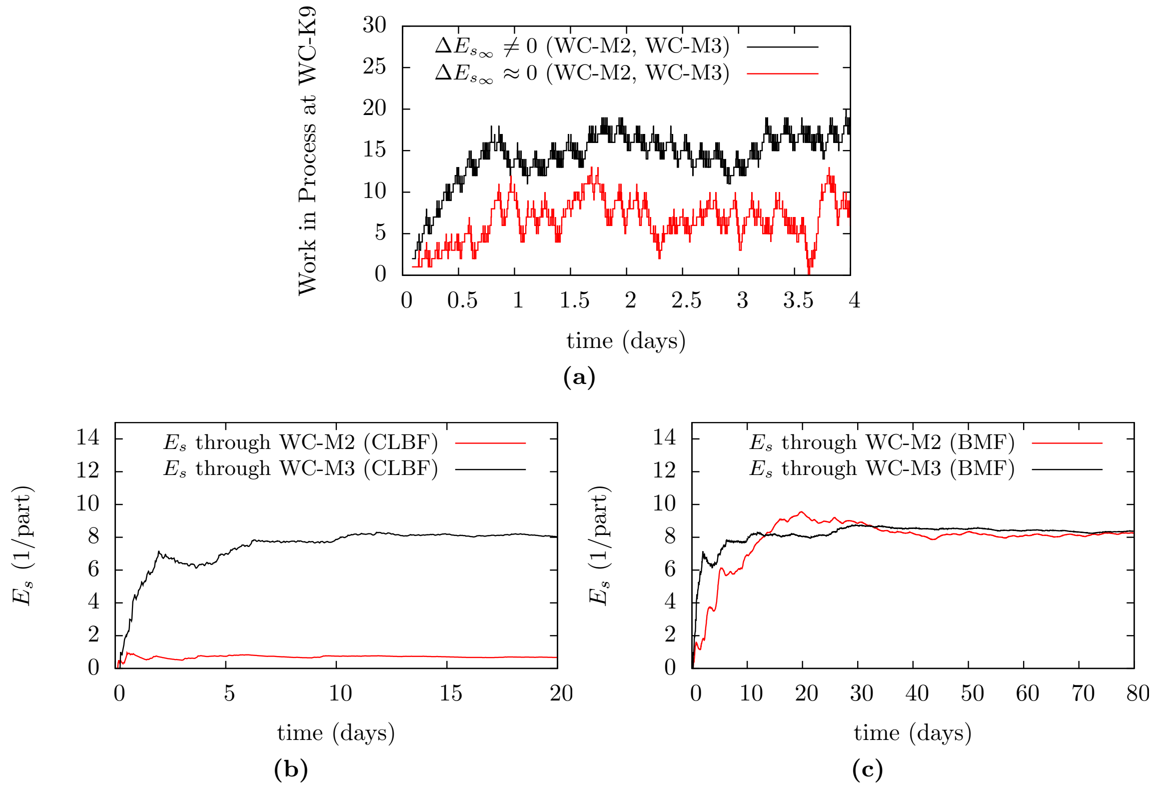


Figure 4.10: Effect of balanced average sequence entropy across stations WC-M3 and WC-M2

Under balanced steady state average sequence entropy, average downstream work-in-process at kitting stations WC-K8 and WC-K9 is lower than that average work-in-process resulting from generalised clearing type flow control policies at upstream processing stations. This is beneficial as the work-in-process at this stage of production is not in an executable state, meaning that assembly can not take place as not all components have arrived from the upstream processing stations.

Since the focus of regulating work-in-process levels to balance average sequence entropy is based on steady state performance, it can be the case that clearing type policies out perform BMF over the short term during system startup, however BMF will always out perform CLBF over the long term. This can be seen in Figure 4.9, where under CLBF, average sequence entropy is more balanced during the first 4 days of production, and in fact BMF over the same time period achieves similar performance in terms of bounding downstream work-in-process. However, over the long term, BMF achieves better performance.

Given the results presented here, it would be beneficial to integrate the approximate method in predicting required work-in-process levels directly into BMF implementations and incorporate short term planning windows in which $|X|_r$ is re-evaluated under consideration of current conditions such that ΔE_s is minimised over the full production period. This proposal in the development of supervisory control structures is covered under future research directions under the concluding remarks in chapter 6.

4.5 Summary

This chapter presented a case study construction of a manufacturing facility producing configurable fly reels. The fly fishing reel market was considered as highly suitable for mass customisation, as customers preferences in reel function and form are largely dependent on personal preference and intended application, as well as experience.

The main component features constituting fly reels were presented and a functional requirement decomposition classification tree (FR/DCT) was developed to isolate those features exposed to customer decisions, as well as the relationships between each product feature. A generic product and process structure was developed based on current trends and technologies used in the industry, in order to map customers' decisions regarding reel configuration onto manufacturing process and assembly variations. The generic process structure was used in developing a simulated manufacturing facility, which simulated the production of configurable fly reels.

The analytic models developed in chapter three were applied in determining control requirements so as to increase manufacturing performance at each simulated assembly station. The approximate method of determining reference work-in-process levels for application of BMF, developed in section 3.5.4, was presented through an example. Simulation results under the application of BMF at key processing stations were compared with results achieved through the application of clearing policy under CLBF. It was shown that BMF is applicable in the active control of distributed manufacturing systems involved in the production of configurable products. It was noted that due to control requirements being predicted in the context of steady state conditions, BMF application may not outperform clearing type policies over the entire period of production, however will certainly outperform CLBF in the long term.

Chapter 5

Discussion

The aim of an argument or discussion should not be victory, but progress

Joseph Joubert, *Pensées 1842*

Contents

Preliminary sections in this chapter discuss the method used in conducting this research, as well as some implications for manufacturing system analysis due to the main results achieved. Control requirements due to trends in product and process platform design are discussed prior to the models developed in chapter three. The properties and characteristics of biased minimum feedback control are discussed in the context of short and long term performance. Consideration of discrete event simulation methods and results ends the discussion.

5.1 Method Rationale

The method used in conducting this research into MCM control requirements was based on the premise that solving a simpler problem may provide insight into the more involved problem space. This rationale often serves to provide solutions to complex problems by extracting key characteristics which provide a basis for further analysis.

5.1.1 Analysis Technique

A preliminary description of the response characteristics of stable distributed control implementations was developed by analysing the steady state behaviour of flow controlled manufacturing systems under clearing policy and uniform demand for each job type. By doing this, model derivations were tractable from first principles, thus providing closed form descriptions which allow for direct algebraic interpretation. The author considers this an advantage in concept communication as properties can be viewed and interpreted graphically. Although one may argue that model derivation based on uniform demand may indeed be too restrictive in the context of MCM, if one considers the research output presented in Blecker and Abdelkafi [11], this assumption is valid. In their research, it was determined that delayed differentiation implementation, within assemble-to-order operations, is only reliable if the selection probabilities of module variants are equal at each assembly stage. It would then be the case that in steady state, average demand would converge to that associated with uniform demand for each job type. The definition of average cumulative correlation also subscribes to this requirement, in the sense that the probability of consecutive customers selecting the same module variant is equal, i.e. $P(X = 1) = \frac{1}{n_v}$.

The application of a probabilistic model to describe the effects on manufacturing system response due to customers' decision processes in product configuration was treated as a separate problem space at first, in line with problem decomposition techniques. Combining the probabilistic model representing the correlation in customers decisions in product configuration, with the closed form models of stable manufacturing system behaviour, occurred through empirical reasoning from data sets formed through discrete event simulation. The author feels that this method of investigation is best described as a convolution of analytic reasoning from first principles, with approximate methods resolved through empirical data analysis. In this regard, it was important to validate the data sets achieved through discrete event simulation against Little's law, as these data sets formed the basis for empirical reasoning in extending the closed form relationships describing steady state average setup frequency and steady state average sequence entropy. Little's law provided a formal sanity check on simulation data without further rigour.

5.1.2 Results of Interest

Job-type set independence, for system loads above the critical system load ϕ^*, is an interesting property of steady state average setup frequency under the application of clearing based control policy. This behaviour can be interpreted as a form of saturation as the manufacturing system is governed to remain stable under sub unity loads. The critical load represents that system load upon which a transition occurs whereby steady state setup frequency saturates with respect to increasing number of job types flowing through the manufacturing system. This is a significant property to characterise as it allows for determination of whether the manufacturing system will operate in a saturated state during operation. Preliminary design of the manufacturing system, such as a minicell, and product architecture for that matter, can consider this behaviour *a priori*. This insight can aid in determining required staffing levels if such setups require manual intervention.

Another interesting result regarded work-in-process regulation. It was determined that apart from bounding work-in-process through the implementation of stable flow control, regulation of work-in-process at upstream processing stations has the potential to increase the performance of downstream assembly systems, when those upstream stations are competing in parallel. Whether or not this aspect of the analysis presented in chapter three could allow for new metrics to be developed and incorporated into the design of assembly systems for delayed differentiation operations is an interesting future prospect.

A discussion on the variety management problem in MCM and its effect on valid product and process design follows. Since control requirements are derived in part from product and process design, it is necessary to include a discussion of the effects with which developments made in addressing the variety management problem have had on manufacturing control requirements.

5.2 Product and Process Platforms

The main differentiator in the implementation of MCM over high variety production lies in the need to characterise functional perturbations of a product family and associated generic process implementations. In the high variety case, production decisions are resolved under objectives of matching demand for each product type, where as in the context of MCM, the objectives are customer specific. This can be thought of as the difference between small batch production and batch of one. Modular product design, and those methods involving axiomatic principles have been major contributors in both the front-end problem of customer-manufacturer interaction, as well as the back-end problem of production execution and complexity mitigation.

5.2.1 Research Implications for Manufacturing System Design and Facility Layout

The effects of product and process platform design on plant layout, in the context of MCM implementation, can be seen as the projection of job-shop flexibility onto flow line formalisms. Investigations into manufacturing system design, such as the research presented in Badurdeen and Masel [4], have formalised, both in method and concept, the establishment of plant layout for MCM. In their minicell concept, cells are designed to mimic job-shops which produce a set of variants, not classified according to group technology in the pure sense, but rather according to requirements in fulfilling a configuration space associated with custom product instantiation in the functional domain.

Although their concept may not necessarily utilise group technology formalisms explicitly, the grouping of machines within each minicell according to product variant sets can be considered as group technology for MCM implementation. Research, such as Suh *et al.* [61], where infrastructure requirements in the design of feasible product and process platforms was considered, exposed the need for increased investment in tooling and fixtures to absorb increased product variety while maintaining manufacturing agility. This necessary requirement can be viewed as a duplication of resources at processing points, rather than the implementation of routing variations, in order to achieve near flow line efficiency's in the long term. Such conclusions in research inquiry support the well documented strong inverse relationships that exist between product variety and production volume.

With these trends derived through research, the author considers that the assumptions made with regard to the transfer of customers' decisions in product configuration onto associated process variations are valid. In other words, by localising process variations to each manufacturing system means that the models developed in chapter three are applicable to generalised MCM systems. Considering the presentation in sections 3.1.2 and 3.1.3, where the effects on process variations due to continuous and discrete perturbations of product platform's functional configuration were formalised, operating ranges of the random variables f and g can be predicted during the planning phases of production. This is beneficial both during the development of a MCM production system, as well as in active control implementation.

5.3 Characteristic Response Surfaces

The characteristic response surfaces presented in chapter three are valuable in both active control of produce-to-order systems, as well as in the design and planning of the system itself. Uncertainty is a characteristic of all complex systems, of which the determination of steady state behaviour through probabilistic inference can aid in resolving expected performance bounds. For this reason, an understanding of the steady state behaviour of flow controlled manufacturing systems, through analysis presented in section 3.2 is important in the implementation of MCM.

5.3.1 Characteristic Setup Frequency

Valid use and interpretation of the steady state average setup frequency response surface, developed in section 3.2.1, is dependent on the existence of a critical system load $\phi^* = \frac{n_v}{\mu r_{ci}+1}$, for $\mu r_{ci} > n_v - 1$. For large capacity, small setup period systems, the characterisation of limiting setup frequency Equation 3.10 is not applicable. This drawback limits the applicability of the response surface model to specific cases with inherent critical system loads. However, when critical system loads exist, specifically when they are below $\phi = 0.8$, these response surfaces are valuable analytic models for predicting required steady state staffing levels, assuming manual reconfiguration of manufacturing systems.

The non-existence of critical system loads is an indication that there exists sufficient flexibility in the manufacturing system, either as a result of large production capacity or minimal setup time requirements. This suggests that in the cases where ϕ^* does not exist, then formal active control is not a factor in determining steady state performance. In the context of machine interference, such as the problem considered in the preliminary sections of Buzacott and Shanthikumar [13], it would be an interesting investigation to resolve optimal staffing levels based on expected steady state setup frequencies for each manufacturing system. Staff in this context would be those employees which are dedicated to implementing manufacturing cell reconfigurations.

The steady state average setup frequency response surface can be considered to build on an investigation by Gershwin [21], where the author used adjusted Markov balance equations in determining required steady state setup frequencies, in order to maintain stability based on demand and required setup time. The response surface presented in this research considers the effects of job arrival sequence correlations in closed form, thus the determination of steady state requirements is resolved without further analysis. By having approximate response surfaces allows for a complete view of system behaviour, without resolving Markov based equations, which is beneficial in the planning phase of production.

The response surface also has an interpretation under batch production operations. Increasing correlation in arrival sequences is analogous to increasing batch size, allowing production engineers to determine batch sizes which would produce a specific average setup frequency. If setup frequency is constrained to a maximum value based on staffing levels, then this interpretation is of particular interest. At this stage, one could argue that the synthesis of control requirements based on correlation measures is unnecessary as the problem could be solved through batching orders prior to dispatching them to the shop floor, and implementing local FIFO policy at each manufacturing system. This is not the case however, as depending on the correlation in customers' decision processes among various configuration parameters, batching requirements at different manufacturing systems may still differ, thus the job sequence problem is not totally avoided.

Figure 5.1 shows the response surface of steady state setup frequency for $r_{ci} = 20$ minutes and a production capacity of 9 jobs per hour and $n_v = 2$ job types. Critical system load exists in such a situation and is $\phi^* = \frac{2}{(20.0)(0.155)+1} = 0.48$, or 48% load. An interesting aspect of the response surface is that it is independent of the number of job types processed at the manufacturing system for loads above this value. Proof of this behaviour was covered in section A.1.1 of the Appendix.

5.3.2 Characteristic Sequence Entropy

A closed form description of steady state average sequence entropy aids in both planning and control of MCM production systems. An instance of a steady state average sequence

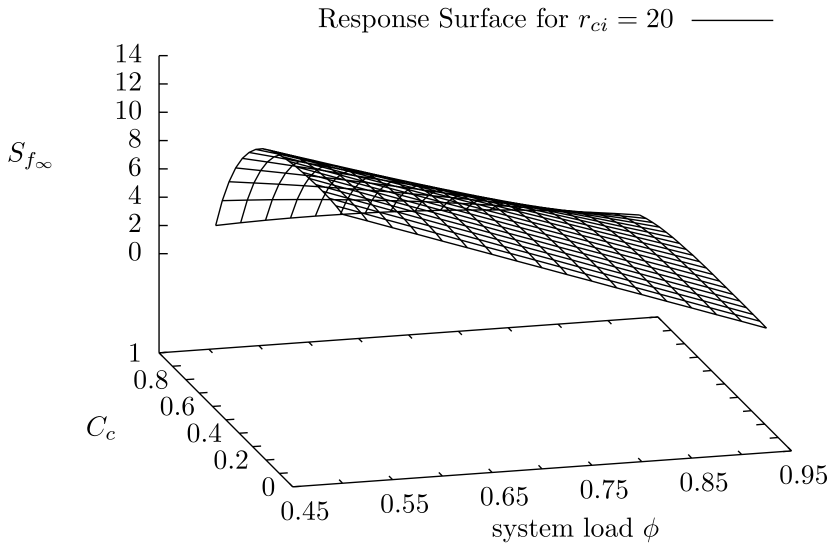


Figure 5.1: Setup frequency response surface for inter job-type setup time of $r_{ci} = 20.0$ minutes

entropy response surface for $n_v = 4$ and $r_{ci} = 20.0$ is shown in Figure 5.2. Although one could develop other such models using discrete event analysis, the use of continuous approximations and closed form finite arithmetic sums allows for simple derivation in closed form. From analysis into assembly system performance due to varying average cumulative correlation in arrival sequences, section 3.4, steady state average sequence entropy is an important state variable. Furthermore, the description of steady state average sequence entropy developed during this research, Equation 3.6, contains parameters which are either known not to change over time due to manufacturing system design and generic process platforms, such as n_v, or parameters which can be measured through statistical analysis of trial runs prior to production, such as r_{ci}.

One drawback associated with the model developed during this research is that it is based on uniform demand for each job type. However, if it is expected that demand is non-uniform for the particular variant set exposed to customers decision processes, then it would be beneficial to limit the range of offerings such that demand can be considered uniform over the product variant offerings. This statement can be considered valid in the context of research such as Blecker and Abdelkafi [11], in which delayed differentiation was researched and found to be a reliable strategy only under uniform selection probabilities among variants at each assembly stage.

Another aspect to consider is that the analysis presented in this research was based on steady state behaviour, and so balanced average sequence entropy is only guaranteed in the limit, under the formulations presented in this research. Figure 5.3, taken from chapter four

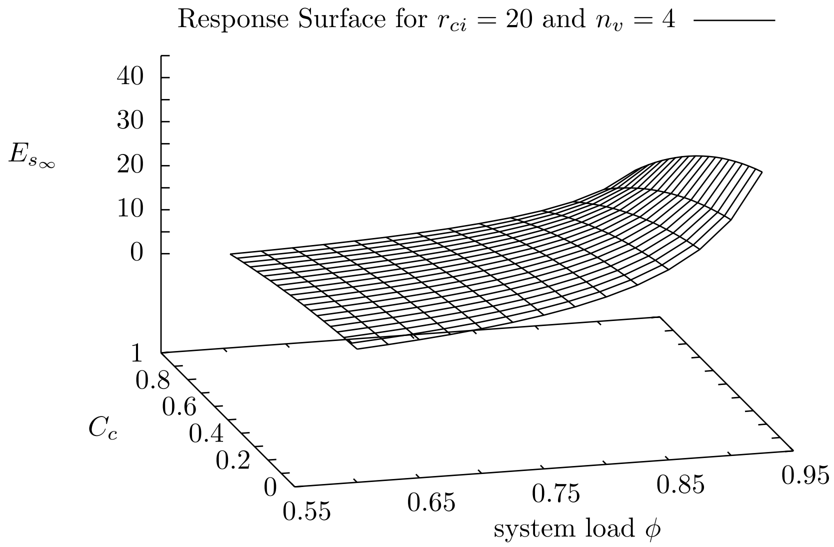


Figure 5.2: Steady state average sequence entropy response surface for $r_{ci} = 20$ minutes and $n_v = 4$ job types

and presented here for convenience, captures this aspect of analysis.

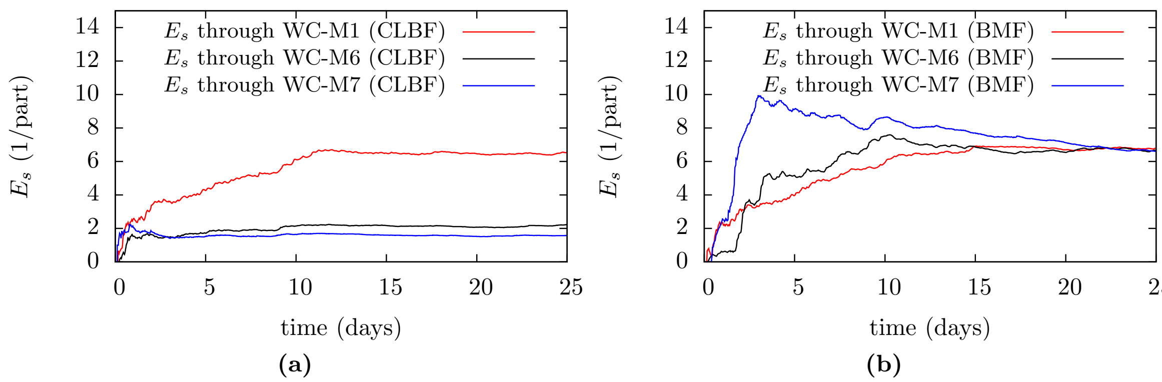


Figure 5.3: Average sequence entropy response showing the need for tracking control in order to achieve balance before steady state conditions are reached

With reference for Figure 5.3b, it is the case that due to the characteristics of station WC-M7, i.e. low system load ϕ and relatively large setup time r_{ci}, average sequence entropy response under the application of BMF tends to overshoot required steady state levels. To a certain extent, this overshoot can be lessened by lowering the value of parameter A in the work-in-process regulation function that forms part of BMF implementation, Equation 3.16. By doing so, one can lower the rate at which work-in-process increases to required levels, thus diminishing the rate in which average sequence entropy increases. This momentary unbalance can therefore be considered to occur, in part, as a result of the limitations imposed by steady state analysis, as well as poor tuning of the BMF implementation on station WC-M7.

5.4 Biased Minimum Feedback

An important aspect to consider in the implementation of distributed manufacturing system control is that active flow control is only applicable when there exists the potential for control decisions to significantly change work-in-process dynamics and/or downstream work-in-process. A duality exists between variation and control application, in which one requires the other. If variation in processing requirements exists as a result of customers' decision behaviour in product configuration, then active control is necessary in order to maintain performance bounds. On the other hand, in order for such control to be effective, variation must exist within the processing requirements of job arrivals such that flow control policies have the potential to implement job selection decisions between the job types, so as to stabilise and regulate work-in-process. This duality is akin to that which exists between variations and buffer requirements. Variation in the upstream and downstream performance of manufacturing systems requires intermediate buffer storage allocation, however buffer allocation indirectly effects the resultant variation within the entire manufacturing facility.

Biased minimum feedback control can be considered to vary job type selection trajectories according to the amount of potential variation entering the manufacturing system. If variation does not exists, i.e. constant cycle times, totally reliable manufacturing systems and zero setup times, then FIFO control policy not only suffices, but is the best policy. In other words, unconstrained flexibility does not need active control. This is natural as if no variety exists within the entire manufacturing facility, then there should be no need to implement control policies other than FIFO. Stability in this case is purely dependent on system load ϕ. For sub unity loads, the system would be stable and control development falls under capacity planning and buffer storage allocation. The synthesis of BMF is based on this fundamental premise that control is only necessary when variations exist in the processing requirements of job arrivals entering the manufacturing system.

The ability to regulate work-in-process at levels above those steady state levels achieved with clearing policies is beneficial as it holds the potential to increase the performance of downstream assembly stations constrained to operate only when complete sets of unique constituent components have arrived from upstream processing stations. Although work-in-process is increased at upstream stations under BMF, the benefit of lower work-in-process at downstream stations increases performance in the long term under the consideration of higher costs associated with buffering partially finished items.

5.5 Viewpoint in Establishing Deterministic Response Behaviour

If one views the variety management problem form two perspectives, planning and control, planning through product platform design, generic process development and manufacturing system layout design can be considered as a passive measure in ensuring bounded system behaviour, i.e. system behaviour that has a level of determinism under uncertain input disturbances brought about by customers decision behaviour in product configuration. MCM control through the application of BMF can be considered as the active counterpart of this concept. Uncertainty is a fundamental property of all complex systems, including MCM systems, and the ability to predict and maintain steady state performance bounds under customer induced uncertainty is the main goal of analysis into the effects of customer decision behaviour on manufacturing control requirements.

5.5.1 Implications for Planning and Control

It is a characteristic of analysis, that as solution approaches are applied to problem sets of larger scope, the problem becomes one of planning rather than control. Given that application of mathematical programming techniques in solving production control problems leads to NP-hard combinatorial problem spaces, it is beneficial to characterise steady state response under stable dispatching rules in order to allow for active control of manufacturing systems in real-time. In this regard, it has been the case of prior research efforts, that the planning and control problem domains, in the context of MCM, have been addressed as separate problem spaces. The models developed during this research have the potential to integrate the problem of planning at the production design level, in terms of product, process and supply chain design, with the problem space of distributed control implementation, as one can determine the effects of product design decisions and their expected customer-manufacturer interaction on the resulting steady state performance of a production system.

5.6 Summary

This chapter presented a discussion on the outputs achieved during this research study, within the context of trends in product, process, and manufacturing system design and implementation, due to past research in the field of MCM implementation. Due to trends in manufacturing system design and layout implementation, the assumptions made in developing descriptions of process variations due to customers decisions in product configuration were considered valid. The job type set independence property of stable flow controlled manufacturing system was highlighted as this property has particular implications in determining staffing levels in MCM implementation, with regard to executing manufacturing system setups. The application of BMF in establishing work-in-process distributions which increase the performance of downstream assembly stations was discussed. The need to actively regulate work-in-process levels was considered as the principle requirement in effective control implementation in MCM operations. The duality between active flow control and variations in processing requirements was discussed with reference to the properties of BMF control. It was noted that BMF implementation only decouples from FIFO selection policy when there exists the potential to actively change work-in-process levels.

The discussion ended by presenting a particular viewpoint on the variety management problem in MCM implementation. It was rationalised that the key goal in variety management was the implementation of passive measures, i.e. product, process and manufacturing system design, and active measures, i.e. BMF control, such that deterministic manufacturing performance persists in steady state, even under the fundamentally stochastic input disturbances brought about the customers decision behaviour in product configuration.

CHAPTER 6

Conclusion

The true function of philosophy is to educate us in the principles of reasoning and not to put an end to further reasoning by the introduction of fixed conclusions

George Henry Lewes

Contents

6.1 Research Summary

This study researched steady state distributed control requirements in the implementation of mass customisation manufacturing (MCM). Customers decisions in product configuration were modelled as stochastic processes, which were considered to generate partially correlated sequences of job arrivals into each distributed manufacturing system. The research method was based on the characterisation of correlation metrics, as a measure of the impact with which customers' decisions in product configuration through time effect the limiting behaviour of stable flow controlled manufacturing systems involved in MCM. Of particular interest was the analysis of work-in-process distributions which increase downstream assembly performance under varying job arrival sequences into parallel upstream processing stations, controlled under stable clearing policy.

6.1.1 Principle Objectives

The aim of this research was to:

- Interpret fundamental characteristics in the current state of the art in MCM production system design and control implementation.
- Develop closed form analytic models that describe the effect of customer decision processes in product configuration, on steady state manufacturing control requirements.
- Determine whether new system properties exist under MCM, that can be measured and used in increasing the performance of distributed control, specifically for those operations which supply unique components into assembly stations.

6.1.2 Method

The method used in conducting this research involved both analytic reasoning through the development of closed form models under simplifying assumptions, as well as empirical reasoning via analysis of data sets generated through discrete event simulation. Closed form models were developed using continuous approximations upon which polynomial curve fitting procedures were implemented to take into account and characterise more complex cases involving many job types and arrival sequences. The analytic models developed were validated by testing them against data sets achieved through discrete event simulation. Simulation data sets were in turn validated against a well known law governing the limiting behaviour of stable queuing systems, i.e. Little's law.

6.1.3 Research Contributions

This study made the following research contributions:

- For stable flow controlled manufacturing systems with non-negligible setup times, characteristic response surfaces can be determined over the domains of system load and job type arrival sequence correlation. These response surfaces are useful in determining steady state resource and control requirements at each manufacturing system.
- For manufacturing systems operating under stable flow control policy, steady state average setup frequency saturates under increasing job type set size, when system load is above a critical system load. Furthermore, a critical system load exists if and only if the product of setup time and production capacity is greater than $n_v - 1$, where n_v is the number of different job types entering the manufacturing system.
- Distributed flow control can be achieved through the use of biased minimum feedback (BMF). It was shown that BMF is capable of adjusting work-in-process distributions to suit changing correlation in job arrival sequences into distributed manufacturing systems. This was shown to be beneficial in increasing the performance of downstream

assembly stations, when each customer's product requires a unique one to one component match during assembly operations.

6.2 MCM Control Implementation

The effective impact on steady state control requirements, due to increased variety in the implementation of MCM, is dependent on the correlation in product configuration decisions made by consecutive customers. Since it is the customers who are ultimately inducing variability in production requirements, the quantitative modelling of customers for use in control synthesis is beneficial in establishing favourable steady state performance. In this line of thought, mass production can be considered as a special case of MCM in which each and every customer selects the same product configuration resulting in an emphasis towards production planning over active control implementation. In other words, active distributed control implementation is only necessary when the probability of uncorrelated production requirements is high. This can be considered as the case with all high variety paradigms including MCM.

6.2.1 The Roles of Planning and Control under Increased Variety

In the past, research into the MCM control problem has been approached from two perspectives, design or planning, and active control. As product variety increases, time horizons in the planning phase of production decrease. In the specific case of MCM, formal planning requirements originate at the manufacturing interface as a result of customer decision processes in product configuration, and as such the planning phase has been collapsed onto necessary requirements in product, process and supply chain design to minimise internal manufacturing complexity. This shift in production system implementation is most readily observed in the establishment of delayed product differentiation, which has been the main approach in overcoming the small time horizon planning problem. Product and process platforming, product design methods involving commonality and modularity, minicell implementation and assemble-to-order operations have evolved in accordance with meeting agility requirements while under the planning horizon constraints imposed by MCM.

Although production system planning and design is a necessity in the implementation of MCM, planning and design efforts only provide passive measures in ensuring performance. Active control is necessary to ensure that customers decision processes in product configuration are handled effectively on the plant floor, especially when uncertainty is a characteristic of the system.

6.2.2 Application of Analytic Models in Planning and Control

Analytic modelling provides the opportunity to interpret fundamental characteristics in a clear and concise manner. A drawback of analytic reasoning in analysing production planning and control problems lies in the NP-hard nature of resulting problem sets. Although analytic methods provide the opportunity to resolve optimal solutions, prior assumptions made in simplifying the problem to allow for analytic tractability often prevents valid real world implementation.

The closed form models of steady state average setup frequency and steady state average sequence entropy, Equations 3.10 and 3.11 respectively, are useful in the planning phase of production, as well as in active control implementation. Equation 3.10 along with the job-type set independence property of stable flow controlled manufacturing systems, has implications for the determination of steady state staffing levels, if such staffing is required to implement manufacturing system setup changes. During the planning phase of production, it would be beneficial to assign capacity to each manufacturing system such that the system runs at loads above the critical system load. Under this condition, steady state average setup frequency would converge onto a relatively deterministic value, which would be known during the planning phase of production.

With regard to active measures, control implementation can formally consider the changes in steady state behaviour, as suggested by Equations 3.10 and 3.11, by adjusting work-in-process distributions so as to maintain performance bounds when customers' decision behaviour in product configuration, induce changes in job arrival sequences into each manufacturing system. Through this research, Equation 3.19 and the implementation of biased minimum feedback, provides the necessary tools to implement such an active control strategy.

Past research paths have treated planning and control as separate problem spaces in MCM. The work by Stecke [59] highlights this perspective, where the author decomposes the flexible manufacturing system operation space into one of planning and one of control. The models developed and validated during this research are applicable in both the planning and active control phases of production and as such provide a valuable tool for future MCM implementation.

6.3 Future Research in Manufacturing System Control

The need for research into MCM implementation is clear and fundamentally important for future consumer market facilitation. The variety management problem has to be solved at all levels of production system implementation, from product design through to process implementation and manufacturing control. To a large extent, manufacturing is still constrained to operate according to the inverse relationship between product variety and production quantity.

The implementation of MCM relies on holistic interpretations of the problem space exposed by increased variety within constrained capacity manufacturing systems. Past research covered in chapter two suggested that MCM implementation relies on an explicit understanding of consumer markets, and the facilitation of customers at the manufacturing interface. Considering these past research efforts, if one accepts the notion that progression is consequential in the convergence of ideas, results, solution methods and interpretations, then MCM implementation is limiting towards a systems approach that:

1. Maximises external variety within game theoretic notions that prevent price deflation due to decreasing product differentiation between competing manufacturers.

2. Minimises internal manufacturing complexity through the implementation of product and process platforming, as well as delayed differentiation strategy.

3. Utilises active distributed control systems which are sythesised under the explicit characterisation of customers decision processes in product configuration.

Regarding future research into the planning phase of production, an understanding of expected steady state behaviour through the models developed during this research study could be used in formulating new objective functions in the combinatorial optimisation of machine groupings and variant set assignments to each manufacturing cell. The author feels that this is a particularly interesting future prospect for research into manufacturing system design for MCM implementation.

From an active control perspective, the development of average sequence entropy tracking control would be an important contribution to increasing the performance of biased minimum feedback control implementation, as short term performance could be increased along with long term performance. Future research could consider the development of centralised supervisory control structures that are capable of adjusting reference work-in-process requirements at each manufacturing system. An interesting research problem would be the determination of an optimal planning window, in which required work-in-process, i.e. $|X|_r$, is re-evaluated according to Equation 3.19, so as to balance steady state average sequence entropy across competing stations.

Appendix A

Appendix

A.1 Proofs

A.1.1 Job Type Set Independence

Theorem 1 (Job Type Set Independence)**.** *Let $\mathbb{T}$, $|\mathbb{T}| \geq 2$ be a countable set of job types processed at a manufacturing system with clear largest buffer first (CLBF) flow control policy. Let r_{ci} be the setup period, λ, the average job arrival rate, and μ, the average service rate. If system load $\phi \triangleq \sum_{k=1}^{n} \frac{\lambda_k}{\mu_k}$, $n = |\mathbb{T}|$ is greater than $\phi^* \triangleq \frac{n_v}{\mu r_{ci}+1}$, then steady state setup frequency is independent of $|\mathbb{T}|$.*

Proof. By construction;

Characteristic scenario:
A stable flow controlled flexible manufacturing system facilitating the production requirements of n_v job types at a production rate of μ, with a setup time of r_{ci} between each job type, Figure A.1.

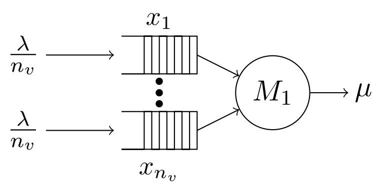


Figure A.1: Flow controlled flexible manufacturing system under CLBF policy

The load value $\phi^* = \frac{n_v}{\mu r_{ci}+1}$, termed a critical system load, is easily constructed. If the inter-arrival period of each job type $\frac{n_v}{\lambda}$, assuming uniform demand per job type, is greater than the time to set up the manufacturing system plus the time to process each job type, then each job arrival event will produce a setup event when the cumulative correlation of the arrival sequence is zero, i.e.

$$\begin{aligned}
\frac{n_v}{\lambda} &\geq r_{ci} + \frac{1}{\mu} \\
\frac{n_v}{\lambda} &\geq \frac{\mu r_{ci} + 1}{\mu} \\
\lambda &\leq \frac{n_v \mu}{\mu r_{ci} + 1} \\
\phi &\leq \frac{n_v}{\mu r_{ci} + 1}
\end{aligned}$$

From the individual work-in-process trajectories, for $n_v = 2$, shown in Figure A.2, which result for system loads $\phi > \phi^*$, the relationship between setup period Δt_{n+1} and Δt_n can be resolved as Equation A.1.

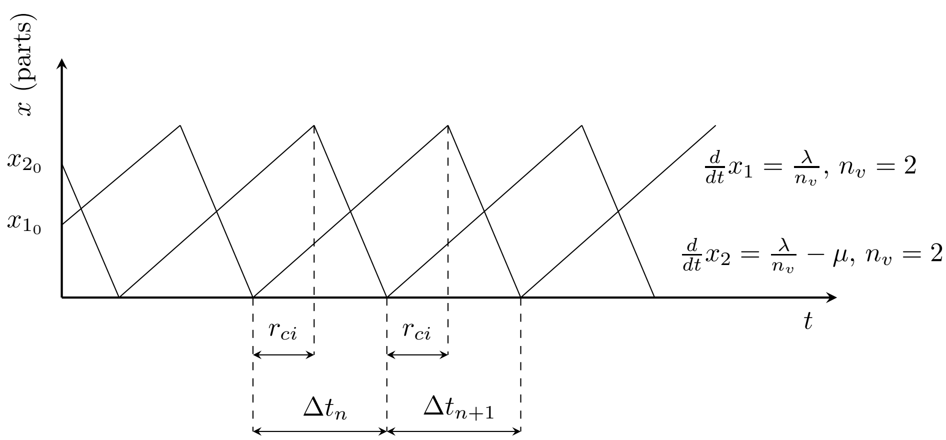


Figure A.2: State trajectory for a two job type system

$$\Delta t_{n+1} = r_{ci} + \frac{\frac{\lambda}{n_v}\left[n_v r_{ci} + (n_v - 1)[\Delta t_n - r_{ci}]\right]}{|\frac{\lambda}{n_v} - \mu|} \tag{A.1}$$

Assuming that, $\lim_{t\to\infty}(\Delta t_{n+1} - \Delta t_n) \to 0$, i.e. $\Delta t_{n+1} = \Delta t_n = \Delta t$, then the limiting inter-setup period for $r_{ci} > 0, n_v \geq 2$, can be resolved as Equation A.2.

$$\Delta t = r_{ci} + \frac{\frac{\lambda}{n_v}\big[n_v r_{ci} + (n_v - 1)[\Delta t - r_{ci}]\big]}{|\frac{\lambda}{n_v} - \mu|}$$

$$\Delta t = r_{ci} + \frac{\frac{\lambda}{n_v}[r_{ci} + (n_v - 1)\Delta t]}{|\frac{\lambda}{n} - \mu|}$$

$$\Delta t - (n_v - 1)\frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}\Delta t = r_{ci} + \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}} r_{ci}$$

$$\big[1 - (n_v - 1)\frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}\big]\Delta t = r_{ci}\big[1 + \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}\big]$$

$$\Delta t = \frac{r_{ci}\big[1 + \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}\big]}{1 - (n_v - 1)\frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}} \tag{A.2}$$

Therefore, an approximation of limiting setup frequency as a function of the number of job types, n_v, the total demand λ, capacity μ, and setup period r_{ci}, is;

$$S_f(n_v, \lambda, \mu, r_{ci}) = \frac{1 - (n_v - 1)\frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}}{r_{ci}\big[1 + \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}\big]} \tag{A.3}$$

It is the case that,

$$S_f(n_v, \lambda, \mu, r_{ci}) = S_f(\lambda, \mu, r_{ci}) \iff A(n_v) = C > 0 \quad \forall\, n_v \geq 2$$

where C is a constant and the auxiliary function;

$$A(n_v) = \frac{1 - (n_v - 1)\frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}}{1 + \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}}$$

represents a constant function.

Let $n_v = k \in \mathbb{K}$, where $\mathbb{K} \triangleq \mathbb{Z}^+ \setminus 1$, then;

$$A(k) = \frac{1-(k-1)\frac{\frac{\lambda}{k}}{\mu-\frac{\lambda}{k}}}{1+\frac{\frac{\lambda}{k}}{\mu-\frac{\lambda}{k}}}, \qquad \times\frac{\left(\mu-\frac{\lambda}{k}\right)}{\left(\mu-\frac{\lambda}{k}\right)}$$

$$= \frac{\mu-\frac{\lambda}{k}-(k-1)\frac{\lambda}{k}}{\mu-\frac{\lambda}{k}+\frac{\lambda}{k}}$$

$$= \frac{\mu-\lambda+\frac{1}{k}(\lambda-\lambda)}{\mu}$$

$$= C > 0, \ \forall\, k$$

Since $n_v = k \in \mathbb{K}$, then $A(k) = C > 0\ \forall\, k \implies A(n_v) = C > 0\ \forall\, n_v \geq 2$. Note that 1 has been strictly excluded from the set $\mathbb{K}$ as single job type instances are not relevant to flow controlled manufacturing systems. This concludes the proof. $\square$

A.2 Derivations

A.2.1 Steady State Average Sequence Entropy

It is shown that under Clear Largest Buffer First flow control policy, Equation A.4,

$$E_{s_\infty}(\mu, \lambda, n_v, r_{ci}) = \frac{n_v \lambda r_{ci}\left[1 + \frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}\right]}{4\left[1 - (n_v - 1)\frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}\right]} \tag{A.4}$$

is a continuous approximation to steady state average sequence entropy per part produced. Steady state average sequence entropy per part is in turn defined as, $\lim_{n\to\infty} \frac{1}{n}\sum_{k=1}^{n} |(S_i - S_o)|_k$, where n is the number of parts produced, S_i is the input sequence position of a parts arrival event at a manufacturing system and S_o is the associated sequence position of the parts departure event from a manufacturing system.

Consider the scenario of Figure A.3 and Figure A.4, within the time frame $[t_0, t_2]$, where b_i is the buffer assigned to store the job components of job type v_i, and x_i is the number of jobs of job type v_i in buffer b_i, $i \in \{1, 2\}$.

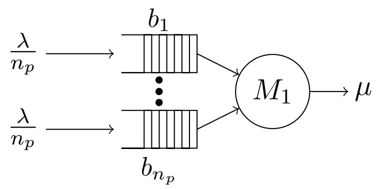


Figure A.3: In this figure, M_1 can be considered as a flexible machining cell, which requires a setup time of r_{ci} between setups, to produce each part type at a production rate of μ. The total demand into the system is λ.

Furthermore, consider that at $t = t_0$, the input sequence is reset to zero, and at $t = t_1$ the output sequence is identically set to zero. At $t = t_1$, the number of parts in buffer b_1 is;

$$x_1 = \frac{\lambda}{n_v}\big[(n_v r_{ci} + (n_v - 1)(\Delta t_n - r_{ci})\big]$$

At $t = t_2$, the number of additional arrivals is equal to;

$$\Delta x_1 = \frac{\lambda}{n_v}(\Delta t_{n+1} - r_{ci})$$

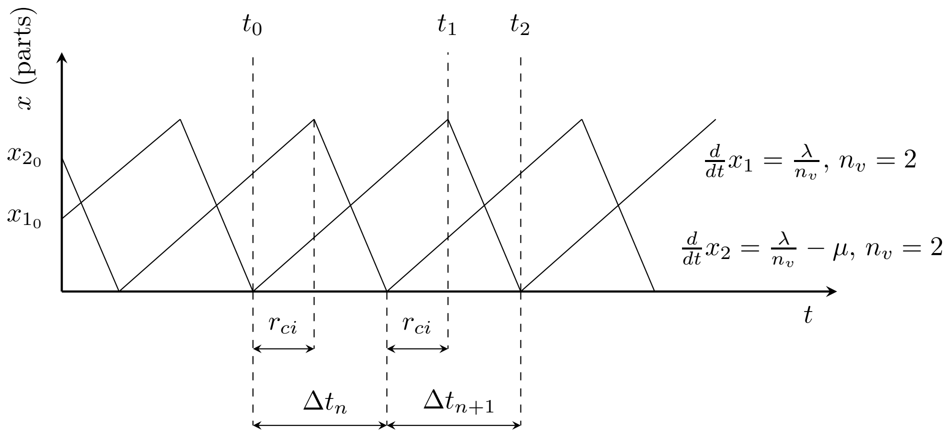


Figure A.4: Trajectory for a two job type system under CLBF flow control policy

Assuming that $\lim_{t\to\infty}(\Delta t_{n+1} - \Delta_{t_n}) \to 0$, the total number of part arrivals, also equal to the number of part departures, at $t = t_2$ can be determined as;

$$\begin{aligned} x_1 + \Delta x_1 &= \frac{\lambda}{n_v}(n_v \Delta t) \\ &= \lambda \Delta t \end{aligned}$$

Arrival events for each job type evolve according to a countable state Markov process where each state index i represents an arrival event of job type v_i. For a cumulative correlation of zero, the probability of self transition is zero, i.e. $p_{ii} = 0$, and $p_{ij} = \frac{1}{n_v - 1}$, Figure A.5.

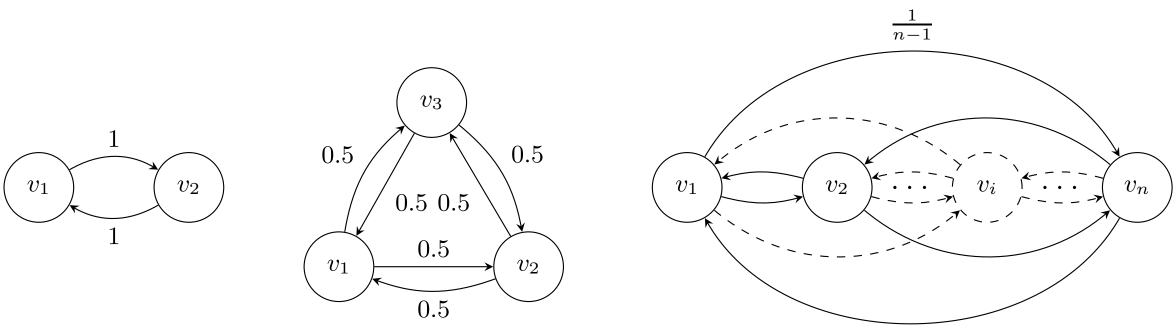


Figure A.5: Markov process representing customers decisions in generating job arrival sequences

For the special case of $n_v = 2$, the event trajectories are deterministic. Arrival sequence positions, S_i, under this case, evolve according to the arithmetic sequences;

$$\begin{aligned} v_k :& \quad 1, 3, 5, 7, \ldots, 2k-1 \\ v_{k+1} :& \quad 2, 4, 6, 8, \ldots, 2k \end{aligned}$$

where $k \in \{1, 2\}$ (mod 2). This is equivalent to a round robin dispatching discipline. The output sequence in turn evolves according to successive integers $1, 2, 3, 4, \ldots, n$.

By letting $\lambda \Delta t = \gamma$, and using the closed form finite sums;

$$\begin{aligned} \sum_{k=1}^{n} 2k - 1 &= n^2 \\ \sum_{k=1}^{n} 2k &= n(n+1) \\ \sum_{k=1}^{n} k &= \frac{n(n+1)}{2} \end{aligned}$$

the average sequence entropy for the deterministic case can be found by averaging over the number of job types;

$$\begin{aligned} E_{s_\infty} &= \frac{1}{2}\Big[\frac{1}{\gamma}\sum_{k=1}^{\gamma} |S_{i_1} - S_o|_k + \frac{1}{\gamma}\sum_{k=1}^{\gamma} |S_{i_2} - S_o|_k\Big] \\ &= \frac{1}{2\gamma}\Big[\gamma^2 + \gamma(\gamma+1) - 2\frac{\gamma(\gamma+1)}{2}\Big] \\ &= \frac{\gamma}{2} \end{aligned}$$

For reasons to be explained shortly, assume that the result above is $n_v\phi$, for $n_v = 2$, where $\phi = \frac{\gamma}{4}$ is the average sequence entropy contribution per deterministic transition in the associated Markov process. The non-deterministic arrival trajectories for job type sets greater than two poses a problem in the characterisation of the sequence positions for each job type arrival. Since it is the steady state behaviour which is of interest, provided the demand for each job type is uniform, the non-deterministic Markov processes for $n_v > 2$ can be transformed into deterministic round robin dispatching schemes, Figure A.6. Note that for $n_v = m$, there are m ϕ transitions, and as such, one can determine that average sequence entropy limits towards $n_v\phi$.

Furthermore γ is resolved from Equation A.2, where steady state Δt is known to be;

$$\Delta t = \Big[\frac{r_{ci}(1+\beta)}{1-(n_v-1)\beta}\Big], \quad \beta = \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}$$

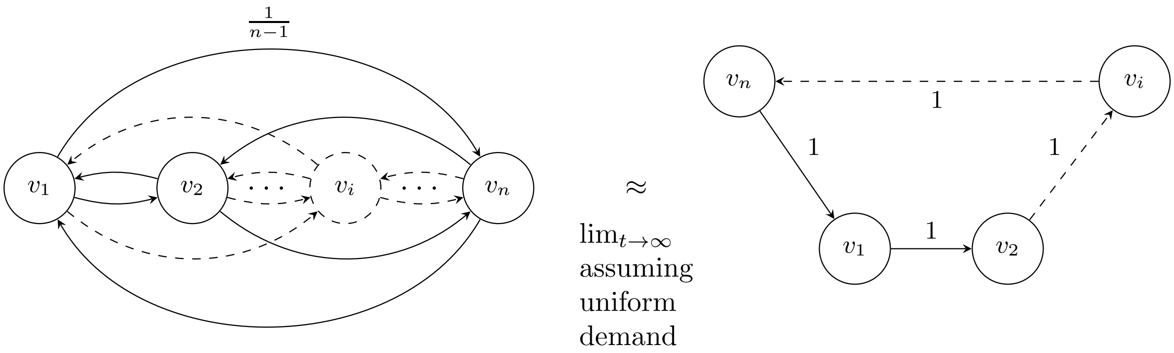


Figure A.6: Simplifying approximation of a non-deterministic Markov process into a round robin sequence assuming uniform demand

Therefore;

$$\gamma = \frac{\lambda r_{ci}(1+\beta)}{1-(n_v-1)\beta}, \quad \beta = \frac{\frac{\lambda}{n_v}}{\mu - \frac{\lambda}{n_v}}$$

which results in;

$$\begin{aligned} E_{s_\infty}(\mu, \lambda, n_v, r_{ci}) &= n_v \phi \\ &= n_v \frac{\gamma}{4} \\ &= \frac{n_v \lambda r_{ci}\left[1 + \frac{\frac{\lambda}{n_p}}{\mu - \frac{\lambda}{n_p}}\right]}{4\left[1-(n_v-1)\frac{\frac{\lambda}{n_p}}{\mu-\frac{\lambda}{n_p}}\right]} \end{aligned}$$

which is Equation A.4.

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