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Anarchic Manufacturing

A methodology for modelling manufacturing systems as distributed free market systems

Anarchic Manufacturing: A methodology for modelling manufacturing systems as distributed free market systems

Applying a distributed production system against simple discrete, assembly and product transition manufacture

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Abstract

Manufacturing systems are traditionally organised hierarchically. The hierarchy works well for systems with simple and static organisation of manufacturing resources, where management layers and predetermined rules provide effective production. However, new demands for customised products with rapid delivery, have led to the rise and pervasion of smart manufacturing, where intelligent objects interact in a Cyber-Physical System. In these systems, the organisation of resources and the manufacturing environment tend to be highly complex and volatile. Consequently, centralised and hierarchical systems have exhibited shortcomings as the result of their being too rigid.

This thesis proposes the ‘anarchic manufacturing system’ as a viable alternative for such scenarios. A manufacturing system is defined as ‘anarchic’ if the production planning and control system is decentralised and underpinned by emergent synthesis, utilising a free market structure without central control, coordination or monitoring. Such systems were compared to centralised and hierarchical systems in multi-agent simulation experiments covering three scenarios: simple discrete manufacture, assembly and product transition to identify the affordances of the proposed system over the existing planning and control approaches.

The main contributions of this research are the methodology to model a manufacturing system as a distributed free market system, including advanced assembly and product transition scenarios which were previously unfulfilled, additionally the design principles for anarchic manufacturing and the associated system characteristics. The manufacturing systems were modelled within an agent based modelling environment, enabling advanced individual decision making capabilities that could operate within a free market based system. The design principles outline and justify the free market system and its mechanics, thereby defining how distributed anarchic manufacturing systems create an effective emergent outcome. Anarchic system’s effective deployment to assembly and production transition scenarios is the first of any purely distributed system and demonstrates the retention of distributed characteristics in these scenarios; most notably self-organisation and flexibility.

The experimental results in the thesis demonstrate that centralised and hierarchical systems are not inherently better than distributed systems, and that complexity and volatility can effectively be managed through distributed systems. This thesis replaces the traditional ‘simplify to improve’ mantra in production systems, with ‘embrace complexity to achieve flexibility’ through the anarchic manufacturing system.

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Without the diligent guidance and thorough appraisal of my work by my supervisor Aydin Nassehi, I would not have been able complete this PhD. I sincerely thank Aydin for this opportunity to research an exciting topic and how throughout he has robustly evaluated my arguments and driven me to achieve more.

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Without the love and support of my parents I would have fallen far short of my potential, I would like to thank them for a fantastic education that goes beyond the classroom.

Finally, I would like to thank Frankie Talbot for her encouragement and love throughout the PhD, she ensures all days are much brighter and our future adventures are incredibly exciting.

Author’s declaration

“I declare that the work in this dissertation was carried out in accordance with the requirements of the University’s Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate’s own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.”

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Abbreviations and Acronyms

Item	Meaning
AI	Artificial Intelligence
ABM	Agent-Based Modelling
AGV	Automated Guided Vehicle
BMS	Biological Manufacturing Systems
CAD	Computer Aided Design
CM	Cloud Manufacturing
CNC	Computer Numerical Control
CPS	Cyber-Physical System
DNA	Deoxyribonucleic acid
EANN	Evolutionary Artificial Neural Networks
EDD	Earliest Due Date
ERP	Enterprise Resource Planning
FIFO	First In First Out
FMS	Flexible Manufacturing Systems
I4.0	Industry 4.0
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
ISO	International Organisation for Standardisation
IT	Information Technology
MAS	Multi Agent System
MCDM	Multiple Criteria Decision Matrix
MES	Manufacturing Execution System
NP-hard	Non-deterministic Polynomial-time hardness
OTIF	On Time In Full
RAMI4.0	Reference Architecture Model for Industry 4.0
RFID	Radio Frequency Identification
RMS	Reconfigurable Manufacturing Systems
TOPSIS	Technique for preference by similarity to the ideal solution

Symbols

Symbol	Meaning
$J_{i\,c}$	Job *i* of class *c*
$\gamma_i(t)$	Budget remaining for job *i* at time *t*
$\Psi_i(t)$	Number of operations remaining for job *i* at time *t*
n	Bid round
C_j	Capability *j* (operational capability required by a job's operation and provided by a MT)
M_k	Machine Tool *k*
$\alpha_i(t)$	Bidding cost threshold for job *i* at time *t*
$\beta_{k\,n}(t)$	Bid for MT *k* for bid round *n* at time *t*
$\omega_k(t)$	Utilisation for MT *k* at time *t*
$Qe_k(t)$	Queue length expected for MT *k* at time *t*
$Qc_k(t)$	Current queue length for MT *k* at time *t*
Op_{plan}	Number of operations within the planning horizon
$\sigma_k(t)$	Change in bid cost for MT *k* at time *t*
$\rho\ i\ (t)$	Risk factor impacting the bidding threshold for job *i* at time *t*
$CF_i(t)$	Cash factor impacting the bidding threshold for job *i* at time *t*
$LF_i(t)$	Lateness factor impacting the bidding threshold for job *i* at time *t*
$CScr(t)$	Cash score (cash performance against objective) at time *t*
$D_i(t)$	Due date for job *i* at time *t*
$E_i(t)$	Expected due date for job *i* at time *t*
$\kappa_i(t)$	Percentage complete for job *i* at time *t*
Mdl_p	Model *p* (that a job or group of jobs can become to form a product)
$\tau_k(t)$	Bid success for resource *k* at time *t*
$Eff_{k\,p}(t)$	Efficiency for MT *k* for model *p* at time *t*
$F_{k\,p}(t)$	Failure rate for MT *k* for model *p* at time *t*

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1 Introduction

Production systems are typically organised into centralised hierarchies, using simplification, predetermined rules and top-down management to achieve high productivity. A radical alternative uses a distributed structure, without any hierarchy or predetermined rules to follow. This thesis disposes of the ethos ‘simplify to improve’ and instead embraces complexity through a distributed system that adapts to the needs of production, using a free market structure and mechanisms aiming to improve flexibility and manage complexity.

Smart manufacturing utilises state-of-the-art manufacturing production models and digital technologies to fulfil a vision for adaptive manufacturing systems, optimising the use of resources in response to disruption, in order to produce high-quality products. This thesis proposes the ‘anarchic manufacturing system’, a distributed production planning and control system, for smart manufacturing. It is evaluated through comparison to traditional centralised and hierarchical structures in three manufacturing scenarios.

Smart manufacturing is the response to the current and projected environment, in which increasingly volatile and variable market demands are coupled with evolving business objectives. Mass customisation is a key market demand, resulting in highly variable products and manufacturing processes. Additionally, manufacturers must meet traditional objectives of profitability and growth as well as becoming environmentally and socially responsible producers. These factors place growing demand on the planning and control systems to manage complex products and manufacturing processes whilst flexibly adapting to increasing volatility.

Traditional centralised and hierarchical structures have been criticised for being too rigid and inflexible for modern manufacturing demands; this is likely to be exacerbated by the trajectory of smart manufacturing. A fundamentally different production planning and control system, via distributed decision-making structures, naturally embraces the problem complexity and can adapt to volatile environments. It harnesses low-level technology proliferation to create ‘intelligent objects’ that operate within a smart manufacturing environment. The anarchic manufacturing system uses a distributed architecture and employs profit maximising agents in direct competition with one another to achieve global objectives and improve efficiency, directly contrasting the traditional centralised method for managing manufacturing systems. Within an anarchic system the system elements can pursue individual objectives with independence and behave as anarchists, aligning to the following definition of anarchy:

'Absence of government; a state of lawlessness due to the absence or inefficiency of the supreme power; political disorder.

Or

A theoretical social state in which there is no governing person or body of persons, but each individual has absolute liberty (without implication of disorder)' (Oxford University Press, 2019).

There has been a resurgence in research into distributed structures for manufacturing; the previous phase did not develop these distributed systems and few were implemented. The renewed interest in distributed structures for smart manufacturing is a result of their applicability to new production models and modern enabling technologies, such as the Internet of Things, cloud computing and edge devices applied to cyber-physical systems and digital twins. The proposed benefits of distributed systems are highly desirable, given the direction of smart manufacturing; high adaptability, flexibility and robustness that do not have the rigidity and central communication reliance of centralised and hierarchical system. However, distributed production planning and control decision-making structures for smart manufacturing, in the current state of the art, are poorly evaluated by the research community. This is likely due to a lack of interest within industry to radically change effective existing systems and a prior inability to implement such systems, however, this is changing with the rise of IoT technologies and localised computational capabilities.

The ultimate goal to evaluate the overall performance of distributed production planning and control systems is beyond the scope of this thesis. However, a hypothesis is proposed and evaluated, that the anarchic manufacturing system, a distributed production planning and control system, can be applied to a range of manufacturing scenarios and has beneficial affordances compared to centralised and hierarchical systems. This thesis presents the creation of a suitable methodology to model a manufacturing system in a distributed free market system and how to evaluate performance of these systems through simulation modelling experiments. Anarchic manufacturing is a distributed system using a free market structure in which independent agents, pursuing individual objectives, have complete decision-making authority and autonomy. An emergent productive system is realised through their low-level and local interactions. The hypothesis is tested through the observation and comparison of characteristics of anarchic against centralised and hierarchical systems in three manufacturing scenarios; simple discrete manufacture, assembly, and product transition scenarios. This extends knowledge of distributed systems which have not previously fulfilled the latter two manufacturing scenarios.

The overarching structure of this thesis, divided into chapters, is shown in Figure 1-1. The first chapter introduces the subject area and establishes the aim and objectives. This is followed by a review of existing literature, covering the broader subject area of smart manufacturing and a review of the production planning and control problem. Subsequently, an overview of different system architectures is provided, with a detailed explanation and a list of different distributed manufacturing systems. The literature review is concluded with a critique and research gap identification. The research framework determines the scope, boundaries and research methodologies of the thesis. In Chapter 4 the anarchic manufacturing system is proposed, explaining the design principles and attributes behind anarchic manufacturing and the core system structure and mechanics. Three experimental studies evaluate the anarchic system against centralised and hierarchical systems; using agent-based simulations on the AnyLogic platform. These scenarios are simple discrete manufacture in Chapter 5, assembly in Chapter 6 and product transition in Chapter 7. Theorised scenarios are evaluated throughout, supplemented by a validatory automotive case study in the product transition study in Chapter 7. A discussion on all research conducted in this thesis is provided in Chapter 8. Finally, research conclusions are drawn, and further research is identified in Chapter 9.

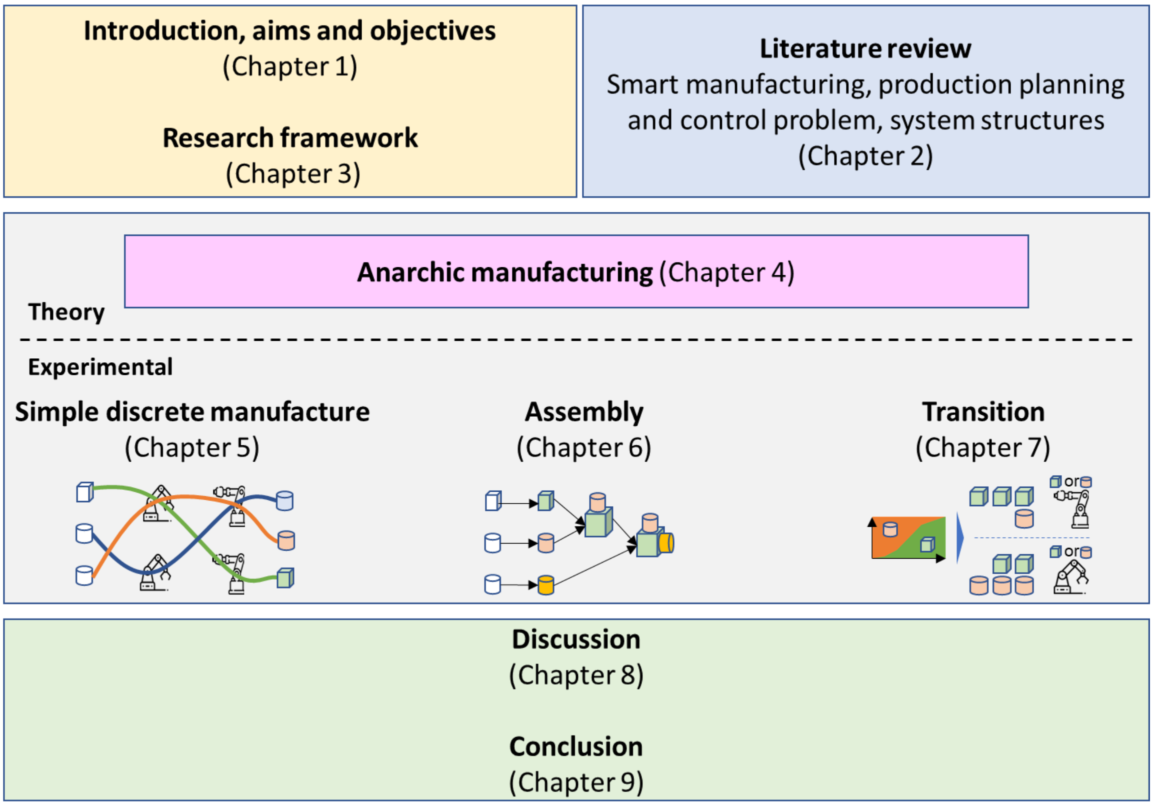

Figure 1-1: Thesis organisation

1.1 Research aim and objectives

In the evolving concept of smart manufacturing, the methods and systems for production planning and control are far from established. Meeting current business objectives in the smart manufacturing environment brings many different challenges that test the capabilities of traditional planning and control. Distributed systems are heralded as the future for smart manufacturing, emerging from increasingly complex and dynamic challenges and the creation of enabling technologies to realise these systems. The hypothesis, that distributed systems are best suited for smart manufacturing, is too broad for this thesis. However, a framework for a distributed system is created, its prototype developed and evaluated against centralised and hierarchical systems in three current manufacturing scenarios to determine its affordances. This thesis documents the process of applying a manufacturing system within the distributed system's framework and testing through simulation experiments. This thesis aims to:

Create and develop a new methodology that enables manufacturing systems to be modelled as distributed free market systems for production planning and control.

In meeting this aim the following research objectives were realised:

1) *Review the state of the art of smart manufacturing, the production planning and control problem and existing solution architectures, within the boundaries and scope of the research, and identify research gaps and existing solutions*

2) *Create a prototype distributed planning and control system (the anarchic manufacturing system), to be applied to manufacturing scenarios*

3) *Apply the prototype system against a range of manufacturing scenarios using a suitable modelling method and document the process undertaken, these scenarios are:*

    - *Simple discrete manufacturing scenarios, for jobs that are independent of each other*

    - *Mixed-model assembly scenarios, jobs must join to complete a product*

    - *Product transition, a manufacturing system that has a prolonged transition between concurrently produced products*

4) *Evaluate the performance of the anarchic manufacturing system relative to centralised and hierarchical systems against the created scenarios through simulation experiments.*

2 Literature review

2.1 Introduction

This chapter presents the state of the art in manufacturing production planning and control structures as a literature review, fulfilling the first research objective. First, a broad contextual understanding of smart manufacturing is provided; covering smart manufacturing trends, new manufacturing paradigms, driving technologies and business objectives including market conditions. These establish the context that manufacturing systems operate in and thereby informing experimental scenario creation. This is followed by a review of the production planning and control problem and the solutions provided in literature, highlighting the most significant characteristics of complexity and volatility that a manufacturing system must consider. Finally, an overview of available system structures is presented with a deeper evaluation of distributed system solutions. This overview highlights the benefits and drawbacks of existing systems and indicates where anarchic manufacturing sits relative to other manufacturing systems. This review, by covering smart manufacturing aspects that impact planning and control, alongside the planning and control problem and solution structures, enables research gaps identification; this is detailed in Section 2.5.

A list of journal and conference publications by the author in this field is provided in Appendix 11A.

2.2 Smart manufacturing

2.2.1 A short introduction to smart manufacturing

Smart manufacturing is an emerging form of production that utilises the benefits of digital technologies in a collaborative manufacturing system that responds in real-time to meet changing demands and conditions (Kusiak, 2018). Manufacturing since the 1990s has predominately been focused on lean production, through eliminating non-value-add processes and simplification, which has improved productivity (Kolberg and Zühlke, 2015). However, with modern and near-future technology, a significantly more sophisticated manufacturing production model called smart manufacturing is expected to emerge. The definition of smart manufacturing within ISO and IEC, obtained at the SMCC meeting of 2018-02/20 (ISO, 2018b) is:

'*Manufacturing that improves its performance aspects with integrated and intelligent use of processes and resources in cyber, physical and human spheres to create and deliver products and services, which also collaborates with other domains within enterprises' values chains.*'

At a lower level, ‘Smart Factories’ envision highly efficient production systems, where intelligent objects and resources consider their own situation and subsequently communicate and make decisions based on local and global information (Bendul and Blunck, 2019). The associated smart manufacturing technologies are focused on information and communication that combine with features of preceding manufacturing production models. Digitising all aspects of manufacturing processes and enterprises improves interoperability and can facilitate greater productivity through connected devices and distributed intelligence.

Smart manufacturing has trends of decentralisation, interoperability, and automation, resulting in advanced manufacturing production models that pursue greater flexibility and functionality such as Cyber-Physical Systems (CPS) and Cloud Manufacturing (CM). In general recent manufacturing system paradigms have shifted their focus, from production maximisation to cost reduction, from process standardisation to mass customisation and from production-centric to service-oriented (Lu, Xu and Xu, 2014). These manufacturing production models will be enabled by combining smart manufacturing and non-manufacturing technology, including Internet of Things (IoT), monitoring sensors, RFID (Radio Frequency Identification), robotics, modular and reconfigurable machine tools, additive manufacturing, Artificial Intelligence (AI), big data, machine learning, blockchain, cloud computing, data transfer, and cyber communications.

There are two main reference models proposed to realise smart manufacturing and Industry 4.0 (I4.0); I4.0 is an industry derived production model that closely aligns to smart manufacturing. A reference model is a domain-specific ontology that clearly links defined concepts for clear communication. The smart manufacturing reference models are the Industrial Internet Reference Architecture (IIRA) and Reference Architecture Model for I4.0 (RAMI4.0) (Pedone and Mezgár, 2018). Both models cover similar concepts, although the IIRA represents stakeholder perspectives, covering business, usage, functional and implementation viewpoints (Cimini, Pinto and Cavalieri, 2017). Figure 2-1 depicts the layered RAMI4.0 model with three dimensions. The three dimensions are hierarchical layers of control system integration, product and service life cycle and value stream representing the life cycles of entities, layers is the vertical axis are the decomposition of entities (Pisching *et al.*, 2018).

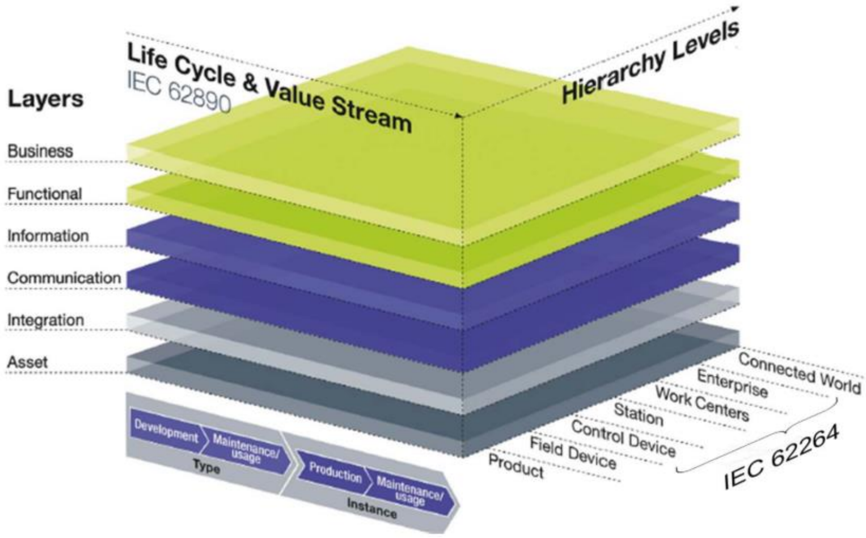

Figure 2-1: RAMI 4.0, layered model (Schweichhart, 2019)

2.2.2 Smart manufacturing trends

Recent technology trends both in manufacturing and other fields have been integral in the emergence of smart manufacturing, these include:

Decentralisation

Decentralisation is the movement from centralised administration and processing to local and distributed. It is a remerging research topic, particularly with Multi-Agent Systems (MAS) and holonic systems (Cantamessa, 1997; Shen and Norrie, 1999; Sousa and Ramos, 1999; Heragu *et al.*, 2002; Scholz-Reiter and Freitag, 2007; Windt, Böse and Philipp, 2008; Monostori *et al.*, 2016a; Srai *et al.*, 2016; Tang *et al.*, 2018), see section 2.4.4 for a review of decentralised decision-making systems. Decentralisation enables autonomous control by distributing decision-making functions to the system elements (Windt, Böse and Philipp, 2008), and has the potential to create emergent benefits of self-organisation, self-regulation, and efficiency (Hofmann and Rüsch, 2017). Distributed control is an area with increasing interest for I4.0 and smart manufacturing applications, which improves logistics performance (Bendul and Blunck, 2019). Figure 2-2 depicts the transition from a traditional automation pyramid to a more decentralised structure (Monostori *et al.*, 2016a). Decentralisation has commonly faced the criticism of creating global sub-optimal solutions (Shen and Norrie, 1999), however, comparisons are often made ignoring real-world context, real-world context to the production planning and control problem is discussed in section 2.3.

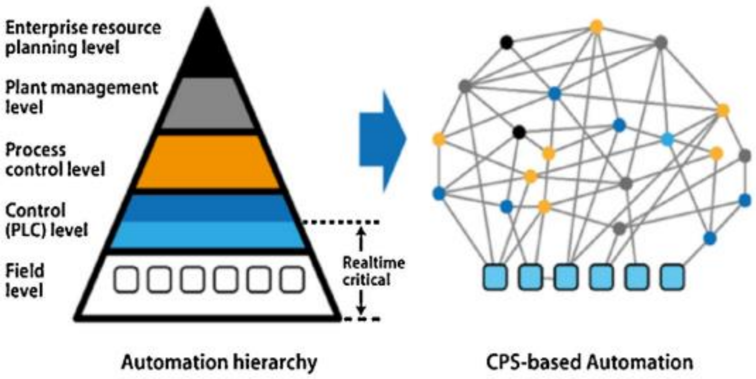

Figure 2-2: Decomposition of an automation hierarchy with distributed services (Monostori *et al.*, 2016a)

Interoperability

Interoperability is defined in ISO16300 as *"the ability for two or more entities that can exchange or share certain items in order to perform their respective tasks"* (ISO, 2018a); this is extended for this thesis to all types of resources and entities, although they may be facilitated through a digital portal or agent. Interoperability is viewed as a key enabler for manufacturing to realise operations across heterogenous digital systems (Liu, Wang, Y. Wang, *et al.*, 2018), and is still a central problem to industrial implementation of new information and communication technologies (Pedone and Mezgár, 2018). Manufacturing systems that utilise diverse and distributed resources across enterprises will have different operating systems, interoperability entails unified ontology (Lu, Xu and Xu, 2014). Figure 2-3 diagrammatically shows that interoperability is very important for global manufacturers, due to the number of distributed processes required to realise a product. Leitão *et al.* state interoperability in vertical and horizontal integrations, along with low-level control from MAS, is required to realise CPS. Standards addressing information exchange and interfaces with legacy systems must be considered for heterogenous interoperability (Leitão *et al.*, 2015). Delaram and Valilai define an interoperability model that mirrors logistics providers, moving from machines that can interoperate with other systems, to enable integration as a service (Delaram and Valilai, 2017).

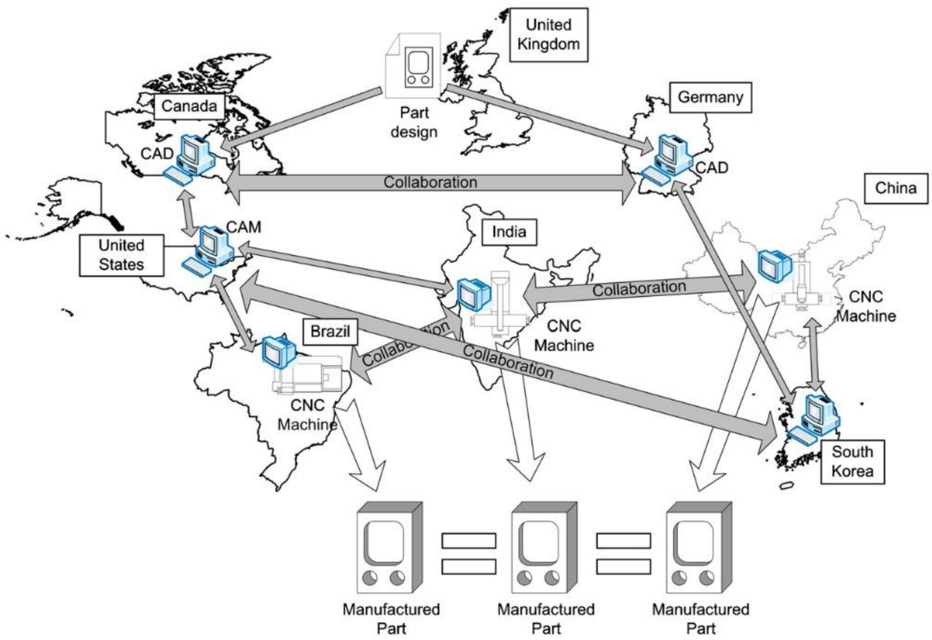

Figure 2-3: Interoperability for global CNC machining (Newman *et al.*, 2008)

Automation

Oxford Dictionaries define automation as “the use or introduction of automatic equipment in a manufacturing or other process or facility” (Simpson and Weiner, 1989); this thesis includes all virtual and physical operations and processes across the whole supply chain. Leitão *et al.* state that traditional production models for industrial automation are becoming increasingly inadequate, with the need for flexibility, scalability, high product variations and cost-effective real-time reactivity (Leitão, Colombo and Karnouskos, 2016). Leitão *et al.* view CPS as the future for industrial automation, by combining MAS, service-oriented architectures and cloud computing. Kolberg and Zühlke observe an opportunity to improve lean production methods with smart manufacturing technologies, e.g. CPS, to provide a lean automation system (Kolberg and Zühlke, 2015). This still relies on Kanban systems and makes no references to fulfilling proposed smart manufacturing objectives beyond improving production incrementally, such as mass customisation, vertical integration and smart products. Smart manufacturing is viewed to provide both consumers and manufacturers with a much broader benefit, see section 2.2.5 which discusses the business objectives.

2.2.3 New manufacturing production models

Current and relevant production models, as a result of smart manufacturing trends, are explained in this subsection, the majority of these aim to increase flexibility by leveraging digital technologies. These production models indicate the operational vision for smart manufacturing and indicate the functional capabilities required of its manufacturing system.

Production models covered are Flexible Manufacturing Systems (FMS), Reconfigurable Manufacturing Systems (RMS), Cloud Manufacturing, Cyber-Physical Systems and digital twins. Further production models are not discussed as they do not feature manufacturing production planning and control aspects as part of their core functionality, these include; lean production, virtual enterprise, concurrent engineering (Bi *et al.*, 2008).

Flexible Manufacturing Systems

Flexible Manufacturing Systems and Reconfigurable Manufacturing Systems are manufacturing models aiming to improve flexibility (Jovane, Koren and Boer, 2003; Koren and Shpitalni, 2010). FMS utilises mechanisation and low-level automation to improve flexibility and product variety (Jovane, Koren and Boer, 2003); however, high software complexity, investment and maintenance cost with low reconfigurability for structural changes have limited FMS take up (Mehrabi, Ulsoy and Koren, 2000; Haddou Benderbal, Dahane and Benyoucef, 2017). FMSs are typically a collection of machining centres connected by an autonomous guided vehicle, machining centres are autonomously fed jobs; as shown in Figure 2-4 machines are fed jobs by a loop-oriented conveyor.

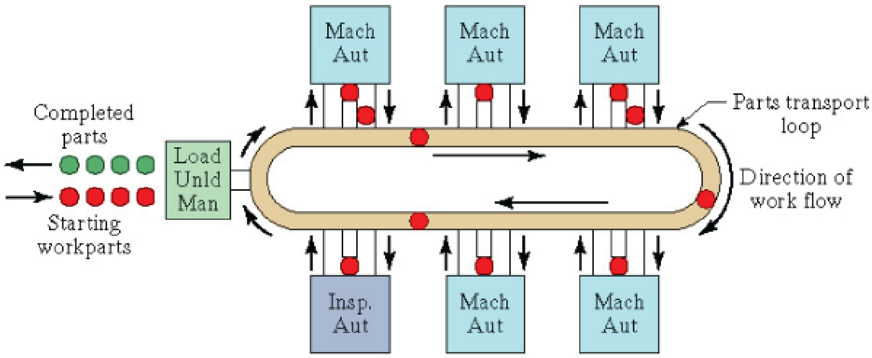

Figure 2-4: Flexible Manufacturing System loop layout (Fadzly, Saad and Shayfull, 2017)

Reconfigurable Manufacturing Systems

Reconfigurable Manufacturing Systems utilise reconfigurable and modular elements to significantly reduce ramp-up time whilst maintaining reliability and high throughput. There are conflicting RMS descriptions: an intermediate production model between mass production and FMS, an advanced production model that is more flexible than FMS, an extension or subset of FMS with little significant difference; the first description is the most widely accepted (Bi *et al.*, 2008). RMS is defined as a manufacturing system allowing a rapid change in structure, of hardware and software components, to quickly adjust production capacity and functionality to respond to sudden market changes or regulatory requirements (Koren *et al.*, 1999); Figure 2-5 depicts the layout of a practical reconfigurable manufacturing system. Koren *et al.* compare dedicated manufacturing lines, FMS and RMS showing their relative limitations and benefits, additionally, the enabling technologies and improvements for RMS are discussed (Koren *et al.*, 1999); Figure 2-6 shows the capacity and functionality areas that dedicated lines, RMS and FMS ideally operate in. Recent research into RMS can be categorised into machining systems, fixturing systems, assembly systems, material handling, methodologies for architecture design (Bi *et al.*, 2008). To realise RMS flexibility and responsiveness benefits, improvements in interrelated technologies and design for reconfigurability are required. FMS and RMS have focused on improving flexibility but have been cited as too complex to implement and realise benefits.

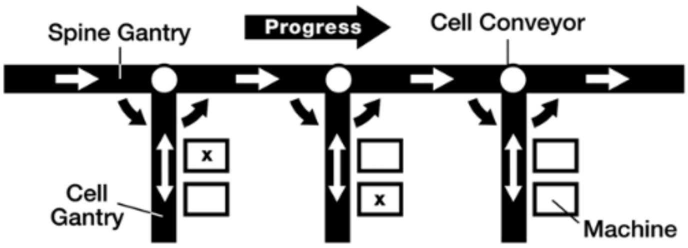

Figure 2-5: A practical reconfigurable manufacturing system (Koren and Shpitalni, 2010)

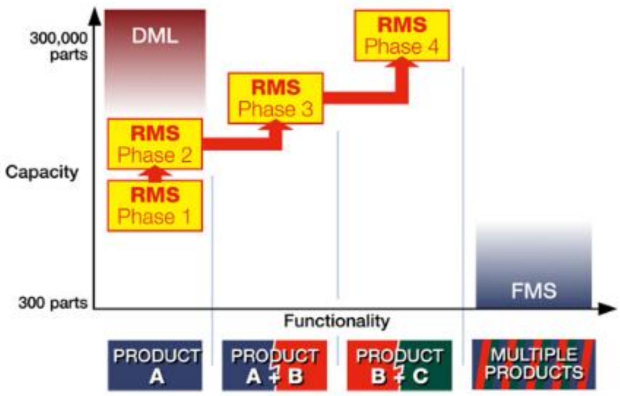

Figure 2-6: Dedicated manufacturing lines, FMS and RMS capabilities
(Koren and Shpitalni, 2010)

Recent work to realise RMS control architectures have included distributed control, most previous methods have approached reconfiguration from a hierarchical and centralised structure. RMS control should be autonomous, distributed, scalable and self-reconfigurable (Bi *et al.*, 2008); these are all claimed by MAS and heterarchical systems, see section 2.4.4 for an introduction to these systems. Reconfigurable resource elements have been modelled mathematically for a RMS to improve its adaptability to customised products, where production lines had distributed control and exchanged jobs or resources to fulfil demand (Li *et al.*, 2018). The author notes that the mathematical model created is intractable, due to the complexity of RMS operations for simultaneous optimisation allocations for increasingly diverse heterogeneous resources. To overcome the complexity, each production line searches for near-optimal solutions using a genetic algorithm. This solution method questions the true scalability of the proposed semi-distributed system; scalability is one of the most important characteristics for RMS (Koren, Wang and Gu, 2017). Decisions are made on a production line level which is synonymous to a cell structure. Holonic architectures have been proposed for RMS, see section 2.4.3 for an introduction to holonic systems, utilising a hybrid control approach with self-governing RMS stations utilising modular hardware mapped to autonomous holons that operate in defined boundaries (Hoffman and Basson, 2016). These hybrid holonic structures allow some degree of autonomy but are impeded by their bounded environments, global system reconfiguration is achieved through a hierarchical exchange of resources, which can limit the scalability of the system.

Cloud Manufacturing

Cloud manufacturing is a recent smart manufacturing production model, providing a differentiated offering of manufacturing as a service. This immature production model lacks a clear and agreed definition, it is still in the research and proof-of-concept stage (Zhong *et al.*, 2017) and has multiple purposes and resultant interpretations. In general, CM is a service-oriented production model and operates on a cloud platform by providing access to a network of virtualised manufacturing capabilities as services, often described as a product-service system (Charro and Schaefer, 2018), which can be diverse and disparate in nature and location. This brief explanation hints at the proposed benefits of CM, which directly aligns to the smart manufacturing agenda, covered in section 2.2.1. Current CM research has been focused on the concept and resources, how to virtualise and encapsulate them into services and how to centrally search and combine resources for task fulfilment and their optimal solutions (Adamson *et al.*, 2017).

There is currently no single agreed clear definition of CM, this is representative of the immature production model but also of the multiple interpretations of what it is. The production model uses several versatile technologies that can be purposed in different configurations to solve different problems. One dominant definition is:

> *"A customer centric manufacturing model that exploits on-demand access to a shared collection of diversified and distributed manufacturing resources to form temporary, reconfigurable production lines which enhance efficiency, reduce product lifecycle costs, and allow for optimal resource loading in response to variable-demand customer*

generated tasking. From a share-to-gain philosophy as resources and expertise are shared" (Wu, Matthew J Greer, *et al.*, 2013).

CM is viewed as an example smart manufacturing production model, as it is enabled by many of the technologies and follows the trends of smart manufacturing to achieve the CM service offering. CPS will allow a cyber representation of manufacturing services to market their capabilities and credentials, as well as allocate tasks effectively in the cloud which utilises intelligent autonomous decision-making, which follows current smart manufacturing trends of decentralisation and automation.

Cyber-Physical Systems

Cyber-Physical Systems are seen as a key component of smart manufacturing, connecting physical entities to the cyber, world where decision-making and communications occur (Hermann, Pentek and Otto, 2016; Leitão, Colombo and Karnouskos, 2016; Monostori *et al.*, 2016a; Hofmann and Rüsch, 2017; Lu, 2017; Meissner, Ilsen and Aurich, 2017). CPS is often referenced alongside the Internet of Things and digital twins, which are overlapping and related technologies. There are currently a number of recent and on-going projects such as; SOCRADES (Colombo and Karnouskos, 1998), GRACE (Cristalli *et al.*, 2013), IMC-AESOP (Colombo, Bangemann and Karnouskos, 2014), ARUM (Leitão *et al.*, 2015).

CPS represents the convergence of computer science and manufacturing science and technology, bringing the virtual and physical worlds within the field of manufacturing (Monostori *et al.*, 2016a). Figure 2-7 diagrammatically shows a CPS system that links the physical and cyberspace, in cyberspace the entities communicate and make decisions whose actions are executable in the physical space (Nassehi, 2017). The key enablers from computer science have been the development of MAS, wireless communication and sensors, embedded systems and cloud computing; and from the physical world Computer Integrated Manufacturing (CIM), manufacturing track and trace to cloud services for manufacturing. CPS has three main characteristics; intelligence, connectedness and responsiveness (Monostori *et al.*, 2016a). Current research into CPS discusses how and to what benefit a connected physical to the virtual world would bring, at a high level; there has, however, been few propositions on how this will be achieved and little verification of these claims. Leitão *et al.* detail the key challenges to CPS and outline the difficulty level, priority and likely timeframe of achieving technology readiness level 7 (achieve maturity) in these, which are up to 7-10+ years (from date of publishing in 2016) (Leitão, Colombo and Karnouskos, 2016).

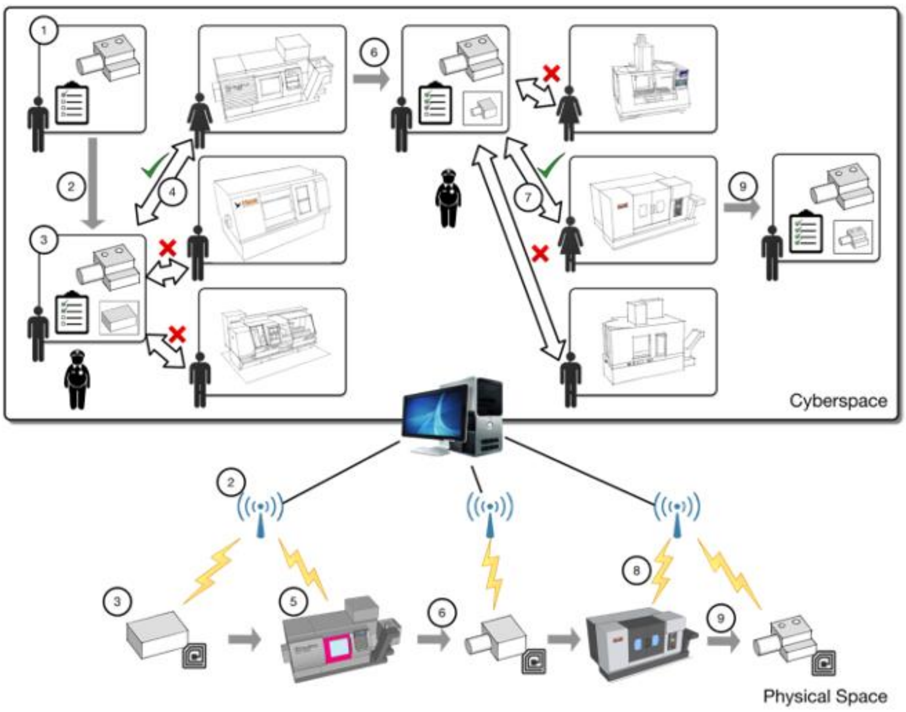

Figure 2-7: Cyber-physical systems, the relationship between cyber and physical space (Nassehi, 2017)

Digital twins

Digital twins are viewed as a key tool to realising Cyber-Physical Systems and smart manufacturing, by creating a virtual copy of a physical resource, real-time monitoring and communications can be achieved in the virtual world; Figure 2-8 illustrates the role of a digital twin and its feedback to the physical domain. Smart machines use real-time sensing and can interact with each other, CPS smart machines are envisaged to capture real-time data in central cloud-based storage and for their digital twins to communicate with each other (Zhong *et al.*, 2017). Digital twins are viewed as a prerequisite to CPS, allowing centralised analysis and control of production processes (Uhlemann, Lehmann and Steinhilper, 2017). There is a clear reliance on machine sensor networks, communications and data transfer for digital twins to be realised, this centralised system has significant cyber risk and heavy reliance on infrastructure.

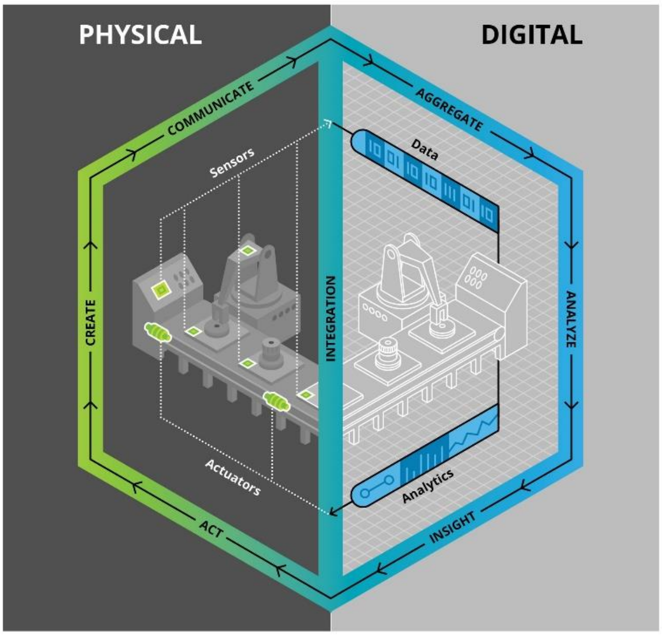

Figure 2-8: Digital twin model of a manufacturing process (Parrott and Lane, 2017)

2.2.4 Technologies driving smart manufacturing

There are several related smart manufacturing technologies that could be used to realise anarchic manufacturing, these are briefly explained in this section and demonstrate that the required technology does currently exist. Figure 2-9 graphically displays how these smart manufacturing technologies relate to each other and the manufacturing environment. It depicts internet connectivity through the cloud, which may connect facilities and devices in other locations, as well as technologies that exist within the physical bounds of a manufacturing facility. Elements within the manufacturing facility are monitored by sensors that produce performance data, this data can be locally processed through edge devices or passed onwards (potentially through the internet or cloud computing infrastructure) for analysis using artificial intelligence techniques.

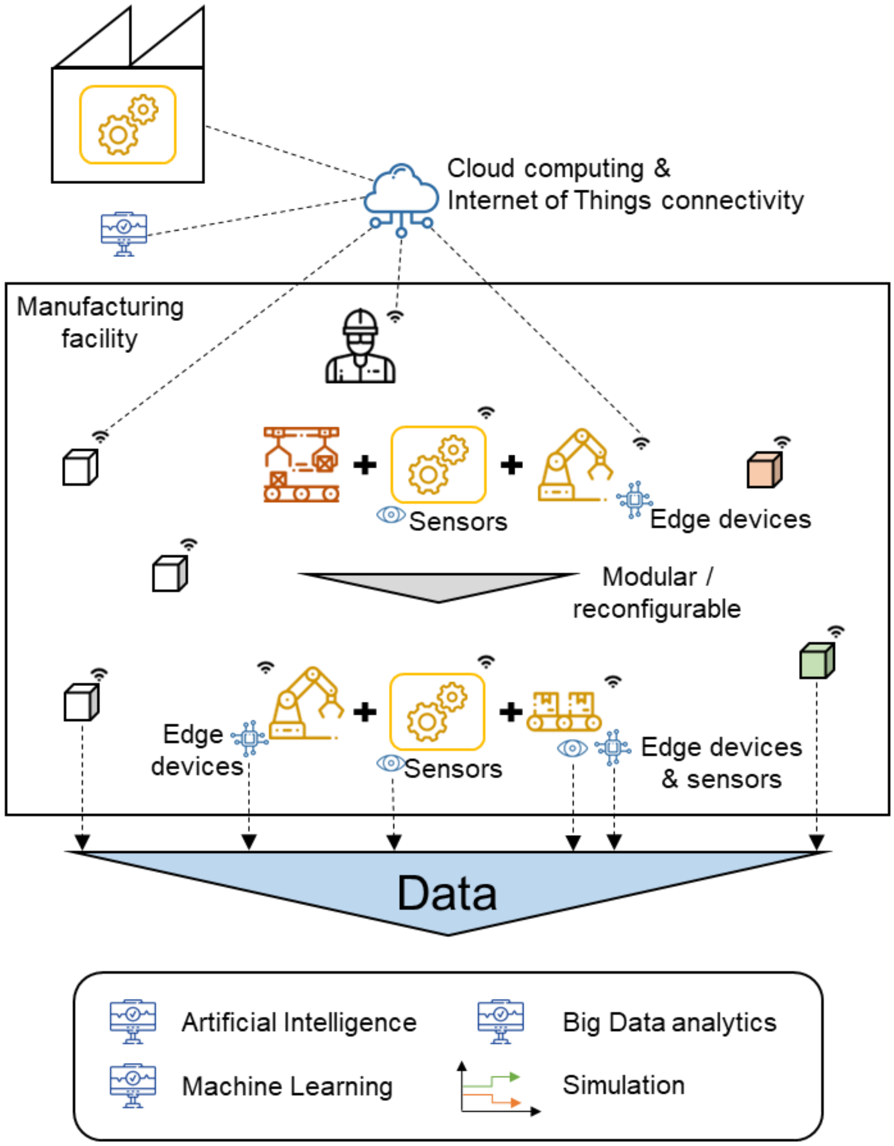

Figure 2-9: Graphical representation of smart manufacturing technologies

Cloud computing

Cloud computing is a computing service provision, where a shared pool of configurable computing resources can be rapidly scaled with minimal management effort or service provider interaction (Mell and Grance, 2011). Cloud computing offers on-demand and strategic outsourcing for Information Technology (IT) services and computing resources. Common services are Software-as-a-Service, Platform-as-a-Service and Infrastructure-as-a-Service; these three core offerings have overlapping characteristics. These are used by manufacturers to support or outsource their IT systems, including planning, scheduling and control applications, such as Enterprise Resource Planning (ERP), Computer Aided Design (CAD), Manufacturing Executing System (MES). It can also provide the infrastructure for the internet of things communications and data storage.

Internet of things

The Internet of Things is a smart manufacturing technology that integrates various devices equipped with sensors, identification, processing, communication and network capabilities; as well as connecting all parties along the supply chain (Lu, 2017). Within IoT, a digital representation of a physical element is used as a smart manufacturing object (Zhong *et al.*, 2017). This is similarly proposed by Cyber-Physical Systems which uses the internet for communication. This is likely to be facilitated by cloud computing infrastructure, where IoT enabled physical devices can collate information through monitoring sensors.

Monitoring sensors and RFID

Monitoring sensors are devices that read changes in physical stimulus informing the state of a physical object (Gao, 2014). Sensors have become increasingly important as the trend towards unsupervised machining centres with open architecture controllers has significantly changed the manufacturing environment (Kurada and Bradley, 1997), this has become even more important with the rise of automation and human-less manufacturing systems.

Radio Frequency Identification (RFID) is an automatic identification technology, offering track and trace capabilities, RFID tags can be used to find objects without significant time or difficulty (Chongwatpol and Sharda, 2013). RFID is used heavily for track and trace purposes in factories and throughout the supply chain, and it can be used as part of IoT technologies for intelligent perception and connecting resources for real-time perception and scheduling (Liu, Wang, X. V. Wang, *et al.*, 2018).

Sensor information or RFID enabled tracking can be processed locally, this will be fulfilled by edge devices, either for a preliminary filter process or for security.

Edge devices and computing

Edge devices and computing conduct data processing at the 'network edge', i.e. locally at the data source, to address latency, security and bandwidth costs (Shi and Dustdar, 2016). Despite the rise of cloud computing and IoT devices, the need for edge and local computing is increasing to reduce the burden on centralised communication, particularly with high bandwidth costs, and ever-increasing data capture and processing demand. These edge devices are likely to capture sensor information for complex manufacturing machines and resources, the advanced robotics and modular machine tool fields are pushing the capabilities of complex manufacturing resources.

Advanced robotics

An industrial robot is an automatically controlled, reprogrammable multipurpose manipulator that is programmable in three or more axes (Lien, 2014). Advanced robotics and smart machines are capable of accepting high-level mission-oriented commands, navigation and perform complex tasks in a semi-structure environment with a minimum of human intervention (Gray and Caldwell, 1996). Within manufacturing, advanced robots or smart machines can additionally communicate directly with manufacturing systems, solve problems and make decisions independent of humans. Modular machine tools provide an additional level of flexibility to advanced robotics through reconfigurability.

Modular and reconfigurable machine tools

Reconfigurable and modular machine tools are a part of reconfigurable manufacturing systems providing flexibility for manufacturing capabilities, some use smart building block systems of passive, smart and active modules (Uhlmann and Peukert, 2019). Conventional Computer Numerical Controlled (CNC) machines are general-purpose machines, reconfigurable machine tools are designed for a specific and customised range of operational requirements that can be converted cost-effectively as required (Landers and Koren, 2001).

Many of the aforementioned smart manufacturing technologies provide flexible physical capabilities, however analytic tools are required to inform the decision-making process; which is the focus of this thesis. The remainder of this section, on technologies driving smart manufacturing, covers these analytic tools.

Artificial intelligence

Artificial Intelligence is *"the science and engineering of making intelligent machines, especially intelligent computer programs that exhibit characteristics associated with intelligence in human behaviour including among other faculties of reasoning, learning, goal seeking, problem-solving, and adaptability"* (Monostori, 2014). AI provides learning, reasoning and acting, thereby minimising human involvement in intelligent manufacturing systems through automation; these AI techniques include intelligent job scheduling (Zhong *et al.*, 2017). AI intelligence and decision-making are informed by analytical techniques, these include machine learning statistical techniques, big data analytics and simulation methods.

Machine Learning

Machine learning methods are computational methods using experience to improve performance or to make accurate predictions (Mohri, Rostamizadeh and Talwakler, 2012). Multi-agent system with learning and coordination have been shown to improve a distributed control system, clearly displaying the impact learning agents have (Vrabič *et al.*, 2018). Vrabič additionally states that as it is difficult to predict global behaviour from local interactions only, learning is required for rationally bounded agents in a large complex system without prior knowledge of the system or its role.

Big data and data analytics

Big data is high-volume, high-velocity and high-variety information assets that require cost-effective forms of processing for enhanced insight and decision-making, data analytics is the insight extraction process (Gandomi and Haider, 2015). For operational organisations and manufacturers, with a large amount of operational data that cannot be analysed conventionally, big data and advanced analytics are critical to uncovering hidden patterns, correlations, market trends and business information (Zhong *et al.*, 2017). Advanced analytics through machine learning and big data aids decision-making by reflecting on past trends, this is complemented by simulation which evaluates potential future scenarios.

Simulation

Simulation is the dynamic observation of an abstract model of a system through time with particular attention to the system's key attributes (Nassehi, 2014), it has largely been used in scheduling and supply chain management (Jahangirian *et al.*, 2010). Simulation models are executable, when run they build a trajectory of the system's state changes over time, they generally can handle service systems of any complexity and scale well (Borshchev, 2013). Simulation is increasingly used for different functionalities; to support off-line decision-making and sensitivity analysis of uncertainties, on-line proactive anticipation for plan deviations using simulation in advance for short-term actions, and on-line reactive analysis of actions after a disturbance (Monostori *et al.*, 2016a). Agent-based simulation is a practical way of addressing issues of theoretical analysis and has become one of the standard tools to investigate long term MAS behaviour against a range of scenarios (Monostori *et al.*, 2014). Figure 2-10 displays the role of simulation for on-line proactive and reactive applications for manufacturing systems decision support.

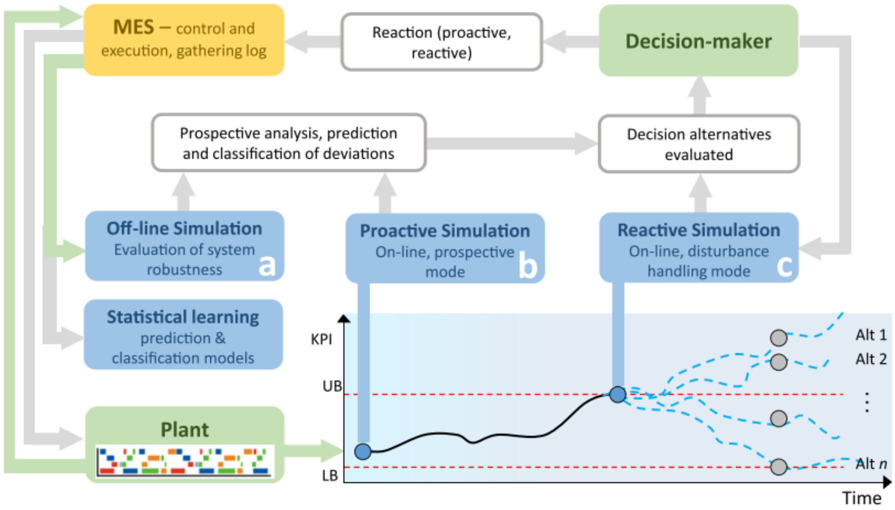

Figure 2-10: Simulation in manufacturing systems disturbance handling

(Monostori *et al.*, 2016a)

2.2.5 Smart manufacturing business objectives

New smart manufacturing production models are viewed as revolutionary and have been dubbed Industry 4.0 (Liu and Xu, 2016). To fully benefit from the reported upcoming industrial revolution, businesses must approach manufacturing differently by setting appropriate business objectives that align with the smart manufacturing vision. Current industry and business consulting thought leadership cannot clearly articulate the smart manufacturing vision.

The likely business objectives, considering smart manufacturing, to fulfil market demands are; operating in a volatile and rapidly changing environment, mass customisation, broader non-manufacturing concerns and vertical supply chain integration. These have created several manufacturing business production models and subsequent characteristics that will shape smart manufacturing. The anarchic manufacturing system has the potential to overcome many of these challenges through a radical approach.

Figure 2-11 depicts the broader smart manufacturing business perspective, considering how end consumers and market demands influence manufacturers' behaviour upstream. These market demands include rapid speed to market, volatile product demand leading to mass customisation and a broader range of demands for ethical business practice, and have increased vertical integration. These shape future manufacturing business objectives and resultant business characteristics.

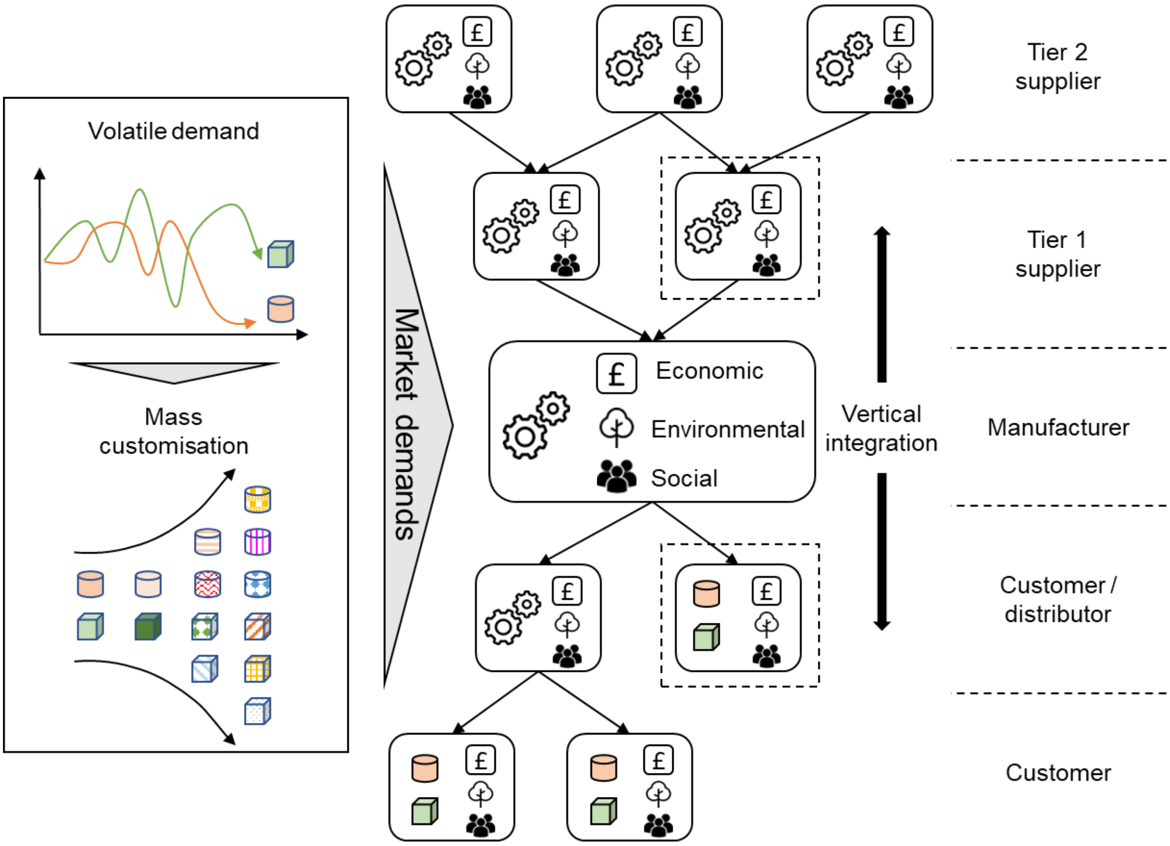

Figure 2-11: Graphical representation of smart manufacturing business influences

Industry and business consulting perspective

The industry and business consulting perspective have lacked a clear vision of smart manufacturing and Industry 4.0, this has resulted in poor developmental progress and an inability to determine the value-add proposition to manufacturers and customers. From reviewing recent white paper publications of business consultancy thought leaders (BCG, McKinsey, and Deloitte), there is a clear lack of vision as to what smart manufacturing and Industry 4.0 would provide (Wee *et al.*, 2015; Küpper *et al.*, 2016; Parrott and Lane, 2017). What is evident is a myopic thought process, that focuses on short term incremental benefit, gained from implementing individual pieces of technology. The technologies and production models cited are those recently researched in the academic community, such as; smart robots, digital twins, factory digitisation, modular line setup, multidirectional factory layout, augmented reality, big data and decentralised production steering (Küpper *et al.*, 2016). Wee *et al.* (McKinsey) report that there is a lot of potential for I4.0 and high expectations of its benefits, however, there is a lack of progression and only by a few manufacturers (Wee *et al.*, 2016). From these publications there have been zero case studies or successful examples beyond data integration and analysis; this is contrary to normal consulting practice, leading to suspicion of any likely real-world success. All these factors have resulted in an inability to articulate a value-add proposition to both manufacturers and customers; and a degree of disillusionment to the term 'Industry 4.0' (Wee *et al.*, 2016). This indicates strong interest from industry, but few practicable means of development towards implementation.

Demand volatility and manufacturer agility

Dealing with volatile demand and rapid speed to market are current market demands, often referred to as a need for manufacturers to become agile and flexible (Elmoselhy, 2013). Volatile demand refers to rapidly transient customer expectations and values; speed to market refers to the time taken from order placement to a customer's receipt of goods, applying to both consumer and business customers, and may include the design and manufacture of the product. Businesses view this agility as a source of competitive advantage, by navigating volatile demand (He, Zhang and Li, 2014) and to aid mass customisation (Gunasekaran *et al.*, 2018). Colombo and Karnouskos state that due to the competitive nature of business, real-time information systems are being developed to become more agile and flexible, and businesses are trending toward service-oriented infrastructures (Colombo and Karnouskos, 1998). Dynamic and volatile environments are common for modern manufacturers, the ability to cope with these has become essential (Scholz-Reiter, Rekersbrink and Görges, 2010).

Because of demand volatility, businesses are becoming customer-centric, they are focusing on customer relationships, recently Customer Relationship Management tools have been used. However, Bolton states this does not go far enough and business processes must become customer-centric to change the underlying culture (Bolton, 2004). Customer orientation has been shown to improve product innovativeness for manufacturers, through supplier collaboration and technological capability (Wang, Zhao and Voss, 2016).

Demand has become increasingly volatile, however, an increasing need for personalisation and customisation has extended demand volatility for businesses. This new market demand calls for further flexibility than high demand volatility, as the product specification is unknown until order submission.

Mass customisation

Mass customisation aims to provide consumers with customised goods and services at prices consistent with mass production, but this has yet to be fully realised (Ferguson *et al.*, 2018). Mass customisation aims to eliminate the 'sacrifice gaps' where average requirements are insufficient to individual customers' needs, it will lead to very low batches sizes and increase the complexity of planning, scheduling and tracking (Lee, Rahimifard and Newman, 2004).

Platforming and modular design with late configuration are viewed as part of the mass customisation trend, as well as unique tailoring of components (Mikkola and Skjøtt-Larsen, 2004; Ferguson *et al.*, 2018). Whereas Lee *et al.* view mass customisation as increased demand and execution of make-to-order manufacturing, producing varied and individually customised products at the price of standardised, mass-produced alternatives. Zhang and Efstathiou state that inventory holding for mass customisation manufacturing systems depend on the point of customer influence, which acts as a decoupling point between stocking components to creating the product to match customer requirements (Zhang and Efstathiou, 2006). As lean and total quality management increased, companies realised the increasing demands for customisation and subsequently they had become too lean and rigid and should focus on creating agile supply chains to adapt to changing demand (Stevens and Johnson, 2015).

The democratisation of design is a new trend that is as a result of mass customisation, where end consumers influence and participate in the design process directly. Tao *et al.* state that society is having a significant influence on manufacturing, from resource sharing to user participation in design and manufacture (Tao *et al.*, 2017). Goudswaard *et al.* describe how users may modify existing models and products to tailor them to their needs (Goudswaard *et al.*, 2017). Democratisation of design highlights the extent to how mass customisation is influencing the manufacturing process and that manufacturers should incorporate this trend into their own businesses.

Given mass customisation, product variants have grown considerably. Vogel and Lasch state that variant management was the first step to complexity management for manufacturers; and that the term ‘complexity driver’ can be attributed to the term ‘variant driver’ (Vogel and Lasch, 2016).

Mass customisation has significantly increased the diversity of product requirements and specification, this is extended further by a growing awareness of ethical business practices. This has pushed businesses to consider environmental and social concerns, as well as traditional economic profitability.

Environmental and social concerns

Markets, through both consumers and governing bodies, are demanding a wider range of manufacturing requirements, these include environmental and social concerns to ensure manufacturing has broader societal benefit. The triple bottom line (economic, environmental, social) highlights the importance of sustainability and the need for corporate social responsibility (Govindan, Khodaverdi and Jafarian, 2013) and is targeted at manufacturing and production partly by changing perceptions of value creation for a sustainable society (Ueda *et al.*, 2009; Kaihara *et al.*, 2018). Rauch *et al.* envisage customer value will be realised through socially and environmentally responsible and economically efficient manufacturing, which encourages positive societal effects in addition to quality and cost of goods and services (Rauch, Dallasega and Matt, 2016). Rauch *et al.* view decentralised, adaptable and flexible mini-factories as a possible solution to sustainable manufacturing whilst supporting growth and development of regional economic cycles. Governing bodies have introduced a number of incentives and punishments to promote environmental and social concerns, the most well-known of these is the carbon emissions trading scheme (Smale *et al.*, 2006). The broader range of market demands increases complexity, manufacturers will subsequently pursue multiple objectives to meet these demands.

The growing diversity of demands on manufacturers has significantly increased the number of and types of business concerns, these concerns propagate throughout the supply chain. To improve both product quality and ethical business practice, vertical supply chain integration has increased; allowing OEMs to increase their influence and control over their suppliers and ensure increasingly individualised customer feedback can be enacted within the supply chain.

Vertical supply chain integration

Businesses have subsequently increased vertical integration with suppliers and customers to manage the associated complexity of increased customisation and improve agility. Supply chain integration is the alignment, linking and coordination of people, processes, information, knowledge, and strategies across the supply chain. This facilitates the efficient and effective flow of material, money, information, and knowledge in response to customer needs (Stevens and Johnson, 2015). Roh *et al.* define the key implementation practices of a successful responsive supply chain as sharing information with customers, collaboration with suppliers and the use of advanced manufacturing technology as part of a strategy for inter-organisational integration of resources (Roh, Hong and Min, 2014). Supply chain integration was cited as the key to supply chain management, improving customer service, reducing inventory and operating costs in 1989 and is just as important today (Stevens and Johnson, 2015). Stevens and Johnson suggest that supply chains are transitioning to devolved collaborative supply chain clusters, which are easier to manage; they use fashion brand Zara as an example, who has popularised a localised and collaborative cluster model, whilst within the automotive industry, lead suppliers (tier 1) coordinate clusters of upstream suppliers. This supply chain operating model is transitioning towards distributed control; although not discussed explicitly in this thesis, the anarchic manufacturing system can be applied to supply chain structures and problems which is already evolving into a distributed structure.

2.3 Planning and control problem

2.3.1 Traditional and smart manufacturing

The smart manufacturing scheduling and control problem extends traditional problems, by considering job allocation to smart resources, which have advanced digital capabilities. Modern industry and market demands extend the smart manufacturing problem through a more volatile environment and increasing customisation; however, complexity and managing volatility remain the most difficult characteristics.

Traditional production planning and control problem characteristics have been derived from traditional problem formulations whilst considering real-world applications. Scheduling is defined as an optimisation process to allocate limited resources over time between parallel and sequential activities (Shen and Norrie, 1999). Production planning tasks are termed as the repetitive tasks for the management of value creation processes, spanning multiple time horizons from production network design to machine setup (Bendul and Blunck, 2019). Control is the dispatching, monitoring, diagnosis, error recovery and machine/device control of a factory typically on a short-term horizon (Leitão, 2009). Scheduling, planning and control have become increasingly difficult as businesses and manufacturing production models have vied for competitive advantage, for example FMS and RMS have increased flexibility but have increased difficulty in finding optimal solutions. This is likely to become more difficult as manufacturing trends tend toward mass customisation and small-batch production (Ferguson *et al.*, 2018). Many of these traditional problems are seen as very complex, and some are known to be Non-deterministic Polynomial-time hardness (NP-hard) (Van Dyke Parunak, 1991).

General methods to deal with the scheduling and control problem are predominately associated with simplification or autonomous control. Allwood *et al.* state that increasing variety in a manufacturers' product mix results in a decrease in productivity, subsequently the predominate response to managing complexity has been to design products in 'families' or 'platforms' (Allwood *et al.*, 2015). This reduces complexity through standardisation by creating structure and predetermined rules to follow. During their study, Allwood *et al.* found increased variety dramatically increased production time due to conflicting demands; increasing the complexity of the problem.

Scheduling and planning is traditionally completed offline, where decisions are made in advance of a given time period; allowing evaluation of 'what-if' scenarios through simulation (Monostori *et al.*, 2016b) and static (near) optimised schedules through dedicated algorithms but these cannot be realised in real-time (Sahin *et al.*, 2017). The majority of previous studies have only used offline methods, however, online methods are increasingly researched as means to deal with volatility by reacting in real-time to disruptions for dynamic scheduling (Sahin *et al.*, 2017).

Smart manufacturing production models, in turn, have planning and control problem characteristics that extend from the traditional problem. These problem characteristics can be best understood through weaving together how market demands and business objectives influence a manufacturer's operations and their associated planning and control aspects. Smart manufacturing scheduling, planning and control are viewed as the highest layer for implementing intelligent manufacturing systems framework and as key research challenges (Zhong *et al.*, 2017).

Volatile market demands, from unpredictable customer requirements, dynamically changing orders and rapid lead times, have forced manufacturers to become more agile and flexible (Elmoselhy, 2013). Agile business processes matching volatile demands have created customer-centric business models and a dynamic scheduling, planning and control problem; due to inevitable unpredictable real-time events causing changes to scheduled plans (Ouelhadj and Petrovic, 2009).

Mass customisation results in high product variety and the requirement for dynamic production capabilities, this increases complexity and requires flexibility. Mass customisation will result in a very high number of small batches that will increase the complexity of planning, scheduling and tracking (Lee, Rahimifard and Newman, 2004). The constant product turnover will lead to uncertain and inconsistent production durations and different resources required at any point in the production process; creating a complex manufacturing system with high uncertainty that must be flexible to meet the broad range of capability requirements. Diversity of individual customer requirements, going beyond the traditional demands of cost, quality and lead time, are increasing and can be treated similarly to individualised requirements of mass customisation. Distributed systems are more likely to be able to represent unique requirements through product-led manufacturing via intelligent products. Borangiu *et al.* implemented a distributed manufacturing control system using intelligent products which allowed each entity to retain its own objectives (Borangiu *et al.*, 2014).

Manufacturers must balance dynamic multiple objectives to meet the smart manufacturing scheduling and control problem; which include overarching and traditional business objectives, for example: increase profits, improve the cash position and reduce supply chain risk. To fulfil smart manufacturing business objectives, as discussed in section 2.2.5, manufacturers need a wide range of capabilities, be responsive to market demands and have customer-centric business processes; all of these require resources that a business may not be able to fulfil whilst remaining profitable or cash positive, which results in multiple and conflicting objectives.

2.3.2 Complexity and complicatedness

Complexity and complicatedness are poorly defined concepts within manufacturing; however, they relate directly to smart manufacturing and the associated planning and control problem. Increasing complexity is often noted as a key challenge to future manufacturing (Papakostas *et al.*, 2009), as predicting global behaviour becomes more difficult based on local interactions between the system's constituents (Vrabič *et al.*, 2018), and complexity is cited as one of the largest issues to manufacturers (Vogel and Lasch, 2016). Complexity is a resultant characteristic that manufacturers must face as a necessity (Váncza *et al.*, 2011), Section 2.2.5 discusses how increased market volatility, mass customisation, and additional market demands increase complexity.

Definitions for manufacturing complexity attempt to classify types of complexity, such as dynamic and structural, or use entropy and heuristic approaches to quantify complexity (Kuzgunkaya and ElMaraghy, 2006; Elmaraghy *et al.*, 2012). Structural complexity is described as the level of interference between different production paths (Vrabič, Husejnagic and Butala, 2012). Elmaraghy defines complexity as a sliding scale of uncertainty, transitioning from simple, to complicated, to complex and to chaos (Kuzgunkaya and ElMaraghy, 2006). Increasing constraints and reducing flexibility increases system complicatedness, Kuzgunkaya compares several manufacturing system configurations, arguing that reduced versatility and flexibility of resources increase complexity (Kuzgunkaya and ElMaraghy, 2006). Considering an entropic definition of complexity (Huaccho Huatuco *et al.*, 2009), as the number of system elements or the number of non-coupled shared resources required per operation increases, the number of states the whole system can be in rises exponentially; this is denoted as $O(a^N)$ an exponential complexity problem. There are known NP-hard problems in manufacturing, such as job shop scheduling (Van Dyke Parunak, 1991).

As the demands of smart manufacturing increase, notably mass customisation, speed to fulfilment and customer-centric business processes, the complexity of manufacturing operations will also increase. Manufacturing has moved from simple mass production assembly lines to flexible networked manufacturing systems of shared resources producing complicated products. It is envisaged in smart manufacturing that highly differentiated and complex products will become common (Esmaeilian, Behdad and Wang, 2016). The associated uncertainty and highly dynamic marketplace for complex products require a broad and adaptable manufacturing capability; this is extended by representing the customer during manufacturing for customer-centric business processes. Complex products are currently fulfilled by complex supply chains of specialist manufacturers in disparate locations; however, this is unlikely to meet market expectations or competitive advantage in smart manufacturing's demands for rapid order to fulfilment lead times. Therefore, manufacturing must become more versatile to deliver mass customisation at very low lead times, proposing a highly complex planning and control problem.

2.3.3 Volatility and dynamic multiple objectives

Complexity and multidimensionality are the only clear aspect of manufacturing flexibility (Sethi and Sethi, 1990), managing volatility and balancing dynamic multiple objectives are achieved through flexibility. Flexibility, with respects to production planning and control, is defined as the capacity of a system to adjust itself in response to changing requirements with significant cost with respects to time, effort, cost of performance (De Toni and Tonchia, 1998). There is a trade-off between flexibility and efficiency, where, from an organisational perspective, efficiency requires a bureaucratic form of organisation with high standardisation, specialisation and hierarchy, however, bureaucracy impedes flexibility (Adler, Goldoftas and Levine, 1999). Enterprises achieving organisation ambidexterity, where both adaptabilities to change and efficiency are realised, aim to use flexibility without the trade-off for efficiency (Raisch and Birkinshaw, 2008). Cantamessa describes manufacturing flexibility as; the ability in the short term for systems to adapt to changes in product mix, process plans, and machine status, and in the medium and long term the ability to sustain changes in demand, product characteristics, quantity and quality (Cantamessa, 1997). Chaudhuri *et al.* define flexibility as the ability to cope with variation without major time and cost implications, which does not necessarily affect the probability, but may reduce the impact of risk (Chaudhuri, Boer and Taran, 2018). Dynamic multiple objectives are many business and technical objectives that change over time, these may be conflicting and must be balanced to best achieve the current set of objectives. All manufacturers face multiple conflicting objectives, yet the majority of research has focused on single or static objectives.

Flexibility, alongside agility, is often cited as a key aspect of smart manufacturing, bringing competitive advantage (Zhou, Liu and Zhou, 2016), however, it is unsure how this will be fulfilled. Existing methods for production planning and control cannot handle the highly dynamic and subsequent complex conditions of modern manufacturing (Kim and Duffie, 2004). Ivanov *et al.* state that the four major flexibility drives are: resilience to disruption and the ripple effect in the supply chain; digitisation and smart operations; sustainability and closed-loop supply chains; and supplier integration and behavioural flexibility (Ivanov, Das and Choi, 2018). Smart manufacturing production models are pursuing many of these cited flexibility drivers, as discussed in section 2.2.3, in response to recent increases in integration. And in response to rigid, centralised or hierarchical control architectures that cannot manage a volatile manufacturing environment (Monostori *et al.*, 2014).

Smart digital manufacturing requires a high degree of flexibility to quickly adapt and fulfil mass customisation (Tao *et al.*, 2017), where there is high product variability and expected low lead time and speed to market (Elmoselhy, 2013). Borangiu *et al.* state that the need for robustness, due to unforeseen disruption and agility at market demand, requires solutions to switch from classical centralised to decentralised control, where each entity keeps its own objectives (Borangiu *et al.*, 2014). Flexibility may be achieved more easily with distributed systems, particularly for large complex systems.

Manufacturers have always faced multiple objectives, as all businesses do, traditionally their main objectives are cost reduction, quality, productivity, sustainability and flexibility maximisation (Malakooti, 2013). Multicriteria Decision-making (MCDM) approaches have been typically used in industry to resolve conflicting objectives for decision-making (Malakooti, 2013). Malakooti states that objectives are often conflicting and sophisticated multi-criteria methods, for many objectives with many alternatives, may not be helpful for solving realistic problems. TOPSIS (technique for preference by similarity to the ideal solution) is an established technique that aims to minimise the distance from an ideal point and maximises the distance from a nadir point (Olson, 2004).

2.4 System architectures

2.4.1 Introduction

There are several proposed scheduling and control architectures, these range from hierarchical to anarchic (fully distributed). Duffie and Piper define three control architectures, a centralised controller (hierarchical), a hierarchical controller with dynamic scheduling (semi-heterarchical) and fully distributed heterarchical structure with intelligent system elements (heterarchical/anarchic) (Duffie and Piper, 1987), this thesis extends these architectures by one to highlight the difference between mediator and truly distributed and anarchic structures.

Hierarchical architectures are those that have a layered management structure, with decreasing authority and autonomy. These hierarchical and centralised structures typically have a master/slave relationship, and traditionally use structure to handle complexity through decomposition and simplification (Heragu *et al.*, 2002). They are the predominant management structure in industry, particularly for non-autonomous human-centred shop-floors, which often use simple dispatch heuristics. There has been extensive research into advanced centralised methods, for example advanced search heuristics, to obtain optimal solutions. Centralised methods are criticised for being too rigid, very poor at reacting to dynamic situations and difficult to design control systems that encompass all interrelationships and failure modes (Heragu *et al.*, 2002; He, Zhang and Li, 2014).

Semi-heterarchical structures, also referred to as hybrid structures, allow low-level autonomous decision-making within certain bounds as established by the hierarchy above. These aim to merge the benefits of both hierarchical and heterarchical systems; by creating stability and reducing complexity from a hierarchical structure, whilst enabling an emergent outcome from low-level autonomy (Ryu and Jung, 2003).

Heterarchical with mediator structures allow low-level decision-making and interaction, however, they use a mediator for conflict and deadlock resolution or to mediate communications (Shen and Norrie, 1999). The decision-making and influence by mediator agents are minimised whilst ensuring system stability, they control coordination between heterarchical resources to ensure global objectives can be achieved (He, Zhang and Li, 2014). Mediators will monitor the system and typically adopt roles of; facilitator, broker or mediator.

The anarchic manufacturing system is an extremely distributed heterarchical structure, where decision-making is made at the lowest level only. Anarchic manufacturing is the focus of this thesis and explores a Multi-Agent System that has no centralised mediator. All system elements, for example resources and jobs, have complete decision-making authority and autonomy. See section 2.4.4 for an introduction and relevant current literature for distributed systems, and Chapter 4 for a detailed explanation of the anarchic manufacturing system's theoretical framework, including design principles and mechanisms used.

2.4.2 Hierarchical and centralised systems

Hierarchical and centralised systems fulfil the planning and control functions from a single point, which may cascade down management layers; heuristics, advanced search heuristics and simulation modelling methods are the main categories of hierarchical and centralised systems. Hierarchical structures have multiple control layers, with distributed decision-making between layers, improving robustness, but disturbances significantly reduce performance (Leitão, 2009). Classical approaches to production planning and organisational structure have preferred function decomposition, resulting in a hierarchy of decision-makers that are coordinated through a bureaucratic structure (Malone and Crowston, 1994). Heuristics are a problem specific and rule-based scheduling and control method, it is unlikely to find an optimal solution but can find a reasonably good solution in a short time period (Ouelhadj and Petrovic, 2009). Schedule repair methods, such as right-shift repair or match-up repair, and dispatch rules, e.g. First In First Out (FIFO) and Earliest Due Date (EDD), both fall into the heuristics category.

Advanced search algorithms, such as meta-heuristics and genetic algorithms, improve on local search algorithms to escape local optima, by using efficient solution space search methods (Ouelhadj and Petrovic, 2009). As with all other hierarchical and centralised systems, these advanced search algorithms require all information at a single point. Their performance is suitable to find optimal solutions for small problem instances of few jobs, too slow for complex problems; for example, NP-hard flexible flow shops problems, where they struggle with large dynamic flows (Scholz-Reiter, Rekersbrink and Görges, 2010), due to computational complexity (Cantamessa, 1997). Therefore, advanced search heuristics are not suitable for a scenario where there is vast scale and complexity, as well as a highly dynamic environment.

Simulation modelling methods for shop-floor scheduling, planning and control have recently increased to plan and forecast likely outcomes; using packages such as Simio. This provides the ability to model the whole complex manufacturing systems in detail and observe likely emergent outcomes, depending on how the system is modelled. Monostori *et al.* state the time taken to complete data acquisition and analysis, quick response and instantaneous feedback prevent simulation modelling techniques from becoming real-time control systems. Resultantly decision-makers apply simulation primarily as off-line decision support tools, e.g. in sensitivity analysis of schedules and disturbance handling, rather than critical on-line decision-making (Monostori *et al.*, 2010). Yang and Takakuwa have connected a simulation scheduling tool (Simio) to the manufacturing execution system to schedule and reschedule a FMS in parallel to operation (Yang and Soemon, 2017). Simulation modelling methods are unsuitable for real-time and dynamic control methods, as they can only operate effectively off-line, predominately for high-level strategic decisions, rather than low-level operational decisions.

2.4.3 Hybrid systems

Hybrid systems aim to combine benefits of structure from hierarchical systems and emergent outcomes from heterarchical systems; combining the benefits of distributed control architecture for short-term optimisation and centralised control for long-term optimisation (Trentesaux, 2009). Fractal manufacturing systems and Holonic manufacturing systems are example hybrid systems that can represent complex hierarchies of a manufacturing system (He, Zhang and Li, 2014).

Fractal manufacturing systems are another agent-based method for distributed manufacturing systems, where each 'fractal' represents a part of a system at any level of abstraction (Ryu and Jung, 2003). Fractals pursue goals independently whilst resolving conflicts through cooperation, coordination and negotiation; agents within fractals have specific and differing functionalities. They combine hierarchical structure with distributed decision-making; any element or sub-system can be viewed as a fractal. The main reported characteristics of fractals are self-organisation, self-optimisation, goal-orientation, self-similarity and dynamic responsivity. Fractal manufacturing systems cannot, however, produce globally optimal solutions due to local interactions based on the Contract Net Protocol or regroup flexibly between boundaries due to the rigid structure (He, Zhang and Li, 2014).

Holonic manufacturing systems are similarly hybrid in nature, utilising low-level autonomy within a high-level structure. Heragu et al. define a hybrid holonic structure that aims to combine the flexibility of distributed autonomous systems with a high-level structure to pursue system-wide objectives, by allowing low-level autonomous decision-making within boundary conditions prescribed by high-level holons (Heragu *et al.*, 2002). Holonic manufacturing systems use multi-agent systems to model individual agents and their roles. But permit some distributed decision-making, these production models suggest some form of hierarchy will be required in future smart manufacturing (Leitão, 2009).

Hybrid systems are currently a heavily researched solution, however, their design principles of merging the benefits of both hierarchical and distributed systems have not been proven or investigated in detail.

2.4.4 Distributed and mediator systems

Introduction

Heterarchical distributed systems allow system elements to have low-level decision-making intelligence and autonomy, enabling them to coordinate and interact with each other and the environment (Cantamessa, 1997). There is no active central decision-making or hierarchical/layered structure; many have loosely coupled temporary relationships rather than a predefined and fixed structure. Distributed systems solve problems through the entities assuming responsibility for generating and maintaining a solution over a decomposed part of the problem, i.e. the local problem (Tharumarajah, 2001). A central entity passively providing global information as a common repository point is not deemed to be a mediator. Heterarchical with mediator architectures enable low-level decision-making but have centralised agents with specialist roles, these are used to avoid conflict and ensure global objectives are met, these centralised agents have active roles. There are no clear guidelines for the design and control of distributed architectures (Bendul and Blunck, 2019), however, Shen and Norrie define Autonomous Agent systems which are heterarchical systems, stating they must have the following attributes (Shen and Norrie, 1999):

1. *Not controlled or managed by another software agent or human*
2. *Communicates directly with other agents and external systems*
3. *Knowledge of other agents and their environment*
4. *It has its own goals and associated motivations*

Distributed systems have arisen from the reported rigidity of hierarchical centralised systems, offering benefits that align with the predicted future of smart manufacturing. Traditional centralised and hierarchical systems do not match modern emerging organisational models, based on decentralisation and autonomy (Cantamessa, 1997), and they are vulnerable from a single point of failure (Colombo *et al.*, 2006). Rather decentralised structures have been developed for the scheduling, production planning and control problems, aiming to achieve flexibility and fault-tolerance that hierarchical systems lack (He, Zhang and Li, 2014); exploiting available operational flexibility in a system (Brennan and Norrie, 2003). Operational flexibility is the ability to produce a product mix in different ways (Chryssolouris *et al.*, 2013). A purely distributed system arguably conducts no advanced scheduling, rather it is purely reactive by postponing allocation decisions to the time of execution (Bendul and Blunck, 2019). Heterarchical structures aim to adapt to highly dynamic variations in product requirements (Shen and Norrie, 1999). These structures can foreseeably use intelligent products to represent a customer's interests and align with customer-centric business processes. Distributed systems are the proposed solution for both high variety and high volume production systems (Cantamessa, 1997), which is commonly referred to as mass customisation.

It is envisaged that the role of system design will change, from detailed planning of material flows and resource utilisation to a designer deciding on the existence of intelligent objects and resources and the rules of the system to ‘orchestrate’ a competitive factory that has competitive emergent performance (Bendul and Blunck, 2019). This vision is premised on emergent synthesis as an underpinning design principle of distributed systems. Emergent synthesis is an observable phenomenon that arises from the local interactions of individual elements that collectively display an overall global direction; this contrasts with traditional top-down analytical methods of decomposing systems (Ueda, Markus, *et al.*, 2001; Váncza and Monostori, 2017). Emergent synthetic methods are suited to solving the scheduling and control problem in smart manufacturing; as there is a high degree of uncertainty in both system requirements and operational environment. The core mechanics utilise individual jobs that pursue local objectives, which are to fulfil operations via machines that act as service providers, the emergent outcome arises from jobs becoming finished products and the system becoming globally productive. As a result, heterarchical distributed systems tend to be more flexible with simpler and understandable programmes as they only relate to local data, rather the logic of centralised systems tends to be hidden in the program and global data structure, making modifications difficult (Duffie and Piper, 1987). Additionally, as interactions are on a low level, a system’s reorganisation with different agents/resources would still have the same negotiation process and interactions, making the distributed (and MAS) systems very robust to change (Leitão, 2009) and inherently scalable (Szer-Ming Lee, Harrison and West, 2005); which contrasts remapping hierarchical layers.

There are several heterarchical distributed systems that do not use any sort of centralised decision-making or control. Examples include Biological Manufacturing Systems (Ueda, Vaario and Ohkura, 1997), Contract Net Protocol (Smith, 1980), and dispatch rules (Kouiss, Pierreval and Mebarki, 1997).

The key benefits and criticisms of distributed systems are linked to their inherent structure and design principles. Proposed benefits for distributed systems are self-organisation, flexibility, and adaptability, fault-tolerance, real-time control, dealing with complex scenarios (Duffie and Piper, 1987; Cantamessa, 1997; Shen and Norrie, 1999; Tharumarajah, 2001; Ouelhadj and Petrovic, 2009; Scholz-Reiter, Görges and Philipp, 2009; Bendul and Blunck, 2019). Additionally, distributed and typically agent-based systems are being increasingly researched to achieve real-time scheduling (Sahin *et al.*, 2017). Distributed systems are a promising approach to manage the resultant dynamic and structurally complex production control problems. Aiming to dispose of the traditional trade-off between efficiency and flexibility (Adler, Goldoftas and Levine, 1999) by embracing complexity and managing through local decision-making only. Increasing autonomous control, by increasing the number of agents managed through distributed control, was found to improve logistic performance especially as complexity increased (Scholz-Reiter, Görges and Philipp, 2009).

Key criticisms for distributed systems are myopic decision-making, sub-optimal global solutions, chaotic and unpredictable outcomes, inability to represent complex hierarchical structures (Heragu *et al.*, 2002; He, Zhang and Li, 2014; Monostori *et al.*, 2014; Blunck and Bendul, 2016). As well as the issue of limited information and restricted computation capacity for distributed controllers (Bendul and Blunck, 2019); although distributed information structures are beyond the scope of this research, it is foreseeable for computational capacity to become a reduced issue as technology improves. Heterarchical with mediator structures aim to resolve some of these criticisms, agents representing central or global goals can influence a distributed system without having a rigid hierarchical structure, unlike hybrid systems. Mediator architectures overcome problems in providing globally optimised schedules and predictability in the presence of a large number of agents (Shen and Norrie, 1999; Tharumarajah, 2001; Ouelhadj and Petrovic, 2009).

Despite the existing research into distributed manufacturing systems, there have been few reported industrial or laboratory-based applications developed (Leitão, 2009). DaimlerChrysler implemented a self-organising flexible manufacturing system, based on MAS and job to machine negotiation. Although it achieved flexibility it was not widely implemented due to a poor economic business case and high cost of investment for a potential future benefit (Schild and Bussmann, 2007). In a non-manufacturing scenario, Maturana implemented a MAS distributed intelligent system to manage chilled water, ventilation and heating for US Navy Ships, reducing manning and improving readiness and survivability (Maturana *et al.*, 2004). There have been very few implementations as suitable reconfigurable manufacturing systems are rare and slowly adopted, the cost of distributed systems is relatively high and the technology is relatively very immature compared to centralised systems (Leitão, 2009).

Beyond technical reasoning for the low uptake of distributed systems, in the author’s opinion, there is a significant resistance from a commercial perspective. There is a very high associated risk with an unproven operating system that relinquishes control from management and delegates it to ‘intelligent objects’. Few business leaders would be willing to experiment with such systems, particularly as the proposed technical benefit is realised as volatility, complexity and size increase.

Looking forward many envisioned production systems of smart manufacturing are digitised and networked, e.g. Industry 4.0 and Internet of Things, but all have a common idea of assigning tasks of production control to intelligent objects (Bendul and Blunck, 2019).

Rule-based systems

Distributed rule-based systems allow decision-making and autonomy on the lowest level whilst using simple rule-based heuristics to determine actions. A simple example of these local information methods is a job selecting a capable machine with the shortest queue, this is known as the Queue Length Estimator (Scholz-Reiter, Rekersbrink and Görges, 2010). Pendharkar proposes a learning multi-agent system for dynamic scheduling using a genetic algorithm, where a knowledge base of rules is periodically updated (Pendharkar, 1999). Kanban systems are also rule-based heterarchical structures, where jobs are pulled along the production line according to demand from downstream, the decision when to transfer a job to the next workstation is executed locally (Krishnamurthy, Suri and Vernon, 2004).

Biological systems

Biological Manufacturing Systems (BMS) are inspired by nature and biological systems, for example, ant colonies; many naturally lead to Machine Learning tools such as Artificial Neural Networks. Mak and Shu explain biomimetic design and how it is best utilised when one can abstract a strategy from biological phenomena (Mak and Shu, 2004). Emergent synthesis is the design principle behind BMS, which aims to employ biological features such as self-organisation, learning, and evolution to solve complex class 2 & 3 synthesis problems (Ueda, Hatono, *et al.*, 2001); BMSs have demonstrated self-organisation, adaptation and evolution traits (Monostori *et al.*, 2016a).

BMSs employ mechanisms to mimic biological behaviour and give rise to emergent outcomes; attraction fields and evolution are two examples discussed. To create a self-organising shop-floor organisation, allocating jobs via Automated Guided Vehicles (AGVs) to machines, Ueda *et al.* use attraction fields to strengthen a machine's desire for a particular type of job transported by AGVs (Ueda, Vaario and Fujii, 1998). Attraction fields are very similar to ant colony pheromone-based systems, these use a pheromone type mechanism to inform other agents of 'success' (Ueda, Kito and Fujii, 2006). BMS that mimic ant colony pheromone systems use agents that leave 'traces' of information about the performance at a location, which 'evaporates' using a moving average of pheromone data (Scholz-Reiter, Görges and Philipp, 2009). This can be used for jobs to plot successful routes dynamically through a manufacturing system, informing other job agents. Evolution is a commonly replicated mechanism from biological systems and has given rise to advanced machine learning methods, the main adopted principle utilises a system and its elements that evolve through generations or over time. The two types of evolution are DNA based, passed through generations, and lifetime based, via experience acquired within an agent's lifetime (Ueda *et al.*, 2000).

Further, biologically inspired systems go far beyond the organisational applications discussed in this thesis, computer science has adopted and successfully created machine learning methods, which have in turn been applied to BMS and other engineering applications. From the basis of evolution and learning, mechanisms such as Genetic Algorithms and Neural Networks are commonplace. Ueda *et al.* use an Evolutionary Artificial Neural Network (EANN) for conflict resolution in simultaneous process planning and scheduling to significantly improve decision-making (Ueda, Fujii and Inoue, 2007). Each machine is given an EANN to improve its decision-making strategy by selecting its next job given a changeover time for dissimilar jobs.

Free market systems

Free market systems incorporate free market principles to obtain a globally efficient and dynamic system, many low-level mechanisms have evolved from the Contract Net Protocol (Smith, 1980). Free market economies, unrestricted by centralised planning, have been praised for being globally efficient whilst developing and improving through innovation; despite all individuals pursuing individual selfish goals. Socialist and communist economies, on the other hand, suffer from the inability to transfer information, uncertainty in how to optimise and are unresponsive to a change in conditions (Dias and Stentz, 2000). The main motivation for evaluating the economics of complex systems is to study the self-organising driving forces that act within an economic system (Kaihara *et al.*, 2018). Distributed and centralised manufacturing systems can be compared to free market and communist economies at a high abstraction level; the global efficiency and reactivity of free market economies is the basis for free market manufacturing systems. Constituent agents are regarded as suppliers and demanders in an artificial economy, these achieve Pareto optimal solutions in a perfectly competitive market (Kaihara *et al.*, 2018). Dias and Stentz implemented a free market system in a robotic coordination and control problem, using a bidding mechanism for inter robot negotiation, and found traits of self-organisation, learning, and adaption as well as observing competitive and cooperative behaviour depending on the circumstances (Dias and Stentz, 2000). They found that complementary robots, with different skill sets, were cooperative, however, similar robots were competitive.

Free market systems, using a bidding negotiation mechanism, can apply game and team decision-making theories to improve or better understand system performance and behaviour. Lin and Solberg implemented a market-based distributed multi-agent system for manufacturing control, creating a highly adaptive framework for real-time shopfloor control (Lin and Solberg, 1992). Agents make decisions based on local incomplete knowledge, this is studied in game and team decision-making theories and can be applied to manufacturing scenarios (Cantamessa, 1997). Cantamessa also highlighted the trade-off between agent autonomy and external regulation of overall system behaviour, as well as the complexity of negotiation procedures and the cost of implementation. Pendharkar used game theory to design distributed wireless logistics networks in a MAS and relates them to a manufacturing job shop scenario. Pendharkar concludes that non-cooperative (competitive) MAS systems are best when there are no clear dominant strategies and a high degree of problem complexity (Pendharkar, 2012). Leitão reviewed MAS for manufacturing and covers many market-based systems developed (Leitão, 2009).

Free market systems have a natural parallel to some manufacturing scenarios where there are many non-coupled machines offering differentiated services. CPSs use smart resources that each have intelligence and can interact with their environment autonomously (Monostori *et al.*, 2016a), additionally supply chains are moving towards decentralised cluster structures (Stevens and Johnson, 2015). Each of these types of systems could use a free market distributed planning and control system that aligns with their distributed design philosophy.

A key argument against market-based distributed systems was stated by Parunak, that the use of a single utility function reduces a multi-dimensional complex reality into a single scalar coupled to a fully-instantiated choice (a fully delivered service at a given price), this is a large loss of information of complex future commitments (Monostori *et al.*, 2014).

On a low level, most free market systems use a permutation of the Contract Net Protocol, often through a bidding mechanism. The Contract Net Protocol process involves task announcement, bid process, the award of a contract for the task (Smith, 1980). This framework requests services from service providers, e.g. machines, for a specific task announced by a job, the bidding process from multiple resources for the task mirrors the free market. There have been improvements to the Contract Net Protocol, for example, Kádár's cost factor adaptation on the resource level changes a resource's cost according to its local state variables (i.e. status) and previous observations (Kádár and Monostori, 2001), this improves the allocative efficiency of the whole system as it introduces load balancing and differentiation of machines and jobs. Váncza *et al.* improve agent coordination by using rolling horizon planning for supply networks, incorporating an improved negotiation and payment mechanism that attributes costs to the supplier or consumers, against the accuracy of their forecasts (Váncza, Egri and Monostori, 2008).

The anarchic manufacturing system uses a free market architecture with a low-level permutation of Kádár's contract net with cost factor adaptation; a full explanation of the anarchic manufacturing system is detailed in Chapter 4.

Mediator architectures

Heterarchical with mediator architectures are similar to hybrid systems that combine low-level autonomy with some centralised functions, here the centralised functions are specialist as opposed to guiding boundaries in hybrid architectures; which are hierarchical in global structure. Mediator architectures have been developed by extending the functionality of distributed systems to overcome their criticisms, and have been reported to balance centralised and autonomous distributed control to enhance the performance of decision-making networks (Blunck *et al.*, 2018). Mediator agents operate concurrently to localised distributed agents, actively resolving conflict and representing global system objectives. Mediator agents can advise, impose or update decisions made by other agents to satisfy global objectives or resolve conflict (Ouelhadj and Petrovic, 2009). Architectures that use central agents to facilitate communication, conduct brokering or matchmaking services are often called mediator architectures (Shen, 2002); these, however, can limit the autonomy of local agents by defining their operational boundaries (hybrid systems) or conducting intelligent processes for a local agent.

Several propositions have been made to combine robustness, optimality, and predictability for dynamic scheduling in complex environments (Ouelhadj and Petrovic, 2009). MetaMorph I and II use mediator architectures in multi-agent systems, mediator agents either passively represent the system or actively facilitate scheduling and control. The proposed benefits include knowledge capitalisation which is achieved at the mediator level, reducing communication requirements, improving allocative efficiency through direct low-level communications, and flexibility and scalability arising from the architecture (Shen, Maturana and Norrie, 2000). Sun and Xue created a mediator architecture to respond to unforeseen disturbances, such as machine breakdown or operator absence. This was a dynamic reactive production scheduling mechanism in a match-up and agent-based collaborative approach to modify schedules (Sun and Xue, 2001). Sahin *et al.* created a rule-based heterarchical with mediator multi-agent system, where mediators represent a class or group of agents, for scheduling and control of machines and automated guided vehicles, realising on-line real-time control (Sahin *et al.*, 2017).

Mediator architectures have been criticised for their inability to represent complex hierarchical manufacturing systems, as they can only operate on a single level (He, Zhang and Li, 2014). This comment is relevant for manufacturing systems or supply chains that have been structured in a hierarchical manner; which is currently the common method with dealing with complexity.

List of heterarchical, mediator and hybrid manufacturing systems

Heterarchical, heterarchical with mediator and hybrid architectures all have some low-level inter-element decision-making and interaction. A list of existing systems in literature, displayed in Table 2-1, highlights research gaps and similar systems to anarchic manufacturing. Categorising aspects considered are architecture, mechanisms, application area and functionality. Architecture considers the structure of the system and entity interactions, and whether there are any additional or higher-level entities are structures imposed. Mechanisms consider how the interactions are structured, how they make decisions and communicate if applicable.

Table 2-1: List of heterarchical, mediator and hybrid structures

Architecture	Mechanisms	Reference	Application area	Functionality
Heterarchical	BMS	(Tang *et al.*, 2011, 2018)	Job/flow shop	Scheduling, Control
Heterarchical	BMS	(Ueda, Vaario and Ohkura, 1997; Ueda *et al.*, 2000; Ueda, Hatono, *et al.*, 2001; Ueda, Kito and Fujii, 2006)	Job/flow shop	Scheduling, Control
Heterarchical	Contract net protocol	(Smith, 1980)	Factory	Scheduling, Control
Heterarchical	Contract net protocol	(Kádár and Monostori, 2001)	Job/Flow shop	Production planning, Scheduling, Control
Heterarchical	Contract net protocol	(Kádár *et al.*, 2018)	CM	Production planning, Scheduling
Heterarchical	Contract net protocol, game theory	(Zhang *et al.*, 2017)	CM, job/flow shop	Scheduling, Control
Heterarchical	Contract net protocol, game theory	(Cantamessa, 1997)	Job/flow shop	Production planning, Scheduling, Control
Heterarchical	Free market	(Dias and Stentz, 2002)	Multirobot	Scheduling, Control
Heterarchical	Free market, Contract net protocol	(Bruccoleri, Amico and Perrone, 2003)	RMS	Control
Heterarchical	Free market, Contract net protocol	(Lin and Solberg, 1992)	Factory	Scheduling, Control

Architecture	Mechanisms	Reference	Application area	Functionality
Heterarchical	Free market, Contract net protocol	(Kim, Song and Wang, 1997)	Job/ flow shop	Scheduling, Control
Heterarchical	Rule-based, rationally bounded learning agents	(Vrabič *et al.*, 2018)	Factory (process industry)	Control
Heterarchical	Rule-based	(Freitag, Becker and Duffie, 2015)	CM, job/flow shop	Production planning, Scheduling, Control
Heterarchical	Rule-based	(Duffie, Prabhu and Kaltjob, 2002)	Factory	Scheduling, Control
Heterarchical	Rule-based	(Scholz-Reiter, Rekersbrink and Görges, 2010)	Job/ flow shop	Scheduling, Control
Heterarchical	Rule-based	(Windt, Böse and Philipp, 2008)	Job/ flow shop	Control
Heterarchical	Rule-based	(Rekersbrink, Makuschewitz and Scholz-Reiter, 2009)	Logistics	Scheduling, Control
Heterarchical	Rule-based, Contract net protocol	(Kádár *et al.*, 2018)	CM, RMS	Production planning, Scheduling
Heterarchical	Rule-based, Contract net protocol	(Li *et al.*, 2018)	RMS	Production planning, Control
Heterarchical	Rule-based, learning, Contract net protocol	(Vrabič *et al.*, 2018)	Factory	Control
Heterarchical with mediator	Contract net protocol	(Schild and Bussmann, 2007)	Factory	Control

Architecture	Mechanisms	Reference	Application area	Functionality
Heterarchical with mediator	Contract net protocol	(Colombo *et al.*, 2006)	Factory	Production planning, Scheduling, Control
Heterarchical with mediator	Contract net protocol	(Shen, Lang and Wang, 2005)	Factory	Production planning, Scheduling, Control
Heterarchical with mediator	Contract net protocol	(Guo *et al.*, 2015)	CM	Production planning, Scheduling
Heterarchical with mediator	Contract net protocol	(Caridi and Sianesi, 2000)	Assembly	Production planning, Control
Heterarchical with mediator	Rule-based	(Sun and Xue, 2001)	Factory	Production planning, Scheduling
Heterarchical with mediator	Rule-based	(Maturana *et al.*, 2004)	Industrial systems	Control
Heterarchical with mediator	Rule-based	(Yang *et al.*, 2016)	CM	Scheduling, Control
Heterarchical with mediator	Rule-based	(Sacile, Paolucci and Boccalatte, 2000)	Factory	Production planning, Scheduling, Control
Heterarchical with mediator	Rule-based	(Pendharkar, 2007)	Factory	Scheduling, Control
Heterarchical with mediator	Rule-based, Contract net protocol	(Sahin *et al.*, 2017)	Factory	Scheduling, Control

Architecture	Mechanisms	Reference	Application area	Functionality
Heterarchical with mediator	Rule-based, Contract net protocol	(Wang *et al.*, 2015)	CM	Production planning, Scheduling, Control
Hybrid	Fuzzy rule-based, Contract net protocol	(Brennan, Fletcher and Norrie, 2002)	Factory	Scheduling, Control
Hybrid	Rule-based	(Cristalli *et al.*, 2013)	Factory	Control
Hybrid	Rule-based	(Cheng *et al.*, 2010)	CM	Scheduling
Hybrid	Rule-based	(Valckenaers *et al.*, 1999)	Factory	Scheduling, Control
Hybrid	Rule-based	(Maturana and Norrie, 1996)	Factory	Production planning, Scheduling, Control
Hybrid	Rule-based, Contract net protocol	(Parunak, 1996)	Factory	Scheduling, Control
Hybrid	Rule-based, Contract net protocol	(Sousa and Ramos, 1999)	Factory	Production, Scheduling, Control
Hybrid	Rule-based, Contract net protocol	(Heragu *et al.*, 2002)	Factory	Scheduling, Control

The anarchic manufacturing system is a heterarchical free market system, using a permutation of the contract net protocol, for production planning and control of manufacturing systems. It can be applied to a wide range of scenarios, including assembly and product transition these has not been covered specifically in literature by a distributed system, as displayed in Table 2-1. Additionally, the listed free market heterarchical systems all only have a single budget consideration, or they only consider one transaction at a time, this provides insufficient adaptability to scenarios beyond those listed. This thesis uses the distributed anarchic manufacturing system and applies it to three manufacturing scenarios for production planning and control; simple discrete manufacture, assembly and product transition scenarios.

2.5 Critique and research gap

Smart manufacturing is the response to market demands and business objectives, which are creating an increasingly volatile and complex environment. Traditional methods, using centralised and hierarchical decision-making structures, are used heavily in practice, however, they are rigid; as discussed in section 2.4. Rigidity can be exacerbated by using simplifying and hierarchical structures for complex problems; this is discussed in detail in Section 2.3.2. The extreme alternative uses distributed systems, the aforementioned literature review, most notably Section 2.4.4, proposes distributed system benefits in direct contrast to hierarchical systems; high flexibility, robustness, and adaptability in complex environments. Hybrid and mediator architectures, although a promising mixed alternative to hierarchical and fully distributed systems, have not been investigated as the thesis aims to extend the extremes of knowledge within distributed systems. Evaluating a purely distributed system will clearly determine the impact of distributed structures when it is void of any centralised structure or agents, avoiding the argument of whether an observable characteristic is attributable to the centralised or distributed aspect of a system. Figure 2-12 graphically categorises the organisational structures for planning and control, of these a distributed 'anarchic' system is compared to hierarchical and centralised systems in this thesis. Removing all centralised authorities eliminates their role in decision-making, this enables a clear contribution to characterising distributed systems.

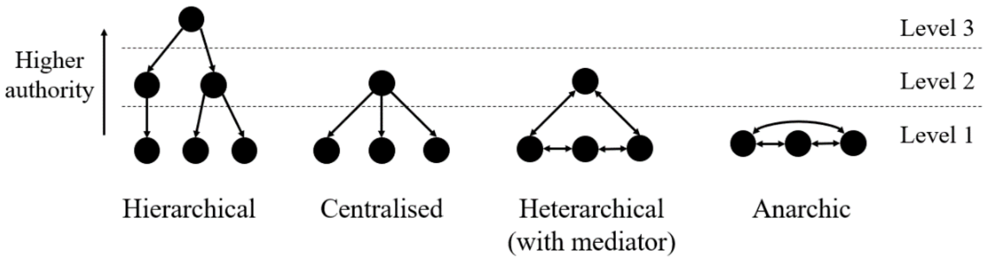

Figure 2-12: Production planning and control architectures

Distributed systems are largely untested, most existing research has focused on simple discrete manufacture and particularly for highly theorised scenarios such as job shops and flowshop problems; this is evidenced by the broad review of distributed systems in Section 2.4.4. These provide value in baselining performance but have little resemblance to real-world problems or significantly expand the realm of practicable knowledge. There is a significant research gap in understanding distributed system performance in more complex and advanced scenarios. Literature review Section 2.4.4 reveals that there are no distributed systems considered to solve assembly or transition scenarios. Further investigation into distributed systems is required to understand the behaviour and characteristics to remedy or avoid faults and exploit benefits. This will increase knowledge of distributed systems and subsequently improve understanding of where best to deploy them.

The distributed systems reviewed are all underpinned by emergent synthesis (Váncza and Monostori, 2017) and have predominately been rule-based, biomimetic or free market; no system is significantly more researched than another. In economics, perfectly competitive free market systems, through the general equilibrium theory, guarantee a Pareto optimal solution (Kaihara *et al.*, 2018). Although these systems consider a long-term static view, it is worthwhile to consider whether a free market system can be successfully applied to distributed manufacturing in a dynamic environment. Of the three logical solution architectures, in the author's opinion and discussed in Section 4.3, free markets have the greatest opportunity due to its malleability and ability to form sophisticated mechanisms; improving the opportunity to counter criticisms of distributed systems, most notably myopic behaviour (Blunck and Bendul, 2016). Biologically inspired systems, forming biological manufacturing systems, have self-optimising traits and are not constrained within defined rule-based systems. However, they may suffer in highly dynamic and customised scenarios and are unable to create highly sophisticated mechanisms; this was found by Scholz-Retier *et al.* on comparing rule-based systems against a BMS based on ant colony pheromones (Scholz-Reiter, Görges and Philipp, 2009). This, in the author's opinion, is due to the BMS using historic information, e.g. ant pheromone trails, to determine current decision-making.

However, the scenario may have changed, and recent past information is unsuitable for current decisions impacting near future actions, ultimately hindering decision-making due to a lack of adaptability to a scenario. Free market type systems should be well understood by the business community, as an agent’s profitability-oriented decisions reflect business management decisions. There is a large area of knowledge within economics and game theory that can be used to understand and develop the mechanics of anarchic manufacturing due to the free market architecture.

A new distributed free market system was developed for anarchic manufacturing. Although anarchic manufacturing uses a free market architecture and the contract net protocol as other systems have, extensions have been required to improve flexibility, ability to manage complexity and adaptability to scenarios. This is due to existing free market systems only having one budget consideration or an even narrower view of a single transaction or operation.

3 Research framework

3.1 Introduction

This chapter outlines the research boundaries and scope, followed by the methodology and tools used. The research boundaries and scope present the manufacturing problem, scenario and solution structures investigated and outline the remit of work conducted to achieve the research objectives. Finally, the research methodology and tools used are presented and justified.

3.2 Research boundaries and scope

3.2.1 Boundaries

The research conducted applied a distributed decision-making structure, using the anarchic manufacturing system, to production planning and control problems. The three manufacturing scenarios considered were simple discrete manufacturing, assembly and product transition; the intersection of these aspects are summarised in Figure 3-1. The decision-making structures considered are hierarchical, centralised and distributed (anarchic), the focus on anarchic manufacturing is justified in Section 2.5 and the hierarchical and central systems are detailed in Section 3.3.2.

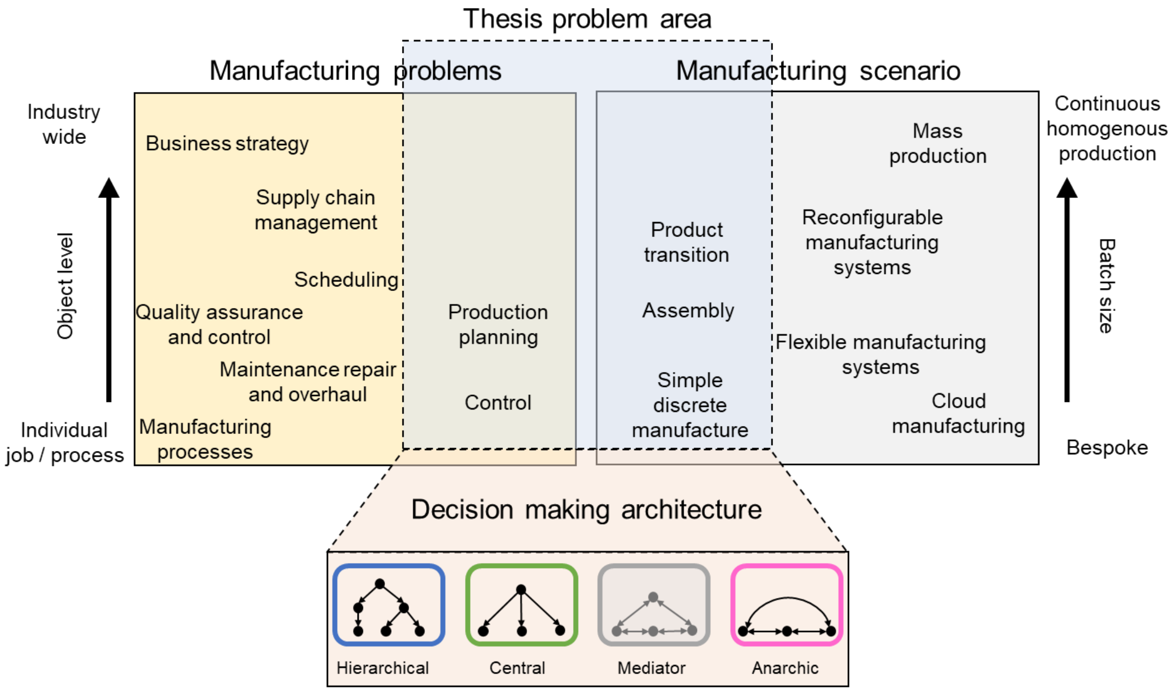

Figure 3-1: Research boundaries for problem area and scenario

The manufacturing problems considered were selected to best represent the benefits for distributed systems, as well as simplifying the problem area so that there were no non-decision-making factors that would overshadow the functionality of the decision-making system. The feasibility of distributed systems for production planning and control, on considering the boundaries as the four walls of a factory, is feasible given smart manufacturing technologies, as discussed in Section 2.2. However, contextual considerations for manufacturing processes, maintenance repair and overhaul and quality manufacturing problems may overshadow any benefit and generalised conclusions are more difficult to ascertain. Similarly, business strategy and supply chain management aspects could have external and uncontrollable factors that significantly impact operations.

Distributed systems are proposed to be highly flexible and self-organising when faced with dynamic environments, subsequently highly volatile and complex scenarios were selected to evaluate the system against. The future application of anarchic manufacturing is likely to be within smart manufacturing, given the required enabling technologies and proposed operating models. However, the anarchic system is evaluated against existing manufacturing scenarios, rather than theoretically proposed smart manufacturing scenarios, as it is likely that these scenarios and their fundamental planning and control problem characteristics will still exist in the smart manufacturing era.

The manufacturing scenario initially selected, simple discrete manufacturing, was used to baseline the performance of the anarchic manufacturing system as well as showcase the most relevant scenario for the proposed benefits of distributed systems; as discussed in Section 2.4.4. These initial experiments focus on significant planning and control problem characteristics, as directed by the literature review above. Subsequently, two further scenarios were selected to significantly extend the knowledge of distributed systems by applying anarchic manufacturing to scenarios that are similarly complex but more difficult to apply distributed structures to; the selection of these is discussed in detail with additional background literature at the beginning of Chapters 6 and 7. Alternate manufacturing scenarios could have been selected, however, evaluating three is sufficient to demonstrate the capabilities of the anarchic manufacturing system.

3.2.2 Scope

The scope of research, informed by the literature review, focuses on building a theoretical model of free market structures in production control and conducting simulation-based experiments based on this theory. The methodology is explored in detail in section 3.3. Analytical methods for evaluation have not been considered, as for the complicated and complex manufacturing scenarios that are of interest to this thesis, the techniques are underdeveloped and detract from the focus of the work.

Functional areas beyond production planning and control are excluded; these are summarised as management decisions, human decision-making and manufacturing processes. Management decisions vital to operating a factory are excluded, these consider the strategic and long-term decisions, for example capital expenditure and resourcing decisions. Human decision-making is assumed to conform to agent decision-making models, as defined within anarchic manufacturing, and not exhibit irrational behaviour. Manufacturing processes are outside of the scope, this covers process planning and the specific operations and activities conducted. Process planning is assumed to be predefined; operations are defined by the resources required and duration. The breakdown of constituent parts and the optimisation of these manufacturing processes, for example speeds and feeds, are not considered and are assumed to be encapsulated within the duration of an operation; an operation is only considered as either completed, in progress or outstanding.

Smart manufacturing and associated implementation considerations are beyond the scope of this thesis and are not expected to impact decision-making systems; these include smart manufacturing technologies, information systems and communication protocols. Smart manufacturing technologies that provide enabling infrastructure, for example Internet of Things and edge devices, are not specified or considered in this research; they are assumed to provide appropriate functionality. The implementation of the anarchic manufacturing system may be considered in future work. Information systems for data handling and recording are beyond the scope of this thesis, for example Enterprise Resource Planning systems. Similarly, communication protocols are expected to function appropriately, all agent messages are simple and are expected to be fulfilled by communication protocols.

3.3 Methodology and tools

3.3.1 Research structure

The literature review in Chapter 2 identified existing knowledge and research gaps, by highlighting the greatest concerns within the academic community for smart manufacturing and distributed planning and control structures. Through an informed understanding of distributed systems, the theoretical framework for anarchic manufacturing was created as a suitable distributed planning and control system; a full and detailed explanation is provided in Chapter 4. Subsequently, this distributed system was tested relative to centralised and hierarchical systems using simulation experiments. Simulation experiments provide an efficient way to evaluate decision-making logic and structures for manufacturing scenarios that would elicit complex behaviours; an explanation as to why simulation was selected, the type of simulation and simulation platform was selected is detailed in section 3.3.2. Multiple experiments were conducted for three different general application scenarios, evaluating different important factors to provide a more rounded characterisation of distributed systems; these experiments are detailed in Chapters 5 to 7.

3.3.2 Literature review methodology

There are three parts to the literature review: smart manufacturing background, the planning and control problem and solution architectures. The first two help establish the context of the research and the last area informs the methodology. The review identified significant interest in smart manufacturing production planning and control as well as the strengths and weaknesses of existing and previously researched distributed systems. The review was seen as the most effective method to ascertain this knowledge and guide subsequent theoretical and experimental research, as smart manufacturing is still an immature concept and there are very few distributed systems in industry. Therefore, there would likely be little gained through observing and evaluating current industrial practice for a future problem area yet to be encountered. Rather the proposed environment within smart manufacturing and documentation of problems and proposed solutions provided greater insight.

3.3.3 Theoretical framework and prototype methodology

In order to address the gap identified in the literature review, the theoretical framework for anarchic manufacturing has been developed based on free market distributed systems as reported in Section 4.2. The justification for selecting a free market architecture is provided in the literature review critique in Section 2.5. Free markets have not been reported to have a significant advantage over other solutions (rule-based and biological), however, existing research distinguishes its promising adaptable nature (Cantamessa, 1997; Dias and Stentz, 2000; Kaihara *et al.*, 2018); the affordances of free markets are provided in Section 4.3.2. This selection process focused on development and adaptability of the distributed architecture for complex problems and scenarios, this was most suitable for the thesis aim and objectives which concerns adapting for a range of manufacturing scenarios.

The theoretical framework determines anarchic manufacturing system’s stance on several important factors, these factors were identified to ensure the free market architecture would function appropriately given the manufacturing problem and scenario context. These underlying principles of the theoretical framework, detailed in Section 4.2, enable the development of a prototype system and all subsequent adaptations.

The embodiment of the theoretical framework through a prototype system is outlined in Section 4.4, the core structure and mechanics were adapted as appropriate for each manufacturing scenario in Chapters 5 to 7. Negotiation, using a permutation of the contract net protocol (Smith, 1980), was selected over alternative methods such as auctions. The use of direct agent to agent negotiation maintains agent independence. An agent can easily baulk, i.e. resist or refuse an offer, through direct negotiation and maintains independence on offering a price. Rather auction methods rely on competitive bidding from a game theoretic perspective (Lorentziadis, 2016), where agents directly influence each other's bids. The need to employ game theoretic devices was avoided to reduce unnecessary system complexity and to follow on from the existing body of research using negotiation methods. Adapting the core system to a given manufacturing scenario, in accordance with the theoretical framework, demonstrates the system's adaptability.

3.3.4 Experimentation methodology and tools

Chapters 5 to 7 of this thesis experimentally evaluate the proposed theoretical framework for anarchic manufacturing detailed in Chapter 4. The experimental methodology selected simulations over analytical methods, subsequently agent-based modelling was selected as the simulation method and the AnyLogic simulation modelling platform was chosen, as discussed below.

Experimental method selection

There are a few ways to evaluate manufacturing systems, this is depicted in a tree structure in Figure 3-2 by Wang and Chatwin, it conveys that the most practicable methods use mathematical models employing analytical or simulation methods as the alternatives are either too costly or are relatively very inefficient to evaluate new systems. Simulation experiments were used to analyse anarchic manufacturing system's behaviour and performance, this method was preferred over analytical methods. Analytical methods employing queuing theory models, based on Markov processes, consider the stochastic arrival and service processing and can predict logistic performance (Nyhuis *et al.*, 2005). Nyhuis *et al.* note from practical experience the predictive performance from queuing models does not reflect reality, most likely due to violations of model premises, which render system behaviour unable to be modelled by standard distribution functions; these violations include incomplete information and dynamic system behaviour. Wang and Chatwin state it is widely accepted that mathematical or analytical modelling techniques are insufficient for detailed analysis of complex manufacturing systems. This is due to an inability to accurately describe stochastic elements and dynamic systems behaviour, futhermore optimisation is not possible through simplifying assumptions (Wang and Chatwin, 2005).

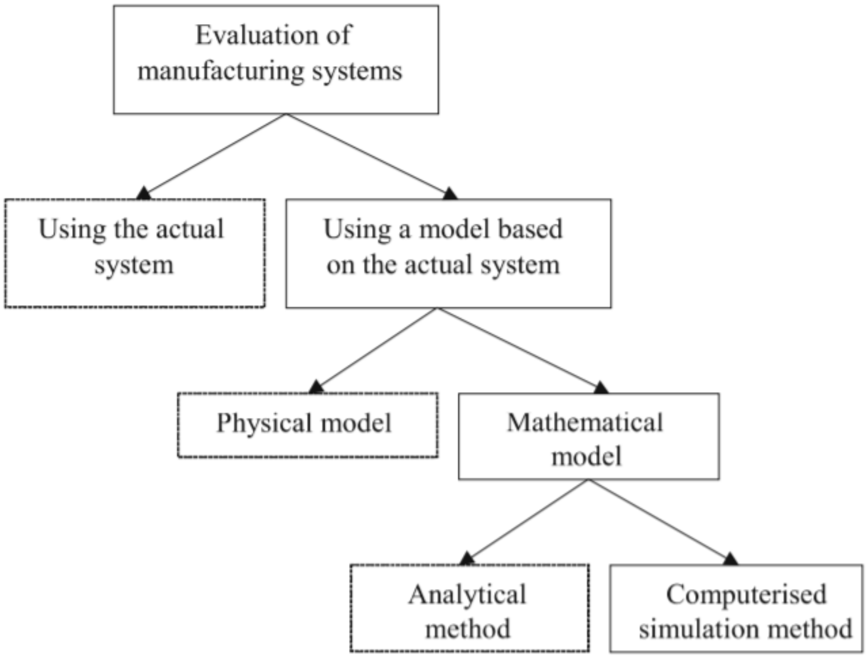

Figure 3-2: Methods for evaluation manufacturing systems (Wang and Chatwin, 2005)

Simulation is a widely used technique for the exploration, design and optimisation of complex production systems (Nyhuis *et al.*, 2005). Nhyuis *et al.* state that many authors hold the opinion that using simulation exclusively can provide the means to evaluate the effects of system load variants, disturbances, changes in logistic routing rules, structure variants or alternative resources sufficiently accurately. Additionally, simulations have a unique advantage that enables the analysis of (real) systems that cannot be described by means of deductive models, as they are too complex and have a low cost on initial model construction in comparison to deductive models (Nyhuis *et al.*, 2005).

The broad range of manufacturing scenarios explored in this thesis all evaluated different decision-making structures in a dynamic environment with many inter-dependent system elements which cumulate into a complex manufacturing system. Given the dynamic and complex nature of the manufacturing scenarios, simulation is reported to be the most effective and suitable means for evaluating the different systems. Although for simulation no general validation is possible, analytic models only provide validity in steady operating states (Nyhuis *et al.*, 2005), therefore validity through analytical models cannot be extended to the dynamic scenarios investigated. The reduced modelling effort (Nyhuis *et al.*, 2005) is an additional benefit and has allowed the author to investigate the broad range of scenarios.

Simulation method selection

Simulation experiments evaluated simplified real-world problems, with a view that increasingly realistic factors can be added; therefore, experiments must have the ability to include stochastic factors, such as operation duration and resource failure rates. There are three main simulation methods: system dynamics, discrete event and agent-based modelling. System dynamics represent resources and dynamics within a system as a set of stocks and flows between them, it captures feedback and delay processes to model system behaviour using stocks to aggregate representations of entities (Swinerd and McNaught, 2012). Discrete event simulation is a modelling technique where only changes in the system states are represented, a queue of events that affect the system state are modelled based on their timings (Alrabghi and Tiwari, 2016). ABM systems comprised of autonomous and interacting agents can augment traditional deductive and inductive reasoning as discovery methods (Macal and North, 2008). ABM is widely used in social sciences and economics, it provides each agent with its own thread of control and macro behaviour is not modelled, rather it emerges from micro-decisions of individual agents (Siebers *et al.*, 2010).

The three simulation methods have differing strengths, however, the most important difference for this research is the model's level of abstraction. Low levels of abstraction are required as each modelled entity or system element must be able to store information locally and execute its own decision-making procedures, as such the most appropriate simulation method for this functionality is ABM (Borshchev, 2013). This low level of decision-making is possible with discrete event simulation; however, ABM is the most suited modelling architecture as its structure relies on distributed decisions and interactions. The social sciences and economics research communities have embraced ABM, as they can leverage the agent interaction aspects to create emergent outcomes (Siebers *et al.*, 2010).

Simulation platform selection

The AnyLogic platform was selected as the most appropriate ABM platform after a study comparing three ABM platforms; AnyLogic, MATLAB and NetLogo. The study incrementally advanced the model functionality until there were observable differences. AnyLogic was selected due to the reliance of synchronous time models for NetLogo and MATLAB and greater real-world representation during simulations with respects to executing events.

The ABM platform selected must have the following capabilities: sensing and interacting with its environment, making decisions, messaging and interacting with other agents, pursue local objectives and best reflect real-world environments. Key features of the three systems are summarised below.

AnyLogic

- Java based platform with Unified Modelling Language
- Agent-based modelling, discrete event, system dynamics modelling and simulation
- Preferentially an asynchronous model, synchronisation can be achieved
- FIFO / LIFO / random event scheduling and execution for simultaneous events

MATLAB

- Bespoke MATLAB modelling language
- Cell arrays were used to model agents, effectively by storing agent data and variables, all methods/functions were global
- Synchronisation on time steps and loops required for inter-agent dependent decision-making, iterate for all agents, update their state by observing other agents – agents call functions and ask other agents to call functions

NetLogo

- Bespoke NetLogo high-level modelling language – limited capabilities and basic structure of code
- Purpose built agent-based modelling tool by an academic
- Agents cannot message each other or change each other's parameters, only read each other's parameters, a lot of data is stored in the central global agent that all can change and read
- Synchronous time stepped simulation, stepping through all agents sequentially or in a random sequence. Like MATLAB, need to cycle through decision-making multiple times due to inter-agent dependent decision-making

The experimental setup incrementally advanced the models until the first observable difference was encountered; this modelled a distributed system which advanced towards the anarchic manufacturing system used in this thesis. The three models created are summarised in Table 3-1.

Table 3-1: Platform comparison models

Model	Features
M1	Heuristic dispatch rule, next available MT by queue length Single op / job, same duration and 1 capability 4 MTs, kept at 94% MT utilisation, 3 jobs / batch
M2	Simple tendering process MT cost based on queue length, bid reduction on tenders since last win Job threshold is budget / ops remaining, increment on tenders since last win
M3	2 ops / job, same duration and capability required MT bid on utilisation and queue length, reduction on bid success

Observable differences started at model 3 where synchronisation and event firing sequence created a small noticeable difference between AnyLogic versus MATLAB and NetLogo. As MATLAB and NetLogo have a sequential and synchronous event firing system, each agent evaluates its state and executes decision-making in sequence. AnyLogic follows asynchronous event firing, scheduling is determined by the order the event was created and queued to the discrete event engine.

The noticeable difference occurred when one operation has finished and the agent tenders its next operation, but simultaneously a new batch of jobs are created and tenders; however, as the create jobs event is queued first this action is executed and subsequently the tendering of new jobs occurs before the retendering of the older job. For NetLogo and MATLAB, each job would sequentially evaluate its state and decision-making, i.e. tendering, by job number; therefore, the older job always has precedence.

The AnyLogic platform was selected based on synchronisation and the ability to reflect real-world manufacturing. Time step synchronisation constrains the simulation to run on a discrete time basis, and repeated decision-making loops within a timestep are required but can create an infinite loop or an incorrect model if not enough are run. Agents are interdependent within a timestep, this poses an issue for more complex and intertwined models as to whether enough decision-making loops have been run. AnyLogic's asynchronous modelling allows all subsequent events to be executed ‘as they occur’. Real-world discrete part manufacturing has several differences to typical models; there are few simultaneous events, events occur on a continuous time basis, and decision-making, information transfer and almost all events are not instantaneous.

AnyLogic nomenclature

The AnyLogic platform uses statecharts within agents to determine actions and processes, Chapter 4 provides a detailed explanation of anarchic manufacturing and how it uses agent-based statecharts. Figure 3-3 below details the nomenclature for statecharts, how an agent can transition between states. AnyLogic can operate on both a discrete and continuous time basis, using a continuous time basis is preferred to avoid simulation modelling issues associated with concurrent activities; such as deadlocking.

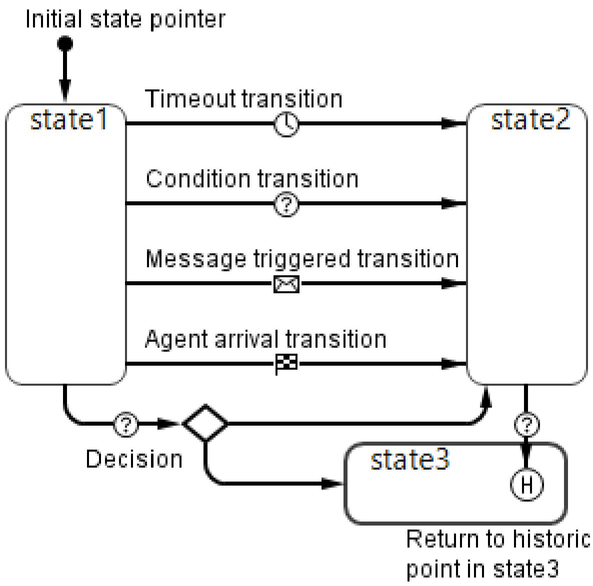

Figure 3-3: AnyLogic statechart nomenclature

Prototype system development

The anarchic manufacturing system is proposed in Chapter 4 and developed throughout the thesis on application to a specific manufacturing scenario. The design principles of the system are discussed and stated in Chapter 4, and these are adhered to throughout the system’s development. The basic negotiation protocol is defined in Section 4.4, this is retained throughout the system development. The factors that contribute to decision making and feed into the negotiation protocol are developed to consider the specific scenario. This most notably has developed the profitability calculations and the decision whether to collaborate with other similar agents. The specific adaptations are documented in the experimentation chapters next to the contextual considerations for the specific manufacturing scenario.

Experimental structure and metrics

Simulation experiments were used to evaluate system behaviour in given scenarios, allowing emergent behaviour. Due to the current immaturity of the research field into distributed systems, general and theorised scenarios and experiments were used rather than any industry specific scenario. This minimised noise within experimentation and enabled clear evaluation of the anarchic manufacturing system against specific problem characteristics. To gain confidence, multiple iterations were run for each set of experimental parameters which had stochastic variables within them. For high-level comparative evaluation, between distributed and centralised systems, a characteristic was embodied and varied as an experimental parameter; for example, to change complexity, scale could be varied. The rate of change in performance was analysed to understand the system's behaviour against an experimental parameter, which infers the behaviour against the characteristic the parameter embodies and enables a relative characterisation. The lack of direct absolute performance comparison, unless the scenario allowed it, reduced the need for equivalence between tested systems. Thereby allowing different system maturities, and mechanisms of varying sophistication, to be used for this high-level comparison.

As the majority of experimentation contained the manufacturing system within the four factory walls, traditional manufacturing metrics were used for consistency with other studies. Most experiments, to maintain steady state stability, determined an expected system utilisation (through a fixed arrival rate of orders/jobs). Therefore, metrics for Work In Progress (WIP), backlog, Time In System (TIS) and waiting time were most appropriate to evaluate performance; scenario specific metrics were also used, as appropriate. Where possible plots displayed the 95% confidence interval of the mean to provide statistical confidence in analysing the results and conclusions drawn. These were shown as areas around the mean and could not be aggregated to a single value due to the dynamic nature of the systems and scenarios.

All experiments undertaken, including those with a very large number of agents (>1,000 agents) were all conducted on a computer locally and did not use more than 8Gb of memory. The simulations, created on the AnyLogic platform, all took at most a few minutes to run, with a full suite of simulations for a particular experiment, including 50 iteration runs for each parameter set, took at most two days to complete and save all results.

Comparative centralised and hierarchical system

To compare the anarchic manufacturing system, simple but representative centralised and hierarchical systems were used. Both used dispatch heuristics to manage a dynamic environment effectively (Ouelhadj and Petrovic, 2009) and have master/slave relationships between tiers of management layers. The two systems are depicted diagrammatically in Figure 3-4, the centralised system considered all resources simultaneously and allocated a job accordingly; e.g. by allocating to the next available resource according to the Earliest Due Date (EDD) heuristic and prioritisation. The hierarchical system had a predefined structure that allocated jobs to the tier below; this is representative of simplification strategies that use structure to reduce the complexity of problems. At first a job, at the global and highest tier, is allocated to the next layer, for example a cell, all subsequent layers allocated downwards until a job is allocated to a specific resource (machine). These tiered allocation processes followed a dispatch heuristic similar to the centralised system. A job, on completion of an operation, reported back to the cell and if that cell had the correct capability for its next operation it is retained. However, if the cell did not contain the correct capability the job reported to the next tier upwards until the tier contained the capability to complete the next operation, the job is subsequently allocated downwards.

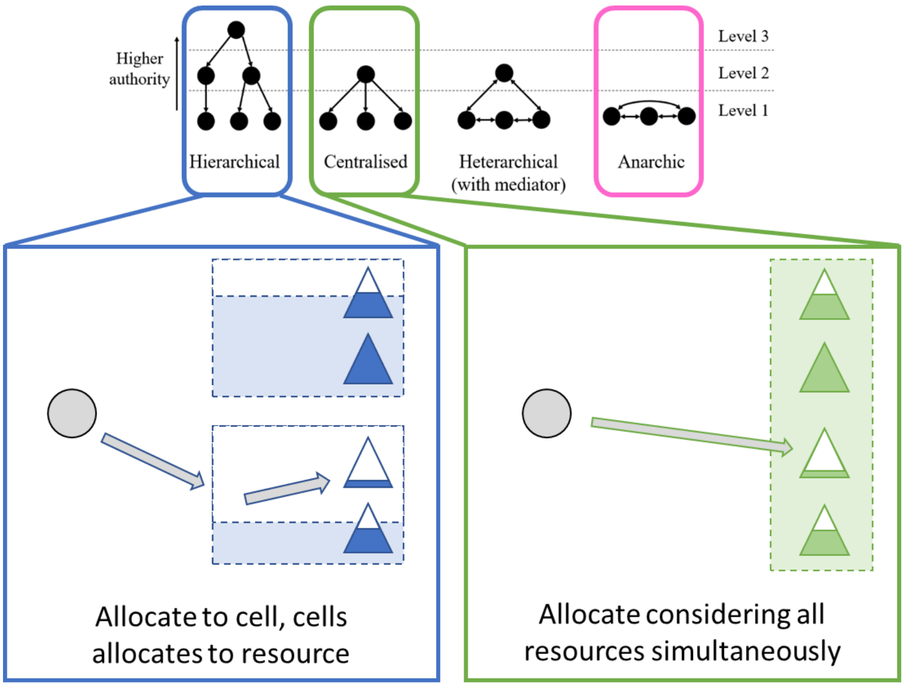

Figure 3-4: Centralised and hierarchical systems

4 Anarchic manufacturing

4.1 Introduction

Production planning and control is currently achieved through centralised decision-making structures, simplification and creating hierarchies have been the traditional methods for dealing with complexity (Heragu *et al.*, 2002). Creating a flat distributed system to embrace complexity directly opposes traditional methods and is a bold proposal.

The distinguished engineer W. E. Deming clearly identified the need for central management and avoidance of competition in systems.

'A system must be managed. It will not manage itself. Left to themselves components become selfish independent profit centres and thus destroy the system. The secret is cooperation between components toward the aim of the organization. We cannot afford the destructive effect of competition' (Deming, 2000).

Despite these assertions, centralised and hierarchical structures have been criticised for being too rigid and inflexible for modern manufacturing demands. This is likely to be exacerbated by the trajectory of smart manufacturing. Distributed systems reject Deming's systems thinking, they propose highly adaptive and flexible production systems. These systems are void of centralised system management and leave the components to become selfish and competitive profit-centres, but they create emergent globally effective production systems as discussed in Section 2.4.4.

Free market structures for distributed systems apply free market principles for global efficiency, agents representing suppliers and demanders in an artificial economy achieve Pareto optimal solutions in a perfectly competitive market (Kaihara *et al.*, 2018). A hypothesis is proposed that free markets can be applied to dynamic production planning and control for manufacturing as a feasible solution, which may bring benefits associated with distributed systems.

The research motivation for this chapter is to detail the hypothesis and underlying principles of anarchic manufacturing, create the theoretical framework and outline the structure and main mechanisms as a prototype system. This chapter fulfils the second and third research objectives outlined in Section 1.1.

This chapter proposes that applying free markets to dynamic production planning and control manufacturing problems will be effective. Subsequently, anarchic manufacturing system's design principles and attributes are argued for covering structure, type of mechanisms used and its position for competitive and cooperative behaviour and ethical decision-making. Following this the core structure and negotiation process are detailed for anarchic manufacturing; this is the basis for the system and adapted as required for experiments in Chapters 5 to 7.

4.2 Hypothesis and definition of anarchic manufacturing

In economics, perfectly competitive free market systems, through the general equilibrium theory, guarantee a Pareto optimal solution (Kaihara *et al.*, 2018); this is for a long term perspective that can be viewed as static. Mapping suppliers to manufacturing resource providers and consumers to jobs requiring operations to a free market structure, this thesis proposes the hypothesis below:

Free markets provide an effective distributed structure to solve dynamic production planning and control problems for manufacturing.

It is conceivable that free market structures in a distributed system for dynamic manufacturing scenarios will be effective, however, Pareto optimality, through stabilising negative feedback (Kaihara *et al.*, 2018), cannot be guaranteed as the dynamic nature suggests there is no long term or final state. The anarchic manufacturing system is used to evaluate this hypothesis and is defined as a distributed system that through independent agents, which all have decision-making authority and autonomy, participate in a free market environment to solve manufacturing problems. This distributed system is likely to bring reported benefits of distributed systems, as documented in Section 2.4.4.

4.3 Design principles and attributes of anarchic manufacturing

Clarifying the theory behind anarchic manufacturing provides insight into the purpose and idealised functionality of the free market distributed production planning and control system. Aspects beyond system structure and mechanics are considered, fundamental issues associated with distributed and multi-agent systems are discussed; these cover competitive and cooperative behaviour and ethical decision-making.

4.3.1 Distributed decision-making authority and autonomy

A distributed system that provides absolute delegated decision-making authority and autonomy enables system elements to act and make decisions as they choose to (Shen *et al.*, 2006), behaving as anarchists. As defined in Section 2.4, any nominally distributed system with centralised decision-makers or active influencers are considered to have hybrid structures or mediator architectures. This subsection discusses how independent decision-making authority and autonomy enables emergent synthesis, adaptive traits, directly individually customisable decisions and removes some drawbacks of centralised systems such as central communication reliance and single points of failure.

Emergent synthesis (Ueda, Markus, *et al.*, 2001), as discussed in Section 2.4.4, utilises individual decision-making to locally solve problems, this in turn influences global behaviour to resolve system imbalances. The anarchic manufacturing system uses a free market architecture where agents pursue profit driven decision-making; this localised action results in a global emergent synthetic outcome. As a consequence distributed systems exhibit traits of self-organising, self-healing and adaptive behaviour (Shen *et al.*, 2006; Scholz-Reiter, Görges and Philipp, 2009; Bendul and Blunck, 2019).

Due to independence, individually customisable decision-making is available, therefore customising system elements is easily achieved. This allows resources to adapt to individual variations in performance and for highly dynamic variations in product requirements (Shen and Norrie, 1999).

Decision-making authority and autonomy removes the reliance on centralised communication and removes single points of failure (Colombo *et al.*, 2006). Independence, with direct agent communication removes any communication or structure centrally and single points of failure improving robustness.

4.3.2 Free market structure and mechanisms

Free market structures use free market principles for global efficiency, agents representing suppliers and demanders in an artificial economy achieve Pareto optimal solutions in a perfectly competitive market (Kaihara *et al.*, 2018). Resource agents represent suppliers, offering their services for a fee, job agents represent consumers (demanders) and require services to complete necessary operations and have currency to pay for services. This translation between a distributed manufacturing system and free markets allows the distributed system to benefit from free market attributes, most notably an ‘invisible hand’, introduced by Adam Smith, that guides the demand and supply of goods to a free market equilibrium (Samuelson, 1997). This is observed as an allocatively efficient system and a global emergent synthetic outcome. Anarchic manufacturing uses ‘artificial’ agents as the predominate decision-makers, as well as humans as appropriate, and assume these agents are all selfish and profit maximising.

Direct agent to agent negotiation based on Smith's contract net protocol (Smith, 1980), explained in detail in Section 4.4 below, maintains agent independence. Negotiation is the mechanism for agreeing to a transaction within the free market, trading a service (to be performed in the future) at a cost (to be transferred on successful completion of the service). The determination of whether to accept the proposed price of a service is governed by a profitability assessment. Many of the distributed systems reviewed in Section 2.4.4, and as listed in Table 2-1, use permutations of the contract net protocol negotiation methods rather than alternatives such as auctions, this method was selected to maintain agent independence as discussed in Section 3.3.3.

The free market employed in the anarchic manufacturing system has one currency, here all factors impacting the completion of a product is translated into currency by each agent; through its individual perception of value associated with each factor. For example, expected operation start time could be perceived differently and therefore valued differently with respects to currency. This highlights the inherent agent individualism in anarchic manufacturing, discussed above in Section 4.3.1. Additionally, anarchic manufacturing utilises the free market and single currency to achieve scalability and adaptability for increasing complexity. Further factors, for example social and environmental concerns detailed in Section 2.2.5, can impact the market when translated to the single currency, however, consideration for these factors is beyond the scope of this thesis.

The overarching mechanism for agents, in the free market structure, is to make decisions in order to maximise profit. There are varying ways that an agent can calculate profit, these are inherently malleable to a given scenario, providing adaptability. Profitability calculations can consider a long term horizon, the lifetime for an agent or other forecasting factors, this will reduce myopia; which is a significant criticism to distributed systems as discussed in Section 2.4.4. Lifetime profitability considerations were applied in Chapter 6 for assembly experimentation to reduce myopia. This was the downfall for the BMS used by Scholz-Reiter *et al.*, which used ant pheromones conveying recent history for decision-making, rather the comparative rule-based system was superior which considered resource queues relating to the near future (Scholz-Reiter, Görges and Philipp, 2009). Additionally, the profitability assessment can be adapted to consider multiple conflicting objectives by translating these into a single currency; this was employed during experimentation for multiple conflicting objectives, as reported in Section 5.3.3. This high-level objective that guides all mechanisms provides sufficient mechanism malleability to any given scenario whilst retaining individual perspectives on the environment.

4.3.3 Competitive and cooperative behaviour

A free market harnesses the benefits of competitive behaviour, suppliers offering the same or similar goods bring market equilibrium by competing on price or offering a differentiated service. Using competitive agents is beneficial when there are no clear dominant strategies and high problem complexity (Pendharkar, 2012) as well as when agents are similar to each other (Dias and Stentz, 2000). Increasing competition in distributed systems has been found to improve performance through experimentation, this is presented in Section 5.3.1, in direct contrast to Deming's assertion that the destructive effects of competition cannot be afforded (Deming, 2000).

Dias and Stentz observed that complementary resources with different skills are best when cooperative (Dias and Stentz, 2000). Additionally, for more advanced scenarios similar agents may benefit from selective cooperation, for example in natural teamworking environments or when there is a global and individual benefit to all parties. Additional mechanisms achieve cooperation between like agents as appropriate. However, they all retain a profit maximising perspective to align with the free market architecture. A profitability assessment can be used to decide whether to cooperate with similar agents; as employed for dynamic batching in Chapter 7.

Certain teamworking scenarios are explored in this thesis, Chapter 6 experimentation for assembly and Chapter 7 for product transition evaluate natural teamworking scenarios where cooperation between job agents is locally and globally beneficial. Joining jobs for assembly requires agent cooperation, to group jobs that have similar goals (to become a particular model), this reduces divergence in objectives and therefore decision-making direction. Similarly, the product transition experimentation used a dynamic batching mechanism to benefit from economies of scale. Cooperation requires ethical decision-making to not undermine other agents, similarly a competitive free market requires ethical transactions to function efficiently; these decision-making ethics are explained in the next section.

4.3.4 Ethical decisions and interactions

An ethical and just society is required for a capitalist economy to function sustainably (Ikerd, 2008). With respects to a free market containing a population of agents, ethical decisions and interactions are required for the effective and efficient function of the free market. Ethically, agents must not deceive another agent in order to undermine or take advantage; for example, collusion, price fixing or intentional misinformation. This is feasible in the proposed manufacturing system, predominately comprised of agent decision-makers whose decisions and actions are defined through models; therefore, their behaviour is known and created to be ethical.

Ethics are required for a distributed system to avoid top-down or centralised administrative bureaucracy. Additionally, this will ensure that the agents avoid disrupting the free market by operating against profit-maximisation, as discussed in the aforementioned Section 4.3.2. No research was conducted into unethical exploitation or flawed communications, i.e. unintentional miscommunication, as it was considered beyond the scope of the thesis, see Section 3.1 for research scope and boundaries.

4.4 System structure and core mechanics

This section provides the system structure and core mechanics of the anarchic manufacturing system. The general system structure is provided, followed by agent descriptions and finally the negotiation structure and mechanisms used; this is the base structure and mechanics of anarchic manufacturing. The anarchic manufacturing system is adapted and applied to each application scenario for experimentation; adaptations are detailed in the relevant application scenario within Chapters 5 to 7.

4.4.1 General structure

Anarchic manufacturing's core structure represents a free market by utilising jobs and machine tools (MT), where jobs negotiate the service of a MT to complete a particular operation. For ease of explanation, all entities within the system can be considered to be inside the four walls of a factory where jobs at first embody orders that fulfil operations, via MTs, to become finished products; the majority of experiments within this thesis consider the anarchic system within a factory. Jobs arrive periodically, each job has a predefined list of operations to complete and is provided currency (a budget) to become a finished product, on completion jobs exit the system. A MT can complete an operation for a job at a cost, they are restricted to operate on one job at a time and can build a queue of jobs which are processed on a FIFO basis.

Jobs negotiate the services of a MT for its next operation by communicating directly to MTs that have the correct capabilities to fulfil the operation. The job and MTs then negotiate, primarily following the contract net protocol (Smith, 1980). On a high-level, the negotiation steps are: the job requests a cost for the operation from all capable MTs; the MTs reply with a cost; the job evaluates these and if the lowest cost MT is within a spending threshold; the contract is awarded to the MT and the job joins the back of the queue for this MT. Figure 4-1 diagrammatically explains this process. On completion of an operation the job repeats the process for the next and all subsequent operations.

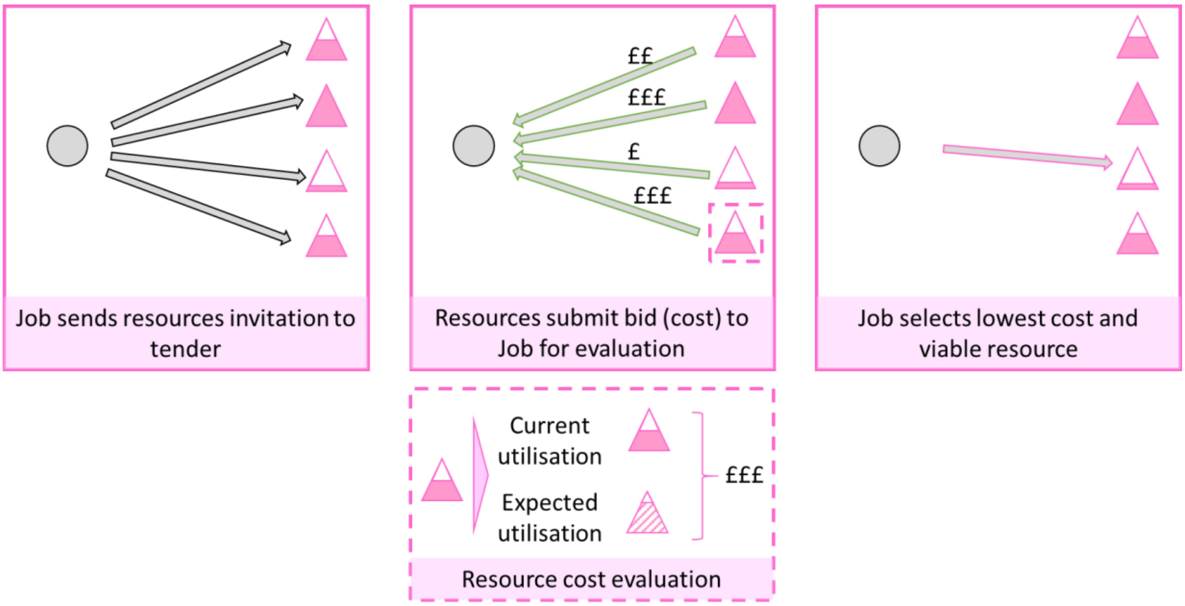

Figure 4-1: Anarchic manufacturing system's negotiation explanation

4.4.2 Agent descriptions

Jobs

Jobs have a predetermined sequence of operations to complete and only plan the next operation rather than determining a route through the whole manufacturing system. Additionally, jobs are given a budget to spend on consuming services; they are also instructed to spend so that they have sufficient budget to complete all their future operations. If there are r jobs in the system and job i is represented by j_i., the job set is composed as:

$$J = \{j_1, j_2, \ldots, j_r\} \tag{4.1}$$

To determine the available budget to spend on a given operation, the job accounts for both its remaining budget and future operations, to ensure its ability to complete all operations. $\gamma_i(t)$ denotes the remaining budget for job i at time t. $\psi_i(t)$ denotes the remaining number of operations for job i at time t. So, if $\lambda_i(t)$ is the allocated budget for an operation for job i at time t, the job allocates remaining budget equally to all remaining operations, following the equation:

$$\lambda_i(t) = \frac{\gamma_i(t)}{\psi_i(t)} \tag{4.2}$$

Job agent behaviour is governed by a statechart, a simplified version is shown in Figure 4-2. For a job's next operation, of capability C_i, it negotiates with capable MTs, of capabilities C_k, through a tendering and bidding process. The set of MTs who qualify to tender is evaluated as:

$$M_{i\,Bid} = \{M_k | C_i \in C_k\} \tag{4.3}$$

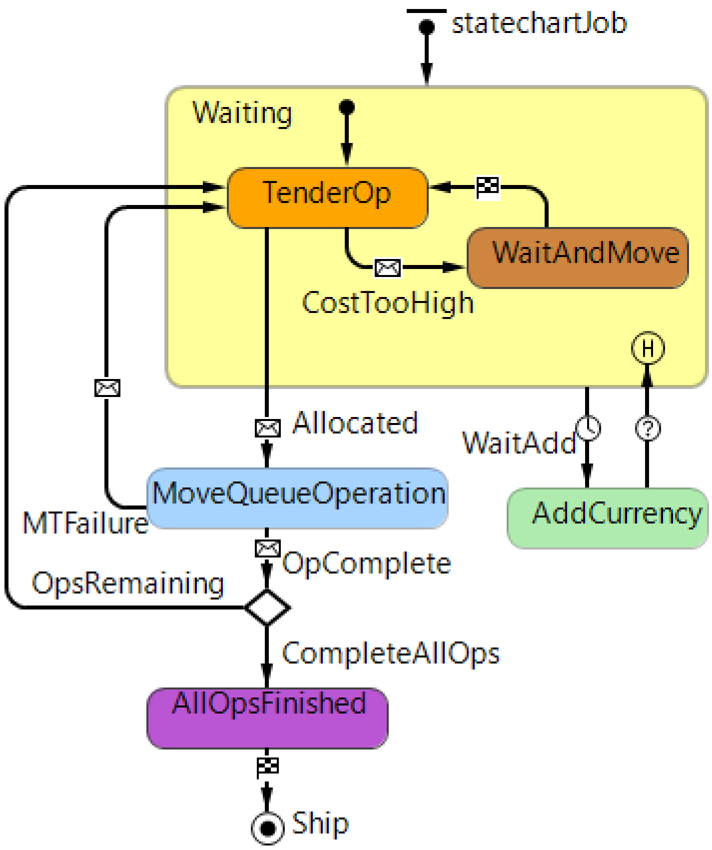

Figure 4-2: Job agent's AnyLogic simplified statechart

MTs tender and bidding is evaluated over a certain number of bidding rounds, to see whether the lowest cost MT of $M_{i\,Bid}$ is below the job's threshold. The Job's cost threshold for each budget in bidding round n, $\alpha_{i\,n}(t)$, is increased by the factor $\rho_i(t)$ between each bidding round; $\rho_i(t)$ is the Job's appetite for risk at time t. The initial thresholds are evaluated by:

$$\alpha_{i\,n}(t) = 0.9\lambda_i(t) \tag{4.4}$$

All subsequent bid rounds, $n+1$, cost thresholds are evaluated by:

$$\alpha_{i\,n+1}(t) = \rho_i(t) \cdot \alpha_{i\,n}(t) \tag{4.5}$$

where the risk factor ρ_i *(t)* is a function of budget remaining and operations remaining at time *t* denoted as:

$$\rho_i(t) = f(\gamma_i\ (t), \psi_i(t)) \tag{4.6}$$

Appetite for risk and the subsequent willingness to spend more contribute to the free market mechanism, where price rises as demand increases against a fixed supply. Additionally, the concept of risk highlights the agent's intelligence and changing behaviour in response to its dynamic environment. If successfully allocated to an MT, the job will join the queue for the MT for processing, if unsuccessful the job will wait to find a suitable MT at a different time. On completing all operations, the job will exit the system. Whilst a job is waiting and unable to find a suitable MT, the budget is regularly increased. Within a free market, a job with insufficient funds would not be processed at all, a regular budget increase negates this for manufacturing, as all jobs must be processed eventually even those with an initial low priority.

Machine tools

Machine Tool agents are service providers on a chargeable basis, enabling Jobs to complete operations and to prioritise operations on behalf of the whole system; a job assigned with a high budget indicates its priority and value to the manufacturing system. Assuming there are *q* machines in the system, the set of machines is defined as:

$$M = \{m_1, m_2, \ldots, m_q\} \tag{4.7}$$

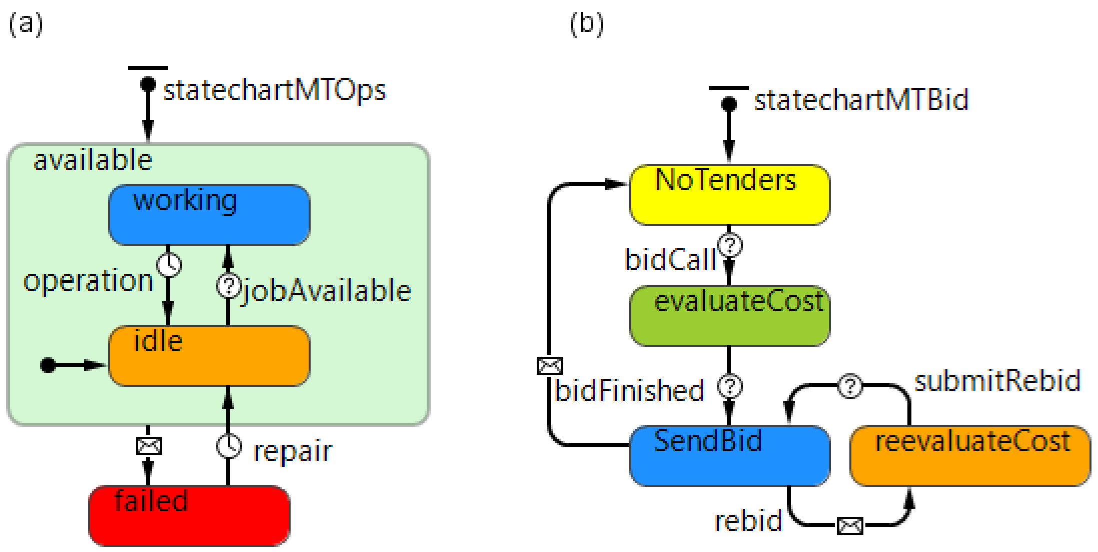

Figure 4-3: Machine Tool agent's AnyLogic simplified statechart, (a) operational (b) bidding

The cost for an operation on machine k at time t is denoted by $\beta_k\ (t)$, M_k has capabilities denoted as C_k. MTs operate operational and bidding processes simultaneously, these are governed by the two statecharts operating concurrently; simplified versions are shown in Figure 4-3. Figure 4-3 (b) governs the bidding process, of an initial cost $\beta_{k\,n}\ (t)$, where n is 0, which is a function of the MT's current utilisation and any subsequent rebidding costs, calculated as:

$$\beta_{k\,n}(t) = \frac{\beta_{max}}{3}\left(\omega_k(t) + max\left(\frac{Qc_k(t)}{Op_{plan}}, 1\right) + max\left(\frac{Qe_k(t)}{Op_{plan}}, 1\right)\right) \tag{4.8}$$

where β_{max} is a predefined maximum MT cost, $\omega_k(t)$ is the utilisation of MT k at time t, $Qc_k\ (t)$ and $Qe_k\ (t)$ are the current and expected queue lengths respectively for MT k at time t and Op_{plan} is the maximum number of operations a MT could fulfil within its planning horizon. The expected queue length, $Qe_k\ (t)$, provides consideration to the immediate and near future and is calculated by:

$$Qe_k(t) = \sum_{j=1}^{n_c} \frac{\sum_{i=1}^{j_r} J_{i\,j}(t)}{\sum_{k=1}^{m_q} R_{k\,j}} \tag{4.9}$$

Where n_c is the number of j capabilities in the system, $J_{i\,j}\,(t)$ is the number of jobs requiring capability j at time t, such that:

$$J_{i\,j} = \begin{cases} 1 & if\ job\ i\ requires\ capability\ j \\ 0 & otherwise \end{cases} \tag{4.10}$$

And the number of resources (MTs) with capability j is $R_{k\,j}$, a binary value defined as:

$$R_{k\,j} = \begin{cases} 1 & if\ resource\ k\ providing\ capability\ j \\ 0 & otherwise \end{cases} \tag{4.11}$$

The MT's cost is lowered between bid rounds by $\delta_k\,(t)$, which is a function of recent bid success at time t, and defined by:

$$\delta_k(t) = \delta_{max}\big(1 - \tau_k(t)\big) \tag{4.12}$$

Where $\tau_k\ (t)$ is the recent bid success of MT k at time t and $\delta_{max}\ (t)$ is the maximum bid reduction. MT costs for the second and all subsequent bid rounds, $n+1$, is calculated as:

$$\beta_{k\,n+1}(t) = \beta_{k\,n}(t) - \delta_k(t) \tag{4.13}$$

All functions used in the anarchic manufacturing model are directionally correct, providing a pragmatic and functional device reflecting the free market analogy; the optimised function construction and parameter selection are beyond the necessities of this research but are identified in future work. Figure 4-3 (a) models the MT's operational status, which includes the possibility of failure.

4.4.3 Negotiation structure

The negotiation framework follows a free market architecture for distributed systems (Dias and Stentz, 2000), with low-level negotiation mechanisms are a combination and adaptation of the contract net protocol with cost factor adaptation (Kádár and Monostori, 2001). There is no predefined structure or objective to maximise flexibility; resources (machine and human) and jobs (materials evolving to products) interact locally to achieve personal goals.

Local negotiation mechanisms use a bidding format where a job invites MTs that are capable of fulfilling its operation tendered, of capability C_i. Initially a job is prepared to pay a preset fraction of its budget, $\lambda_i\,(t)$ following equation 4.2 above, and calculates an initial threshold below this to try to gain market surplus, $\alpha_{i\,n}\,(t)$ is the job's threshold that bids are evaluated against and follows equation 4.4. MTs fluctuate their cost $\beta_{k\,n}\,(t)$ according to their utilisation, $\omega_k\,(t)$, and current and expected queues, $Qc_k\,(t)$ and $Qe_k\,(t)$, following equation 4.8. If the lowest cost MT β_n is below the job's cost threshold, $\alpha_{i\,n}\,(t)$, the Job is assigned to the MT, if not a second round of bidding is started.

For the second and all subsequent rounds of bidding, the job and MTs reconsider their bids, jobs increase their cost threshold, by the job's risk factor $\rho_i\,(t)$ calculated by equation 4.6, and MTs lower their cost by an amount they are willing to concede $\delta_k\,(t)$, according to its bid success, $\tau_k\,(t)$, as indicated by equation 4.12. This mechanism maximises profits for both agent types but still allocates operations. The rebidding mechanism is repeated for a certain number of rounds, and if unsuccessful the job gives up and waits before restarting the tendering process. Figure 4-4 shows the negotiation framework through a flowchart where n is the bid round, α the job cost threshold, ρ a risk factor that changes over time, γ the overall budget, λ the operation budget ψ number of operations remaining, C the capability of a job's operation of the MT's capabilities, β the MT cost, σ the MT cost reduction and MT utilisation and bid success are ω and τ respectively. The subscript notation is i the Job number, k the MT number, j the operation capability and n the bid round.

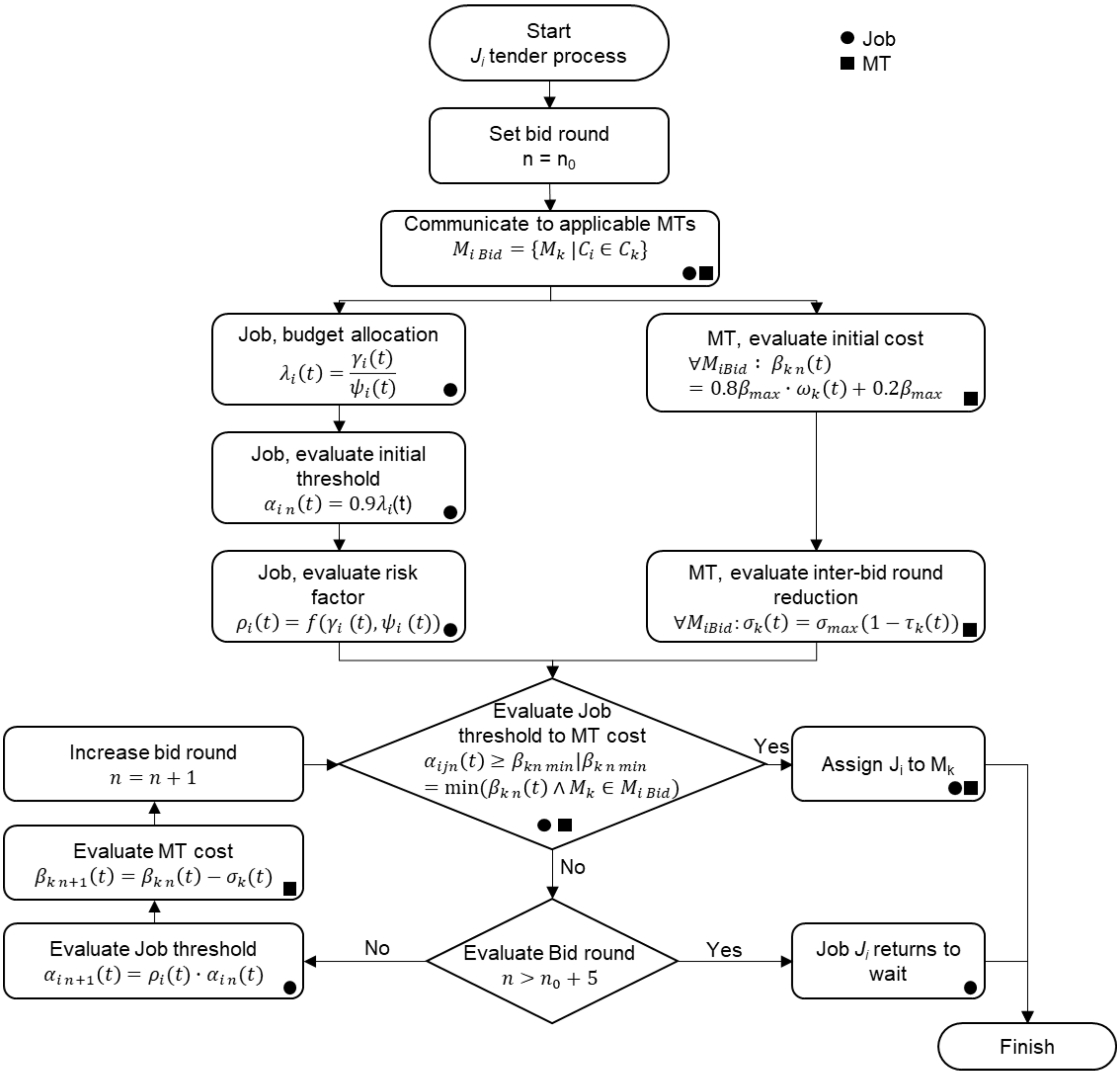

Figure 4-4: Anarchic manufacturing negotiation framework

4.5 Summary

The literature review in Chapter 2 identifies the challenges for smart manufacturing production planning and control as well as the need to evaluate free market distributed systems. This chapter defines design principles and then in Section 4.2 how they are fulfilled and embodied as an anarchic manufacturing system. First, the design principles are detailed, explaining why agent independence is required, why free markets and mechanisms are used and the system's stance on competitive and cooperative behaviour and ethical decision-making. The free market structure, with agent decision-making authority and autonomy, facilitates the rise of emergent synthetic behaviour and has adaptable mechanisms for differing scenarios. The overarching profit maximising mechanisms allow selfish agents to operate in the free market, their mechanisms for calculating profitability and possible collaborative actions to achieve greater profitability enable system development. The system does rely on ethical decisions and actions for the free market to work efficiently, these are ensured through predefined models to govern behaviour. This theoretical underpinning enables the embodiment of anarchic manufacturing, the system structure and core mechanics are explained in Section 4.4. The structure, agents and negotiation protocol are explained in detail, providing the basis for the anarchic manufacturing system.

To test and evaluate anarchic manufacturing, its performance is compared relative to centralised and hierarchical manufacturing systems in the following three chapters, Chapters 5 to 7. The theorised characteristics and affordances of anarchic manufacturing are analysed, for both the system adaptations for a given scenario and the behavioural outcome. The discussion in Chapter 8 evaluates both the theoretical and experimental performances of the anarchic manufacturing system, critiquing the system.

5 Application 1, simple discrete manufacture

5.1 Introduction

The first scenario to evaluate the anarchic manufacturing system considers simple discrete manufacturing in flexible manufacturing environments. Discrete jobs are independent of one another, although they may share the same operation characteristics; they do not need to join as an assembly or be delivered simultaneously and there are no sequence-dependent setup/changeover times. Jobs are provided with a sequence of operations to complete and their sole interaction is through sharing resources.

The research motivation for this chapter is to provide a baseline for the performance of the systems in a known environment, but also extend knowledge into specific scenarios that have not been evaluated for distributed systems. This and the following two chapters fulfil the third and fourth research objective outlined in Section 1.1. Job shop and flowshop style environments are well researched and often used as benchmark problems for algorithm development (Taillard, 1993), for this reason novel permutations of these manufacturing environments were evaluated to provide a baseline. Three scenarios and experiments were evaluated that highlight key characteristics of the planning and control problem in smart manufacturing, the first considered mass customisation and scale to increase the problem complexity. The second evaluated complicatedness and complexity, complicatedness was increased by reducing machine tool capability and therefore resource flexibility, and complexity was increased by adding non-coupled operator selection to the resource chain. The final scenario and experiment considered whether the systems can manage multiple and conflicting objectives, by adjusting the cash and on time delivery objectives. The first two apply the manufacturing systems in steady state environments, allowing the simulations to ramp up and stabilise, rather the third applies disruption as a step change in objectives creating a more dynamic environment. This progression provides the performance baseline and tests thesis hypothesis, stated in Section 4.2, that the free market distributed system can be applied to dynamic environments.

This chapter first reviews additional background literature, then details through each experiment in turn, stating the problem considered, adaptations to the systems used, experiment setup and parameters, displays and discusses experiment results, finally the chapter summarises outcomes from all experiments. A summary table of additional elements to the anarchic system introduced in this chapter are indicated below in Table 5-1.

Table 5-1: Additional anarchic system elements introduced in Chapter 5

Element	Meaning
LF_i	Lateness Factor for job *i*, a consideration for a job of whether it will be early, meet, be late for its individual due date
E_i	Expected due date for job *i*
D_i	Due date for job *i*
OTObj	On Time Objective, the global on time objective performance, i.e. whether the system is reaching its on time objective
CScr	Cash score, the score considering the cash / revenue position against the cash / revenue objective
CF_i	Cash Factor for job *i*, a consideration for a job of whether the global cash position (cash score) will impact its cost threshold
κ_i	Completion percentage for a job, considering the number of operations completed and still outstanding

5.2 Scenario background

Recent manufacturing system production models have shifted their focus; from production maximisation to cost reduction, process standardisation to mass customisation and production-centric to service-oriented (Lu, Xu and Xu, 2014). Smart manufacturing business objectives aim to satisfy greater demand volatility, mass customisation and accommodate non-manufacturing concerns, e.g. social and environmental. One of the most challenging is mass customisation; providing custom goods and services at mass production prices, but this has yet to be fully realised (Ferguson *et al.*, 2018); partly because variants drive complexity (Vogel and Lasch, 2016). For further background to mass customisation please see section 2.2.5.

Manufacturing complexity is poorly defined, many definitions attempt to classify types of complexity, such as dynamic and structural, or use entropy and heuristic approaches to quantify complexity (Kuzgunkaya and ElMaraghy, 2006; Elmaraghy *et al.*, 2012). Increasing constraints and reducing flexibility increases system complicatedness, Kuzgunkaya states reduced versatility and flexibility of resources increases system complexity (Kuzgunkaya and ElMaraghy, 2006). Considering an entropic definition of complexity (Huaccho Huatuco *et al.*, 2009), as the number of agents (scale) or shared resources required per operation increases, the number of states the system can be in rises exponentially, denoted as $O(a^N)$ an exponential complexity problem. For further background to manufacturing complexity please see section 2.3.2.

The multicriteria decision-making approach TOPSIS is used as a comparative tool in this study, to represent traditional methods where multiple distinct alternatives are available. Free markets use a different methodology, where the price of a good / service encodes all factors associated in providing the good / service into a single concise value, allowing locally optimal decisions based on low-bandwidth information (Dias and Stentz, 2000). Anarchic manufacturing, based on the free market, has been adapted to consider multiple objectives by influencing the amount a job is willing to spend on its next operation (bidding thresholds).

5.3 Experimentation

5.3.1 Mass customisation and scale

Mass customisation at scale is a business objective within smart manufacturing. This entails individual job customisation to suit a customer, manufactured in batches of one, at a very large scale. To distil the problem down to its characteristics it is evident, as customisation and scale increase, complexity increases. Increasing customisation, reflected as greater random and diverse operational requirements and durations, increases uncertainty and therefore problem complexity from a planning and control point of view (Elmaraghy *et al.*, 2012). Taking an entropic view of complexity, scale directly increases the complexity of a system, as there is an exponentially increasing number of states the system can be in (Huaccho Huatuco *et al.*, 2009). The anarchic manufacturing system was compared against centralised systems, with hierarchical and flexible structures. Figure 5-1 summarises the scenario and experimental parameters diagrammatically, indicating the experiment variable parameter inputs, the general scenario structure, the decision-making authority structures evaluated, and metrics analysed.

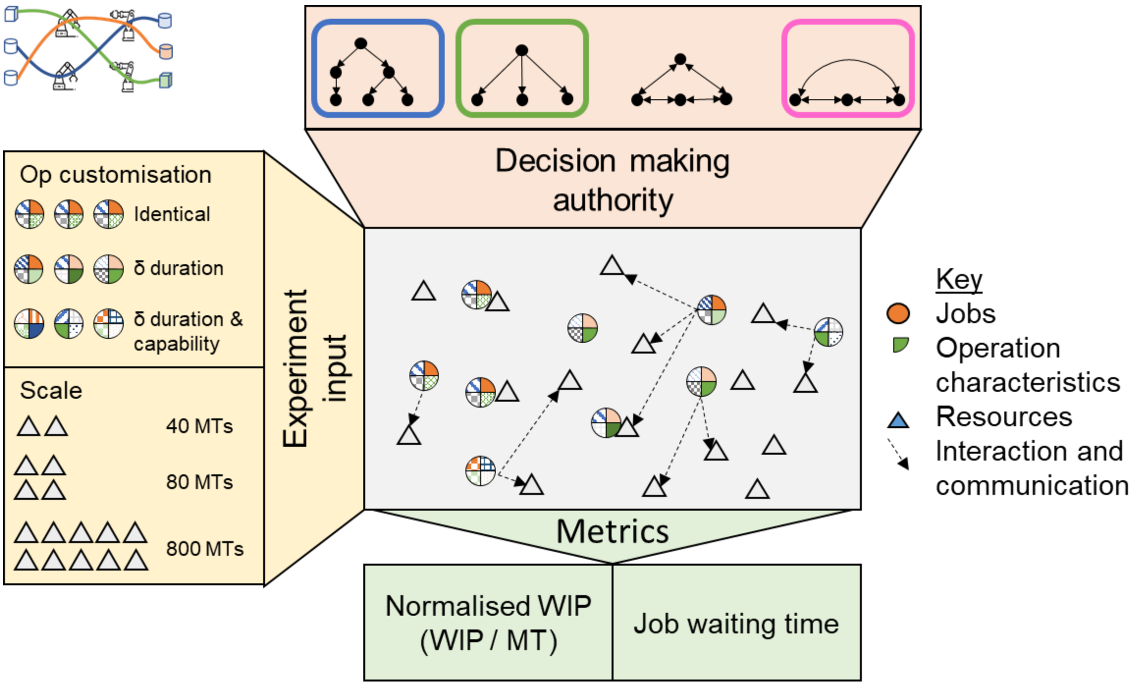

Figure 5-1: Mass customisation and scale experiment summary

System adaptations

The only adaptations for the anarchic system, defined in section 4.2 for this experiment, allowed for jobs to factor in distance and transferring time into the machine tool cost, to prefer closer MTs. This change is highlighted in Figure 5-2, where the job threshold is evaluated against the lowest MT cost multiplied by a distance factor, which accounts for distance to the MT.

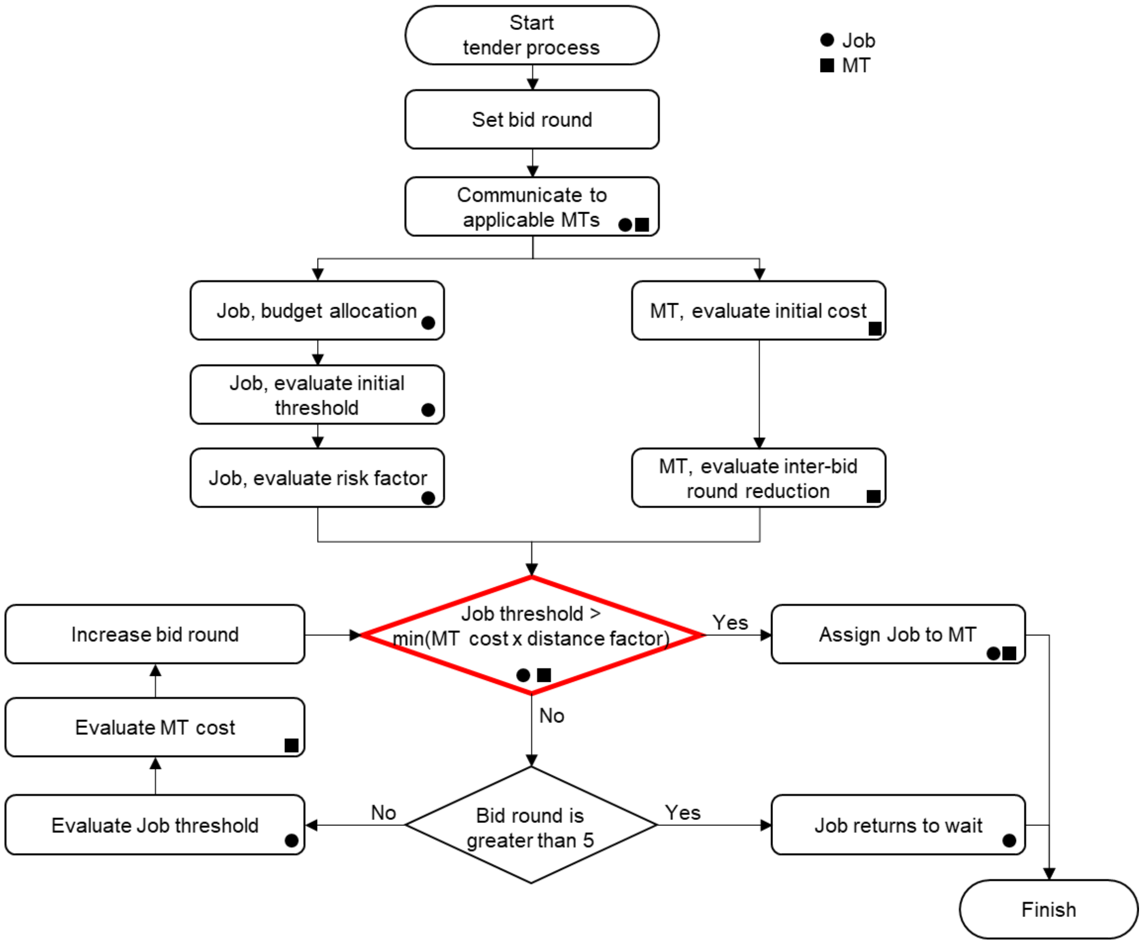

Figure 5-2: Mass customisation and scale adjusted negotiation framework

The centralised systems, hierarchical and centralised flexible as defined in section 3.3.2, use a FIFO dispatch rule and allocates jobs to the next available and capable resource or hierarchy level (decision makers within the hierarchical system only considered the pool of jobs within its range of control in the immediate level below). The hierarchical system had three levels, global, cell and MT and maintained roughly 10 MTs per cell. MTs were allocated to cells by their location.

Experimental framework

The overall experimental setup followed the general experimental structure stated in Section 3.3.4, it involved continuous job arrivals to maintain a holistic 50% MT utilisation and achieve a steady state environment. Each job had four sequential operations, the capabilities and durations of these are varied, see variable parameters below. Overall, there were eight operational capabilities (A-H) of the same nominal duration. MTs had two capabilities (e.g. capability C & D); they were located randomly in the modelling space. On completing all operations, jobs left via a central ship point. Key fixed experimental parameters are summarised in Table 5-2.

Table 5-2: Mass customisation and scale experiment fixed parameters

Fixed parameter	Level
Operations / job	4 operations
Operation duration nominal	10t
System utilisation	50%
No. operation capabilities (classifications)	8
Capabilities / MT	2

Two experimental parameters were varied, the degree of job operation customisation and system scale. Operation customisations were varied by duration and capability required; this parameter is denoted as OpCust. For OpCust = 1, homogenous jobs were produced with identical and deterministic durations with sequential operational capability requirement (i.e. A-B-C-D or E-F-G-H); for OpCust = 2 durations were random uniformly varied, 10t ($\mathcal{U}$ [7.5, 12.5]); for OpCust = 3 durations were random uniformly varied, 10t ($\mathcal{U}$ [5, 15]), and capability of each operation was random uniformly selected from all capabilities (A-H); these OpCust parameter levels are summarised in Table 5-3. The second variable parameter is scale, denoted as Scl and summarised in Table 5-4, levels were: Scl = 1 at 40 MTs, Scl = 2 at 80 MTs, Scl = 3 at 800 MTs. The experiment evaluated all possible combinations of OpCust and Scl, each experiment was repeated for ten runs, each run kept the same random inputs. The metrics recorded were normalised WIP, this by MT i.e. average queue size; and waiting time, which is lead time less operational time (randomly varied) i.e. time for moving and queuing.

Table 5-3: Mass customisation and scale experiment, operation customisation variable parameter

Operation customisation parameter level	Duration	Operation capability sequence
OpCust = 1	10t	A-B-C-D or E-F-G-H
OpCust = 2	10t ($\mathcal{U}$ [7.5, 12.5])	A-B-C-D or E-F-G-H
OpCust = 3	10t ($\mathcal{U}$ [5, 15])	A-H uniform randomly assigned for each operation

Table 5-4: Mass customisation and scale experiment, scale variable parameter

Scale parameter level	No. MTs
Scl = 1	40
Scl = 2	80
Scl = 3	800

Results and discussion

The experimental results were averaged for all runs for each combination of OpCust (operation customisation) and Scl (scale), Figure 5-3 displays the WIP / machine tool results and Figure 5-4 displays the job waiting time results. At a high level, these metrics demonstrate that the centralised system remains consistent for all experiments, rather both the hierarchical and anarchic improve with scale. The absolute superior performance of the anarchic systems is evident, as is the very poor hierarchical cellular system which never reaches system stability.

WIP / MT results, shown in Figure 5-3, displays a clear trend of improving anarchic performance, as WIP / MT decreases on increasing parameter levels and complexity, and the hierarchical cellular system is consistently poor. The flexible centralised system retains a consistent performance. Anarchic system's improving performance is likely to be an emergent outcome of the free market architecture; an increase in competition improves overall system efficiency. Increasing scale increases system complexity and difficulty to become allocatively efficient, the result that the anarchic system improves with scale and therefore complexity, under certain scenarios, is very promising. The hierarchical cellular structure is clearly the worst to fulfil mass customisation, the restrictive architecture heavy detriments performance.

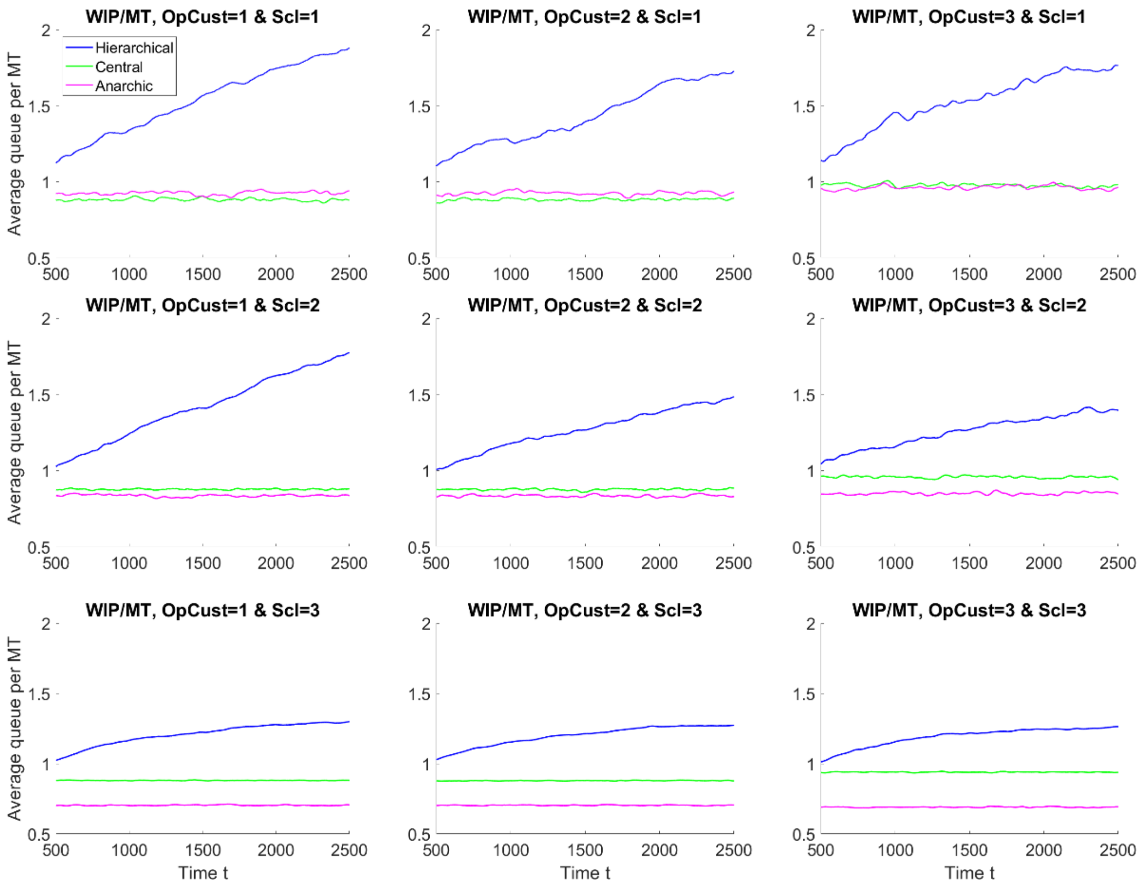

Figure 5-3: Mass customisation and scale WIP / MT results

Waiting time results show a similar outcome, displayed in Figure 5-4, whereby the hierarchical system performs significantly worse, rather the flexible centralised and anarchic perform consistently; with the anarchic being superior in large-scale scenarios (Scl = 3 at 800 MTs). The outcomes are clear from the probability densities and the 90% population mark. The consistency of performance for the centralised and anarchic system is positive, however, the hierarchical cellular structure's long tail is unacceptable for most manufacturing scenarios.

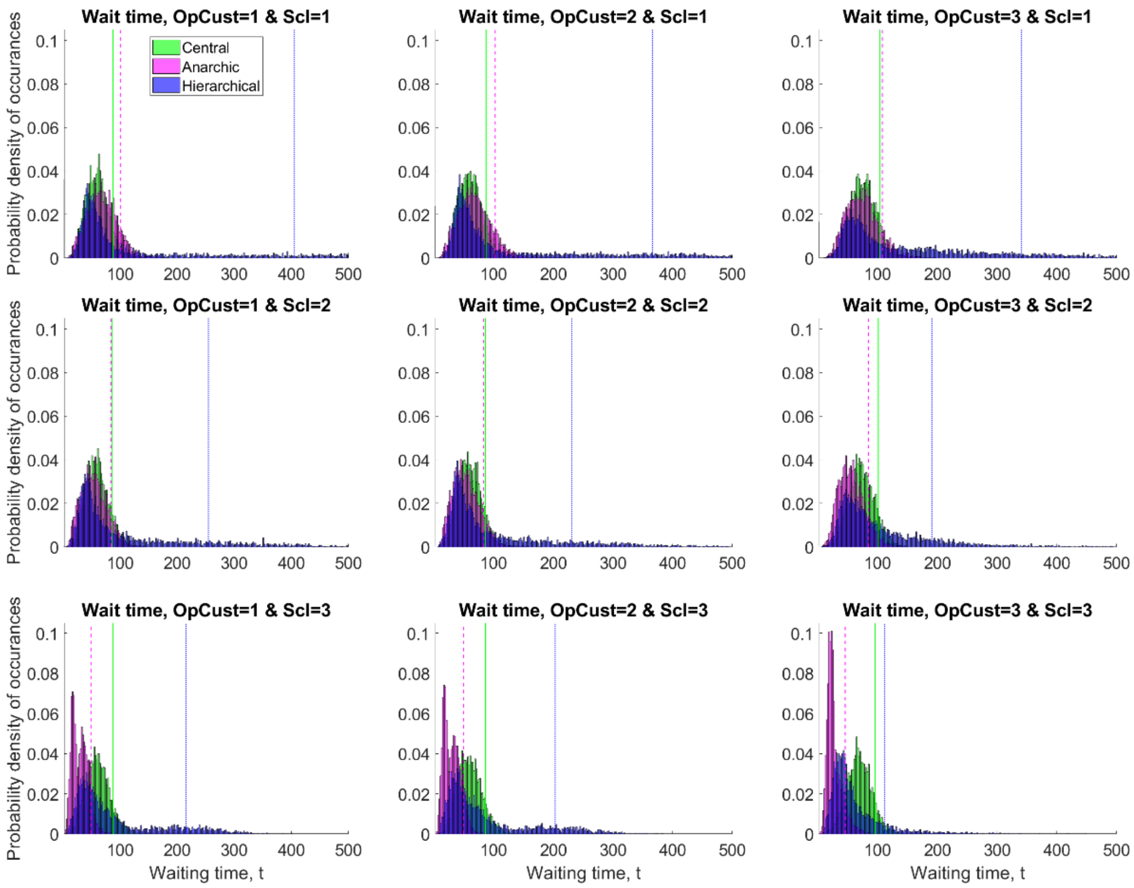

Figure 5-4: Mass customisation and scale waiting time results

Contrary to the traditional methods to deal with complexity, by creating hierarchical structures, a single centralised method or an anarchic distributed system is better. Further levels of hierarchy and cell structures significantly impede overall performance; they will likely restrict flexibility and will not be able to manage the large complexity associated with mass customisation. Anarchic manufacturing provides a novel approach to solving mass customisation through free market principles.

This experiment, evaluating mass customisation and scale, has shown that under certain conditions, where operations become increasingly diverse through a larger duration range and capabilities for operations are randomly assigned, the anarchic system performs best and improves as scale increases; all systems reacted similarly to increasing customisation.

5.3.2 Complicatedness and complexity

Modern smart manufacturing, as it moves away from dedicated mass production lines to smaller batches and flexible manufacturing production models, will become more complex (Lee, Rahimifard and Newman, 2004). The rise in complexity will be compounded through the proposed solution that uses smart factories, utilising advanced digital technologies and systems such as the Internet of Things (Bi, Xu and Wang, 2014) and Cyber-Physical Systems (Monostori *et al.*, 2016a). The number and combinations of system elements, their states and capabilities to be managed will dramatically increase, resulting in a significantly more complex planning and control problem.

This experiment increased complicatedness, by reducing machine tool flexibility, and increased complexity, by mandating a non-coupled operator to the resource chain. Increasing constraints and reducing flexibility increases system complicatedness, Kuzgunkaya compares several manufacturing system configurations and states reduced versatility and flexibility of resources increases system complexity (Kuzgunkaya and ElMaraghy, 2006). Using an entropic view of complexity, reducing the flexibility will not increase the system states exponentially, hence the author is describing this restriction as complicatedness. The need to increase the resource chain, from selecting a MT to also selecting an operator from a pool of shared resources does increase the problem complexity; resulting in an exponential increase in options (Huaccho Huatuco *et al.*, 2009).

The experiment is summarised in Figure 5-5, identifying the variable parameters and planning and control systems used. The capabilities of MTs is reduced and the number of resources required in the resource chain is increased. The anarchic system is compared to a centralised system, and WIP and job waiting time are the metrics analysed.

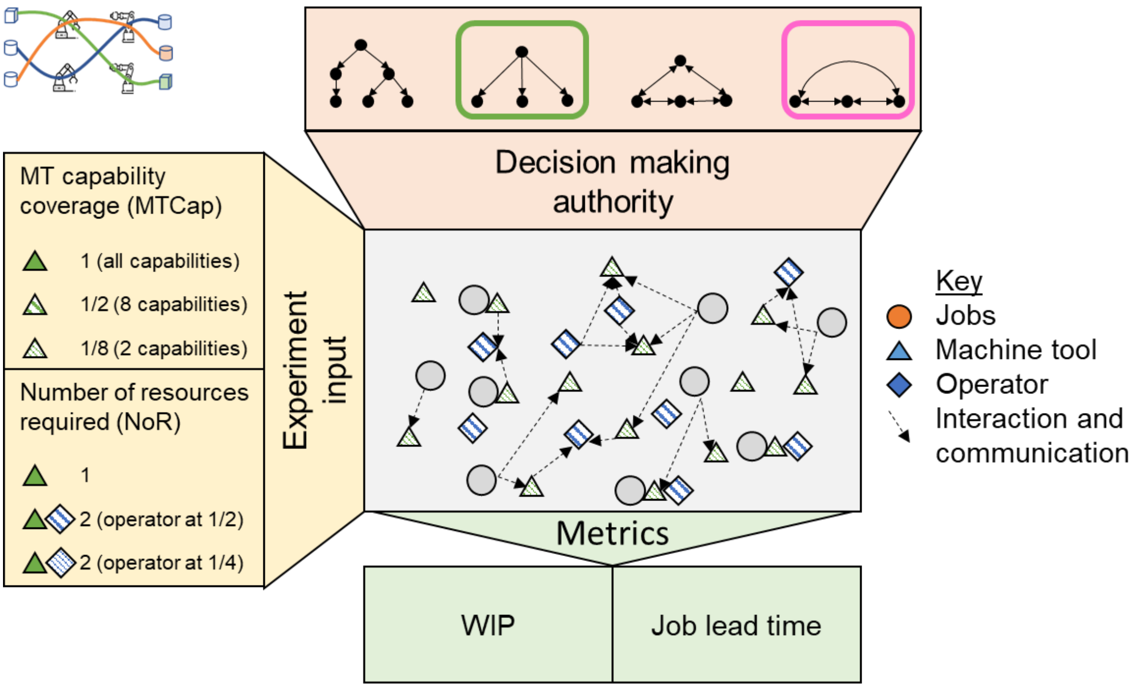

Figure 5-5: Complicatedness and complexity experiment summary

System adaptations

The anarchic manufacturing system has been adapted so that when the resource chain requires an operator, the MT bid for an operator reflecting job to MT negotiation; this is diagrammatically summarised in Figure 5-6 as a two stages negotiation. Using the negotiated cost between the job and resource 1 plus surplus budget accrued by resource 1, each resource tendered and negotiated the next resource along the chain. Otherwise, the anarchic manufacturing system is unchanged.

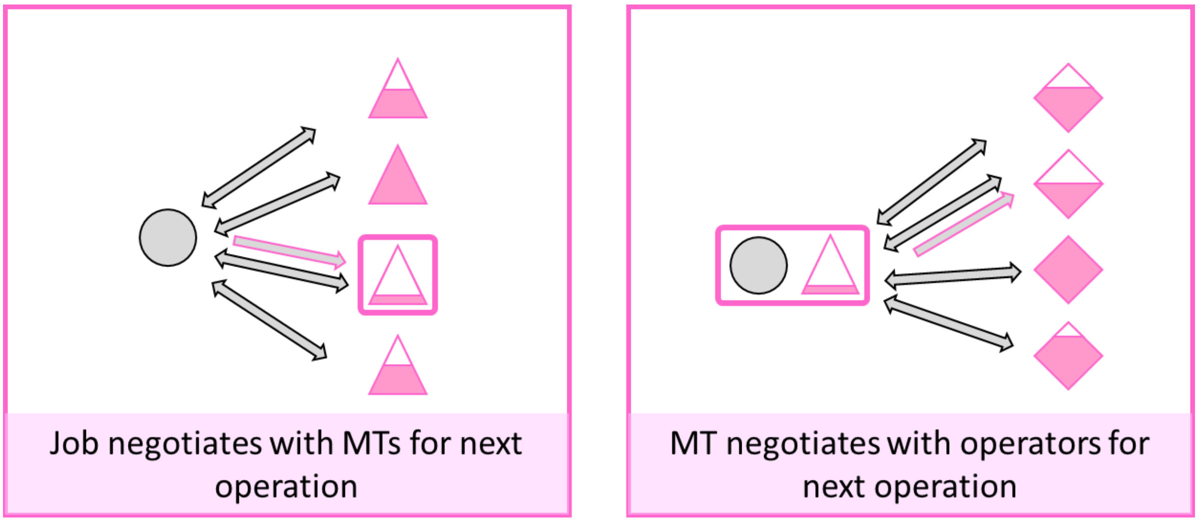

Figure 5-6: Resource chain two stages negotiation

The centralised system managed all resources centrally, allocating to the next available MT on a FIFO basis. For multiple resource scenarios, the job is allocated to resource 1 which is then allocated to resource 2, via the same dispatch rule.

Experimental framework

The experiment simulated a job shop style environment, with complete route flexibility, the jobs had four operations to complete. All operations had the same random uniform duration of 15t ($\mathcal{U}$ [10, 20]) and uniformly allocated one of the 16 capabilities modelled. A stable steady-state environment was created through fixed parameters, which maintained nominal MT utilisation at 68% through a fixed job arrival rate. Resources had multiple and overlapping capabilities, the spread of these capabilities was varied according to the variable experiment parameter. For the anarchic system, all jobs were given the budget of the expected average cost for all operations. A summary of parameter levels is shown in Table 5-5.

Table 5-5: Complicatedness and complexity experiment fixed parameters

Fixed parameter	Level
Operations / job	4 operations
Operation duration (random uniform distribution)	15t ($\mathcal{U}$ [10, 20])
System utilisation	68%
No. operation capabilities (classifications)	16
No. MTs	16
No. operators (if required)	16

Global information was publicly available to both systems including number of resources, number of resources of each capability, capability required of the jobs' operations. Variable parameters reflected an increasingly complicated and complex system, by reducing flexibility through reducing resource capability and increasing the number of shared resource types required respectively; these reflect real-world challenges. The MT capability parameter (MTCap) was denoted by the proportion of all capabilities covered by machine resources; reflecting specialised machines for more difficult operations or lower cost fewer flexible resources. The number of resources parameter required per operation (NoR), machine and operator, was extended by reducing the operators' capabilities, see Table 5-6 for variable parameter levels.

Table 5-6: Complicatedness and complexity variable parameters

Variable parameter	Levels	Value
Machine capability coverage (MTCap)	1	1 (all capabilities/MT)
	2	1/2 (8 capabilities/MT)
	3	1/4 (4 capabilities/MT)
	4	1/8 (2 capabilities/MT)
Number of resources (operator capability coverage), (NoR)	1	1 (MT only)
	2	2 (MT and operator at 1/2 coverage)
	3	2 (MT and operator at 1/4 coverage)

Twelve experiments were run at four levels of variable parameter MTCap (MT capability) and three levels of parameter NoR (number of resources and operator capability), each experiment was run ten times. Each run had identical random number inputs for direct comparability.

Results and discussion

Simulation results, analysing Work In Progress and job waiting time, suggest the anarchic system adapts better to increasing complexity as the resource chain increases, although both deteriorate equally as complicatedness from constraints increase. WIP and waiting time reflect the system state and the job's perspective; both have a lower the better measurement. WIP results, smoothed with a rolling average and then averaged for all runs with a 95% confidence interval, are seen in Figure 5-7. Job waiting time was plotted on histograms with an 80-percentile marker, with a reduced vertical scale insert for clarity, shown in Figure 5-8. Practical implementation considerations notwithstanding, both systems are directly comparable; as one is not significantly more sophisticated or provided unfairly advantageous information.

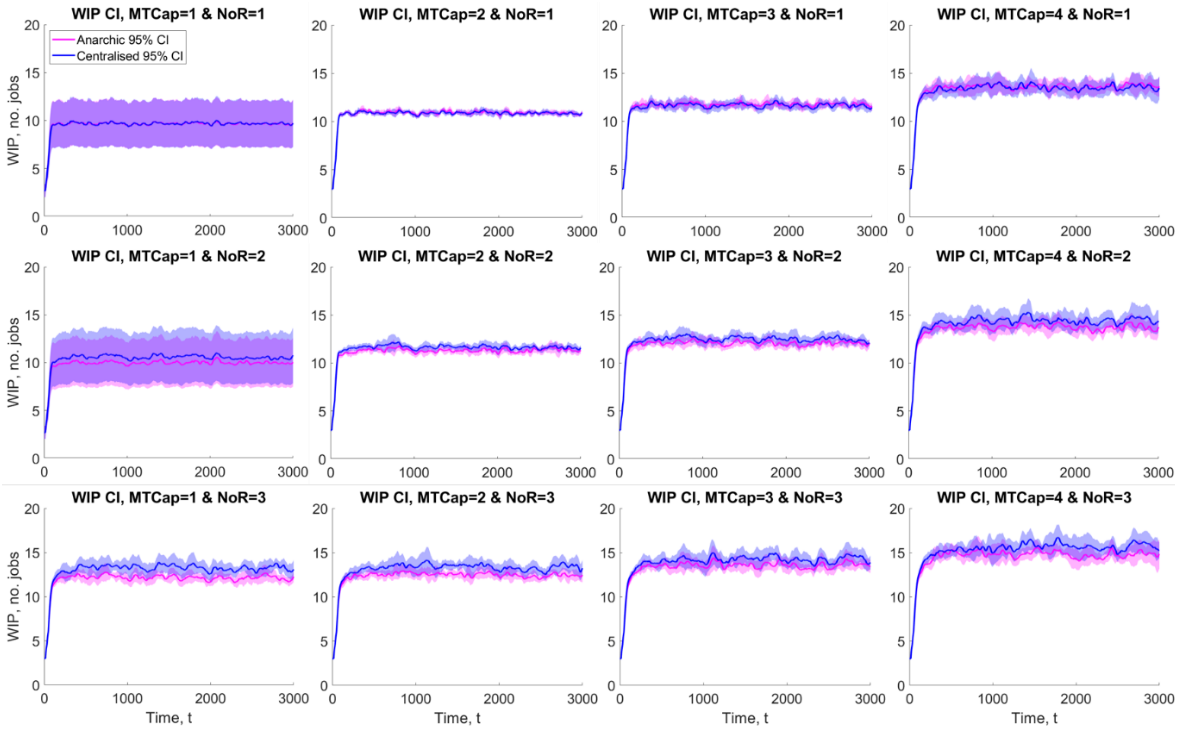

Figure 5-7: Complicatedness and complexity WIP results

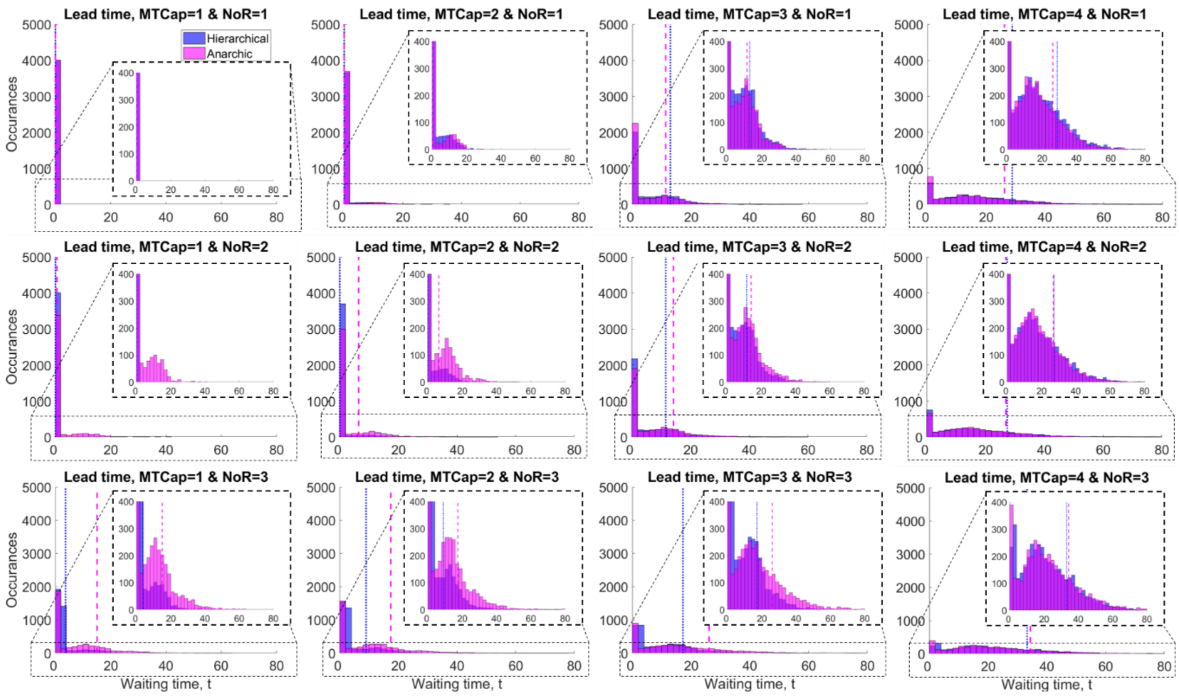

Figure 5-8: Complicatedness and complexity lead time results

The anarchic system is expected to have superior job allocation, due to better foresight. Considering a contrived scenario of two machines, one of capability ‘A’ and the second of ‘A’ and ‘B’, and ten jobs, the first four with capability requirement ‘A’ and the rest ‘B’. The centralised system would allocate the first four jobs evenly and the remaining to machine 2;

whilst the anarchic would consider all upcoming jobs and allocate the first four to machine 1 and the rest to machine 2, this is allocatively more efficient and applied in a more realistic and complex scenario in this thesis.

WIP results show that as variable parameters MTCap and NoR increase, both centralised and anarchic system's performances deteriorate, however, the centralised system deteriorates more as NoR and complexity increases. For NoR = 1, there is no clearly discernible difference. However, an addition to the resource chain immediately causes the centralised system to perform worse. This is extended as the secondary resource's capability reduced (NoR = 3 with operator capability at 1/4 coverage) and maintained as machine capability was reduced. This is at the edge of the 95% confidence interval plotted, observed by comparing the mean value of one system to the confidence interval range (coloured area) of the other.

The anarchic system's superior performance as NoR parameter increases and maintained as MTCap increases suggest that both systems are comparable as the system becomes more complicated, however, as complexity increases the anarchic can manage coordination complexity better. Increasing the number of resources required along the resource chain significantly increases the relative complexity from an $O(a^1)$ to $O(a^2)$. As (machine capability) rises complicatedness increases, and the deteriorating performance difference is maintained; which hinders the flexibility of both systems in a similarly.

The distribution of job waiting time is largely similar for centralised and anarchic systems, particularly in the worst performing scenarios, during less constrained scenarios (MTCap < 4) the centralised system performs slightly better. Waiting time impacts a manufacturer's service level, typically denoted by fulfilling a percentage of orders within a specified time. Service level contributes to the metric On Time In Full (OTIF) (Ahmad and Dhafr, 2002), where there is a greater desire to avoid lateness rather than promote fulfilling early. The 80-percentile marks, shown in Figure 5-8, are broadly similar; however, at the most constrained case of MTCap = 3 (1/8 capability coverage per MT) and worst performing, both systems perform very similarly. Suggesting that system constraints impact anarchic system's waiting time more, but as waiting time becomes a crucial factor both systems perform similarly.

The results indicate that as complexity increases, the anarchic system is likely to be able to deal with complexity and perform better. This is likely to be true for increasingly uncertain scenarios that move from complicated to complex and chaotic, the anarchic should be more adaptable.

5.3.3 Multiple conflicting objectives

Manufacturers and businesses are faced with multiple and often conflicting objectives, as discussed in Section 2.3.3; two of which are meeting due dates (minimizing lateness) and maximizing cash. Businesses need to ensure there is sufficient cash to cover expenditure and remain solvent, additionally customers demand a high On Time In Full (OTIF) performance, usually expressed as a percentage of orders delivered. Considering a short-term horizon, conserving cash can be achieved by delaying expenditure on operations, however, delaying operations will impact lateness. Alternatively, ensuring a job is completed by its due date is likely to entail advanced processing of operations and consequent early expenditure of cash, thereby reducing a manufacturer's cash position. These issues relate to scheduling and control, which determines the allocation of resources to tasks over given time periods (Stecca, 2014), i.e. the timing of specific operations.

This experiment evaluates how different organizational structures can resolve multiple conflicting global objectives, and specifically assesses the capability of the anarchic manufacturing system against conventional approaches; by evaluating their ability to meet on time and cash objectives. This experiment is diagrammatically summarised in Figure 5-9. The main criticism for distributed systems is myopic decision-making; with respects to a short-term time horizon and localised problems rather than global problems. This experiment assesses anarchic manufacturing system's ability to meet changing global objectives and indicates whether local myopic decision-making can be improved.

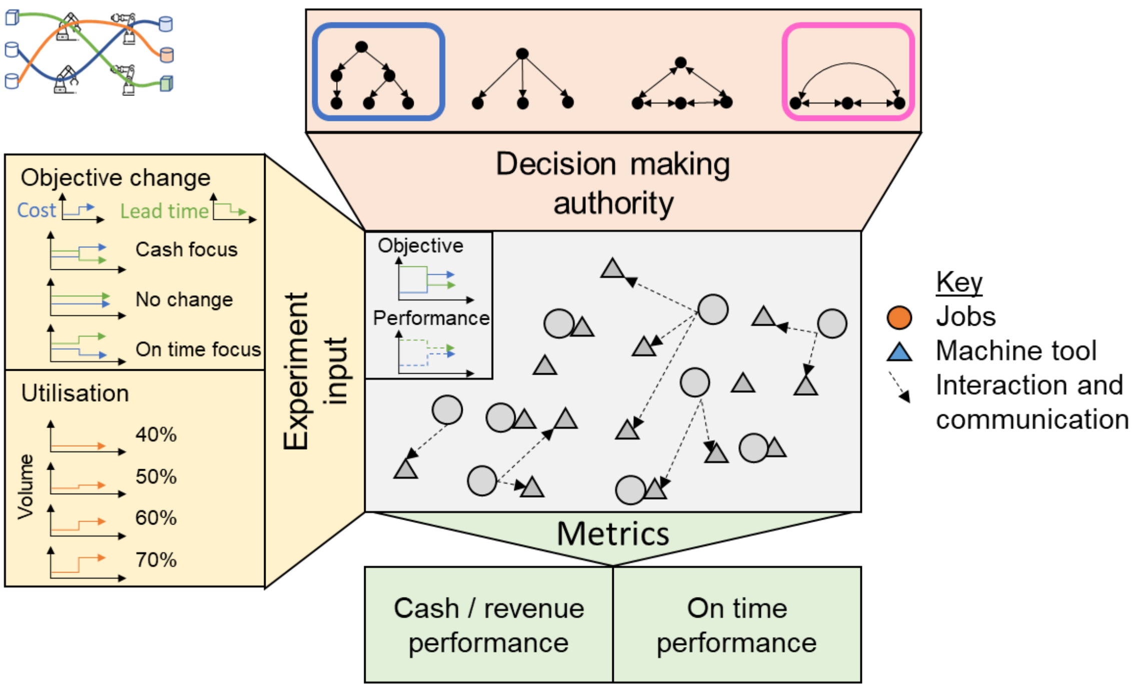

Figure 5-9: Multiple conflicting objectives experiment summary

System adaptations

The manufacturing systems aim to balance dynamic objective levels for on time and cash levels, both are normalised; as the percentage of jobs completed on time and cash as a percentage of revenue. Performance is scored against these objectives, where <1 : 1 : >1 are underachieving : meeting : overachieving.

The anarchic system used in this experiment extended the system disclosed in section 4.2 by considering multiple objectives and adapting the bidding threshold and currency available for each job. The main adaptation was the jobs' budget allocation, which was multiplied by cash and lateness factors instead of a risk factor, this difference is highlighted in Figure 5-10. This was the cost threshold to spend on its next operation and negotiate with capable MTs. This allowed each job to consider its individual likelihood to be on time and the global manufacturer's cash position against the cash objective to account for the system's global multiple objectives. Additionally, jobs were able to renege on arrival to a MT; by paying off and taking the place of the next job in the queue. Reneging improves the overall prioritisation of jobs whilst maintaining free market mechanisms and anarchic manufacturing principles.

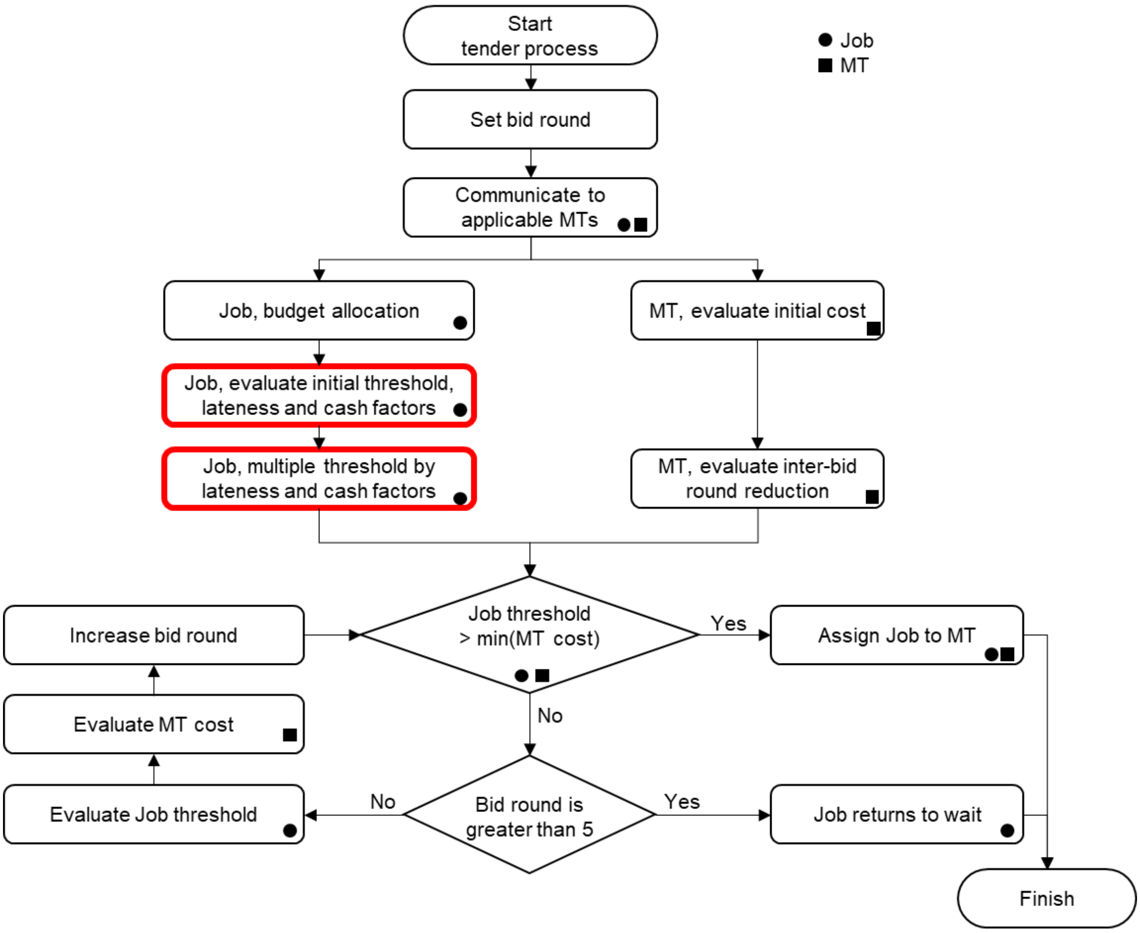

Figure 5-10: Multiple conflicting objectives adjusted negotiation framework

Job i's lateness factor at time t, $LF_i(t)$, was multiplied to the allocated budget for the next operation for the initial bidding threshold and was derived from the job's likelihood to be on time and the manufacturer's objective level. This on time adjustment factor encouraged jobs to spend more to secure an operation sooner within reasonable means of its budget. Due date, $D_i(t)$, and expected due date at t, E_i (t), was compared against the manufacturer's on time objective at time t, $OTObj(t)$, to provide the lateness factor which is bounded by a ceiling of 2, as displayed in equation 5.1.

$$LF_i(t) = \begin{cases} \left(\frac{E_i(t) - D_i(t)}{D_i(t) - t}\right) + OTObj(t) & if \left(\frac{E_i(t) - D_i(t)}{D_i(t) - t}\right) + OTObj(t) \leq 2 \\ 2 & otherwise \end{cases} \tag{5.1}$$

Job i considered the manufacturer's cash score at t, $CScr(t)$, which was determined by comparing the cash/revenue position against the cash/revenue objective, *CObj*, if this was greater or equal to 1 the cash factor, $CF_i(t)$, had no impact ($CF_i(t) = 1$). If the manufacturer's cash factor was below 1, jobs prioritised those nearest completion relative to the population of jobs. The distribution increased dependent on the severity of the cash score and the job's percentage completeness relative to the mean completeness of all jobs. Completion percentage for job i at t is $\kappa_i(t)$, and the mean completion percentage of all jobs at time t is $\bar{\kappa}(t)$. The cash factor calculation follows equation:

$$CF_i(t) = \begin{cases} CScr(t) + (1 - CScr(t))\left(\frac{\kappa_i(t)}{\bar{\kappa}}\right) & if\ CScr(t) < 1 \\ 1 & otherwise \end{cases} \tag{5.2}$$

The redistribution of currency was required for jobs to be able to bid with an increased threshold when the cash factor ($CF_i(t)$) was greater than 1 for job i, without negatively impacting the job in future operations, this additional cash was provided by other jobs with a cash factor less than 1 (below the average completion percentage). Jobs provided the cash that could have been spent on the next operation but chose not to as influenced by the cash factor, i.e. $1 - CF_i(t)$. This currency was available for jobs whose cash factor was greater than 1 and required additional currency to achieve the new threshold, as determined by the cash factor, i.e. $CF_i(t) - 1$, for its next operation. The inter-round bidding increment increased a job's cost threshold, this was calculated as cash and lateness factors multiplied together.

Jobs reneged on arrival at a MT by paying off the job in front if possible, the currency allocated to the next operation but not spent on the MT contracted cost was deemed surplus and available to renege with. The job in front calculated its pay off cost, as the difference between the contracted cost of the operation and a recalculated threshold considering its budget allocation multiplied by lateness factor, $LF_i\,(t)$. This allowed jobs to prioritise themselves within the MT's queue, which otherwise operated on a FIFO basis. This mechanism maintains anarchic manufacturing principles whilst enabling cooperative behaviour, as a job may be willing to delay its operation for a fee which is influenced by the lateness factor.

The hierarchical manufacturing system, diagrammatically shown in Figure 5-11 had four decision-making tiers; global, division, cell and machine tool. The top three tiers used coordinators to allocate jobs to the tier below them through a dispatch rule. The coordinators used a version of the multicriteria decision-making method TOPSIS, selecting the appropriate dispatch rule to improve the poorest performing objective. This was achieved by comparing the global cash position and the likely on time performance of the population of jobs within its hierarchy; e.g. a division coordinator considered the jobs that populate the cells and MTs within its span of control. The dispatch rules selected were Earliest Due Date (EDD) to improve on time performance, and Shortest Processing Time (SPT) to improve the cash position.

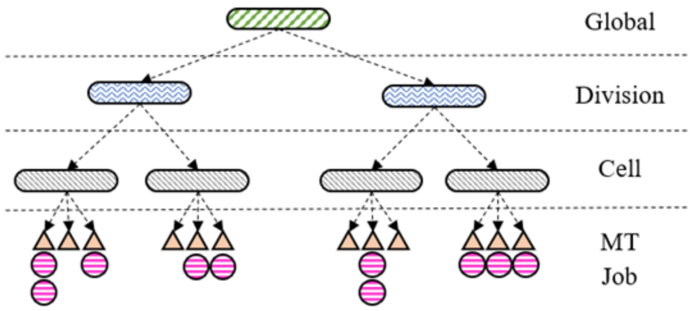

Figure 5-11: Multiple conflicting objectives experiment, hierarchical system structure

Experimental framework

The experiment evaluated whether anarchic and hierarchical systems can balance multiple objectives and trade-off performance to best achieve conflicting objectives. The problem considered a manufacturer with multiple MTs, with different and overlapping capabilities, that processed individually variable jobs. For this experiment, there was a step-change at 1500t, after simulation ramp-up, where system utilisation (demand) increased and objectives may be changed; there were no other disruptions (e.g. MT failure or cash reduction). Each experiment used 100 repeatable runs; each run had different random inputs. Instantaneous communication and decision-making were modelled for greater direct comparability.

Fixed experiment parameters were selected to showcase system behaviour in a realistic scenario whilst reducing noise; these are shown in Table 5-7. Jobs on completing an operation incur a cost, revenue was realised on or after the job's due date when jobs had completed their operations, this revenue was added to the cash available. The value of a job was determined as the sum of the average expected cost of operations multiplied by a profit margin of 10%. The anarchic system's starting currency was the sum of expected operation values. The cost incurred per operation was the cost negotiated for the anarchic system, for the hierarchical a calculated cost by MTs at the time of job assignments was used; this was identical to the anarchic system's MT's initial bid without any bidding surplus. The due date was calculated as the sum of expected operational and waiting durations multiplied by a due date surplus of 20%. Jobs had a variable number of operations to fulfil in a predefined random sequence, the capability required and duration of each was randomly and equally distributed between four capabilities (A-D) and its duration was a capability dependent random uniform distribution, as shown in Table 5-7. There were 48 MTs; for the hierarchical system there were four tiers, one global agent, four divisions, three cells per division (12 total) and four MTs per cell (48 total).

Table 5-7: Multiple conflicting objectives experiment, fixed parameters

Fixed parameter		Level
Expected operation waiting time		30t
No. operations/job		$\mathcal{U}$ [2, 6] operations
Operation values by capability (duration, expected cost):	A	$\mathcal{U}$ [10t, 15t], 30
	B	$\mathcal{U}$ [10t, 20t], 40
	C	$\mathcal{U}$ [15t, 25t], 40
	D	$\mathcal{U}$ [15t, 25t], 60

Variable experiment parameters were objective levels, Objs, and demand impacting utilisation; the two objectives are cash/revenue, *CObj* (t), and on time performance, *OTObj (t)*. The cash objective was determined as cash as a percentage of revenue, and on time performance as a percentage of jobs that had completed all operations within the due date whose due date was within the last 100t. The starting and disruption parameter levels are shown in Table 5-8, disruption was a step change at 1500t. Objective levels, Objs, change objective focus, Objs = 1 was cash focused and Objs = 3 was on time focused; demand and therefore system utilisation increases the stress on the system.

Table 5-8: Multiple conflicting objectives, variable parameters

Parameter	Starting	Level 1	Level 2	Level 3	Level 4
Objs (cash, on time)	0.2, 0.8	0.3, 0.7	0.2, 0.8	0.1, 0.9	NA
Utilisation	0.4	0.4	0.5	0.6	0.7

Results and discussion

Cash/revenue and on time performances were recorded; allowing direct comparison between objective levels, rather than analysing the scores against these objectives. Figure 5-12 and Figure 5-13 display results for cash/revenue and on time performance respectively for each combination of parameter levels. Figure 5-14 and Figure 5-15 compares cash/revenue and Figure 5-16 and Figure 5-17 compares on time performance. When considering either anarchic or hierarchical at a distinct utilisation level; allowing direct comparison between Objs (objective trade-off) levels at each level of system utilisation. All plots display the step-change time (1500t), mean performance and its 95% confidence interval as a shaded corridor against simulation time.

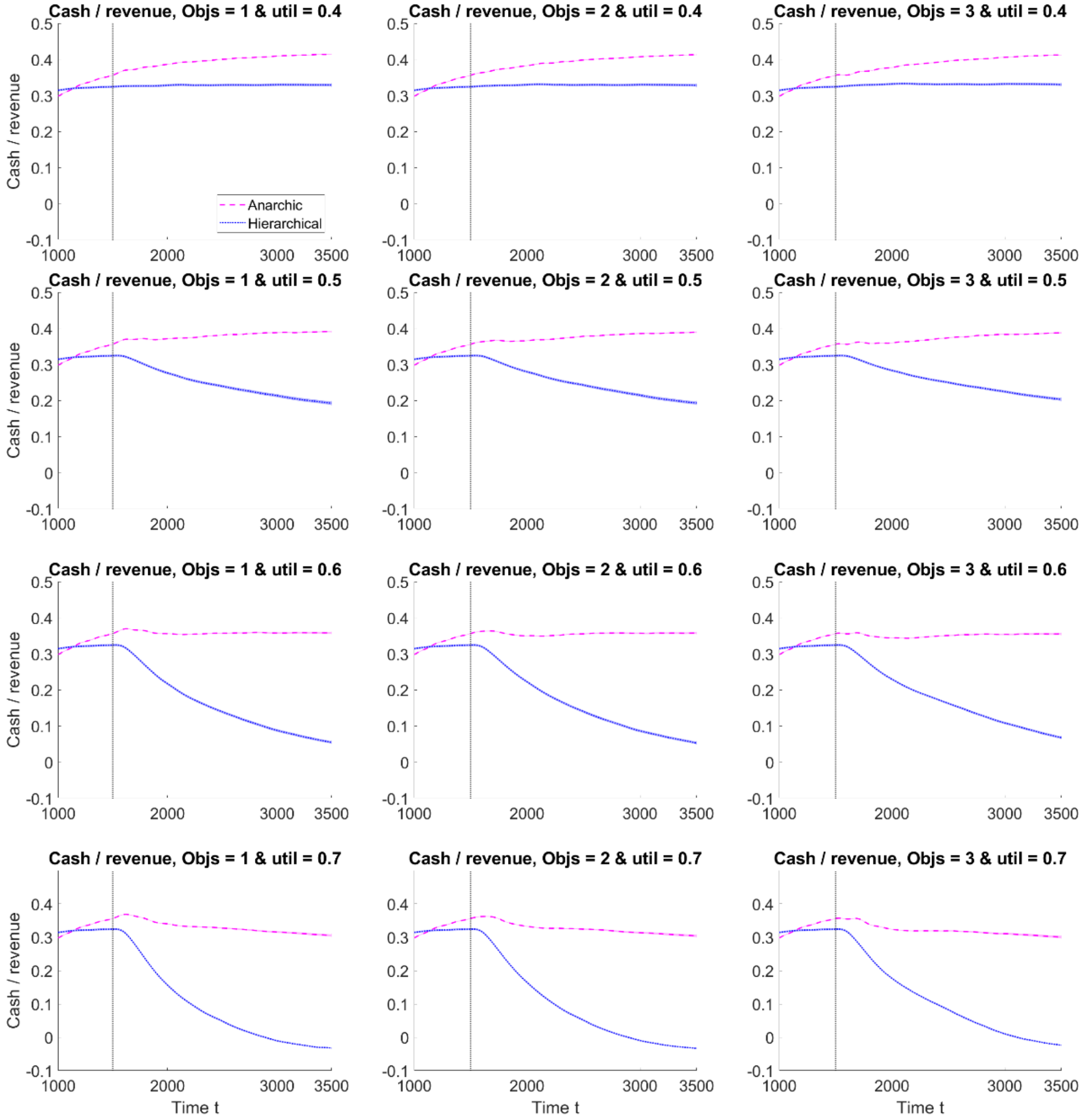

Figure 5-12: Multiple conflicting objectives, cash/revenue objective results

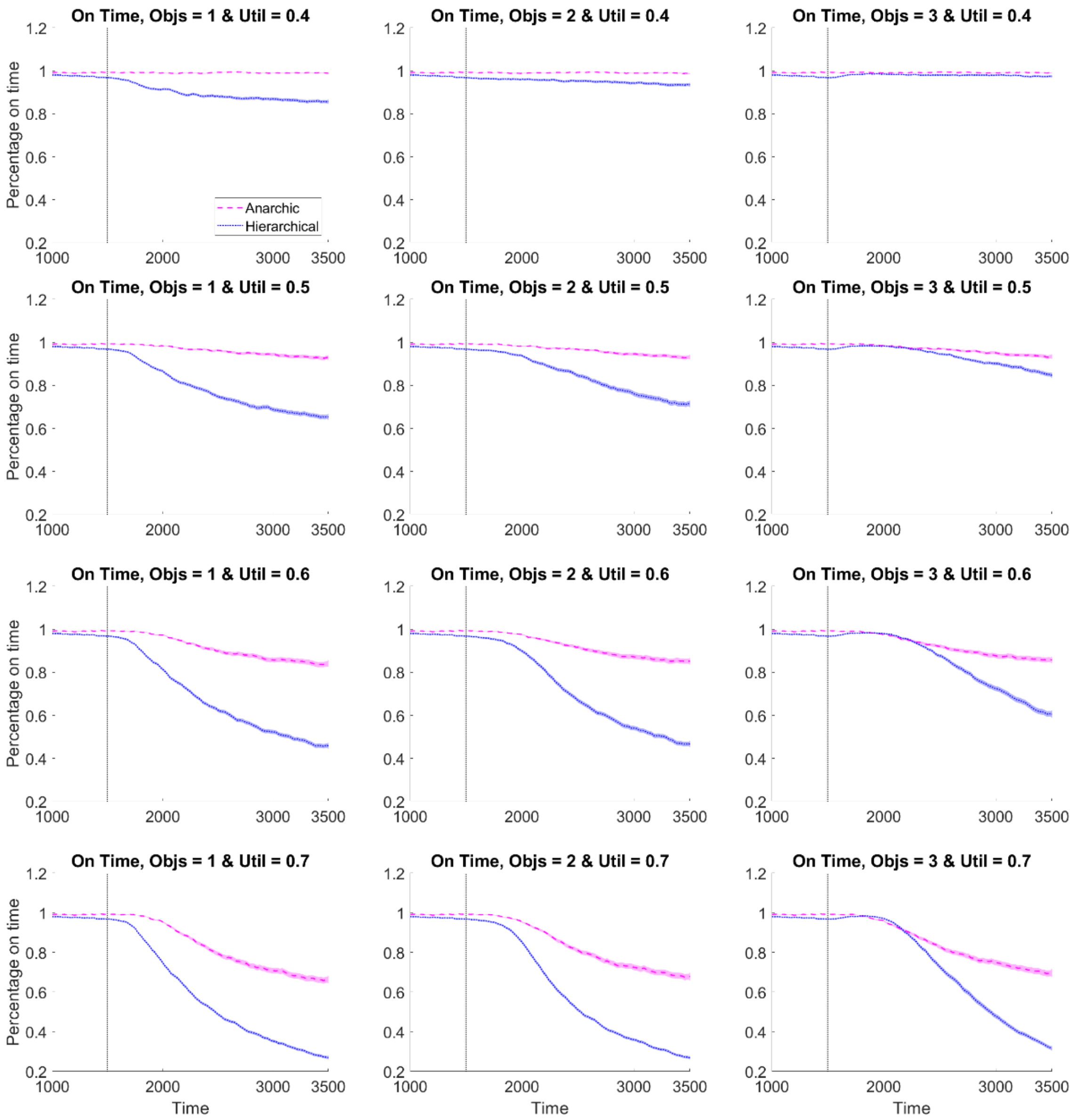

Figure 5-13: Multiple conflicting objectives, on time objective results

Performance plots for each experiment, Figure 5-12 and Figure 5-13, have subplots arranged by increasing parameter levels, Objs changing horizontally from cash to on time focused objectives and utilisation increasing downwards. The overall superior performance of the anarchic system is evident from both figures, particularly as utilisation (demand) increases, the hierarchical system's performance degrades at a faster rate for both cash and on time performance. The changes between Obj levels (objective trade-off) is unclear, but this is evaluated in Figure 5-14 to Figure 5-17. The hierarchical system has poor resilience to change, observed by a significant performance reduction soon after the step change; rather the anarchic system's performance degrades more gradually.

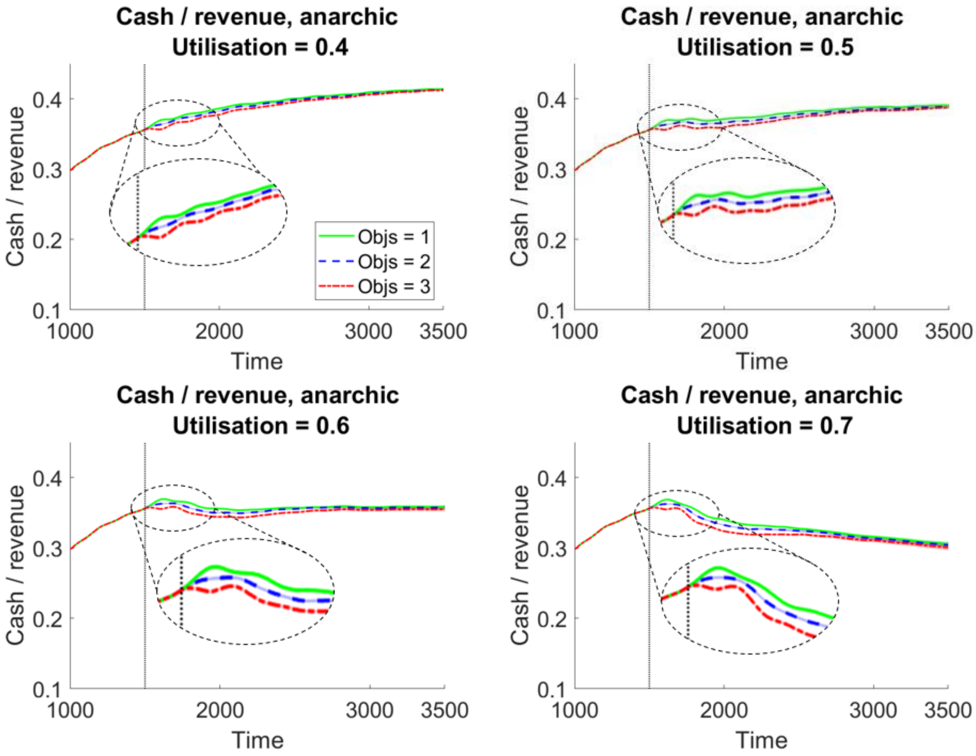

Figure 5-14: Multiple conflicting objectives, anarchic cash/revenue objective comparison

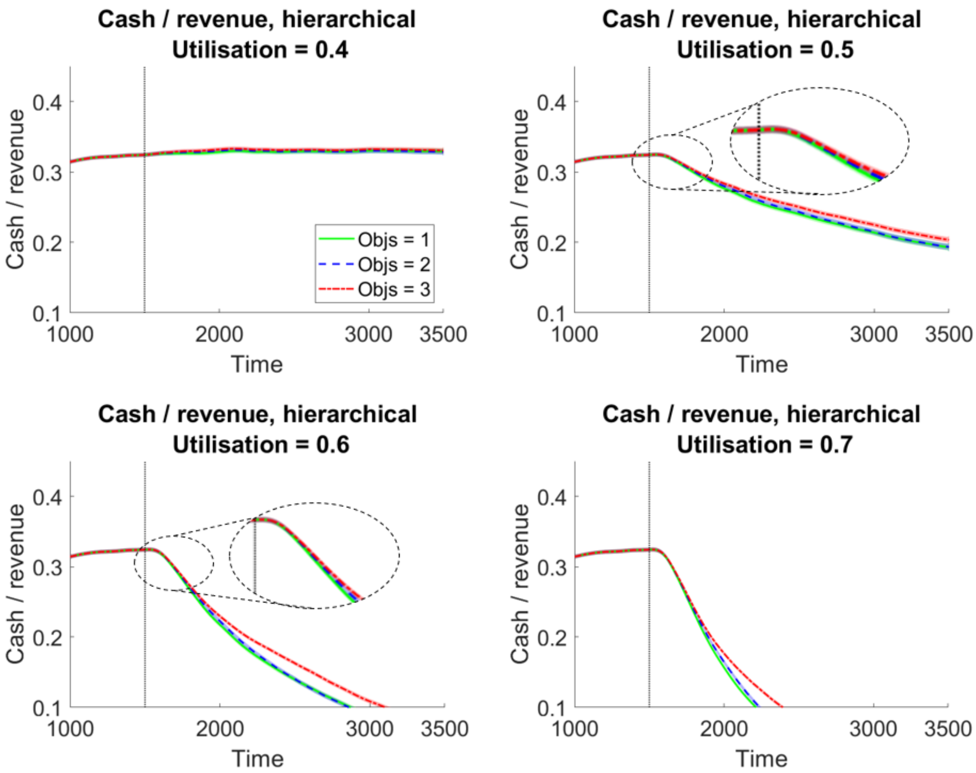

Figure 5-15: Multiple conflicting objectives, hierarchical cash/revenue objective comparison

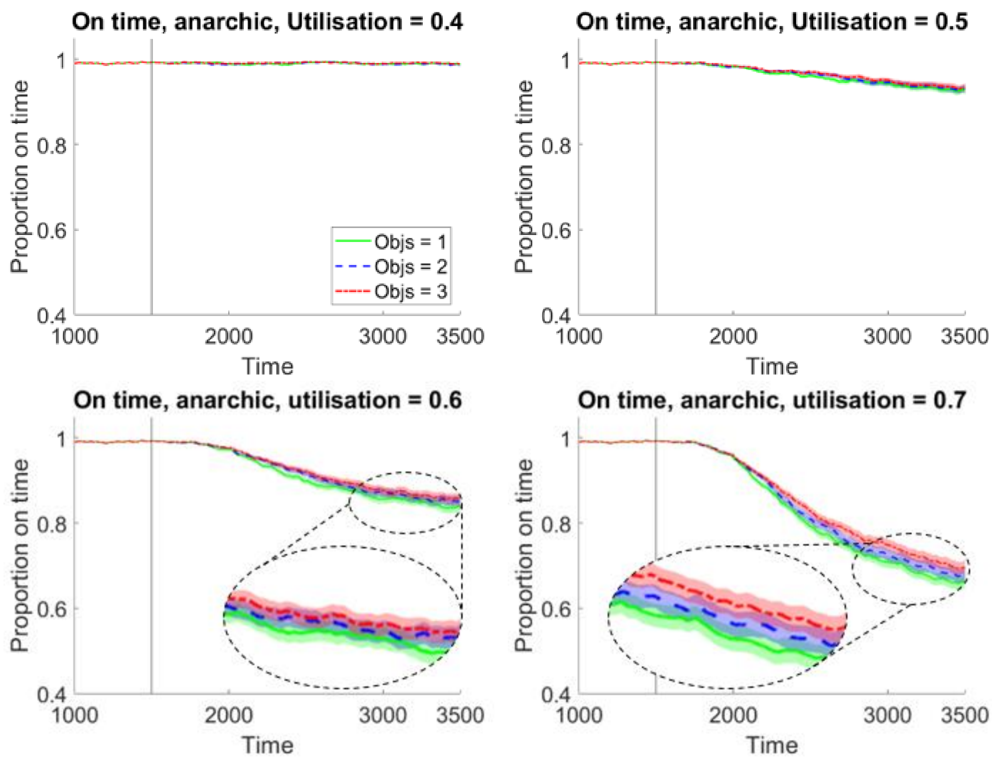

Figure 5-16: Multiple conflicting objectives, anarchic on time objective comparison

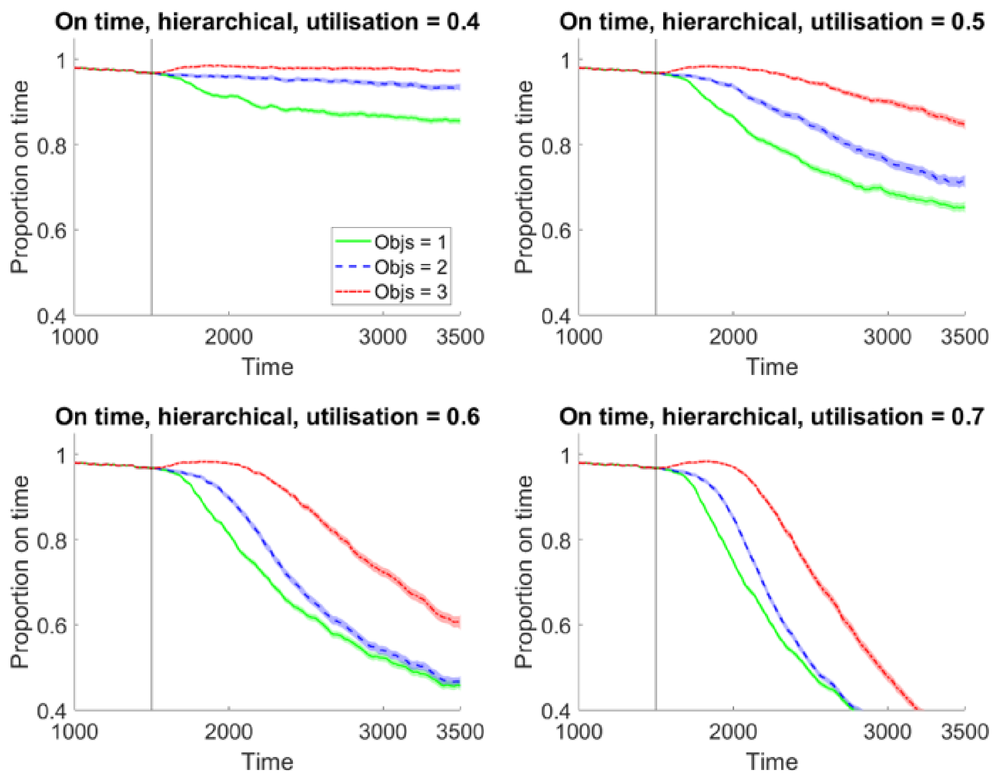

Figure 5-17: Multiple conflicting objectives, hierarchical on time objective comparison

Comparing the impact on Objs levels under the same level of system utilisation, and stress on the system, indicates a system's reactivity to changes and whether behaviour changes to suit the renewed objectives. A system that reacts and accommodates a change in objectives will change its performance to suit. A reactive system, whose objectives sacrifice on time performance for a more demanding cash position, should demonstrate a trade-off in performance between these conflicting objectives. As shown in Figure 5-14 the anarchic system had a clear (at the 95% confidence interval) reduction in cash performance as Objs levels increase (cash is less important), particularly soon after the disruption. This indicates that the anarchic system is willing to exchange a short-term cash position according to the objectives, however as the system recovers from the step change, the anarchic system tended toward a stable position, regardless of objective changes (Objs), governed by utilisation. The anarchic system's on time performance, displayed in Figure 5-16, shows there is a difference between Objs levels (there is a clear difference between Objs = 1 and 3 at the highest utilisation level), however, this was a delayed reaction whereas the cash position changed very quickly; due to the short-term cash mechanism. However, it shows when objectives favour on time performance the anarchic system sacrificed the cash position for an improved-on time performance, and conversely for cash-oriented objective levels. The system's parameters had not been optimised to an effective sensitivity level, but the anarchic system has been shown to work by trading off performance to balance objectives; countering the argument against distributed systems of local myopic decision-making.

The hierarchical system showed no discernible difference in cash/revenue performance when reacting to a change in objectives soon after disruption, indicating that the hierarchical system did not immediately adjust according to changes in objectives (Objs); as seen in Figure 5-15. The hierarchical system did dramatically change its on time performance in response to changing objectives, shown in Figure 5-17, when Objs = 3 on time performance is highly prioritised and subsequently improved. This was a result of clearer alignment between hierarchy levels, which were more likely to select EDD rather than a mix of EDD and SPT where inefficiencies arise. These results suggest that the hierarchal system cannot effectively balance conflicting multiple objectives or has made an indication that it can balance objectives.

5.4 Summary

Simple discrete manufacture scenarios evaluate the anarchic manufacturing system against centralised systems for several scenarios. These provide a baseline understanding of the systems against simple scenarios and contributed to the characterisation for complexity and reactivity to global objectives. Additionally, experimentation aided the development of anarchic manufacturing by accommodating increasingly complex scenarios.

The three experiments covered in this chapter evaluated scenarios for mass customisation and scale, increasing complicatedness and complexity and finally adapting to dynamic and conflicting objectives. Overall, they have found that the anarchic manufacturing system handled complexity well and deteriorated at a slower rate in comparison to centralised and hierarchical systems. The anarchic system was shown to improve with scale, in Section 5.3.1, free market efficiencies were realised as the system increased competition with scale. Additionally, on adapting the systems to consider multiple dynamic global and conflicting objectives in Section 5.3.3, the anarchic system was shown to react to the change in objectives; rather the hierarchical system was unable to. Although small and relatively insubstantial, the anarchic system's indication of a reaction provided insight into the system's ability to adapt to objective changes, reducing myopia with respects to local decision-making. The 95% confidence intervals provided statistical confidence to these observations.

Simple discrete manufacturing scenarios have provided an initial understanding of anarchic system's performance relative to centralised systems. The observed affordances provided by the anarchic manufacturing system directly contribute to the thesis aim. However, the job and flow shop style manufacturing facilities are a relatively small subset of real-world manufacturing. The next chapter adapts anarchic manufacturing for the broader area of assembly, which provides a significantly greater challenge through a structural problem that requires team working and cooperation to join jobs together. This is contrary to existing methods employed in anarchic manufacturing utilising competition to realise free market efficiencies.

6 Application 2, assembly manufacture

6.1 Introduction

Assembly compared to simple discrete manufacture significantly increases system complexity, as jobs must coordinate and cooperate with each other; previously system elements were only in competition with each other for simple discrete manufacture.

Increasing product variety combined with volatile demand and a need for rapid lead time to market has resulted in the transition from dedicated assembly lines to mixed-model production. Volatile demand refers to rapidly transient customer expectations and values, and lead time to market is the time taken from order placement to a customer's receipt of goods. Businesses view flexibility and agility, to satisfy these two characteristics as a source of competitive advantage (He, Zhang and Li, 2014). Assembly is one of the most cost-effective approaches to achieve high product variety, however, variety also causes complexity in manufacturing and assembly systems (Hu *et al.*, 2011).

The research motivation for this chapter is to test whether the anarchic manufacturing system can be effectively adapted for mixed-model assembly and whether proposed benefits of distributed systems can be realised in assembly production planning and control; which requires cooperation between similar agents. The anarchic system is tested against centralised and hierarchical systems in idealised assembly scenarios, considering balanced production and dynamic bottlenecks. These idealised scenarios remove potential noise or overarching factors to clearly show anarchic manufacturing characteristics. The extension into dynamic bottlenecks is selected as they are a significant issue for assembly, which typically arises from cycle time drift (Hu *et al.*, 2011).

This chapter first covers additional background literature on assembly, relevant to the scenarios evaluated; detailing existing research areas in line balancing and assembly sequencing (scheduling), and any relevant literature for distributed assembly systems. In Section 6.3 the experimentation is detailed, explaining the significant system adaptations for assembly and the two experiments carried out for balanced production and dynamic bottleneck production. Finally, the chapter is brought together through a discussion and a summary are provided in Sections 6.4 and 6.5. A summary table of additional elements to the anarchic system introduced in this chapter are indicated below in Table 6-1.

Table 6-1: Additional anarchic system elements introduced in Chapter 6

Element	Meaning
Pft_{ip}	The profitability for job *i* to pursue model *p*
Prc_{ip}	Selling price if job *i* can still fulfil model *p*
$Cexp_{ip}$	Expected total cost to fulfil model *p* for job *i*
Dmd_{p}	Demand for model *p*
Ffl_{cp}	Fulfilment for model *p* by jobs of class *c*
$FWgt_{ip}$	Filfilment model weighting for job *i* considering model *p*, i.e. the consideration of model demand and fulfilment by all job classes for this model
O_{icpj}	Operation of capability *j* is required for job *i* of class *c* for model *p* (binary value)
J_{Ji}	Job *J* is in group containing job *i*
Cp	Job class *c* is required for model *p* (binary value)
$CstHisi_{grp}$	Cost already incurred by all jobs in group containing job *i*
Cry_{grp}	Currency held by all jobs in group
$Qtot_{k}$	Total in queue for resource *k*
Qc_{k}	Queue currently assigned in queue
Qe_{k}	Expected queue length

6.2 Scenario background

Although the concept of assembly is well understood by practitioners, there is no single definition. For the purpose of this thesis, considering planning, scheduling and control, assembly is defined as: “The joining of components or subsystems together, to form a single system, achieved through an operation that may require resource(s) and not instantaneous to complete.” This definition aligns to existing definitions when considering production planning and control (Schenk, Wirth and Müller, 2009; Hu, 2014).

Due to demands for more flexible and versatile production, assembly lines have changed from fixed lines of a single model to mixed-model assembly lines, producing variants of the same product family (Battini *et al.*, 2009). Mixed-model assembly lines use flexible workers and machinery to reduce setup times and costs, so different products can be jointly manufactured in an intermixed product sequence on the same line (Boysen, Fliedner and

Scholl, 2009). Many issues arise from mixed-model facilities having greater task duration variation and drift from the cycle time and a lack of buffers used in industry (Battini *et al.*, 2009). For mixed-model production lines, the production processes of manufactured goods require a minimum level of homogeneity, therefore a common base product, or platform, is typically used which is customisable through a bounded number of and predetermined optional features (Boysen, Fliedner and Scholl, 2009).

The unique problem associated with assembly scheduling, not applicable to independent jobs with only sequential operations, stipulates that a higher level item cannot be processed unless preceding lower level items have been processed and assembled (Reeja and Rajendran, 2000). Reeja and Rajendran state this structural complexity introduces coordination and pacing problems. Typically, the problem is considered in two interrelated aspects spanning multiple planning horizons, sequencing orders (arrival to the assembly line) in the short term and balancing operations in the long term (Battini *et al.*, 2009).

Assembly scheduling is typically referred to as assembly sequencing, which is the order that orders are released (Boysen, Fliedner and Scholl, 2009). Many researchers have focused on the automated generation and optimisation of assembly sequences (Wang *et al.*, 2009), often using meta-heuristic and search algorithms. Sequencing problems are typically solved together with line balancing for mixed-model assembly lines, as line balancing solutions minimise potential workload fluctuations from different models (Hu *et al.*, 2011). Assembly line balancing allocates tasks to work stations whilst considering restrictions and stochasticity (Wang *et al.*, 2009), but is significantly impacted by product variety. Drift is the deviation from cycle time at a workstation, which can result in lost efficiency or bottlenecks (Hu *et al.*, 2011). The assembly scheduling and line balancing typically allude to rigid production system that processes orders in a fixed sequence along sequential workstations; rather than flexible routing between workstations (e.g. flow shops). However, further research is required to realise flexible assembly systems for high product variety and resultant complex systems (Asadi, Jackson and Fundin, 2016). Currently, mixed-model assembly lines can manufacture moderately different models, rather completely different product mixes create short term material supply issues (Battini *et al.*, 2009).

There are few fully distributed systems investigated for assembly, despite recent increasing interest. Wang *et al.* comment that agent-based distributed manufacturing assembly has emerged for adaptive and dynamic process planning (Wang *et al.*, 2009). Additionally, Krüger *et al.* propose combining decentralised and embedded controllers with machine learning for automation, to control system elements, including robotics, for flexible and reconfigurable assembly lines (Krüger *et al.*, 2017). Antzoulatos *et al.* propose a MAS framework, using heterarchical with mediator structure, for plug-in/-out reconfigurable assembly resources (Antzoulatos *et al.*, 2017), these intelligent and distributed resources align to the paradigm of cyber-physical systems (Monostori *et al.*, 2016b). However, none of these systems detail now a distributed system could be applied to assembly, which this chapter fulfils.

6.3 Experimentation

6.3.1 System adaptation, anarchic manufacturing system

For all assembly experiments conducted, the system adaptations were used for both anarchic and centralised systems. The anarchic manufacturing system used had significant changes to incorporate the natural teamworking scenario to join jobs and find group consensus for decision-making, as well as allowing jobs to determine what product they will fulfil. By contrast, the centralised systems retained centralised decision-making, using a push structure and predetermining job groupings for a specific order to fulfil.

The anarchic manufacturing system was adapted for mixed-model assembly scenarios, where jobs are inter-dependent for joining operations and must select one of a limited range of models to fulfil orders. Anarchic manufacturing's design principles were maintained, by retaining dynamic distributed decision-making in a free market environment; where agents maximise profitability through competitive behaviour, baulk at high prices and are opportunistic with lower prices. Global objectives were aligned via the free market structure, by generating demand (orders) and using pricing mechanisms for resource allocation.

The anarchic manufacturing system fulfilled orders by generating demand for the associated model, this influenced profitability and subsequent agent decision-making. The system consisted of jobs, where job i of class c is noted as J_{ic}, jobs were processed into products (finished goods and realisation of models) to fulfil customer orders of models, where model p is noted as Mdl_p and there were n_M models, by using resources (machine tools) to complete operations, where MT k of capability j is noted as M_k. Models had predefined operations that combined different job classes requiring a specific capability and have a nominal duration, these are represented by precedence graphs. These operations could result in a job or sub-assembly becoming customised to a specific model or remain interchangeable with other models. Figure 6-1 presents an example precedence graph and annotations identifying jobs, classes, models and products.

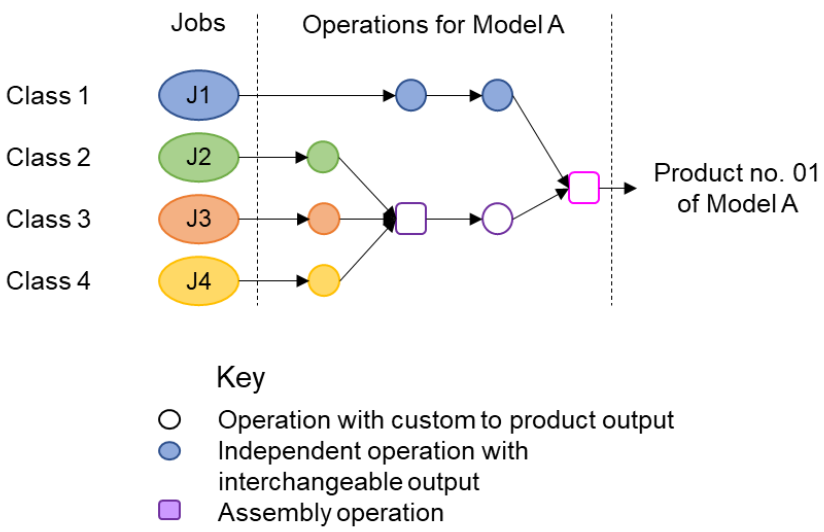

Figure 6-1: Example precedence graph

Orders for specific models were created periodically and fulfilled on a FIFO basis by completed products. Models differed but may have had common jobs until an operation customises the job to a model; i.e. jobs can fulfil multiple models until the point of model customisation. Following the free market structure, there was a product selling price on fulfilling an order; which varied according to the outstanding demand (unfulfilled orders) for the model. The selling price informed incomplete jobs of an estimated profitability on fulfilling a specific model and influenced job decision-making; which is profit maximising. The system created jobs so that there were always enough jobs of each class plus a small buffer; in experimentation there were always three additional jobs of each class to fulfil current outstanding orders.

The anarchic manufacturing system for assembly is best described by following a job's processes. A job considers the profitability of each model and decides which to pursue, it then assesses the next operation for this model and whether additional jobs are required. If so, it will search for jobs and request them in turn to connect. If the request is successful a regrouping process determines, through profit maximisation, which model to pursue and which jobs to group together. Once all required jobs are connected for the next operation, they negotiate with resources individually. As jobs have individual objectives and may prefer different resources, a group consensus method, based on the Borda Count (Zahid and De Swart, 2015), selects the most suitable resource. A (group of) job(s) can renege on arrival to a queue, by paying off the job(s) in front. On completing each operation, the job reassesses which model to pursue and on completing all operations for a model, it is assigned to an order. This process is shown in Figure 6-2, the four key decision-making processes and actions highlighted are covered in depth.

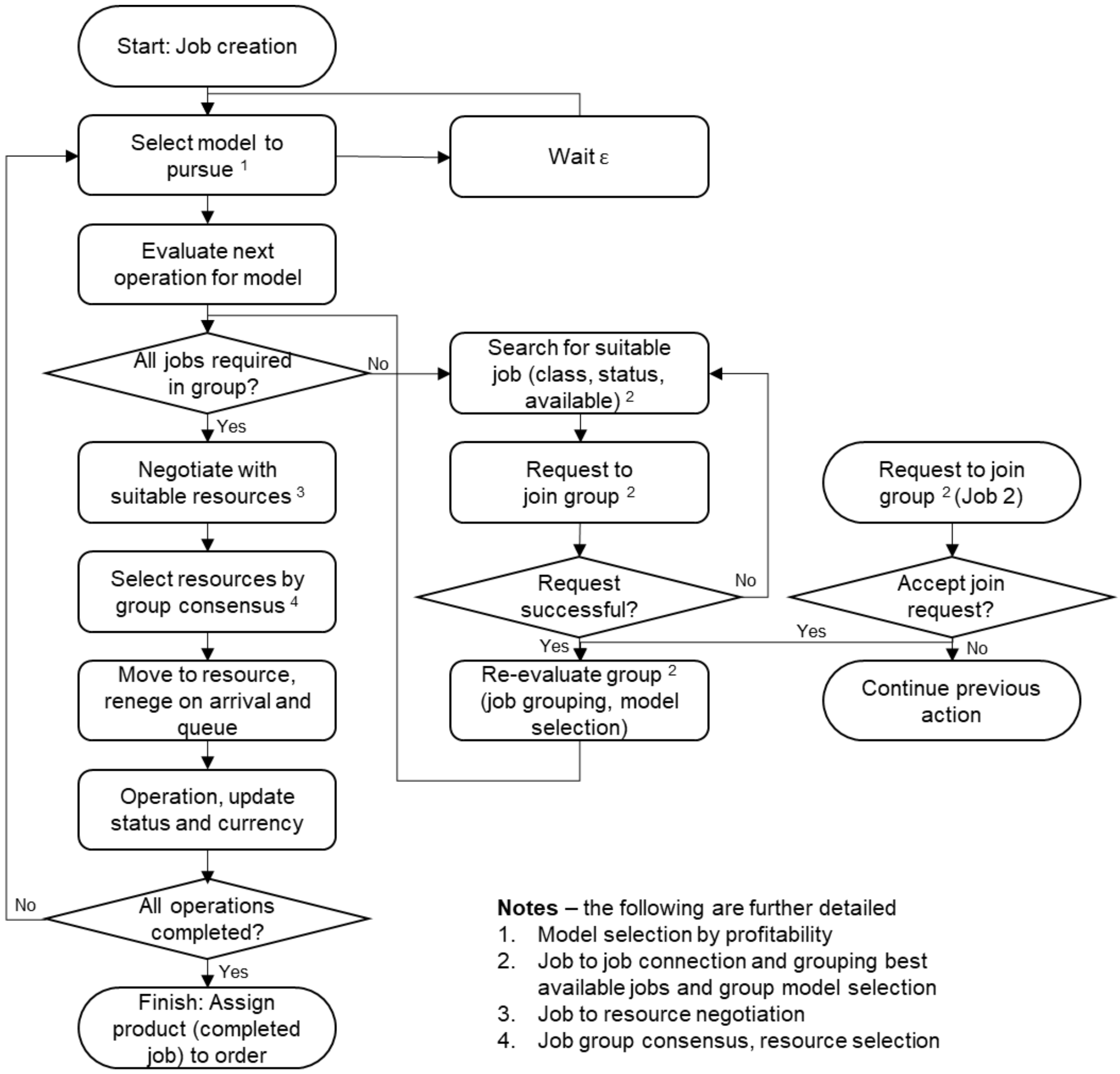

Figure 6-2: Anarchic manufacturing for assembly job flow chart of processes

Model profitability and selection

A job, on creation and after each operation, selects a model to pursue according to profitability, the process shown in Figure 6-2 note 1; using model profitability in a roulette wheel selection process (Lipowski and Lipowska, 2012) is socially beneficial to achieve global goals for the system. Model selection maintains agent independence and through these local objectives a global emergent outcome is achieved of fulfilling all orders and the models that are demanded the most as a priority. This selection process requires calculating the profitability of each model p at time t for Job i of class c, $Pft_{ip}(t)$, determined by Equations 6.1–6.7. Profitability considers the selling price if job i can still fulfil model p (i.e. not beyond the point of model customisation) at time t, $Prc_{ip}(t)$, expected total cost to fulfil this model, $Cexp_{ip}(t)$, which incorporates costs already incurred and currency available, the demand for model p, $Dmd_p(t)$, the number of jobs of the same class fulfilling model p, $Ffl_{cp}(t)$, and the fulfilment model weighting, $FWgt_{ip}(t)$, which considers the model demand and fulfilment by all job classes required to complete the model. The profitability of model *p* for job *i* at time *t*, is calculated by:

$$Pft_{ip}(t) = FWgt_{ip}(t)\left(Prc_{ip}(t) - Cexp_{ip}(t) + 5\left(Dmd_p(t) - Ffl_{cp}(t)\right)\right) \tag{6.1}$$

To evaluate the expected cost, a binary function is used to determine whether an operation of capability *j* is required by job *i* of class *c* (J_{ic}) for model *p* at time *t*, O_{icpj}; given the status of job *i*, i.e. the number of operations required to fulfil model *p* given the operations the job has completed.

$$O_{icpj}(t) = \begin{cases} 1 & \begin{matrix} if\ J_{ic}\ requires\ operation\ O\ of\ capability\ j \\ to\ fulfil\ model\ p\ at\ time\ t \end{matrix} \\ 0 & otherwise \end{cases} \tag{6.2}$$

Another binary function is used to determine whether Job *J* is in the group containing Job *i*, J_{igrp}, at time *t*.

$$J_{Ji}(t) = \begin{cases} 1 & if\ J_J \in J_{igrp}\ at\ time\ t \\ 0 & otherwise \end{cases} \tag{6.3}$$

The expected total cost considers the expected cost of operations outstanding for the job to complete the product and the cost of operations already incurred and all available currency from jobs in the job group containing Job *i* at time *t*, $J_{igrp}(t)$. The expected total cost, $Cexp_{ip}(t)$, uses the average recent cost of capability *j*, $Cst_j(t)$, costs already incurred by all jobs in the group, $CstHis_{igrp}(t)$, and the currency available to Job *J* at time *t*, $Cry_J(t)$, is calculated as:

$$Cexp_{ip}(t) = \sum_{O_p=0}^{n_{Op}} \left(Cst_j(t) \cdot O_{icpj}(t)\right) + \sum_{J=0}^{n_{Job}} \left(J_{Ji}(t)\left(CstHis_{Jgrp}(t) - Cry_J(t)\right)\right) \tag{6.4}$$

Where O_p is the index of operations required for model *p* and n_{op} is the total number of operations.

A job accounts for the demand for a model and the number of other jobs of the same class aiming to fulfil this model. The number of jobs that are similar to Job *i* of class *c* fulfilling model *p*, $Ffl_{cp}(t)$, which sums all the model (profitability) weightings of jobs of a particular class and model (i.e. if a job can fulfil multiple models, the model weighting for each model is taken, each is a fraction of and sum to 1), is calculated as:

$$Ffl_{cp}(t) = \sum_{C_J=C_i \wedge Mdl_J=Mdl_i} \frac{Pft_{Jcp}(t)}{\sum_{Pft_{Jcp}(t)\geq 0} Pft_{Jcp}(t)} \tag{6.5}$$

The fulfilment model weighting for job *i* for model *p* at time *t*, $FWgt_{ip}(t)$, considers the demand for model *p* and the fulfilment by jobs of the same class *c* and then adjusts this by the demand and fulfilment by other job classes required to be joined with for model *p*. The job uses the weighting to assess the demand fulfilment by the same class and is influenced heavily by other classes it is required to join with. This fulfilment model weighting is used during grouping and group model selection to ascertain the commitment of a job to pursuing a model, this influences decision-making by factoring in risk that a job will pursue other interests. A binary function defines the job classes required for model *p,* is defined as:

$$C_p = \begin{cases} 1 & \begin{matrix} if\ class\ c\ is\ required\ for\ model\ p\ and \\ not\ the\ same\ class\ as\ Job\ i \end{matrix} \\ 0 & otherwise \end{cases} \tag{6.6}$$

The fulfilment model weighting, $FWgt_{ip}(t)$, is defined as:

$$\begin{aligned} FWgt_{ip}(t) = {} & 0.5 + 0.5 \min\left(\frac{Dmd_p(t)}{Ffl_{cp}(t)}, 2\right) \\ & + \sum_{C_c=0}^{n_c} \left(0.5\left(\min\left(\frac{C_p \cdot Dmd_p(t)}{Ffl_{cp}(t)}, 2\right) - 1\right)\right) \end{aligned} \tag{6.7}$$

Job connection, grouping and group model selection

If job A requires additional jobs to complete the next operation, it will search for suitable jobs to connect with against class, availability and status criteria; see Figure 6-2 note 2. The grouping mechanism realises cooperative behaviour between like agents, the ability to leave a group if not physically coupled as a subassembly maintains independence and retains competitiveness ensuring global suitability of decisions. Jobs are unavailable if they are complete products or in operation; therefore, a job is available whilst queuing or already in a group. A job's status indicates which operations have been completed. Job A will search for suitable jobs and approach the first, job B, and send job B a request to connect respective groups, $Grp_A(t)$ and $Grp_B(t)$, if the request is accepted a group re-evaluation occurs, if unsuccessful job A approaches the next suitable job. Job B will accept the request to connect subject to the scenario; regarding job A and B's model selection, Mdl_A and Mdl_B, and whether job B has selected and is queuing at a resource (MT), M_B. The acceptance criteria are based on both jobs' model fulfilment weighting, $Ffl_{ip}(t)$, which indicates the level of commitment to model *p* and currency held by each group, Cry_{grp}; these scenarios and criteria are detailed in Table 6-2.

Table 6-2: Anarchic assembly, job request connection criteria

Scenario at time *t*	Criteria
$Mdl_A = Mdl_B \wedge M_B = \emptyset$	$Cry_{grpA}(t) \cdot Ffl_{Ap_A}(t) \geq 0.7 \cdot Cry_{grpB}(t) \cdot Ffl_{Bp_B}(t)$
$Mdl_A \neq Mdl_B \wedge M_B = \emptyset$	$Cry_{grpA}(t) \cdot Ffl_{Ap_A}(t) \geq 1 \cdot Cry_{grpB}(t) \cdot Ffl_{Bp_B}(t)$
$Mdl_A = Mdl_B \wedge M_B \neq \emptyset$	$Cry_{grpA}(t) \cdot Ffl_{Ap_A}(t) \geq 1.5 \cdot Cry_{grpB}(t) \cdot Ffl_{Bp_B}(t)$
$Mdl_A \neq Mdl_B \wedge M_B \neq \emptyset$	$Cry_{grpA}(t) \cdot Ffl_{Ap_A}(t) \geq 2 \cdot Cry_{grpB}(t) \cdot Ffl_{Bp_B}(t)$

Where a job's model fulfilment weighting, Ffl_{ip} *(t)*, determines the proportional weighting of model *p* by profitability against all models for job *i*, is defined as:

$$Ffl_{ip}(t) = \frac{Pft_{ip}(t)}{\sum_{Pft_{ip}(t)\geq 0} Pft_{ip}(t)} \tag{6.8}$$

If job A satisfies the connecting request criteria all jobs connected to jobs A and B are re-evaluated together. On group re-evaluation, a model is selected and the most suitable jobs for it are grouped, both evaluation processes use currency held multiplied by model fulfilment weighting. Model selection is determined by the greatest sum of currency multiplied by model fulfilment for all jobs, subsequently necessary job classes required for it are filled by the same criteria of highest currency multiplied by model fulfilment. This is repeated until all jobs are grouped together and each group has a model to pursue. This process is conducted by a nominated job in the group for administrative purposes only, there is no bias or benefit. This regrouping process selects the best and most suited jobs for the nominated model; therefore, jobs can dynamically change groups up until they are operated on, changing is determined by how attractive the offer is in the scenario.

Job to resource negotiation

A job, after connecting with all required jobs, will each negotiate the next operation with resources, by their own objectives; this relates to the process in Figure 6-2 note 3. The anarchic negotiation protocol follows that covered in Section 4.4.3, but is adapted before the job commits to a MT. The adapted negotiation framework for assembly is detailed in Figure

6-3, with the change noted that MT costs are recorded and jobs are not assigned until group consensus is reached.

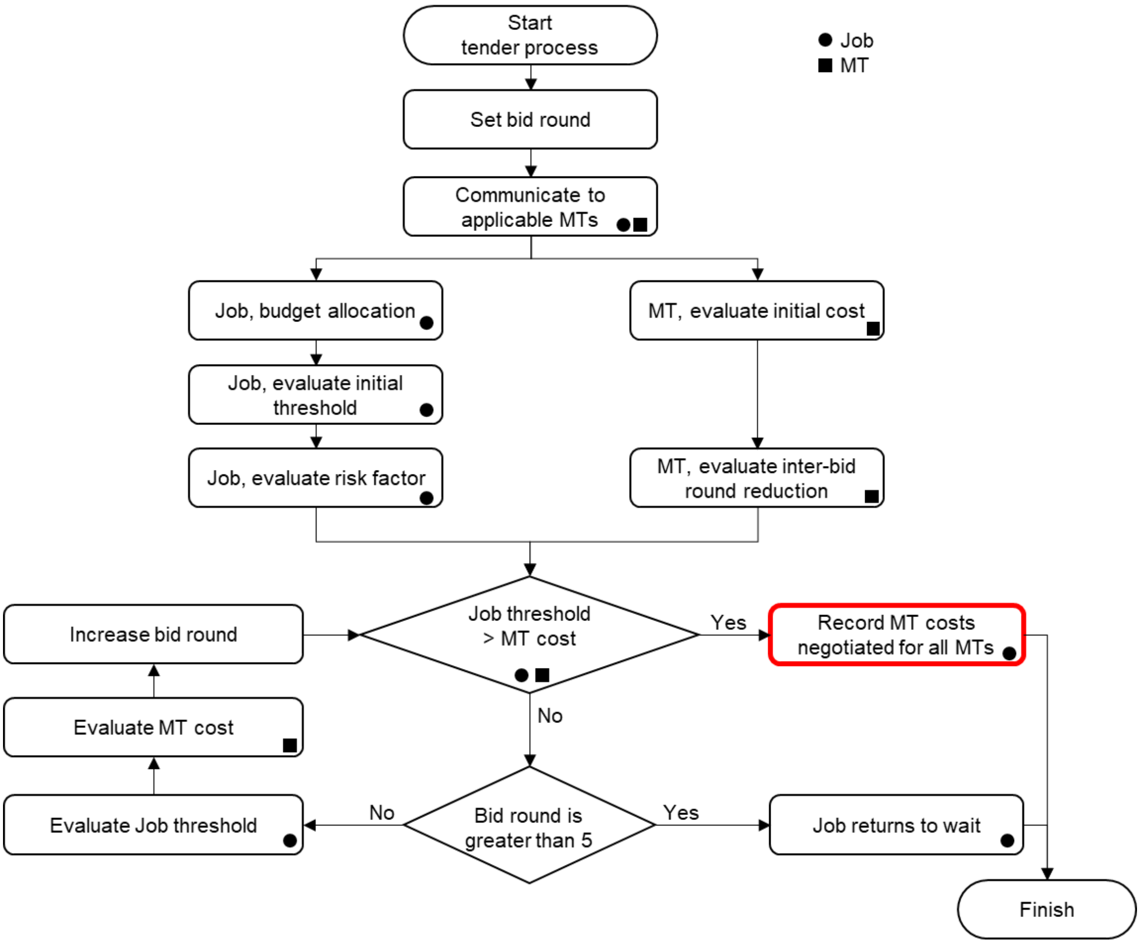

Figure 6-3: Assembly job to resource negotiation adjusted framework

A job will communicate with applicable (capable) resources and invite them to tender, the job evaluates a threshold it is willing to spend on its next operation; by proportioning the combined currency of the group against the value of the next operation over the value of all operations remaining to complete the model. Additionally, the job calculates an inter-bidding round increment as a small proportion of the threshold.

Each resource invited to tender evaluates an initial bid and inter-bid reduction. The resource's initial bid for bid round *n* for MT *k* of capability *j* at time *t*, $\beta_{kjn}(t)$, is a function of recent average cost of capability *j*, $Cst_j(t)$, recent utilisation, ω_k (t), utilisation weighting, U_k, total queue length, $Qtot_k(t)$, which is a combination of current assigned jobs in queue, $Qc_k(t)$, and expected queue length, $Qe_k(t)$; and is defined as:

$$\beta_{kjn} = 1.1Cst_j(t)\left(U_k \cdot \omega_k(t) + \frac{Qtot_k(t)(1-U_k)}{Q_{j\,util}}\right) \tag{6.9}$$

Where 1.1 is an initial surplus value, and utilisation, ω_k (t), and total queue length, $Qtot_k (t)$, is weighted 0.3:0.7, and $Q_{j\,util}$ is the queue size of resources with capability *j* required to meet full utilisation over the planning time horizon. Total queue length, considering the queue already assigned and the expected queue, is defined as:

$$Qtot_k(t) = Qc_k(t) + Qe_k(t) \tag{6.10}$$

To count the number of resources of a capability, MT with capability *j,* M_{Rj}, is represented as a binary value:

$$M_{Rj} = \begin{cases} 1 & if\ resource\ k\ has\ capability\ j \\ 0 & otherwise \end{cases} \tag{6.11}$$

The expected queue is an estimated number of operations in the current pool of jobs requiring capability *j*, considering how many operations of capability *j* are required for a job of class *c* to fulfil model *p,* O_{cpj}, and the number of jobs of class *c* fulfilling model *p*, $Ffl_{cp} (t)$, as defined in Equation 6.5. The expected queue length, $Qe_k (t)$, is defined as:

$$Qe_k(t) = 0.5 \cdot \frac{\sum_{j=j_k} Ffl_{cp}(t) \cdot O_{cpj}}{\sum_{R=0}^{n_R} M_{Rj}} \tag{6.12}$$

The factor of 0.5 is taken, as holistically jobs are expected to be halfway through production.

The resource's inter-bid round reduction, $Red_k (t)$, is bounded between 1 and 10 and is a function of recent bid success, $\tau_k (t)$, and actual job queue over expected job queue; this is defined as:

$$Red_k(t) = 5\left(2 - \tau_k(t) + \frac{Qc_k(t)}{Qe_k(t)}\right) \tag{6.13}$$

After job and resources have evaluated their bidding values, the job evaluates and records all bids, and will continue bidding rounds until a bid received is below the job's threshold or the maximum of five rounds is reached. Between bidding rounds, a job increases its threshold by the increment and resources lower their bids by reduction, $Red_k (t)$. If five bidding rounds have been exceeded the job records the resource bids from the last round and will retender after a short waiting time if another job in its group has not successfully negotiated with resources.

Job group consensus, resource selection

A group of jobs must decide which resource to select, relating to Figure 6-2 note 4, however, with different objectives they may have different preferences; a currency weighted Borda Count method (Zahid and De Swart, 2015) is used to select a single option. The Borda Count gives points for each voting participant to candidates in rank order; for *m* candidates, the highest ranked receives *m* votes and the second *m–1* votes etc.. The highest scoring candidate resource is selected, by multiplying the job's (voter's) currency held and the Borda Count score for all jobs. The lowest negotiated price for the resource by any job is taken.

6.3.2 System adaptation, central and hierarchical systems

System adaptations were made to the two comparative centralised systems, these used a push model, with three levels of hierarchy but different cell structures; see Figure 6-4 for system illustrations. A push system was selected over pull to manage increasing variation in mixed-model production. Krishnamurthy *et al.* state pull strategies are fundamentally handicapped for manufacturing facilities that produce different products with distinct demands and/or processing requirements (Krishnamurthy, Suri and Vernon, 2004).

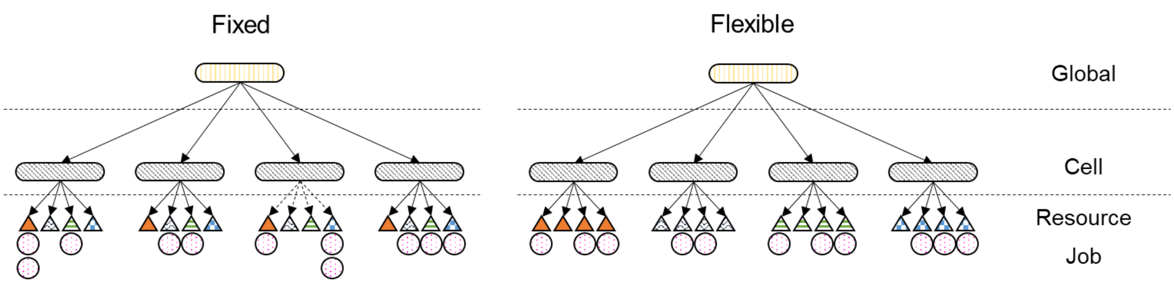

Figure 6-4: Assembly centralised system structures

The fixed system cells contained one of each resource type and cells manufactured all jobs for an order. Whereas the flexible system had a flow shop structure, cells contained and managed all resources of a particular capability. For this flexible system, the global coordinator reassigned jobs to capability cells for each operation. Both systems used the Earliest Due Date (EDD) dispatch rule (heuristic) to allocate jobs at all levels of hierarchy. Both systems used a push system and following Material Resource Planning (MRP) practice, jobs (or materials) are assigned to an order and cannot transfer to another (Lewis and Slack, 2003).

For both centralised systems, no line balancing was required or traditional assembly sequencing. Experimental setup followed nominally balanced production with flexible in cell routing; rather than rigid assembly lines of sequential workstations.

6.3.3 Balanced production

A balanced production experiment evaluated anarchic against centralised systems in an idealised state with increasing levels of drift. Although manufacturers aim to minimise drift, for mixed-model assembly lines it will be almost impossible to balance the line properly, due to differing model characteristics (Hu *et al.*, 2011), this is extended by stochastic operation durations. This nominally balanced production scenario, with increasing levels of drift, will clearly indicate performance regardless of line balancing and is a suitable starting point on applying distributed systems to assembly. Figure 6-5 diagrammatically shows the balanced assembly production experiment, which varies the structural drift through increasing model differences and operation duration variability, additionally interactions between jobs, groups of jobs and jobs to MTs are shown.

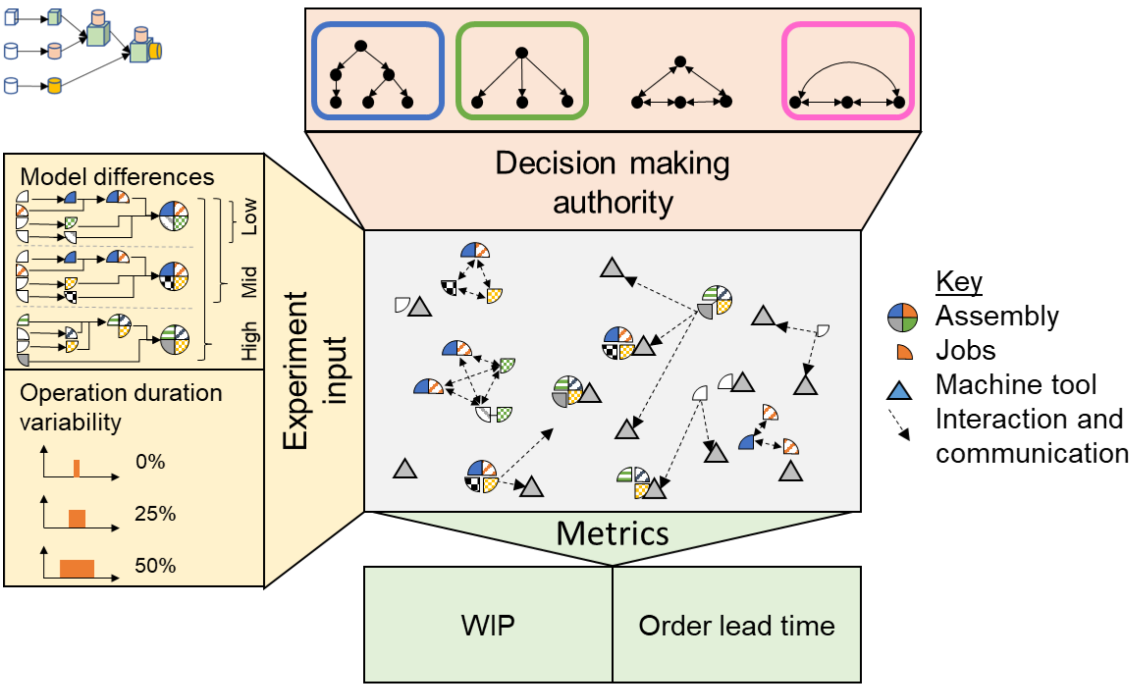

Figure 6-5: Assembly balanced production experiment summary

Experimental framework

Both systems fulfil orders for three models by performing joining and independent operations on jobs. There are 16 resources (machine tools), four of each capability, there are three capabilities (A, B, C) for independent operations and one capability (Z) for joining. Orders arrive at a constant rate, maintaining 60% utilisation, are randomly assigned a model against a split of 0.4:0.4:0.2, see Table 6-2 for a summary of fixed parameters. There are no additional resources required or work in progress restrictions, movement durations are very small relative to operation durations.

Table 6-3: Assembly balanced production fixed parameters

Parameter	Value
No. resources	16 MTs
No. capabilities	4 (4 of each)
No. cells (central fixed and flexible only)	4 cells
Nominal MT utilisation	60%
No. models (weighted split)	3 (0.4:0.4:0.2)
Average operating time/product	160 min
Average operation duration	20 min

The experiment increased levels of drift, both structurally in parameter, Dft, and through stochastic operation durations, OpD; both parameters had three levels. As structural drift, Dft, increases nominal operation duration is more varied, model precedence structures increasingly diverge and job customisation to a particular model is earlier (reducing job interchangeability between models). This parameter progression is shown in Figure 6-6, displaying model precedence graphs with model customisation, operation capability and nominal durations. To maintain nominally balanced production, all models require each capability twice and all models have the same total operation duration. The second parameter increases stochasticity of operation durations, OpD, against a uniform random distribution, increasing from 0 to changes of 0.25 and 0.5 of the nominal duration.

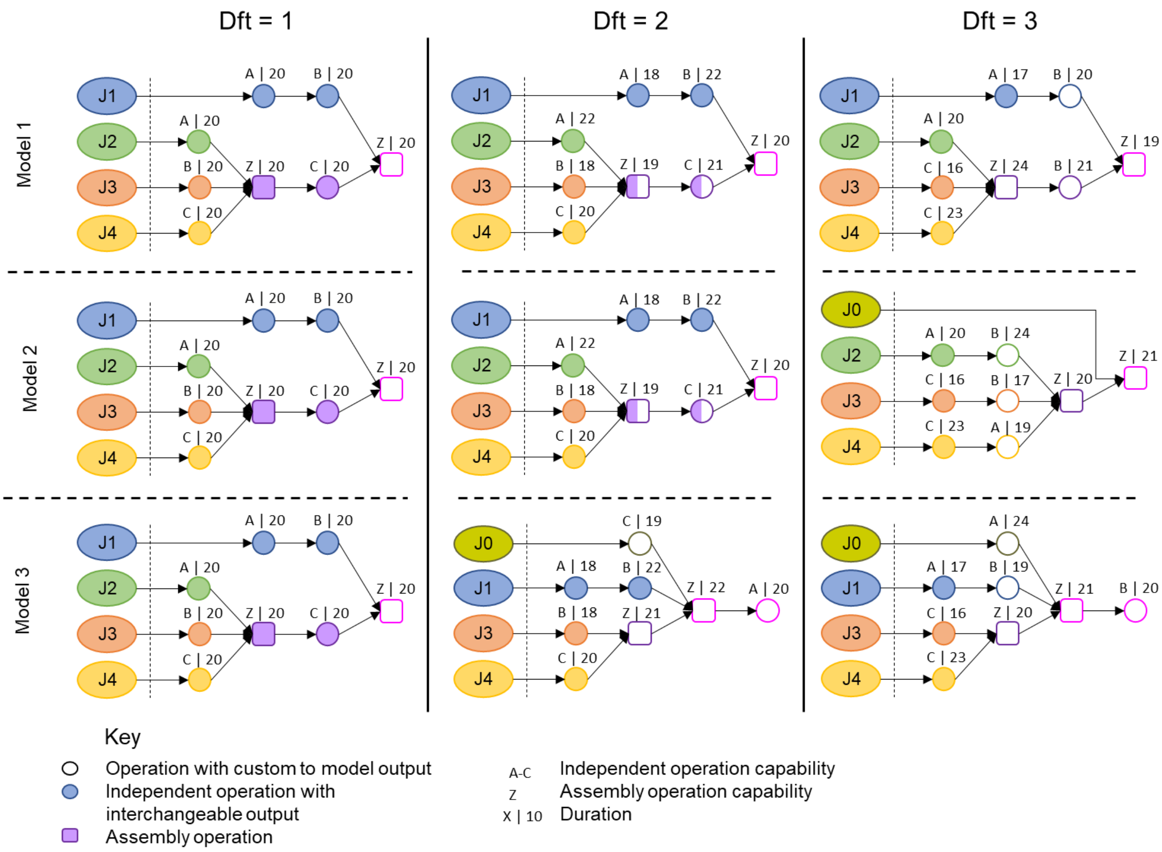

Figure 6-6: Assembly balanced production, structural drift precedence graphs

Results and discussion

The experiment results, shown in Figure 6-7 for WIP jobs with a 95% confidence interval, Figure 6-8 for order lead time and Table 6-4 for lead time population splits, directly compare the three systems. WIP jobs results indicate the anarchic system is significantly better when all models are identical, Dft=1, additionally for moderate structural drift, Dft=2, all systems perform similarly; at both levels the anarchic system maximises flexibility. For Dft=3, the anarchic system's poor performance arises from structural inflexibility, preventing jobs' model transferring due to earlier customisation to a model. Decision-making mechanisms, currency levels and costs were not optimised, these hindered jobs from assessing profitability effectively causing some to go beyond the point of customisation before there was sufficient demand. For most parameter levels, the fixed system's performance was worse than the centralised flexible system. The flexible centralised system performed consistently, by prioritising affectively and reduce waiting time for co-dependent jobs. The fixed system represents a hierarchal structure, with siloed cells that do not communicate; whereas the flexible can effectively manage all resources; a cell manages all interchangeable resources simultaneously. The increasing stochasticity of operation durations, OpD, has little impact on system performances compared to structural drift.

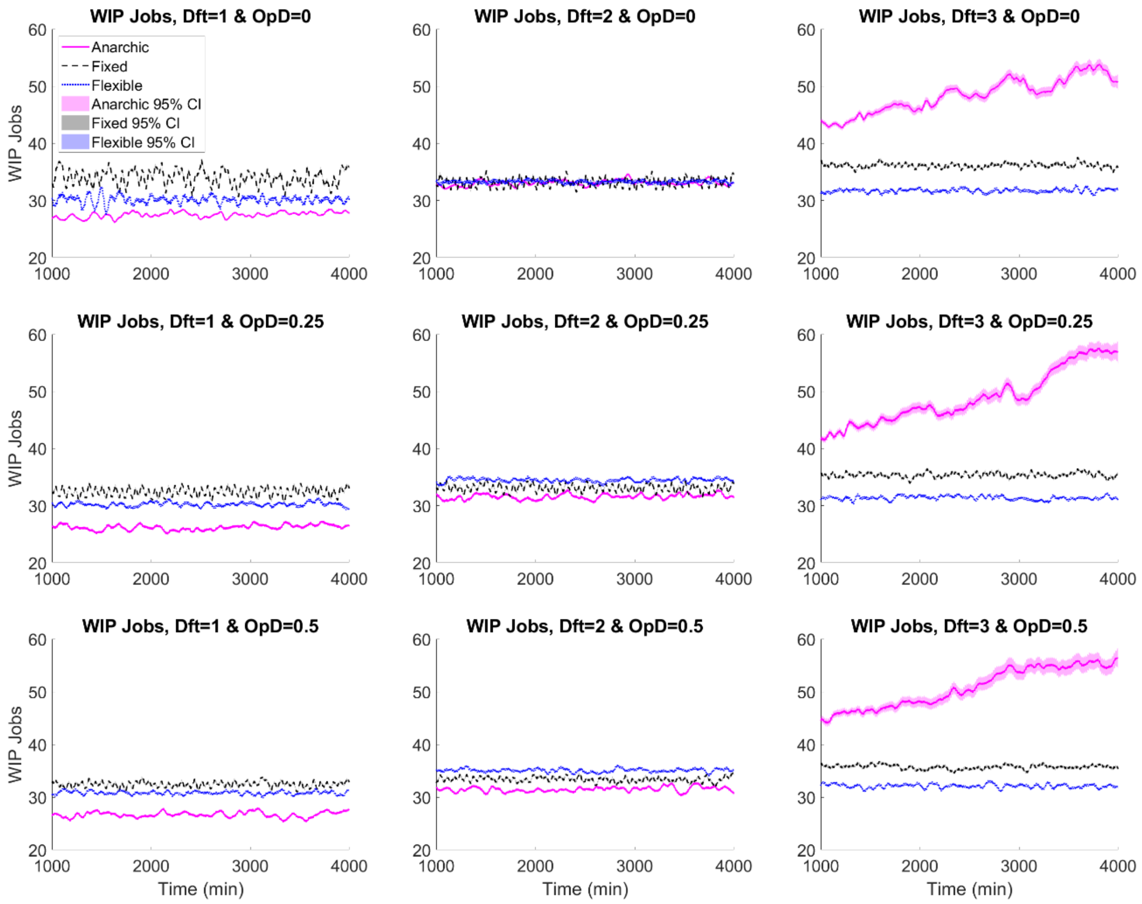

Figure 6-7: Assembly balanced production WIP results

Analysing order lead time results in Figure 6-8 and Table 6-4, the anarchic system outperforms both centralised systems for the majority of orders in all scenarios. The anarchic system, for Dft=1 & 2, significantly outperforms the push systems for all orders; even for moderate structural drift and reduced flexibility for Dft=2. For Dft=3, the anarchic system has a superior performance for the initial 75% of orders, as shown in Figure 6-8, but a longer tail of prolonged order lead times. This is because the anarchic manufacturing system demonstrates anticipatory behaviour, guided by model profitability, whilst utilising dynamic demand-oriented decision-making; producing a strong global result despite the heavily criticised myopic decision-making (which has been reduced as jobs maximise lifetime profitability). The fixed and flexible system performances mimic that of WIP jobs performance, with consistency at all parameter levels. It is unknown why for Dft=2 the flexible system consistently performs worse. Operation duration stochasticity, OpD, does not significantly impact performance; at reduced stochasticity levels all systems have spikes, this is due to repeated identical sequences.

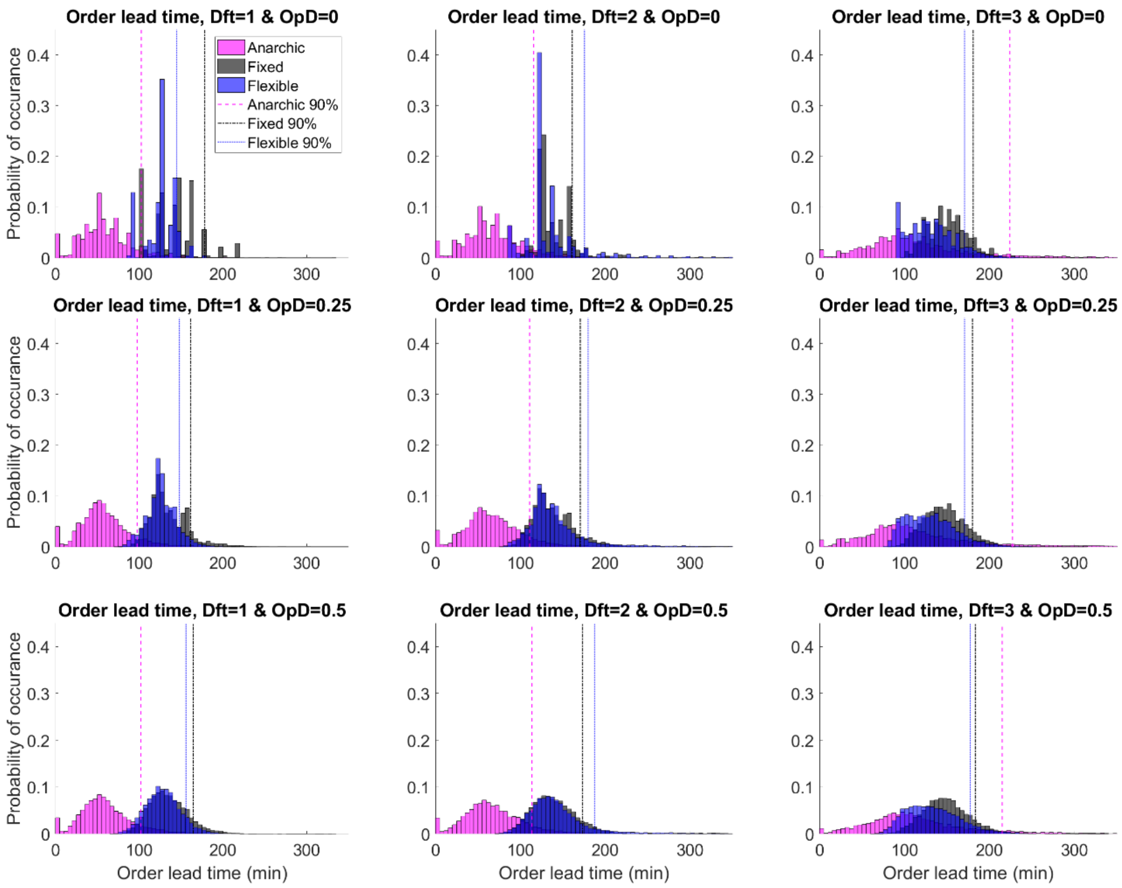

Figure 6-8: Assembly balanced production, order lead time results

Table 6-4: Assembly balanced production, order lead time population split

Order lead time		DfT=1			DfT=2			DfT=3		
		50%	75%	90%	50%	75%	90%	50%	75%	90%
OpD = 0	Anarchic	55.4	75.1	102.5	67.4	88.1	115.7	105.5	146.7	223.8
	Flexible	125.6	139.4	144.9	124.0	140.0	175.6	128.3	150.3	170.6
	Fixed	144.8	161.5	178.2	128.3	151.4	161.1	149.5	164.8	180.8
OpD = 0.25	Anarchic	55.2	73.7	97.7	64.5	86.7	110.9	102.9	148.2	227.0
	Flexible	125.2	137.3	148.1	133.3	150.7	179.8	127.9	149.8	170.6
	Fixed	129.1	150.3	161.2	133.4	153.7	170.6	145.9	163.4	179.9
OpD = 0.5	Anarchic	56.5	76.8	102.1	64.4	88.3	113.7	106.4	146.5	214.9
	Flexible	127.7	141.4	155.8	137.1	156.6	187.3	130.7	154.5	177.2
	Fixed	132.5	149.4	164.6	137.0	155.4	173.3	147.0	165.3	183.2

6.3.4 Dynamic bottleneck production

Bottlenecks can significantly reduce productivity, many current bottleneck detection schemes focus on long-term detection, typically evaluated analytically or through simulation, however, short-term bottleneck detection is increasingly important in operations management (Li, Chang and Ni, 2009). Short-term dynamic bottlenecks are harder to manage and require process control techniques. Bottlenecks is a significant issue in assembly, however they typically arise from cycle time drift (Hu *et al.*, 2011) these conflicts with traditional systems' rigid and centralised structure. This experiment created dynamic bottlenecks by drastically increasingly one operation duration, of a different capability, for each model. Figure 6-9 displays the experiment summary, using fewer model differences and increasing the bottleneck extended operation.

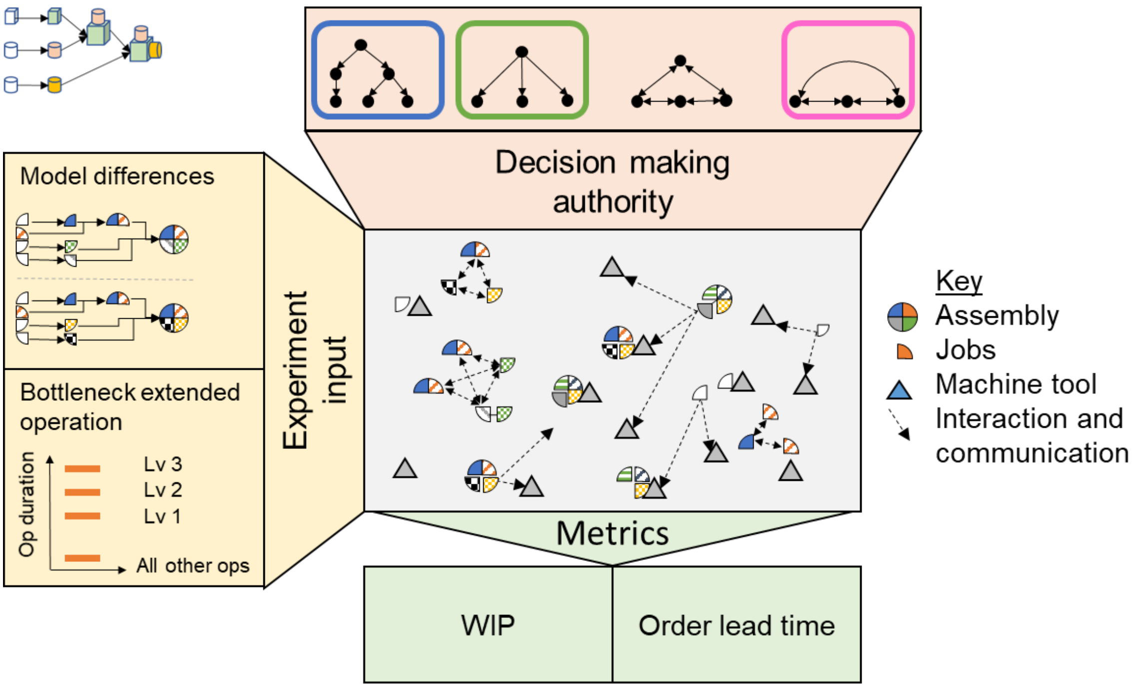

Figure 6-9: Assembly dynamic bottleneck experiment summary

Experimental framework

This experiment adapted the previous experiment for balanced production, covered in section 6.3.3, at Dft=2 and OpD=0.25. Table 6-5 summaries the fixed parameter settings, notably utilisation was increased to 80% (by increasing order arrival rate, adjusted for the extended operation), and order model split is a third each. Average and total model operation durations change by variable parameter and have been omitted.

Table 6-5: Assembly dynamic bottleneck fixed parameters

Parameter	Value
No. machine tools	16 MTs
No. capabilities	4 (4 MTs of each)
No. cells (central fixed and flexible only)	4 cells
Nominal utilisation rate	80%
No. models (order split between models)	3 (0.33:0.33:0.33)

The experiment increases the severity of the bottleneck, by increasing the duration of the single extended operation, this variable parameter is denoted as BtN. A dynamic bottleneck between capabilities is ensured by extending a different capability for each model. Figure 6-10 shows the three model precedence graphs, the extended operation duration is marked 'XX' and durations are detailed in Table 6-6.

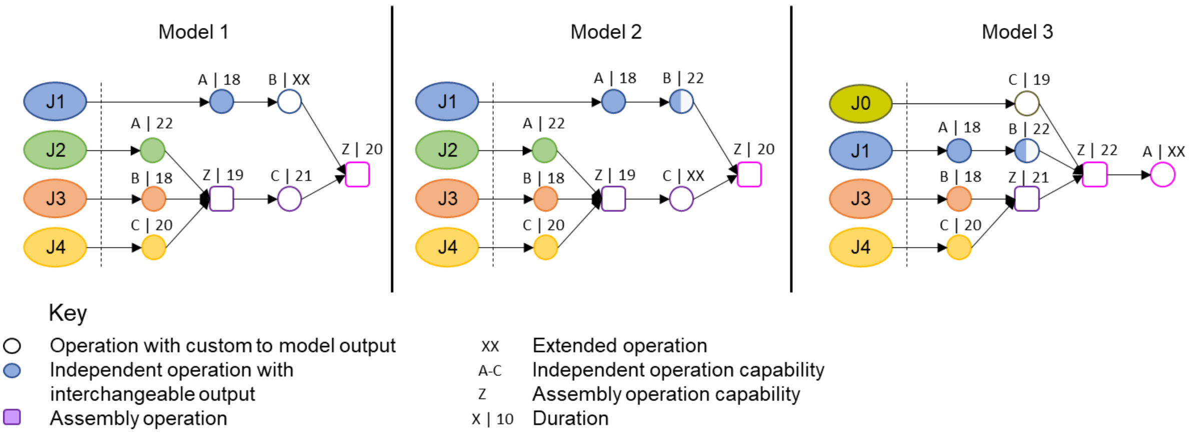

Figure 6-10: Assembly dynamic bottleneck precedence graphs

Table 6-6: Assembly dynamic bottleneck variable parameter levels

Parameter level	Extended operation duration (min)	Proportion of extended operation of the whole process
BtN = 1	50	14%
BtN = 2	75	20%
BtN = 3	100	25%

Results and discussion

Results from dynamic bottleneck production are shown in Figure 6-11 for WIP jobs, Figure 6-12 for order lead time and Table 6-7 for order lead time population splits. WIP jobs results, displayed in Figure 6-11 with a 95% confidence interval, clearly shows the flexible system is best and the anarchic has a similar but slightly worse performance at all parameter levels. The centralised fixed system, with isolated hierarchical cells, performs poorly and for BtN=2 the system is unstable; instability is evident from a continuously increasing trend. All systems are unstable at BtN =3.

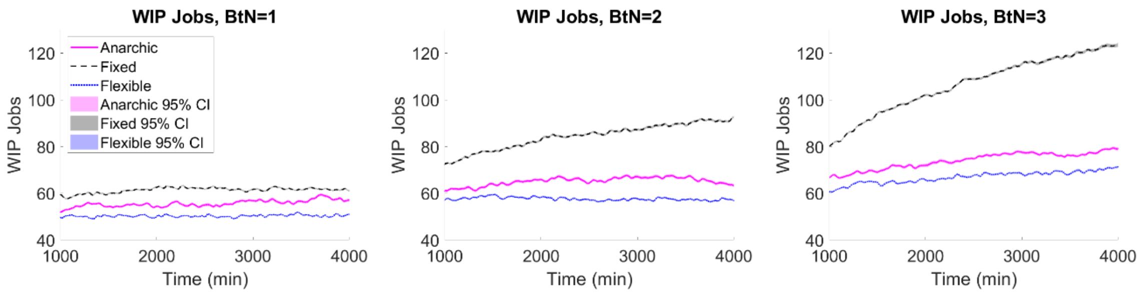

Figure 6-11: Assembly dynamic bottleneck, WIP results

The anarchic system has superior performance at all levels for order lead time. Order lead times increase as BtN increases for all systems, with the anarchic system performing best at all population splits, despite a longer tail than centralised flexible systems. This superior order lead time, improving service level, can be highly attractive to manufacturers. Additionally, it demonstrates the anarchic system's robustness to unforeseen disruption through its ability to manage short-term dynamic bottlenecks.

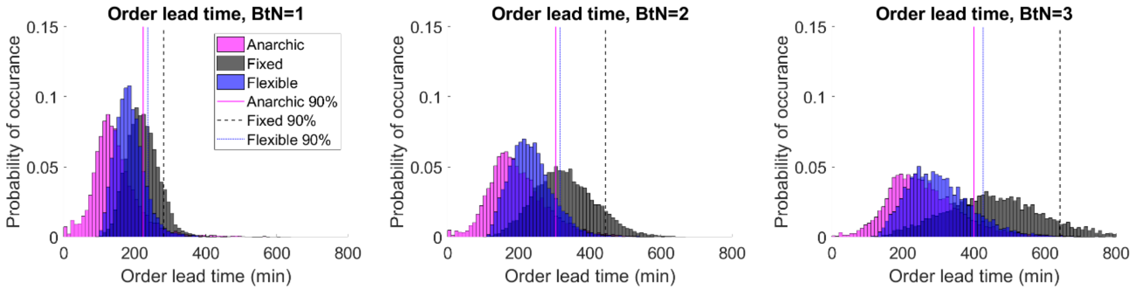

Figure 6-12: Assembly dynamic bottleneck production, order lead time

Table 6-7: Assembly dynamic bottleneck, order lead time population split

Order lead time	BtN=1			BtN =2			BtN =3		
	50%	75%	90%	50%	75%	90%	50%	75%	90%
Anarchic	136.3	174.8	223.7	186.2	240.8	304.0	246.3	320.4	399.4
Flexible	181.8	208.1	236.7	229.3	270.4	316.7	293.0	357.5	425.7
Fixed	219.6	250.9	281.2	325.0	385.3	641.9	452.7	548.1	642.0

6.4 Discussion

The assembly planning and control problem extends independent job manufacture through a coordination problem, assigning jobs to join once all preceding operations have been fulfilled. The anarchic manufacturing system, for both experiments, demonstrated the ability to resolve this coordination problem in a purely distributed manner. The lack of global coordination in distributed systems is argued for the use of mediators and hybrid systems (Blunck and Bendul, 2016); hybrid systems use a hierarchical structure with distributed decision-making (He, Zhang and Li, 2014). However, in this chapter inter-job cooperation is achieved using anarchic manufacturing's design principles by maintaining free market competition and profit maximisation, fulfilling global objectives; by efficiently delivering orders in a relatively short lead time. The balanced production experiment, covered in Section 6.3.3, demonstrates that when ignoring line balancing activities, mixed-model assembly can effectively be fulfilled through anarchy and distributed systems.

The balanced production experiment demonstrates that anarchic manufacturing can fulfil assembly production whilst maximising flexibility in the system. At lower levels of structural drift, most notably for late model customisation, the anarchic system outperformed centralised systems for both WIP jobs and order lead time. Good order lead time was maintained at higher levels of structural drift, however, WIP was poor as reduced flexibility hindered the anarchic system. The dynamic bottleneck production experiment demonstrated the anarchic system's ability to adapt to disruption, as degradation in performance was in line with the centralised flexible system, which operated as a flow shop. Order lead times, although superior for most orders, had a large distribution; this is undesirable for some manufacturers. However, a more aggressive demand and priority-oriented pricing structure will likely resolve this and cut the long tail. This would be achieved by advertising an increased selling price of a highly demanded model to influence job decision-making, whilst maintaining the anarchic/distributed structure.

Anarchic manufacturing's maximising flexibility trait, through inter-changeable jobs/subsystems, could entail that new permutations of existing models can easily be fulfilled without substantial system re-planning. Mixed-model assembly lines typically produced variants from a platform (Battini *et al.*, 2009). An agent's fulfilment by profitability would indicate suitability for higher-level business decisions on product mix and appropriate pricing; as the anarchic system's free market and profitability-oriented mechanisms directly relate to business objectives. Several distributed system traits are exhibited during experimentation, agility and flexibility, self-healing and myopic decision-making, these are discussed in further detail below.

Agility and maximising flexibility

The balanced production experiment increased structural drift and reduced available flexibility in the mixed-model assembly system. It is evident that the flexible centralised system maintained performance, however, the anarchic maximised the flexibility available at the reduced drift and high flexibility scenarios. Centralised systems were unable to maximise the flexibility available, as on aligning to MRP principles the jobs (materials) are assigned an order and cannot change at any point during production. The anarchic manufacturing system's dynamic decision-making for jobs at all stages of production, allowed for an agile and adaptive delayed decision-making; rather than being tied to a specific order from creation.

The anarchic system maximised flexibility by embracing complexity, the less restricted and more complex the system is the more effective flexibility becomes. Considering an entropic view to complexity, as the number of options and selection choices increase the more complex the system is (Elmaraghy *et al.*, 2012). The anarchic system had its limits, as seen in the balanced production experiment in Section 6.3.3, when structural drift was high at Dft=3, earlier customisation limited flexibility and the system's early decisions based on uncertain information were binding thus preventing adaptability to new scenarios. The centralised push systems managed complexity through simplification and structure, by assigning jobs to an order on creation. The flexible system is effective for all experimental parameter levels, but limited its performance; the fixed system with an hierarchical cells structure performed reasonably well until it faced disruptions, as observed in dynamic bottleneck production in Section 6.3.4.

Self-healing system

The anarchic manufacturing system exhibited robust self-healing characteristics against dynamic and unforeseen disturbances, as shown in the dynamic bottleneck experiment in Section 6.3.4. Bottlenecks can significantly impact productivity, even in flexibly structured systems. The anarchic system was able to reallocate operations away from the bottleneck resource to directly interchangeable resources just as effectively as a centralised flexible system that managed all interchangeable resources concurrently. This was observed through similar rates at which WIP jobs, in Figure 6-11, and order lead time, in Figure 6-12, increased for the two systems. This aligns to self-organising and fault-tolerant characteristics proposed for distributed systems (Heragu *et al.*, 2002), and reinforcing previous conclusions from literature (Leitão, 2009) .

Reducing myopic decision-making

Myopic decision-making is a key criticism of distributed systems (He, Zhang and Li, 2014), where short-sighted decisions result in globally suboptimal outcomes. Anarchic manufacturing system for assembly adapted agent decision-making to maximise lifetime profitability; demand impacts a product's selling price and reported recent costs indicate profitability for selecting one model over another. This lifetime profit maximisation is an effective alternative to other myopic decision-making counter measures; re-introducing hierarchy and altering competitive behaviour are likely to impede emergent behaviour (Blunck and Bendul, 2016). Lifetime profitability maximisation is a complex decision with highly uncertain outcomes, the environment is likely to change over the course of a job agent's lifetime. When an early decision was forced, in balanced production in Section 6.3.3 at Dft=3, it impeded agent and global outcomes as agents cannot impact their early decision-making.

For flexible scenarios, with late job to model customisation that allowed agile systems to maximise flexibility, the impact of myopic decision-making was reduced; through delayed and dynamic decision-making throughout an agent's life. However, as shown in the balanced production experiment with reduced flexibility, at Dft=3, early decisions significantly impact the outcome, evident through very high WIP jobs in Figure 6-7. The lack of global coordination has impacted the performance of anarchic manufacturing in this uncertain and inflexible environment.

6.5 Summary

The previous chapter evaluated anarchic manufacturing in simple discrete manufacturing scenarios and found that the anarchic system could manage complexity effectively and adapt to conflicting objectives. This chapter evaluates the anarchic manufacturing system against centralised systems for assembly problems and has extended the breadth of research into distributed systems into assembly as well as confirming some conclusions found previously.

The anarchic manufacturing system has been demonstrated to effectively manage the mixed-model assembly scenario; that uses multiple jobs that are joined to make a product. There is a fundamental coordination problem that extends decision-making processes beyond an individual agent. Independent decision-making was maintained throughout and used group decision-making methods for the natural teamworking scenario, as detailed in Section 6.3.1. Independent decision-making allowed jobs (or subassemblies) to leave a group of jobs if the joining operation had not started. Furthermore, the free market architecture, where system elements maximise profitability, was used for all decision-making. This resulted in an effective system that reduced myopia by maximising life-time profitability, as shown in Section 6.3.3 where jobs were guided by its calculations for expected model profitability. This demonstrated the malleability of the free market system employed to create sophisticated mechanisms and compounds the findings in Chapter 5, which adjusted the system to react to dynamic multiple objectives.

Experiments evaluated an idealised balanced production and dynamic bottleneck scenarios and found the anarchic system is superior when it can embrace complexity to its advantage through maximising flexibility. Additionally, dynamic bottleneck experimentation, that evoked unforeseen disruption, validated previous assertions and studies for the robustness and self-healing nature of distributed systems. Anarchic manufacturing system was able to fulfil mixed-model assembly production, and even exceeded centralised performance under certain circumstances. Several desirable anarchic manufacturing traits were observed, these include agility and maximising flexibility, self-healing, and reduced myopic decision-making. These findings reinforce the conclusions drawn from Chapter 5, where similarly the anarchic manufacturing system was shown to embrace complexity and reduce myopic decision-making through profitability mechanisms.

This chapter considering mixed-model assembly along with the previous chapter using simple discrete manufacturing have analysed anarchic manufacturing relative to centralised systems in subsets of manufacturing scenarios, where long-run and mature behaviour is developed and analysed. Almost all manufacturers face the problem of product transition, where the manufacture of one product is replaced over a prolonged period with another. Subsequently, there is a complex planning and control problem over a finite period, where mature states cannot be achieved, given the dynamic and temporal nature of the problem. The next chapter evaluates this product transition scenario, which gives rise to a highly volatile environment, where anarchic manufacturing may leverage its self-organising and flexible traits.

7 Application 3, product transition

7.1 Introduction

The movement from producing one product to another or between variants, known as manufacturing transition, is a traditional problem facing many manufacturers. The existing planning and control structures focus on mature steady-state environments for high volume and long term performance (Colledani, Tolio and Yemane, 2018); rather than the volatile transitional state, where there are many unforeseen disruptions during ramp-up (Surbier, Alpan and Blanco, 2014). Despite the volatile environment, there has been little focus on managing the transition period with respects to production planning and control.

The research motivation for this chapter is to ascertain whether the anarchic manufacturing system can leverage distributed system traits for an inherently volatile scenario concerning product transition, where traditional methods are at a disadvantage due to the unpredictable and dynamic nature. This chapter investigates a dynamic environment which is characterised by a lack of steady-state behaviour; in preceding chapters, only steady-state or reaction to a step change have been investigated. The anarchic manufacturing system is compared to centralised systems using flexible flowshop and hierarchical cell structures in idealised scenarios to isolate behaviour as well as against an automotive case study, which serves to validate idealised experiments. Important product transition factors are varied and evaluated, most notably the ramp-up/transition curves, learning rate to improve production, failure rate and structural flexibility.

This chapter covers additional relevant background literature for transition, ramp-up, batch production and production structures for transition. Subsequently, the experimentation section initially details the adaptations to the anarchic and centralised systems for transition scenarios and all experimentation, then the section details the four experiments conducted. The first three experiments used idealised scenarios with fabricated data which was validated by a fourth experiment using an automotive case study; all but the second idealised scenario experiment evaluated different ramp-up and down curves. The chapter then discusses all experiments and is concluded with a summary. A summary table of additional elements to the anarchic system introduced in this chapter are indicated below in Table 7-1.

Table 7-1: Additional anarchic system elements introduced in Chapter 7

Element	Meaning
Cop_{kp}	Cost per operation for resource *k* and product *p*
ψ_{kp}	Changeover discount factor

C_{change}	Cost of changeover between products
t_{ojp}	Nominal duration of an operation of capability *j* for product *p*
t_{plan}	Planning horizon (time duration)
$n_{kpresent}$	Number of recent jobs of product p processed at resource *k*

7.2 Scenario background

7.2.1 Transition

Manufacturing transition concerns a manufacturing facility transitioning to produce a new product family or product iteration that is significantly different to the existing product, with regards to manufacturing processes; these new processes require a ramp-up phase to reduce disturbances and improve production efficiency. Product rollover is the replacement of an old product with a new product, the rollover decisions consider when to replace the product and whether to offer both old and new products simultaneously (Katana *et al.*, 2017). A dual rollover, offering both products simultaneously, can include a transition phase when both products are manufactured simultaneously.

For all manufacturing facilities producing multiple product families, product changeover at machines can significantly hinder performance. Changeover typically uses well developed lean manufacturing techniques, most notably SMED (Single Minute Exchange of Die) (Mali and Inamdar, 2012). It is assumed for the experiments in this chapter that a tooling changeover is required when changing between product families, and this is a non-instantaneous task.

7.2.2 Ramp-up

The period between development completion and full capacity utilisation is known as production ramp-up. During this period the production process is poorly understood causing low yield and low production rates (Terwiesch and Bohn, 2001), this requires learning to improve any new production process. Ramp-up management and control aims to achieve rapid time to volume, to ensure fast time to market and full utilisation of production capacity, typically the experience gained during production ramp-up improves production efficiency (Hansen and Grunow, 2015). Ramp-up has increasing importance given the rise of Reconfigurable Manufacturing Systems, product variety and volatility entails manufacturing systems need to change product mix more frequently. RMS is viewed to improve the ramp-up process through rapid reconfiguration using physical technologies (Andersen, Nielsen and Brunoe, 2016), rather than through planning and control techniques.

During production ramp-up, product quality and system disturbances are significant and common issues. Available quality methods focus on high volume production and long term system performance, which lose their effectiveness during system ramp-up (Colledani, Tolio and Yemane, 2018). On implementing a new production process, whether for a new product, new production technology or both, system disturbances are highly likely to lead to unpredictable behaviour (Basse *et al.*, 2014). These disturbances interrupt production and reduce production efficiency and throughput. Insufficient process capabilities of the production technology is one of the main reasons for disturbances (Stauder *et al.*, 2014). Ramp-up key performance indicators concern throughput time and ramp-up efficiency to attain quality and quantity targets in a predetermined lead time at the lowest possible cost (Surbier, Alpan and Blanco, 2014).

Ramp-up production is designed, progressing from pilot production to low and then high volume production phases (Almgren, 2000), increasing new product volumes whilst decreasing that of the old product against defined ramp-up and down curves (Surbier, Alpan and Blanco, 2014). Throughout all ramp-up phases, learning through experiments is important to achieve a rapid time to volume with high yield. Experience gained can be expressed from the cumulative production volume and can be used for production capacity planning (Hansen and Grunow, 2015). Learning aids process improvement but reduces capacity in the short-run, resultantly there is a trade-off between experiments and production (Terwiesch and Bohn, 2001). Terwiesch and Bohn formalised the intertemporal trade-off between short-term opportunity cost of capacity against long-term value of learning and examined the trade-off between production speed and quality.

7.2.3 Batch production

Despite the pervasion of lean manufacturing, there are continuing opportunities and reasons for batch production. These include manufacturers of varying production volumes, batch production provides operational flexibility to try out low volumes of new work (Cooney, 2002). The scenario described aligns to the problem faced in transition and ramp-up of a new product.

The inter-task product changeover at a machine or resource for multi-model production can have a significant impact on performance (Nazarian, Ko and Wang, 2010). In scenarios where there is a significant changeover setup task, batch production will reduce the number of changeovers required between product types and can improve overall production efficiency. This is likely during the transition between two product families and extended if the production facility is designed to produce one or the other rather than both simultaneously.

Almgren details that batch production was used during the low volume ramp-up phase, rather than continuous production for developed high volume production phase (Almgren, 2000). This is most likely to improve learning during early-stage ramp-up production and benefit from batch production traits.

7.2.4 Transition and ramp-up production structures

There are many remedial and investigative methods to improve the ramp-up method; for example, reducing root cause of instabilities (Basse *et al.*, 2014), pilot programmes (Almgren, 2000), gamification for learning (Kampker *et al.*, 2014), copy-exactly ramp-up strategy for learning (Terwiesch and Xu, 2004). However, these cannot improve the planning and control of a system, they are part of the learning process to reduce disturbances and improve production processes.

Strategic planning methods for transition and ramp-up consider temporal plans and task allocation and may use advanced planning simulation tools. Almgren divides the ramp-up phase into low volume learning to high volume production (Almgren, 2000). More detailed methods are used for short-term planning; a method that models technologies, whilst considering stochastic influences, to predict ramp-up behaviour for a given scenario is used within a hybrid simulation model (Klocke *et al.*, 2016). A full factory simulation tool was used as a decision support tool during a transient period of the parallel ramp down of one product and the ramp-up of a new product (Klein and Kalir, 2006). On a network scale, Becker *et al.* consider a strategic ramp-up planning process for automotive production networks. They utilise a hierarchical planning framework to strategically determine ramp-up and down decisions, and show that their strategic ramp-up planning model outperforms sequential planning approaches (Becker, Stolletz and Stäblein, 2017).

Traditionally, hierarchical planning and control structures are used to simplify the overall problem into manageable sizes. This often leads to independent manufacturing cells. During ramp-up, the system's complexity is the cause of instabilities observed as unpredictable and uncontrollable system behaviour (Basse *et al.*, 2014), hence manufacturers aim to reduce complexity through structure. For scenarios with a large setup time between product families, multiple cells are used and each dedicated to a different product family (Miltenburg, 2001). Similar rules can be applied to transition scenarios to simplify the problem, Ford closed their Dearborn Truck Plant for 11 weeks to complete the overhaul and ramp-up for the new aluminium body Ford F-150 pickup (Fleming, 2018). In this example a distinct cut off from one product to manufacturing the other was made; simplifying the problem by avoiding parallel manufacture through a direct changeover transition.

Methods and tools used for managing a ramp-up phase are not specific to the ramp-up conditions, rather they consider mature production conditions, resulting in inaccurate resource planning (Surbier, Alpan and Blanco, 2014). This suggests that production engineers are poorly equipped to manage transition and ramp-up periods, as a long-term steady-state perspective is unsuitable. Due to time pressures and insufficient data, analytically validated decisions are not feasible, inevitably heuristics are applied to decision-making which helps to reduce complexity (Basse *et al.*, 2014).

Distributed management of autonomous reconfigurable manufacturing systems, proposed to reduce ramp-up times through modularity of resources, has been proposed (Li *et al.*, 2018). However, they do not consider the concurrent production of two products but aim to significantly reduce the time between runs of different products, improving through physical manufacturing technologies rather than decision-making.

Distributed systems have not previously been proposed to resolve the transition or ramp-up problem. However, the reported self-organising and agile nature of distributed systems, as discussed in Section 2.4.4, suggest they could solve the highly dynamic and volatile nature of product transition.

7.3 Experimentation

7.3.1 System adaptation, anarchic manufacturing system

The anarchic manufacturing system has been adapted to fulfil the transition scenario. The most significant concern in a generic transition scenario is to determine whether a resource should change the product type it is producing. This will typically require a changeover operation for retooling and setup. The anarchic system, to determine whether it is worthwhile to changeover product, uses temporary syndicate batching agents to achieve collaborative economies of scale; by grouping jobs of the same type requiring the same resource capability. The benefit to a resource, through profitability, of changing over for a different batch of products is compared against market conditions, providing an economic assessment against the global conditions. The resource changeover cost is calculated, as an equivalent lost operational revenue, and charged to the jobs requesting a changeover. The temporary batch, using pooled currency from all jobs within the batch, may overcome the changeover cost, thereby benefiting from economies of scale. This ensures economic viability as the resource charges for the changeover operation and globally it ensures that there is sufficient demand to warrant a resource to changeover products.

Anarchic manufacturing for transition has a structure where dynamic batches of jobs are created, as economically appropriate, and these batches negotiate with resources using the contract net protocol to assign jobs (within the batch) to a resource. Figure 7-1 diagrammatically displays the anarchic system where three jobs of two different types are joining batching agents, which in turn negotiate with resources; these resources illustratively reflect the utilisation and queue cost and product changeover cost.

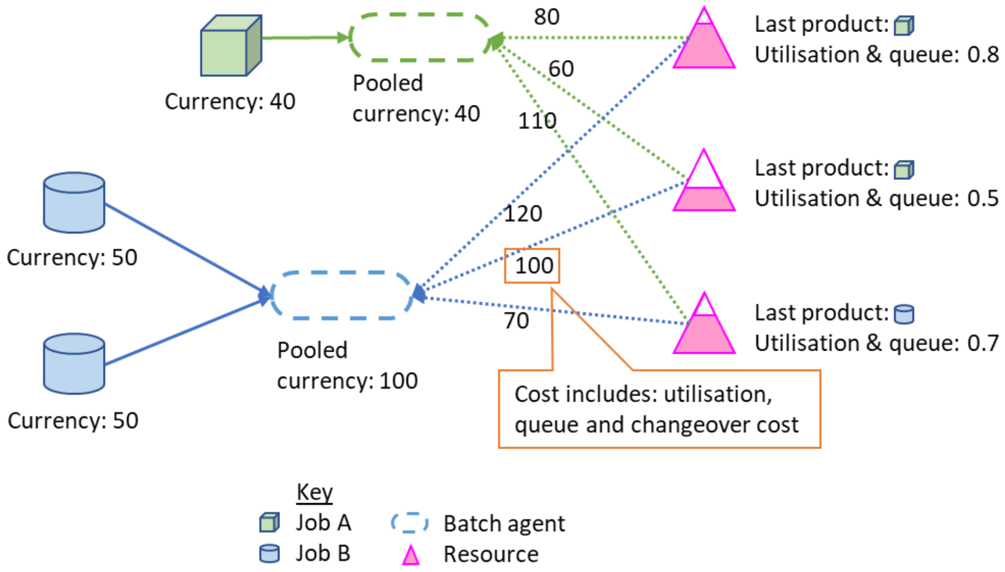

Figure 7-1: Transition, anarchic system for transition with dynamic batching

Jobs join an unassigned batch of the same product type looking for the same resource capability where available. As the batch has not successfully negotiated a resource (MT), it suggests that further jobs are required to pool resources and benefit from economies of scale, overcoming any possible changeover cost. Jobs cannot join assigned batches; therefore, a highly efficient system would process jobs in batches of one, achieving single piece flow through the system.

Batches negotiate with resources using a contract net protocol framework, with up to five rounds of bidding; similar to the anarchic manufacturing system detailed in Section 4.2, except for an adjusted resource cost calculation, explained below. Batches ask resources with suitable capability to bid for the operations within the batch, resources reply with a cost for all the operations, considering any product changeover cost. Each job calculates a threshold, which is the currency held divided by the number of operations remaining. Batches evaluate whether the lowest bid is below the total threshold for all jobs and assigns the jobs to the resource if so, otherwise the batch will ask the resources for a rebid for up to four further rounds. This negotiation process, with highlighted adaptations, is summarised in Figure 7-2 and displayed as a decision flowchart.

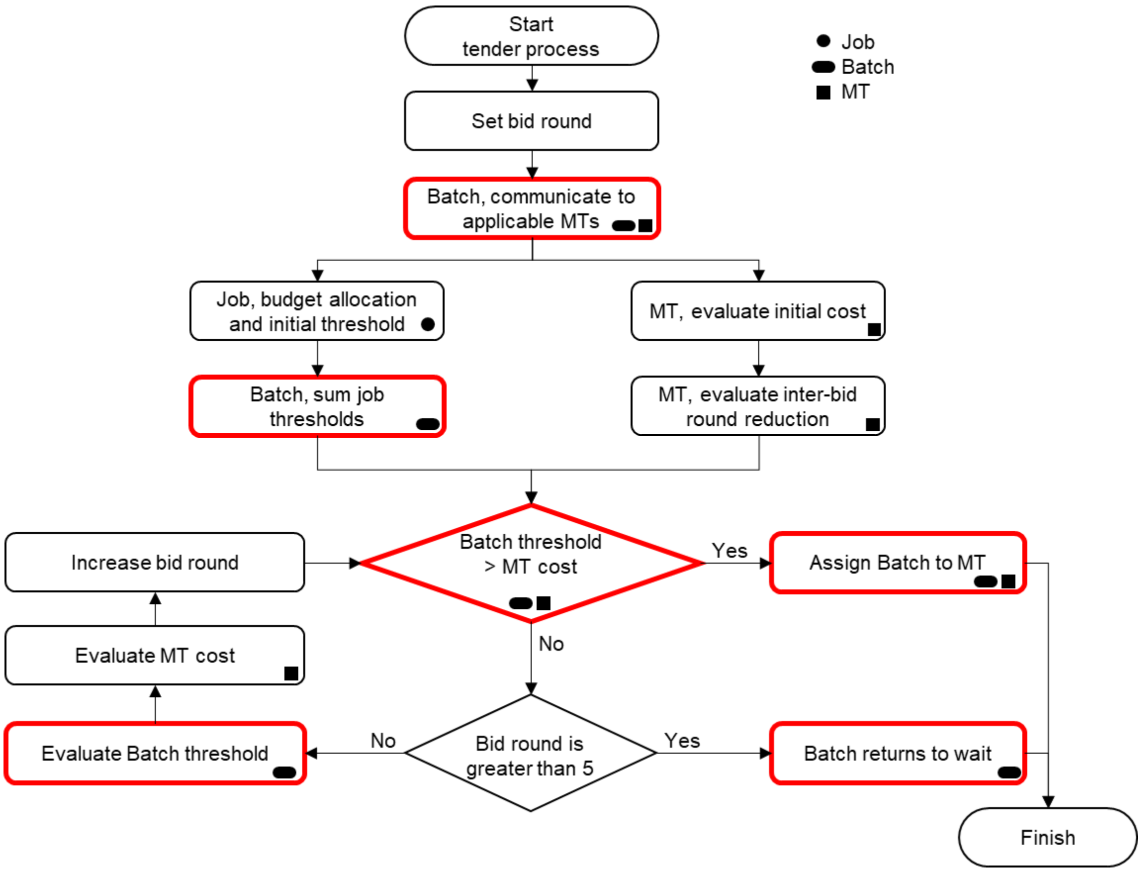

Figure 7-2: Transition adjusted negotiation framework

The MT bidding cost calculation considers the number of jobs to be processed, utilisation and queue at the MT, efficiency of processing the product, the changeover cost and recent history of tendering batches. Equation 1 defines the bidding cost for MT k for model p at time t, $\beta_{kp}(t)$, where n_b is the number of jobs in the tendering batch, $Cop_{kp}(t)$ is the cost per operation for resource k and product p at time t, $\psi_{kp}(t)$ is the changeover discount factor and C_{change} is the cost of changeover.

$$\beta_{kp}(t) = n_b \cdot Cop_{kp}(t) + \psi_{kp}(t) \cdot C_{change} \tag{7.1}$$

The cost per operation, $Cop_{j\,p}(t)$, resource j and product p at time t is calculated as:

$$Cop_{kp}(t) = Cop_{cExp}\left(\omega_k(t) + \frac{Q_k(t) \cdot t_{ojp}}{t_{plan}}\right) \tag{7.2}$$

Where Cop_{cExp} is the expected operational cost for capability c, $\omega_k(t)$ is the utilisation of resource k at time t, $Q_k(t)$ is the queue at resource j, t_{ojp} is the nominal duration of an operation of capability *j* for product p and t_{plan} is the planning horizon.

The changeover discount factor, $\psi_{jp}(t)$, for product p at time t, is calculated as:

$$\psi_{kp}(t) = \begin{cases} 0 & \begin{matrix} if\ product\ is\ the\ same\ as\ the\ last \\ in\ the\ queue\ of\ resource\ k \end{matrix} \\ min\left(1, 2 - \dfrac{2n_{kprecent}(t)}{n_{krecent}(t)}\right) & otherwise \end{cases} \quad (7.3)$$

Where $n_{kprecent}(t)$ is the number of recent jobs of product p processed by resource k at time t, and $n_{kprecent}(t)$ is the total number of recent jobs processed.

7.3.2 System adaptation, central and hierarchical systems

For comparison simple centralised systems are used, following a flexible flowshop style structure and a hierarchical cell structure; both of which use simplifying structures to manage operational complexity. The flexible flowshop structure prioritises older batches, to evenly manage backlogs by product, and nominally processes jobs for product A then B; as diagrammatically shown in Figure 7-3. The flowshop cells contain all the machine tools of a particular capability. Jobs at each stage are allocated to the applicable cell and assigned to the next available MT on arrival to a cell, i.e. the MT with the shortest queue. This enables flexibility on MT failure, as jobs will be reassigned to the next available MT.

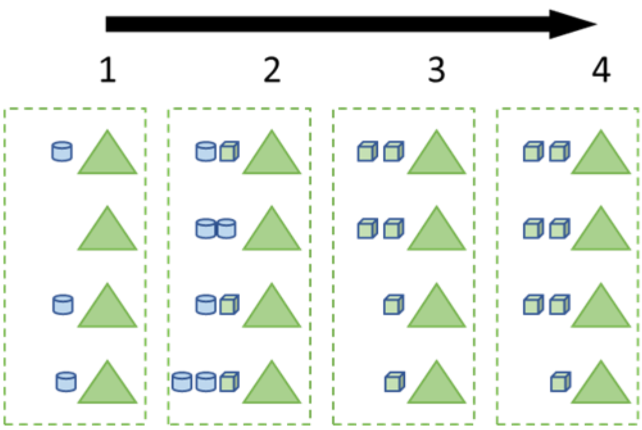

Figure 7-3: Transition, illustrative centralised flexible flowshop structure

The hierarchical cell structure has cells that contain one MT of each capability, and therefore they can complete all operations, jobs cannot move between cells. On arrival of a new batch, at the beginning of each week, the hierarchical system splits the jobs by product A and B and assigns each cell a product, with one cell processing a mix of A and B, each cell gets an equal share of jobs; as diagrammatically shown in Figure 7-4. This system minimises changeovers, as only one cell processes a mix of both product types, and processes these in an A then B sequence. For a MT that is shared between cells, e.g. only 1 MT of a particular capability shared between 2 cells, the MT will prioritise queued jobs by older jobs and secondarily product A over B of jobs within the same batch. This simplifies the allocation problem by dedicating cells to a product, however on MT failure jobs must wait for repair before continuing as they cannot be reassigned between cells.

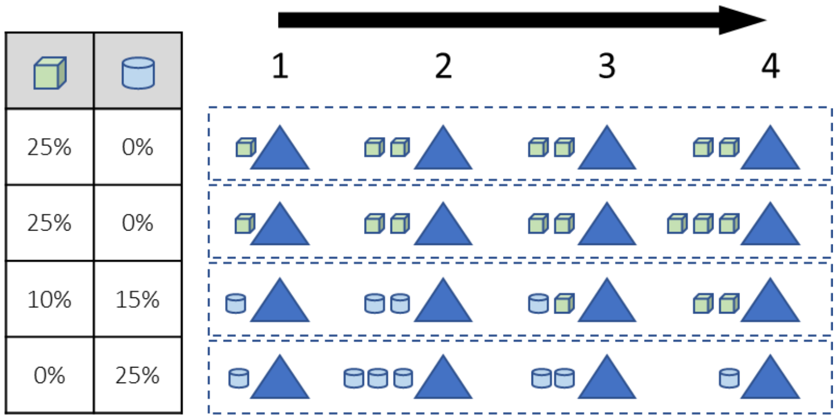

Figure 7-4: Transition, illustrative centralised hierarchical cell structure

7.3.3 Factors impacting experiments

All experiments conducted used stochastic operation durations and failure rates; therefore, each parameter setting was repeated for 50 runs for suitable confidence and statistical significance. Section 7.2 highlights key product transition issues, those that are tested in this chapter are differing ramp-up/product transition curves, the learning rate to improve production efficiency and reduce failures, failure severity itself and the structural flexibility of the manufacturing system. All simulations models were created as agent-based models, using the AnyLogic platform.

For all systems and experiments, resources are impacted by ramp-up issues, most notably high inefficiency and failure rate until learning is achieved through experience. The operation duration, for MT *k* operating on product model *p* at time *t*, is divided by the efficiency rating, $Eff_{kp}\ (t)$, which for a new product type starts at 0.3. Learning through experience improves the efficiency rating, improving by 0.1 for every ke_{pj} number of operations for that product completed globally and locally, for product model *p* by resource capability *j*. MT k, at time t processing model p, has a chance of failure before every operation dependent on the failure rate, $F_{kp}(t)$, which improves through learning and experience, similar to efficiency. The start failure rate, F_{start}, is a probability of 0.4 and similarly improves by 0.1 for every kf_{pj} operations completed for the product model *p* by capability *j*; there is a minimum failure rate of 0.01.

For all experiments, product A was replaced by product B in various ramp-up curves, these changed the volume of production over time; the ramp-up curve used is noted as parameter *RC* and displayed in Figure 7-5. Gradual transition (*RC* = 1) reflects an increasing new product volume and decreasing old product to a predefined ramp-up curve (Surbier, Alpan and Blanco, 2014). Concurrent production (*RC* = 2) maintained equal product volumes for a prolonged duration, to represent equally demanded products. The direct changeover transition (*RC* = 3) has a hard cutover from product A to B, representing a simplified solution of zero concurrent production. At the beginning of each week, orders were released as jobs. The facility operates two shifts in a six-day week providing 96 hrs of production.

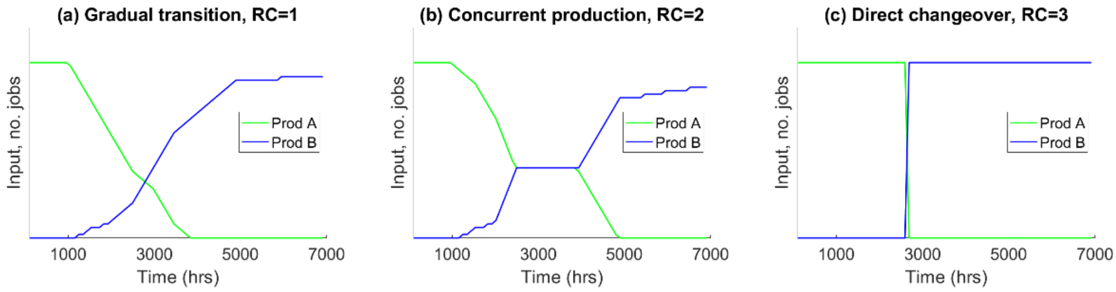

Figure 7-5: Transition ramp-up curves, (a) gradual transition, (b) concurrent production and (c) direct changeover

The idealised scenarios used artificial parameter settings, although these do not relate directly to industry, they have suitable ballpark values and still enabled a relative comparison between systems as parameter levels changed. The relative comparison is suitable to characterise the systems as a factor became more severe.

For the initial idealised experiments, jobs for both product types were required to complete four operations in the same sequence (i.e. A-B-C-D). This could be fulfilled by any capable resource, allowing flexible routing; planning and control structure permitting. Each operation had the same nominal duration which was uniformly randomly varied by 20%. For the first two experiments, varying learning rates and failure severity, there were 16 resources; four resources for each capability. The third experiment varying the structural flexibility of the system varied the number of resources from six to eight.

7.3.4 Learning rate

The first idealised scenario experiment explored the impact of learning rates as well as ramp-up curves. The rate of learning is the focus of much the product transition and ramp-up literature, as covered in section 7.2. This experiment directly investigated whether the speed of learning impacted the performance for distributed and centralised systems and is diagrammatically summarised in Figure 7-6. The learning method and impact of learning was kept consistent for all systems, it was assumed that there would be no difference between systems in how learning was achieved.

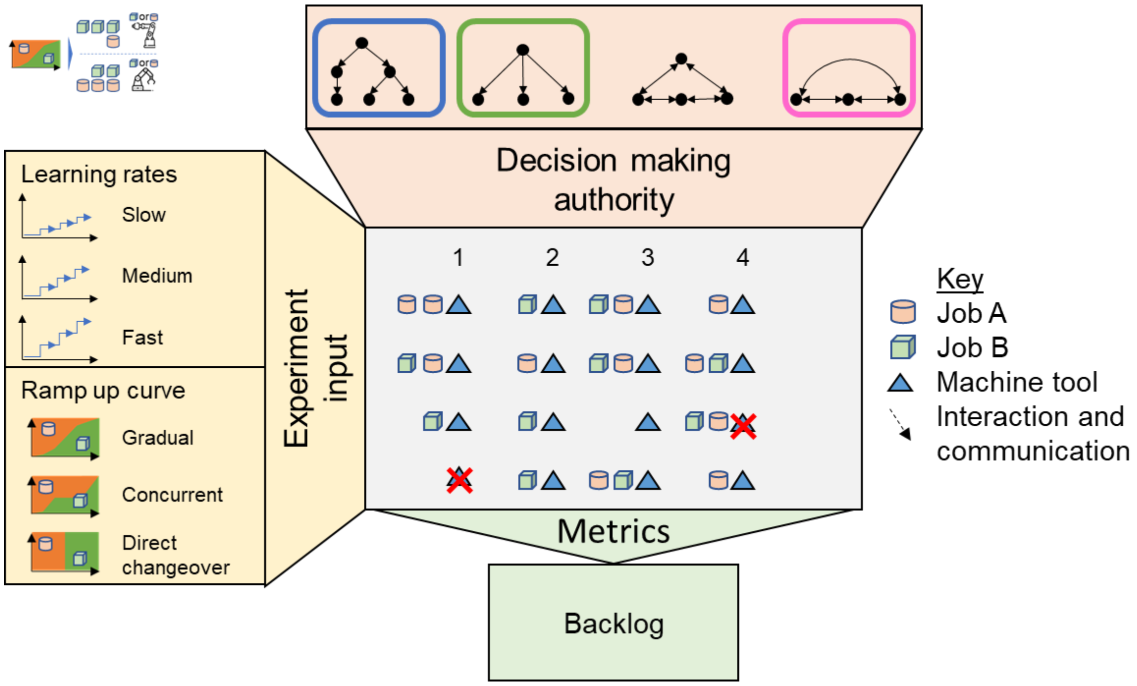

Figure 7-6: Transition learning rates experiment summary

Experimental framework

Learning is the focus of much of the ramp-up and transition literature. Learning rates (LR) were varied in the first experiment, by adapting the number of operations completed, ke_{pj} and kf_{pj}, to improve efficiency and failure rates by 0.1; see Table 7-2 for variable parameter levels. All three ramp-up curves were evaluated, the severity of failure was maintained at 20 hrs repair time.

Table 7-2: Transition learning rate, variable parameter levels

Parameter level	No. operations for efficiency improvement, ke_{pj}, of 0.1	No. operations for failure rate improvement, kf_{pj}, of 0.1

LR = 1	100	50
LR = 2	150	100
LR = 3	200	150

Results and discussion

The first experiment analysed rates of learning, increasing the number of operations required to obtain efficiency gains and reduce failure rates. Figure 7-7 displays the 95% confidence interval of the backlog for each parameter setting, directly comparing anarchic to centralised cell and flexible systems. The plots increase the learning rate (LR) variable horizontally, and the three ramp-up curves (RC) change vertically. It is evident that the anarchic system degraded as learning rates become slower for the gradual transition and direct changeover (RC=1 and 3); as WIP increased at a greater rate than the centralised systems. However, for the concurrent production system, the anarchic was comparable to the centralised flexible system. The two centralised systems performed similarly for gradual (RC=1) and direct changeover (RC=3) scenarios, for the concurrent production scenario (RC=2), the centralised hierarchical cell system performed the best. For the prolonged period of equal production volumes, the centralised cell system divided the resources into two independent operating systems, where there was no need to changeover between products.

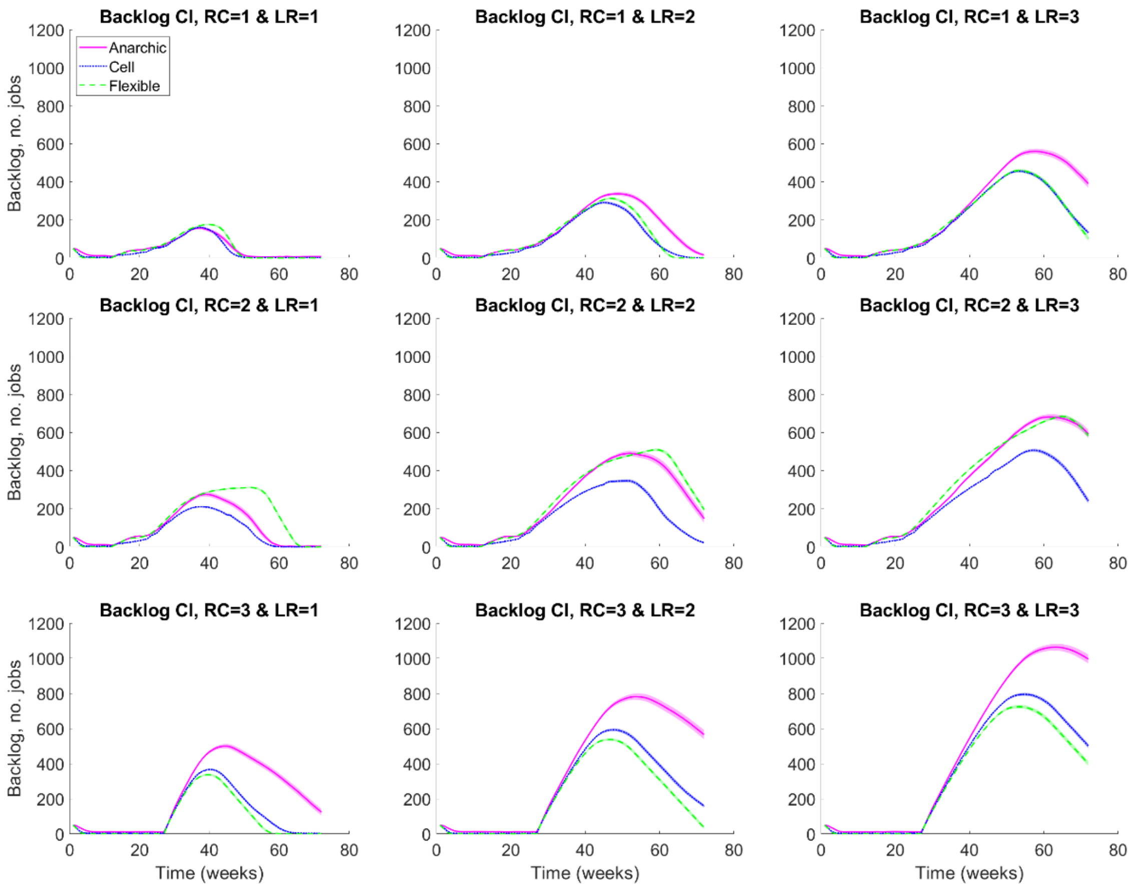

Figure 7-7: Transition learning rate, confidence interval backlog results

7.3.5 Failure severity

Product transition and ramp-up scenarios are inherently volatile, with at first a high failure rate and severity of failure until learning is achieved. Reducing failure and its impact is a source of many disturbances during ramp-up, as noted in the background literature in Section 7.2. Directly evaluating an increasingly severe failure scenario, by lengthening the repair time, would indicate whether anarchic manufacturing would be able to deploy its robust self-healing traits; this experiment is diagrammatically summarised in Figure 7-8, indicating the single gradual ramp-up curve and increasing repair time.

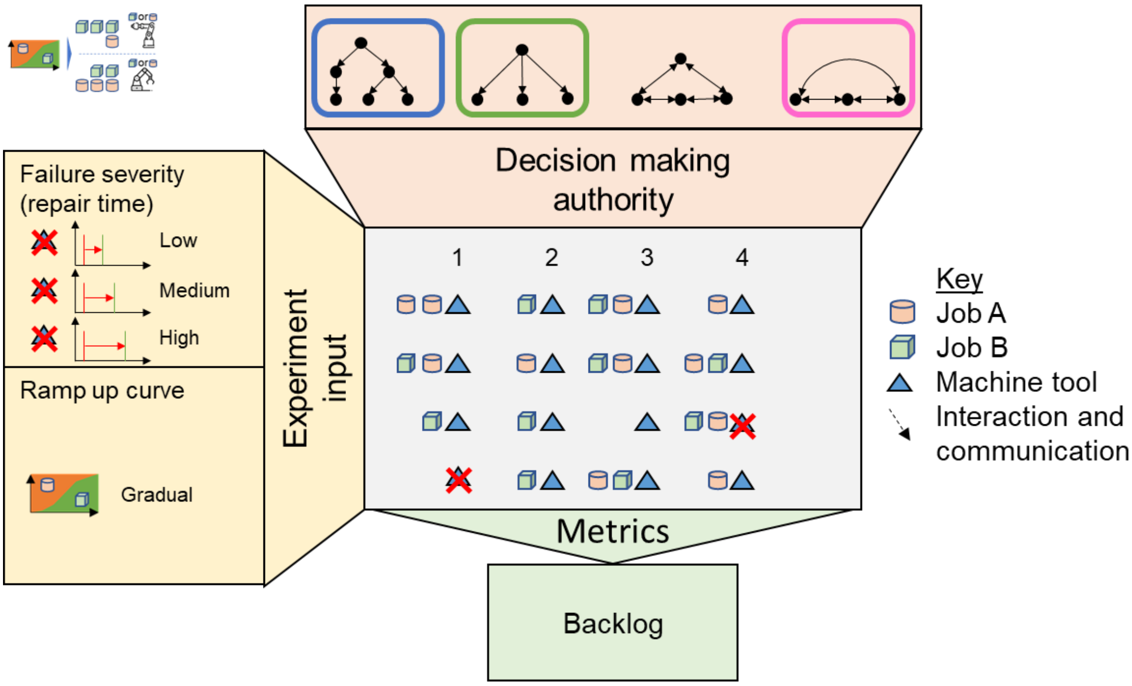

Figure 7-8: Transition failure severity experiment summary

Experimental framework

During production ramp-up of a new product, production failures are more frequent and are the most significant disturbances to production. For the second experiment the severity of these failures was varied by changing the repair time (RT); Table 7-3 details the variable parameters. Learning rates were maintained at LR=2 from the first experiment, ke_{pj}=150 operations and kf_{pj}=100 operations.

Table 7-3: Transition failure severity, variable parameter levels

Parameter level	Repair time on failure
RT = 1	20 hrs
RT = 2	40 hrs
RT = 3	80 hrs

Results and discussion

The second experiment evaluated an increasing failure severity by increasing repair time (RT), the gradual transition ramp-up curve was maintained (RC = 1), backlog plots at the 95% confidence interval display the results in Figure 7-9. As the impact of failure became more severe, by increasing repair time, the anarchic system became superior as it was less sensitive to the disruption and flexibly managed the scenario; adapting to disruptions and exploiting available flexibility. This was particularly apparent at the most severe parameter level, RT=3, where there is a clear separation between the 95% confidence interval ranges for a significant proportion of the simulation and at the peak levels of backlog. Similarly, the centralised flexible system has a similarly degrading performance as repair time increased, however, the fixed hierarchical cell system performed very poorly as the parameter level was increased; highlighting the rigidity and lack of flexibility in the cell structured system.

The anarchic system had the best robustness to disruption, through adaptability. This was achieved by embracing the complexity of the system and maximising available flexibility, as it is not constrained by a simplifying structure.

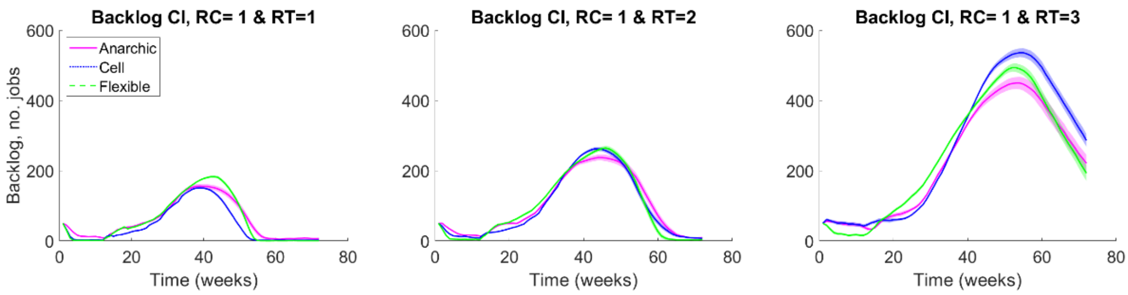

Figure 7-9: Transition failure severity, confidence interval backlog results

7.3.6 Structural flexibility

Few factories have the idealised flowshop set up as the previous experiments in this chapter have investigated. Often factories have reduced number of MTs for a given process to reduce capital expenditure for MTs or increase MTs for a process to eliminate a bottleneck and improve throughput. Subsequently, the structural flexibility of the system will change and will require coordination across multiple MTs; this was evaluated and the experiment is summarised in Figure 7-10. Reducing the structural flexibility was achieved by first reducing the system to two MTs per stage and then ensuring there were bottleneck resources; by only providing one MT for a stage, that was twice as fast to maintain balance.

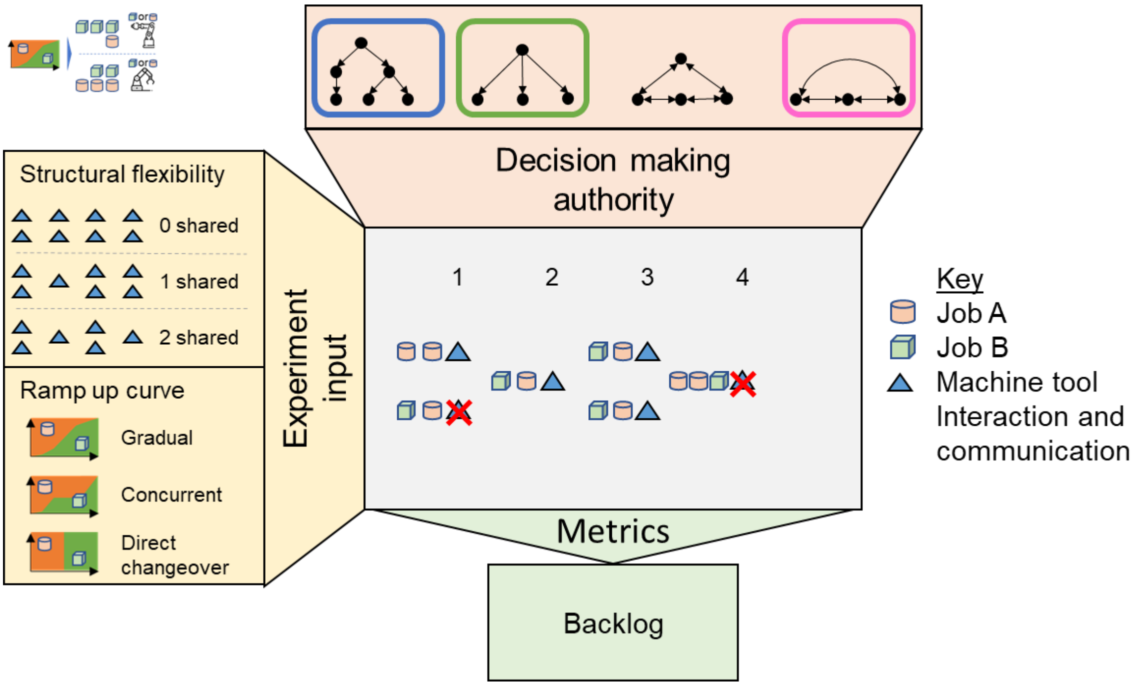

Figure 7-10: Transition structural flexibility experiment summary

Experimental framework

Reducing the structural flexibility of a system reflects planning and control problem of real systems, bottleneck resources can imitate this scenario; reducing the structural flexibility of the system if there is only one resource of a particular capability. The third experiment reduced the structural flexibility of the system (SF), for the first level there are two resources for each capability and no bottleneck resources, for level two the second capability has only one resource and for the third level the second and fourth have only one resource; these variable parameter levels are summarised in Table 7-4. Learning rates were maintained at LR=2 from the first experiment, ke_{pj}=150 operations and kf_{pj}=100 operations. Additionally, repair time on failure was maintained at RT=2, 40 hours.

Table 7-4: Transition structural flexibility, variable parameter levels

Parameter level	No. capabilities with one resource only
SF = 1	0
SF = 2	1 (2nd operation)
SF = 3	2 (2nd and 4th operation)

Results and discussion

Experiment 3 changed the number of bottleneck shared resources in a reduced manufacturing system reducing the structural flexibility (SF). This was compared against all three ramp-up curves. Figure 7-11 displays the backlog confidence interval plots for all parameter settings, directly comparing the three systems. Figure 7-12 to Figure 7-14 similarly displays the backlog confidence interval but compares the three structural flexibility levels against each other for a particular system and ramp-up curve (RC).

Backlog and overall performance show that as shared resources go from 0 to 1 (SF 0 to 1) there was a significant degradation in performance for most systems and ramp-up curves. The anarchic was very poor at the direct changeover scenario, RC=3. During concurrent production, RC=2, the cell system significantly reduced performance as 1 resource was shared. Generally, the centralised systems performed similarly whilst the anarchic was worse for all scenarios.

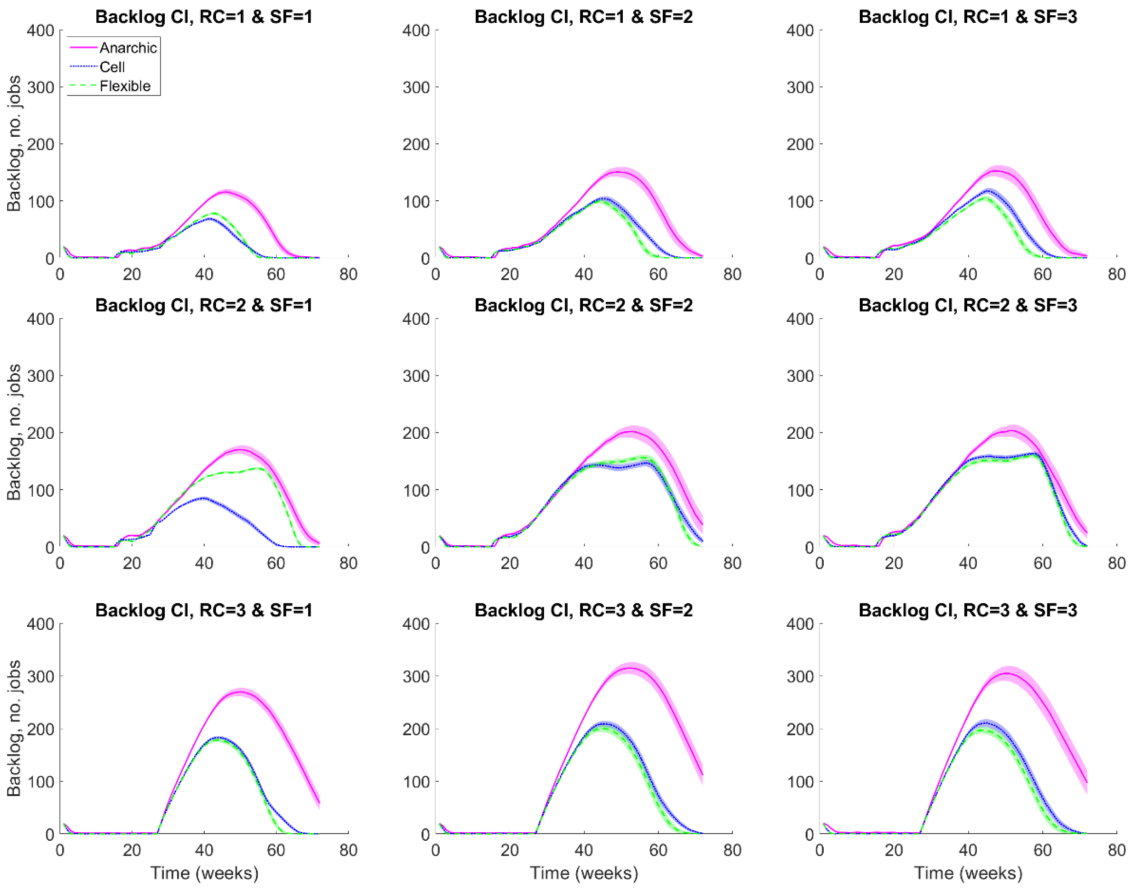

Figure 7-11: Transition, structural flexibility, confidence interval backlog results

On evaluating the performance differences between parameter levels more closely, shown in Figure 7-12 to Figure 7-14, further characterisation can be elicited. Comparing the system performance as the number of shared resources increased directly, using the 95% confidence interval, indicated the response to a scenario with reduced flexibility.

Considering the gradual transition and the concurrent production ramp-up curves. The anarchic system for SF=2 and 3 (1 and 2 shared resources) did not have a significant difference in performance at the 95% confidence interval; observed through overlapping confidence interval ranges. This was in contrast to the hierarchical cell system, displayed in Figure 7-13, which showed a significant difference, at the 95% confidence interval, between each level of shared resources. Performance reduced as there are more shared resources. This indicated that the hierarchical cell system degraded at a faster rate and was less robust to this structural change. The hierarchical system was less effective at adapting to a more constrained system, reducing the effectiveness of the hierarchical cell structure. The centralised flexible system adapted similarly to the anarchic system, with little difference when at least one resource was shared.

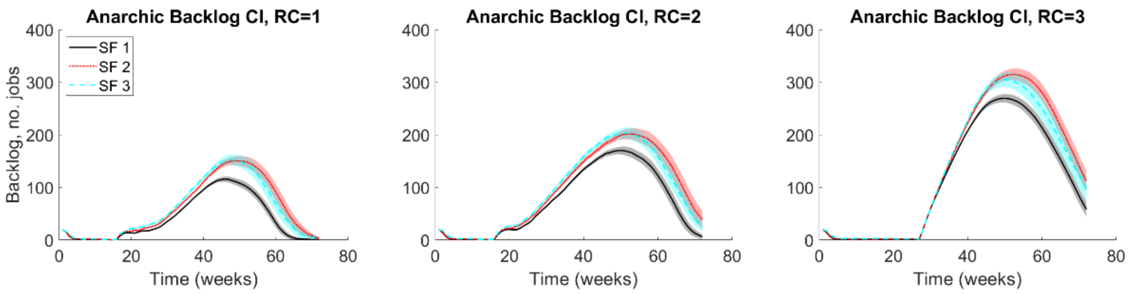

Figure 7-12: Transition structural flexibility, anarchic system confidence interval backlog results

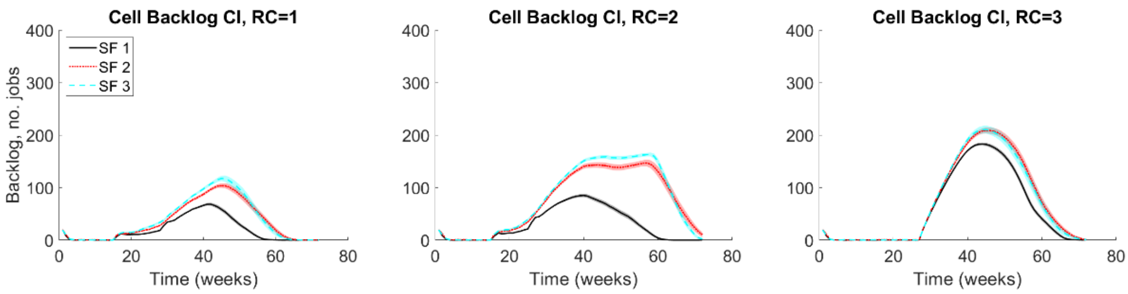

Figure 7-13: Transition structural flexibility, centralised cell system confidence interval backlog results

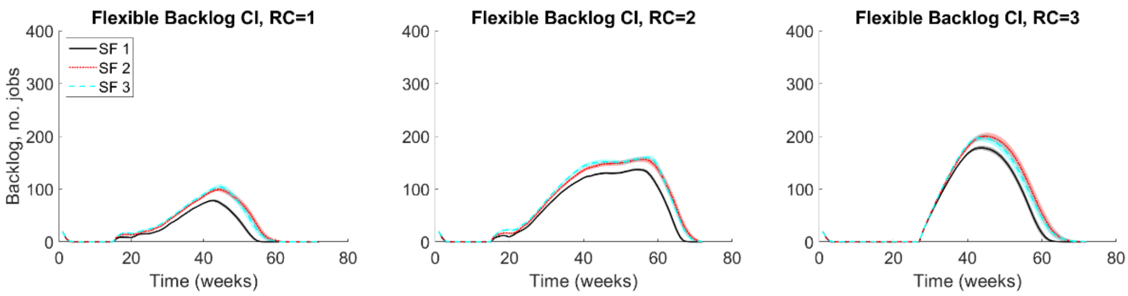

Figure 7-14: Transition structural flexibility, centralised flexible system confidence interval backlog results

7.3.7 Automotive case study

An automotive industrial case study was used to validate findings against a real-world problem. By reflecting a real factory setup and restrictions in a simulation experiment, it was evaluated whether the anarchic, centralised and hierarchical systems operated similarly to previous experiments. The case study utilised a flexible flowshop facility, where jobs can select any of the unrelated parallel machines in a production stage, to produce small automotive components for a medium-sized manufacturer (Frantzén, 2013). The manufacturing facility produces approximately 7,000 units per week and has 10 production stages; which have between one and seven parallel machines; products do not require all production stages. The ramp-up curve and demand level (units per week) are varied in this experiment, this is summarised in Figure 7-15.

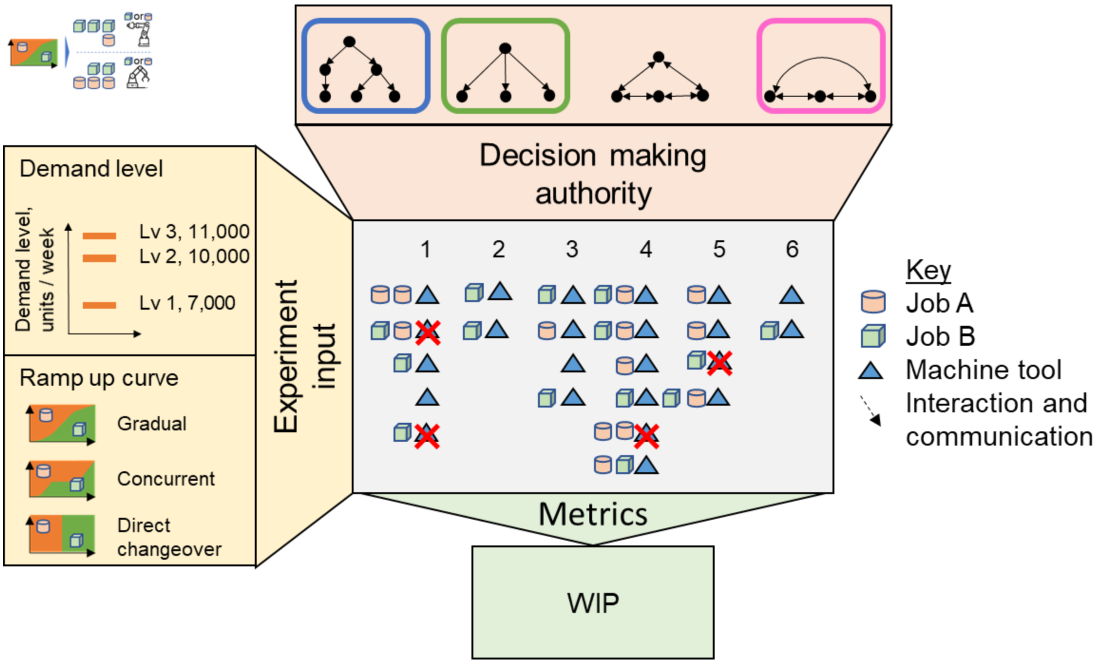

Figure 7-15: Transition automotive case study experiment summary

Experimental framework

The case study, which informs the mature steady-state environment, was simplified for the purposes of this research, ignoring machine settings, safety stocks, buffers and inter-machine transferring, and the two highest demanded of the many variants produced (10 and 13) were used to represent the two main product groups. Key data available included product specific operation durations, sequence-dependent setup/changeover durations, machine specific mean time between failure (MTBF) and mean time to repair (MTTR) exponential distribution means. MTBF and MTTR indicate a high failure rate but a fast repair time. Additionally, unavailable data was fabricated to reasonable industry values, these included: learning rates impacting production efficiency and failure rates, and the long-term transition time horizon. These values are not expected to significantly impact the simulation outcomes. The number of operations to improve learning rates ke_{pj} and kf_{pj} are 75,000 and 40,000 operations respectively for a 0.1 improvement. Table 7-5 summarises the case study experimental parameters for production stages taken from Frantzén (Frantzén, 2013).

Table 7-5: Transition automotive case study, production facility data (Frantzén, 2013)

Production stage	No. MTs/ stage	Op duration A (s / unit)	Op duration B (s / unit)	Product changeover duration (s)	MTBF (min)	MTTR (min)
1	5	99	125	60	55-72	8-15
2	1	-	-	-	-	-
3	2	-	48	300	80	8
4	3	59	-	1200	50	8-12
5	3	40	43	1440	60-80	8-14
6	7	94	133	900	50-68	7-25
7	3	33	44	2700	68-70	10-12
8	1	14	14	0	150	5
9	2	32	-	24	140	6-7
10	2	27	37	24	72	8

The experiment varied the transition ramp-up curves and the overall demand on the system. The transition ramp-up curves are identical for the experiments above (RC = 1, 2 & 3), using a gradual, concurrent and direct change transitions; as shown in Figure 7-5. The transition period is modelled over 18 months, which was representative for the automotive case study. The overall system demand was varied from the nominal 7,000 units/week produced to 11,000 units/week; these are detailed in Table 7-6.

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Table 7-6: Transition automotive case study, variable parameter levels

Parameter level	Demand, units/week
Dmd = 1	7,000
Dmd = 2	10,000
Dmd = 3	11,000

Results and discussion

The automotive case study experiment varied the demand (Dmd) put on the system, increasing system utilisation, which was run against the three ramp-up curves (RC). Figure 7-16 plots the mean work in progress within a week, including its 95% confidence interval; the confidence intervals are very small but can be seen on the magnification inset for RC=1 and Dmd=2. There was no backlog created for gradual and concurrent transition ramp-up curves, therefore WIP was plotted.

For the gradual and concurrent changeovers, RC=1 and 2, all systems are able to manage the scenario and had zero backlog; this suggested that the real-world scenario did not strain the systems enough to gain valuable insight to their performance differences. For the direct changeover scenario, RC=3, the anarchic system performed very poorly and did not overcome the sharp change at high demand levels; a large backlog was created. This was due to the anarchic system being influenced by the recent past, its perception of the current market conditions was very different from the current and future reality. The market conditions were not fast enough to respond to a sudden and very different change; a forecasting mechanism that pro-actively influences the market conditions would correct this. Subsequently, the system was unable to effectively price according to new market conditions, impacting allocative efficiency.

For gradual and concurrent changeovers, the anarchic system performed worse during the changeover period but managed the scenario and maintained WIP at a controllable level, to eliminate any backlog and ultimately recover. Additionally, at the highest demand level, Dmd=3, and concurrent ramp-up curves, RC=2, the anarchic performed better than the fixed centralised system. This highlights anarchic manufacturing's flexibility as demand and high utilisation stress the system.

The flexible centralised system performed best overall for all scenarios. The hierarchical (pre-planned and fixed) centralised system performed well, however for the highest demand, Dmd=3, the performance deteriorated and recovery was slow. For the concurrent high demand scenario, RC=2 and Dmd=3, the pre-planned hierarchical system was very poor. This was due to high resource sharing and cross over resulting in an inability to implement an effective hierarchical or cell structure. This indicated the downfall of the hierarchical fixed system, suffering from high rigidity and inflexibility, in a real-world scenario.

This automotive case study provided real-world validation to the previous simulation experiments, as observed by similar outcomes. It can be concluded that the anarchic manufacturing system is functional against a real-world case study, but not the best performing. However, as no systems produced a backlog for gradual and concurrent changeovers, there were no serious considerations in performance between systems. Flexible dispatch heuristics performed well, and for most scenarios the anarchic manufacturing system maintained a good performance that was comparable to the centralised flexible system in particular scenarios. The anarchic system at times of high stress was superior to the hierarchical structure.

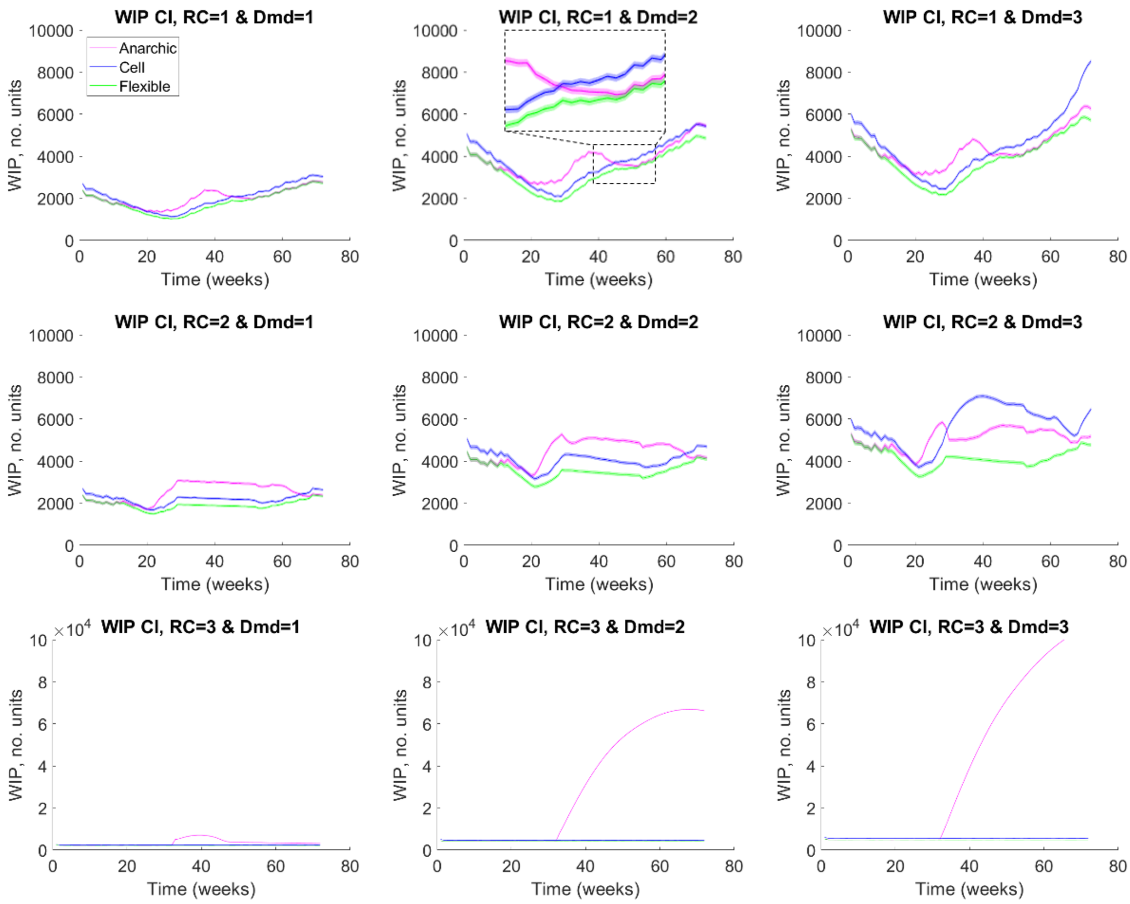

Figure 7-16: Transition automotive case study, confidence interval WIP results

7.4 Discussion

From the four experiments conducted, there was no overall superior system. The centralised systems had mixed performances, although the hierarchical cell system was the most allocatively efficient in the simplest of scenarios. The simplification methods, implemented as a hierarchical cell structure, reduced flexibility. This was evident through relative low performance as structural flexibility reduced and severity of failure increased.

The anarchic manufacturing system is shown to perform well in all scenarios using a gradual and concurrent production transition ramp-up curve, leading to the conclusion that distributed systems can manage a product transition scenario effectively. The self-organising anarchic system performed best when flexibility was required, particularly for the second experiment which increased failure severity. Additionally, the automotive case study validated the anarchic system's performance in a real-world context; showing comparable performance, which in high demand and high-stress scenarios could outperform the hierarchical manufacturing system.

Anarchic manufacturing was shown to manage the product transition scenario effectively and warrant further investigation as to whether the benefits of distributed systems can be leveraged in the volatile transition scenario. This chapter evaluated an automotive case study to validate simulation experiments. However, all scenarios assumed flexible routing and ignored transportation issues and safety stock levels; these do not detract from the conclusions drawn but highlight that the system requires further development and investigation before real-world implementation.

7.5 Summary

The preceding two chapters detailed experiments using steady-state or step-change scenarios, whereas this chapter evaluated a transitional scenario where there is high volatility. Product transition proposes many challenges which have resulted in manufacturers resorting to simple dispatch rules, as discussed in Section 7.2. The anarchic manufacturing system was found to manage the dynamic product transition scenario, warranting further investigation as to whether the characteristics of distributed systems can be leveraged.

To manage the natural teamworking and cooperative problem, anarchic manufacturing used dynamic batching; this maintained distributed decision-making and anarchic freedom. It leveraged economies of scale and enabled effective decision-making by directly evaluating the profitability of a changeover and processing a batch of alternate products. The profitability assessment was relatable to the overall environment and an agent's individual circumstance, this in turn reduced system myopia; whilst aligning to the free market paradigm and individual decision-making autonomy. Reducing myopia through profitability assessments further demonstrated the malleability of anarchic manufacturing that was observed in Chapter 5 for dynamic multiple objectives and Chapter 6 for model selection in mixed-model assembly.

Four experiments were conducted in Section 7.3, three using idealised scenario parameters and the fourth used an automotive case study to validate the preceding experiments. They found that the anarchic manufacturing system was able to manage the product transition scenario effectively and that the system demonstrated self-healing traits. This was prevalent under the second experiment in Section 7.3.5, where the anarchic system deteriorated at a relatively slower rate compared to centralised systems under increasing failure severity. Anarchic manufacturing's effectiveness was achieved through entities following individual profitability and leveraging economies of scales with cooperative teamworking in dynamic batches, in the free market environment.

This chapter has provided evidence that anarchic manufacturing can manage a volatile transitional scenario by using self-organisation characteristics and leveraging cooperative interactions in a system with distributed decision-making that maximises profit. Chapters 5 to 7 have experimentally shown the capabilities of the anarchic manufacturing system, noting the associated affordances which contributes to the thesis aim. The next chapter discusses in depth the outcomes from these in combination with the theory proposed in Chapter 4.

8 Discussion

8.1 Introduction

The preceding Chapters 4 to 7 detail the theory and experimentation for anarchic manufacturing. This chapter discusses the findings in the context of the research aims and objectives, discusses how the theory was realised through experimentation, articulates the real-world impact of anarchic systems, discusses the limitations of the research conducted and highlights future work.

8.2 Evaluation of aim and objectives

This section discusses the achievement of objectives enumerated in section 1.1.

1) *Review the state of the art of smart manufacturing, the production planning and control problem and existing solution architectures, within the boundaries and scope of the research, and identify research gaps and existing solutions*

The literature review in Chapter 2 covered relevant background areas, split into three categories, smart manufacturing, the production planning and control problem and existing solution architectures. The literature was critiqued, and research gap identified in Section 2.5, this informed the subsequent theoretical framework with the need to extend existing free market systems to improve functionality and adaptability, and identified that there is no literature that applies a distributed system to assembly or product transition scenarios.

2) *Create a prototype distributed planning and control system (the anarchic manufacturing system), to be applied to manufacturing scenarios*

Section 4.4 details the core structure and mechanics of the anarchic manufacturing system, creating a prototype for the system; the negotiation procedure is detailed with all factors explicitly defined through equations. This prototype is adapted appropriately for the manufacturing scenarios tested in Chapters 5 to 7, whilst maintaining the design principles of anarchic manufacturing.

*Apply the prototype system against a range of manufacturing scenarios using a suitable modelling method and document the process undertaken, these scenarios were: simple discrete manufacturing, mixed-model assembly and product transition*The three manufacturing scenarios created are detailed in the three experimental Chapters 5 to 7. All use idealised scenarios to evaluate the manufacturing systems, additionally, an automotive case study was used in Chapter 7. All scenarios extended knowledge of both the anarchic system and the application of a distributed system in a new environment or evaluated untested factors. The process of adapting the anarchic manufacturing suitable to a particular scenario is documented, explicitly defining the mechanisms used and how they still align to the anarchic system's design principles.

3) *Evaluate the performance of the anarchic manufacturing system relative to centralised and hierarchical systems against the created scenarios through simulation experiments*

Chapters 5 to 7 evaluate the performance of the anarchic manufacturing system against centralised and hierarchical systems within the specific scenario using simulation experiments. Each of these chapters discuss the experimental findings, comparing performance and highlighting observable characteristics and affordances of anarchic manufacturing. Chapter 5 found that the anarchic manufacturing system handled complexity well and deteriorated at a slower rate in comparison to centralised and hierarchical systems. Chapter 6 extended these observations and found that the anarchic system was superior when it embraced complexity to its advantage through maximising flexibility. Both Chapter 6 and 7 successfully applied a distributed system to advanced manufacturing scenarios, mixed-model assembly and product transition, these had not previously been fulfilled. Additionally, for both scenarios several traits were evident, these included self-healing, robustness and reduced myopic decision-making.

Chapter 8 discusses and integrates all research findings, relating experimental findings to the theory and discussing the impact to the real world. The contribution to knowledge is defined in Chapter 9, which highlights the methodology to apply anarchic manufacturing to a range of manufacturing scenarios, two of which have not previously fulfilled by a distributed system.

Research aim: Create and develop a new methodology that enables manufacturing systems to be modelled as distributed free market systems for production planning and control.

The thesis aim, restated above, has been realised through achieving the research objectives. The process of applying a distributed free market system against various manufacturing scenarios, to fulfil the planning and control functions, has been documented. The anarchic manufacturing system has been developed into prototypes which have been applied through simulation experiments to three smart manufacturing scenarios; two of which have not previously been fulfilled by a distributed system. Relevant characteristics have been highlighted and discussed as a result of experimental evidence and the realisation of theoretical principles.

8.3 Realisation of theory

The hypothesis and theory for anarchic manufacturing are proposed in Chapter 4, detailing the design principles and attributes as to why the system would work. This theory was verified through simulation experiments, presented in Chapters 5 to 7, observations were made for independent agents using the free market structure, extending the profitability mechanism for scenarios and applying competitive and cooperative behaviour as appropriate.

The hypothesis proposed in Section 4.2, that distributed free market systems can be applied to dynamic environments, was found to be true during experimentation. It is evident throughout that anarchic manufacturing, using a free market architecture, can effectively fulfil the production planning and control problem.

Agent decision-making independence was required throughout and evident through observing self-organising and adaptability characteristics. Section 5.3.3 detailed the anarchic system's ability to adapt to changes in objectives and Sections 6.3.4 and 7.3.5 demonstrated the system's ability to self-organise from bottleneck and failure disruptions respectively; this self-organising capability was evident across all scenarios including the advanced assembly and product transition scenarios.

The benefits of free market competition and the malleability of the profitability mechanism were evident in all scenarios. Increasing scale, in Section 5.3.1, increased the problem complexity, however, the free market structure embraced this complexity by simultaneously increasing competition and resultantly improved performance globally. This free market benefit was evident as structural flexibility was reduced, the more options available to the system and less constrained it was the greater the performance. This was evident in Section 6.3.3 as WIP was lower due to a job's delayed model selection in a mixed-model assembly idealised balanced production scenario. The profitability mechanism was adapted for all scenarios whilst retaining the same core anarchic manufacturing negotiation protocol detailed in Section 4.4, demonstrating the malleability of the anarchic manufacturing system and aptitude for further development. Additionally, the profitability mechanism was adapted for a far-sighted agent lifetime perspective (for job agents) in all experimental chapters, which resulted in reduced system myopia.

The benefits of competition in the free market are evident to ensure fair market pricing and resultant efficient allocation of resources according to demand; the benefits of competition through scale is discussed above. Scenarios requiring cooperation were investigated, the profitability assessment considered the benefits of cooperating whilst agent independence was retained. The distributed systems are shown to cooperate effectively when required, as documented in Chapter 6 for assembly and Chapter 7 for dynamic batching in product transition scenarios. Agent independence was maintained throughout, allowing agents to leave a cooperative group for another, unless they were physically coupled by an operation, this ensured the system remained truly distributed.

Several advantageous characteristics were observed in the anarchic system on experimentation, many of these have been documented in literature, as reviewed in Section 2.4.4. Self-organisation, self-healing and adaptive behaviour were evident on disruption in Sections 5.3.3, 6.3.4 and 7.3.5. Similarly, scalability was evident in Section 5.3.1 and flexibility was used in all scenarios. Anarchic manufacturing was shown to maximise flexibility by embracing complexity, previously documented by Scholz-Reiter *et al.* by stating logistic performance improved as complexity increased whilst using a distributed system (Scholz-Reiter, Görges and Philipp, 2009), but this observation is not prevalent in most commentaries on distributed systems. This research, in Chapters 6 and 7, found that the anarchic system's flexibility improved by increasing the complexity of the solution space. In Section 6.3 experimentation for assembly the system maximised flexibility by delaying model selection for jobs, this increased the solution complexity but also improved performance. The longer there were multiple options available during the agent's lifetime the more flexible the system was. The most significant criticism of distributed systems is myopic decision-making (Blunck and Bendul, 2016), this has been reduced by anarchic manufacturing by considering the lifetime profitability for an agent; as evidenced in Section 5.3.3 and 7.3.

8.4 Real-world impact

The literature review in Chapter 2 identified the potential use for distributed systems in smart manufacturing, by leveraging reported characteristics of distributed systems for an ever-increasingly volatile and complex environment. The implementation of distributed systems is possible with existing and developing technologies, as discussed in Section 2.2.4, and may be required to effectively realise the production models noted in Section 2.2.3. Distributed systems enable a radically different operating model for internet of things enabled cyber-physical systems (Monostori *et al.*, 2016a), these as found by this research would not be hindered by the associated high scale and complexity expansion and may even improve performance. However, distributed systems research, this thesis included, currently evaluates systems in idealised simulation environments to characterise the benefits and drawbacks; the associated limitations are discussed in Section 8.5 below. The affordances of the anarchic manufacturing system improve the proposition for distributed systems and could be used if the projection of smart manufacturing is fulfilled by highly dynamic production models.

The Anarchic manufacturing system can be applied where a distributed system is advantageous, including non-manufacturing scenarios; these reasons could include removing reliance on centralised systems, a structural benefit from removing central systems or the need for highly dynamic systems for volatile and complex environments. Military systems may benefit from removing centralised actors which may become single points of failure, and the robustness provided by distributed systems could mitigate the volatility and hostile environment (Beautement *et al.*, 2005). Certain scenarios with structural constraints would also benefit from removing central entities. An example is cloud manufacturing, discussed in Section 2.2.3, which utilises distributed manufacturing from many suppliers for many consumers (Wu, Matthew J. Greer, *et al.*, 2013), the delegation of tasks is best not to be facilitated by a central entity from a competition point of view. This would remove bias and allow fair competition between suppliers, additionally, it would provide scalability.

8.5 Limitations

There were some limitations to the research conducted, these are associated with theoretical and experimental aspects. The theoretical proposal of anarchic manufacturing, detailed in Chapter 4, utilises independent and selfish agents in the free market environment. The limitations of the theory are associated with ethical decisions and actions as well as unrelated or hard to quantify factors with regards to currency. The effectiveness of the free market is reliant on the environment to reflect perfect competition. The most significant factor that could undermine this is ethical decisions and actions, this could come apparent through agents ‘gaming’ the system or colluding for price-fixing. Using anarchic manufacturing, or other free market-based systems, within a closed environment would reduce the likelihood of unethical behaviour. However, it is unknown whether using learning systems, for example reinforcement learning, would result in agents manipulating their interactions through unethical behaviour. This research used profit maximising models to regulate agent behaviour these were predetermined and aligned ethically, this mitigates against unethical behaviour. However, these mechanisms to determine behaviour have not been optimised and would require further detailed analysis to improve them rather than leaving it to learning methods. Vrabič *et al.* used reinforcement learning for rationally bounded agents for control in a process industry production system (Vrabič *et al.*, 2018), however, the agents did not communicate with each other and only considered a very localised operating environment which excluded any other agents. Future work, detailed in Section 8.6, identifies an opportunity to explore unethical behaviour utilising reinforcement learning and predetermined models.

The anarchic manufacturing system researched for this thesis uses a single currency, additional factors that are unrelated or hard to quantitively relate to the single currency were not considered. Social and environmental factors, discussed in Section 2.2.5, are difficult to relate to monetary currency, but manufacturers are increasingly pushed to consider value mechanisms of other systems for a sustainable society (Ueda *et al.*, 2009). The anarchic system could be manipulated to have additional currencies that either could be traded, a dynamic exchange rate would quantify the relationship between factors, or retained as separate parallel currencies to act as concurrent requirements. This limitation has not been investigated as there are scenarios of greater value yet to be evaluated.

The experimental limitations, relating to Chapters 5 to 7, include the contrived parameter selection, the simplistic comparative centralised systems and relative results analysis. For all experiments, except for the automotive case study investigated in Section 7.3.7, the scenarios and parameter selection are fabricated and can be viewed as contrived. This was done to reduce experimental noise and allow results to clearly evaluate the variable parameters. These parameter levels have not been validated against real-world scenarios and therefore lack direct relevance to real-world manufacturing. To address this, as was conducted for the product transition automotive case study, real-world industrial case studies can inform parameter selection. However, as found in Section 7.3.7, the results may lack clarity or insight into the relative performance if all systems behave similarly; experimenting in fabricated scenarios allowed the performance boundaries to be evaluated.

The comparative centralised systems, used in Chapters 5 to 7, employing centralised and hierarchical structures, used simplistic dispatch rules to govern decision-making rather than advanced techniques or the state-of-the-art. The comparative method to evaluate results, considering the rate of change against a variable parameter detailed in Section 3.3.2, negated the need for system equivalence. Additionally, certain scenarios in industry, for example during ramp-up as discussed in Section 7.2.2, do not use advanced centralised systems due to their high volatility and defer to simple dispatch heuristics (Basse *et al.*, 2014). This has limited the research to a relative commentary between systems. Comparison against advanced centralised systems, for example meta-heuristic search algorithms, would provide absolute performance information and progress the system for industry use; advancing the Technology Readiness Level beyond level two / three.

The relative results analysis compared performance of a system as a parameter level changed the rate of deterioration was compared between systems, this enabled results analysis without the need for comparable systems. However, the associated limitations prevent an absolute comparison of system performance against the scenario. This analysis method is necessary on applying systems to real-world scenarios, however, almost all experiments used fabricated scenarios for clarity of results and relative performance characterisation.

8.6 Future work

Future work can be categorised into theoretical and implementation research, each extending research by different aspects.

Theoretical future work will investigate the role of ethics and whether machine learning techniques could undermine this design principle established in Section 4.3.4. Ethical actions and decision-making are required for the distributed system to work effectively, however human actors or machine learning methods may ‘game’ the system. Ethics is the study of moral principles (Oxford English Dictionary, 2020) and refers to decisions that purposefully detriment other actors in the system. The impact of this will be investigated as well as whether machine learning techniques, such as reinforcement learning, can be applied effectively considering ethical behaviour.

Future work will analyse the impact of unreliable communications on decision-making to determine the robustness of the system. An agent may have inaccurate data that would impact its decision-making. These unintentional errors could arise through faulty sensors or delayed analytics and communication. Whether these can be detected and their impact within a highly dynamic system.

Further theoretical future work will improve the anarchic system’s mechanics by evaluating the mechanisms used for decision making. The directional mechanisms to calculate various factors that impact decisions, such as bidding cost and threshold, will be reviewed through a sensitivity analysis. This will determine whether optimisation of these factors is required or whether the free market structure is effective at handling directional factors; this will aid implementation future work on creating physical prototypes.

Implementation future work will evaluate the technologies required to realise anarchic manufacturing and create a physical prototype. Existing technologies are discussed in Section 2.2.4 as theoretically feasible, however, a physical prototype employing IoT in a CPS production model will validate this and increase the technology readiness level.

9 Conclusion

9.1 Introduction

This thesis proposes anarchic manufacturing, a distributed production planning and control system, by creating a framework and demonstrating the effectiveness by applying prototype implementations of the framework as simulated systems to three manufacturing scenarios, noting affordances of the systems and demonstrating the system's adaptability.

9.2 Conclusions

The literature review in Chapter 2 surveys the background and system architectures, indicating the most likely way to address the inadequacies of current systems. The review identifies that smart manufacturing must manage an increasingly volatile and complex environment, where traditional centralised decision-making structures may suffer from rigidity. Distributed systems, categorised as rule-based, biomimetic and free market, are a radical alternative and are all underpinned by emergent synthesis. They have been reported to have flexible, robust and adaptable characteristics, these would be highly desirable in complex and volatile environments. Free market distributed systems were highlighted as a worthy system to pursue, due to the adaptability of a free market structure and its mechanisms to various scenarios.

The theoretical framework and core structure and mechanics of the anarchic manufacturing system are proposed in Chapter 4. The design principles of anarchic manufacturing argue the need for independent decision-making agents, a free market structure with profit maximising mechanisms, both competitive and cooperative behaviour, and ethical decisions and interactions. All these factors enable the emergent synthetic system to operate effectively. A prototype system embodies the theoretical framework and is presented in Section 4.4, detailing the structure and core mechanics by stating the role of different agents and their interactions through negotiation. This core system provides the basis for the anarchic manufacturing system, enabling adaptation as suitable for any scenario.

Chapters 5 to 7 experimentally evaluates the anarchic manufacturing system, by developing and applying it to a given manufacturing scenario. The anarchic system is compared to centralised and hierarchical systems in simple discrete manufacturing, assembly and product transition manufacturing scenarios. The system development, following the framework detailed in Chapter 4, highlights the system's malleability.

Chapter 5 evaluates three simple discrete manufacturing scenarios. The first experiment found that the anarchic manufacturing system managed customisation well and even improved with scale, which increased problem complexity. This improvement with scale demonstrated some of the free market capabilities as improvements were realised with increased competition. The second experiment increased complicatedness and complexity, it found that the anarchic system deteriorated at a slower rate relative to centralised and hierarchical systems, which suggests a superior performance as complexity increased. The final experiment for simple discrete manufacture scenarios demonstrated the ability to adapt to dynamic and conflicting objectives, rather the hierarchical system was unable to. This experiment demonstrated anarchic manufacturing system's ability to adapt and reduce myopia, which is a significant criticism of distributed systems. Overall, the anarchic manufacturing system was shown to manage complexity well and were superior to centralised and hierarchical systems in certain scenarios.

Chapter 6 applied the systems to idealised assembly scenarios, considering balanced production and dynamic bottlenecks. Anarchic manufacturing effectively managed mixed-model assembly scenarios, an area not previously evaluated in literature, resolving the coordination problem in a distributed manner. The distributed system embraced complexity, this resulted in a more flexible system. As problem constraints reduced complexity the flexibility and resultant performance deteriorated; additionally, life-time profit maximising mechanisms reduced myopia. These attributes are highly desirable considering the trajectory of smart manufacturing, systems that can embrace and improve with complexity align with the vision for self-organising intelligent objects that operate within a smart factory (Bendul and Blunck, 2019).

Experimentation documented in Chapter 7 considered product transition scenarios, using idealised parameters and an automotive case study. The dynamic batching mechanism employed maintains distributed decision-making and anarchic freedom via a profitability assessment that considers economies of scale within a batch. The four experiments found the anarchic system was able to manage the product transition scenario effectively, demonstrating self-healing traits. The successful application of anarchic manufacturing to a highly volatile scenario, where centralised systems resort to simple dispatch rules over advanced methods (Basse *et al.*, 2014), is promising for smart manufacturing where volatility is likely to increase.

This thesis proposes an alternative to hierarchical systems that 'simplify to improve', with anarchic manufacturing that 'embraces complexity to achieve flexibility'. The experimental results demonstrated that centralised and hierarchical systems are not inherently better than distributed systems. Complexity and volatility can effectively be managed through distributed systems. Therefore, it is worthwhile to further investigate distributed systems for manufacturing to benefit from its adaptive and flexible characteristics.

9.3 Contribution to knowledge

The research presented in this thesis contributes to knowledge by documenting the process undertaken to model the anarchic manufacturing system in a range of scenarios, particularly advanced problems of assembly and product transition which has previously been fulfilled; additionally, the design principles for anarchic manufacturing and the observed system characteristics are highlighted. The theoretical framework and design principles for anarchic manufacturing are verifyed through experimentation, and demonstrate the systems' capabilities against scenarios not previously fulfilled by distributed systems. Additionally, the research contributes to the knowledge of distributed systems, reinforcing previous conclusions as well as highlighting new or sparsely reported characteristics. These culminate in the argument to further evaluate distributed systems, which could unlock and realise the potential of the Internet of Things and Cyber-Physical Systems by providing an alternative operating model.

The theoretical framework for anarchic manufacturing, delivered in Chapter 4, created an effective distributed system for malleability and adaptability. The sophistication of the free market structure and profit maximising mechanisms enabled adaptability whilst benefitting from distributed system characteristics.

Experimentation in Chapters 5 to 7 not only demonstrates how a distributed system can be applied to new scenarios but reinforces previously reported and new or unestablished conclusions in literature. Assembly and product transition scenarios have not previously been resolved by a purely distributed systems, as discussed in background Sections 6.1 and 7.2. The novel process of adapting the anarchic manufacturing system to fulfil these scenarios is documented, explicitly detailing how the distributed system considers the specific advanced scenario characteristics to contribute to its profit-maximising decisions and operate effectively in the free market structure. The research has shown the application of a distributed to advanced scenarios can be achieved whilst retaining distributed system characteristics. Distributed characteristics of self-organisation, robustness and adaptability have been reported in literature (Shen *et al.*, 2006), but reducing myopia, found in all experimental Chapters 5 to 7, and embracing complexity to improve flexibility, discussed in Sections 5.3.1 and 6.4, have seldom been reported.

The aforementioned contributions to knowledge demonstrate that a free market distributed system can be applied to advanced manufacturing scenarios and improve the argument for distributed systems, justifying further research and development. Distributed systems enable a radically alternative operating model that could unlock the potential of the internet of things and cyber-physical systems. Providing a competitive advantage of high flexibility in complex environments. The associated scale and complexity of IoT enabled 'intelligent objects' in a CPS environment may be too difficult for a centralised or hierarchical system to manage. Distributed systems and associated operating models could remove centralised inefficiencies.

10 References

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11 Appendices

A Author publications

The author has published several peer reviewed journal and conference papers, these are detailed below.

Journal articles

- Ma, A., Nassehi, A. and Snider, C. (2019) ‘Anarchic manufacturing’, International Journal of Production Research, 57(8), pp. 2514–2530. doi: 10.1080/00207543.2018.1521534.
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