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Anarchic manufacturing: distributed control for product transition

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Abstract

Manufacturers are poorly equipped to manage product transition scenarios, when moving from one product to another. Most tools consider a mature system, yet during transition and ramp up disturbances and inefficiency are common. The traditional methods, using centralised planning and control structures are too rigid and often resort to simple dispatch heuristics in this highly dynamic environment. Distributed systems have been proposed to leverage their self-organising and flexible traits to manage highly volatile and complex scenarios.

Anarchic manufacturing, a free market based distributed planning and control system, delegates decision-making authority and autonomy to system elements at the lowest level; this system has previously been shown to manage job and flowshop style problems. The system has been adapted to use a dynamic batching mechanism, where jobs cooperate to benefit from economies of scale. The batch enables a direct economic viability assessment within the free market architecture, whether an individual machine should changeover production to another product type. This profitability assessment considers the overall system state and an agent's individual circumstance, which in turn reduces system myopia. Four experiments, including a real-world automotive case study, evaluate the anarchic manufacturing system against two centralised systems, using three different ramp-up curves. Although not always best performing against centralised systems, the anarchic manufacturing system is shown to manage transition scenarios effectively, displaying self-organising and flexible characteristics. The hierarchical system was shown to be impeded by its simplifying structure, as a result of structural rigidity.

Keywords: Simulation, planning and control, distributed systems

1 Introduction

Manufacturing transition, when moving from producing one product to another or between variants, 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, & Yemane, 2018); rather than the volatile transitional state, where there are many unforeseen disruptions during ramp up (Surbier, Alpan, & Blanco, 2014). Despite the volatile environment, there has been little focus on managing the transition period with respects to production planning and control.

Distributed systems have been proposed as radically alternative decision making structures that have self-organising, flexible and highly adaptable characteristics (Ma, Nassehi, & Snider, 2019a); this self-healing trait is highly desirable during the transition and ramp up phase. Given the rise of smart manufacturing exploiting cyber-physical systems and Internet of Things technologies that provide low level computation capabilities (Monostori et al., 2016; Napoleone, Macchi, & Pozzetti, 2020), distributed systems for planning and control can be realised. To date, there have been no previous studies into applying distributed decision-making architectures to the transition problem.

This paper utilises the anarchic manufacturing system (Ma et al., 2019a) and compares it against centralised systems in idealised transition scenarios and a real-world automotive case study. The generalised product transition scenario simulated, considers a manufacturing system that must move from producing one product to another, following predetermined ramp down and up curves over a prolonged duration. Orders of the two products are released weekly, these products must complete a series of predetermined operations. There are multiple capable machines for each operation, with flexible routing between them, that can fulfil the operations; but, changing from producing one product to another requires a changeover task. The comparison considers WIP and backlog metrics. The artificial scenarios created provide a clearer relative comparison between systems as a parameter is varied. The real-world automotive case study validates the artificial scenarios by observing similar outcomes.

The paper aims to show that the anarchic manufacturing system, a distributed planning and control structure, can effectively fulfil product transition scenarios; this indicates whether further research could explore how to leverage distributed system traits. Section two covers all relevant background literature concerning transition, ramp up, batching and relevant planning and control structures. The paper then introduces and explains anarchic manufacturing systems, including the dynamic batching adaptations for transition scenarios, before explaining the comparative centralised systems in section four. Section five explains the experimental framework for both artificial and case study scenarios, the experiment findings are presented and analysed in section six, finally a conclusion is provided.

2 Background

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, Eriksson, Hilletofth, &

Eriksson, 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 & Inamdar, 2012). It is assumed for this paper that a tooling changeover is required when changing between product families, and this is a non-instantaneous task.

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 & Bohn, 2001). 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 & Grunow, 2015). Ramp up has increasing importance given the rise of Reconfigurable Manufacturing Systems (RMS) (Koren & Shpitalni, 2010), 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, & 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 et al., 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, Schmitt, Gartzen, & Schmitt, 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, Buchholz, Klocke, & Mattfeld, 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 et al., 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 et al., 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 & Grunow, 2015). Learning aids process improvement but reduces capacity in the short-run, resultantly there is a trade-off between experiments and production (Terwiesch & 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.

2.3 Batch production

Despite the rise of lean manufacturing, there are continuing opportunities and reasons for batch production. Batch production manufactures a set of different parts together, designated as a batch, where the parts within the batch follow the same production path but each receives its own operations (Dolgui, Levin, & Rozin, 2019). The rise in batch production includes manufacturers of varying production volumes, batch production provides operational flexibility to try out low volumes of new work (Cooney, 2002). These batch production scenarios align with the problem faced in transition and ramp up of a new product which require varying volumes and requiring operational flexibility.

The inter-task product changeover at a machine or resource for multi-model production can have a significant impact on performance (Nazarian, Ko, & Wang, 2010). Multi-model production considers facilities that produce more than one product using the same resources and is not a dedicated manufacturing line. 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 transition between two product families and extended if the production facility is designed to produce one or the other rather than both simultaneously.

Almgren detailed 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.

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, Deutskens, Deutschmann, Maue, & Haunreiter, 2014), copy-exactly ramp up strategy for learning (Terwiesch & 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 divided the ramp up phase into low volume learning to high volume production (Almgren, 2000). More detailed methods are used for short-term planning. Kloche *et al.* used a hybrid stochastic simulation model to predict ramp up behaviour for a given scenario for short-term planning(Klocke, Stauder, Mattfeld, & Müller, 2016). A full factory simulation tool was used as a decision support tool during a transient period of parallel ramp down of one product and the ramp up of a new product (Klein & Kalir, 2006). On a network scale, Becker *et al.* considered a strategic ramp-up planning process for automotive production networks. They utilised 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, & 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 et al., 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 also help to reduce complexity (Basse et al., 2014).

Distributed structures offer a completely different approach to transition and ramp up, given the volatile and unpredictable nature the proposed self-organising, flexible and adaptable characteristics of distributed systems (Ma et al., 2019a; Ouelhadj & Petrovic, 2009; Shen & Norrie, 1999) would be highly desirable. Distributed systems have been investigated for a variety of production scenarios and applications, for example the resource management of automated guided vehicles (De Ryck, Versteyhe, & Shariatmadar, 2020) and to integrate multiple planning functions for manufacturing (Kumar, Manjrekar, Singh, & Kumar Lad, 2020). The distributed management of autonomous reconfigurable manufacturing systems have been proposed to reduce ramp up times through modularity of resources (Li, Bayrak, Epureanu, & Koren, 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 decision-making systems have not previously been analysed to resolve the transition or ramp up problem for producing concurrent products.

3 Anarchic systems for transition

3.1 Introduction

The anarchic manufacturing system is a distributed production planning and control structure allowing system elements to autonomously interact and communicate. The system uses a free market architecture with a low level permutation of the contract net protocol (Ma et al., 2019a). Jobs are provided currency and continuously enter the system and must fulfil predetermined operations, they negotiate with resources to fulfil these operations at a cost. Decision making authority and autonomy is delegated to the lowest system levels, i.e. to the jobs and resources, to determine resource selection and sequence of operations. Individual elements pursue personal objectives without any central oversight or control, which globally creates an emergent productive society (Ma, Nassehi, & Snider, 2019b).

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.

3.2 Overview and adaptations for transition

An overview of the anarchic system and its adaptations for transition are detailed below, covering; an overview of agent interactions and structure, dynamic batching agents and how jobs determine whether to join and adjust the resource costing method.

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 3-1 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.

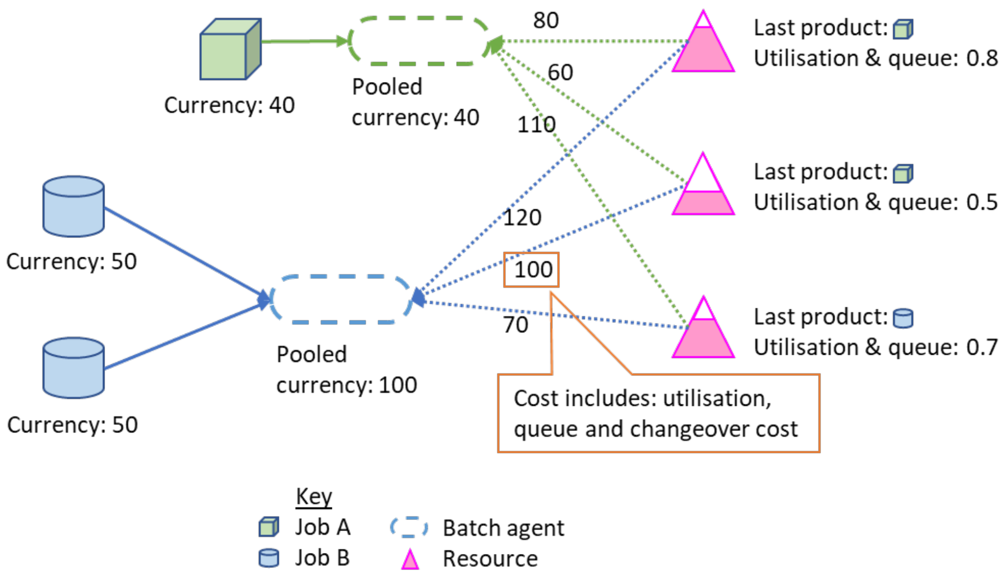

Figure 3-1: Anarchic system for transition with dynamic batching

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, 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; using Ma *et al.*'s anarchic manufacturing system (Ma et al., 2019a), 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. The increase and decrease of job threshold and resource bids follows that of Ma *et al.'s* anarchic manufacturing system (Ma et al., 2019a). Additionally, if a job is unable to contract a resource it is periodically provided more currency. This ensures that the job can progress and not get stuck as its currency and buying power increases. This negotiation process is summarised in Figure 3-2 and displayed as a decision flowchart.

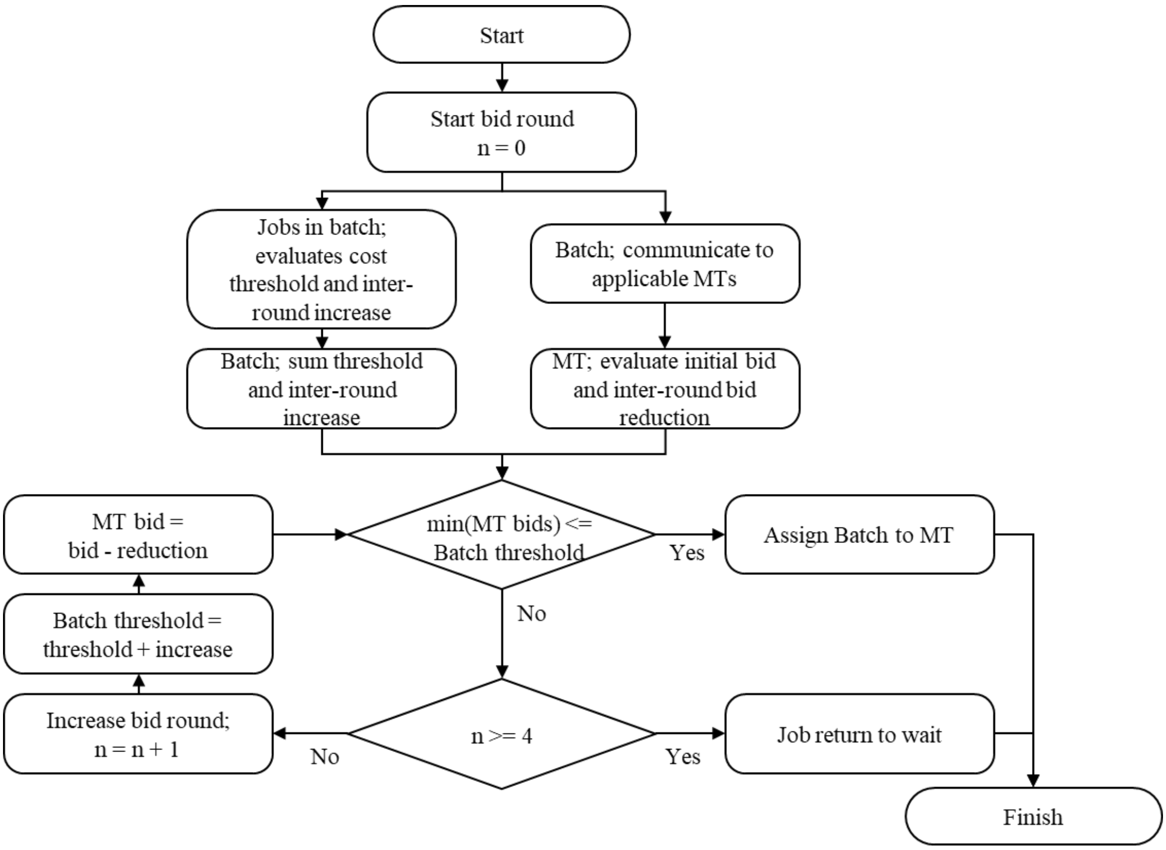

Figure 3-2: Anarchic manufacturing negotiation process

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

$$\beta_{jp}(t) = n_b \cdot Cop_{j\,p}(t) + \psi_{j\,p}(t) \cdot C_{change} \tag{1}$$

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

$$Cop_{jp}(t) = Cop_{c\,Exp}\left(\omega_j(t) + \frac{Q_j(t) \cdot t_{o\,c\,p}}{t_{plan}}\right) \tag{2}$$

Where $Cop_{c\,Exp}$ is the expected operational cost for capability c, $\omega_j(t)$ is the utilisation of resource j at time t, $Q_j(t)$ is the queue at resource j, $t_{o\,c\,p}$ is the nominal duration of an operation of capability c for product p and t_{plan} is the planning horizon.

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

$$\psi_{j\,p}(t) = \begin{cases} 0 & \begin{matrix} if\ product\ is\ the\ same\ as\ the\ last \\ in\ the\ queue\ of\ resource\ j \end{matrix} \\ min\left(1, 2 - \frac{2n_{\,jp\,recent}(t)}{n_{j\,recent}(t)}\right) & otherwise \end{cases} \tag{3}$$

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

4 Centralised 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 4-1. The flowshop cells contain all the machine tools (MT, i.e. resources) of a particular capability. Jobs at each stage are allocated to 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.

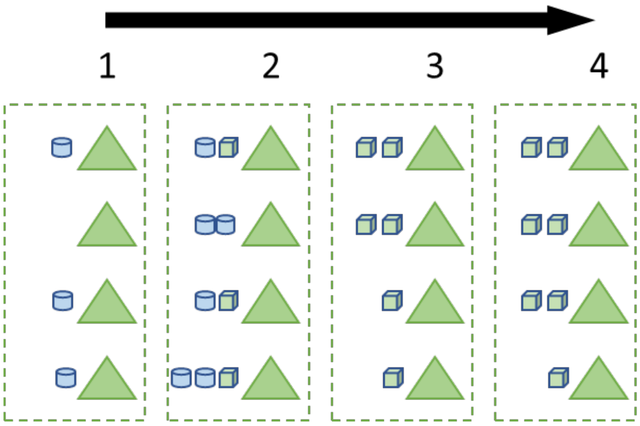

Figure 4-1: Illustrative centralised flexible flowshop structure

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 4-2. 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.

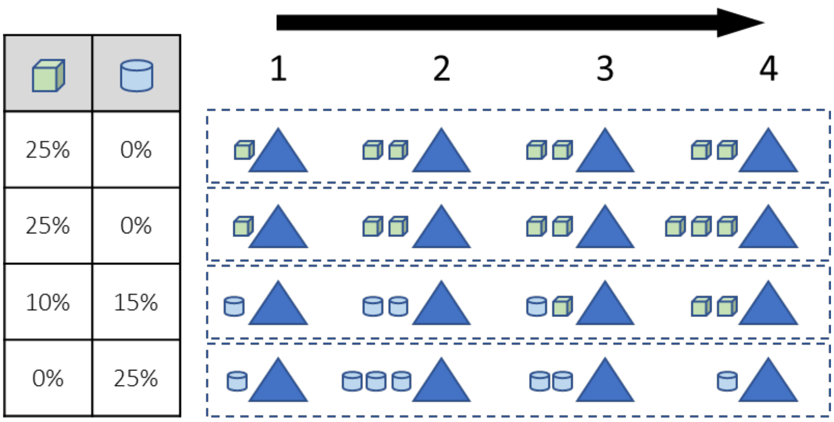

Figure 4-2: Illustrative centralised hierarchical cell structure

5 Experimental framework

Idealised scenario experiments were conducted to understand the characteristics of the anarchic and centralised systems, additionally a validatory experiment using an industrial case study confirmed conclusions. 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. 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. 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. To model inefficiency the operation duration, considering resource *j* operating on product *p* at time *t*, is divided by the efficiency rating, $E_{j\,p}\,(t)$, which for a new product type starts at 0.3. Learning through experience improves the efficiency rating, improving by 0.1 for every $ke_{p\,c}$ number of operations for that product completed globally and locally, for product *p* by resource capability *c*. 100% efficiency can be reached, as this is the mature operational state and efficiency after ramp up. Resource j, at time t processing product $p,$ has a chance of failure before every operation dependent on the failure rate, $F_{j\,p}(t)$, 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 $kf_{p\,c}$ operations completed for the product *p* by the capability *c*; there is a minimum failure rate of 0.01 regardless of improvement through learning.

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 5-1. Gradual transition (*RC* = 1) reflects an increasing new product volume and decreasing old product to a predefined ramp up curve (Surbier et al., 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 96hrs of production.

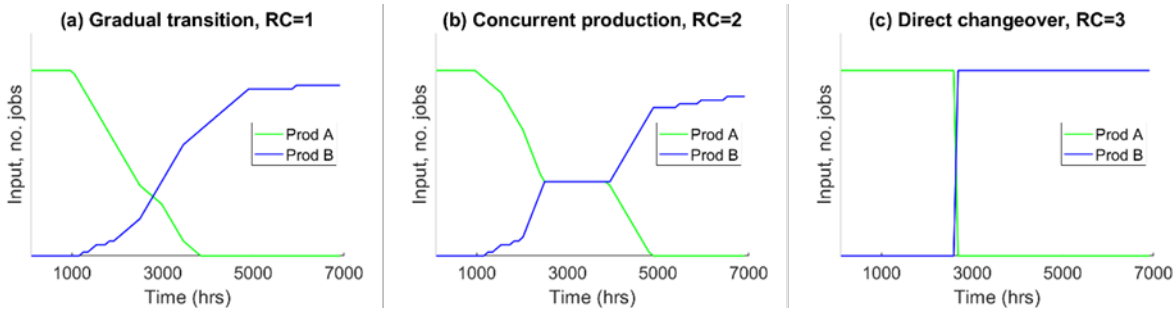

Figure 5-1: Ramp-up curves, (a) gradual transition, (b) concurrent production and (c) direct changeover

5.1 Idealised scenario experiments

The idealised scenarios fabricated data to evaluate a generalised transition scenario within a nominally balanced production environment, providing clarity of results for the parameter varied. Three experiments were run to evaluate the impact of: rates of learning, different ramp up curves, severity of failure and the structural flexibility of the system.

For these initial 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. 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.

5.1.1 Experiment 1, learning rates

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, $ke_{p\,c}$ and $kf_{p\,c}$, to improve efficiency and failure rates by 0.1; see Table 1 for variable parameter levels. All three ramp-up curves were evaluated, the severity of failure was maintained at 20 hrs repair time.

Table 1: Experiment 1, learning rates variable parameter level

Parameter level	No. operations for efficiency improvement, $ke_{p\,c}$, of 0.1	No. operations for failure rate improvement, $kf_{p\,c}$, of 0.1
LR = 1	100	50
LR = 2	150	100
LR = 3	200	150

5.1.2 Experiment 2, failure severity

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

Table 2: Experiment 2, repair time on failure variable parameter level

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

5.1.3 Experiment 3, structural flexibility

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. Experiment 3 reduces 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 3. Learning rates were maintained at LR=2 from the first experiment, $ke_{p\,c}$=150 operations and $kf_{p\,c}$=100 operations. Additionally, repair time on failure was maintained at RT=2, 40 hours.

Table 3: Experiment 3, number of single resourced operations variable parameter level

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

5.2 Validatory industrial case study

An automotive industrial case study was used to validate previous experiments and relevant findings, by applying the systems against a real-world problem and considering how similar the performance was between fabricated and real-world experiments. This was achieved by reflecting an automotive factory setup and associated operational restrictions in the simulation experiments. The case study utilises 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 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 most produced products were considered. Key data provided include: 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. 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. The number of operations to improve learning rates $ke_{p\,c}$ and $kf_{p\,c}$ are 75,000 and 40,000 operations respectively for a 0.1 improvement. Table 4 summarises the case study experimental parameters for production stages taken from Frantzén (Frantzén, 2013).

Table 4: 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 5-1. The transition period is modelled over 18 months, which is 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 5.

Table 5: Automotive case study, demand variable parameter level

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

6 Results and discussion

6.1 Idealised scenario results and discussion

Simulation experiment results were predominately analysed by plotting the 95% confidence interval of the backlog, directly comparing the three operating systems; 50 runs at each parameter setting provides suitable confidence. Further analysis was conducted if appropriate.

6.1.1 Experiment 1, learning rates

The first experiment analysed rates of learning, increasing the number of operations required to obtain efficiency gains and reduce failure rates. Figure 6-1 displays the 95% confidence interval of the backlog for each parameter setting in the hashed area around the mean line, 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 manufacturing system degrades as learning rates become slower for the gradual transition and direct changeover (RC=1 and 3); as backlog increases at a greater rate than the centralised systems. However, for the concurrent production system, the anarchic is comparable to the centralised flexible system. The two centralised systems perform similarly for gradual (RC=1) and direct changeover (RC=3) scenarios, for the concurrent production scenario (RC=2), the centralised hierarchical cell system performs the best. For the prolonged period of equal production volumes, the centralised cell system divides the resources into two independent operating systems, where there is no need to changeover between products.

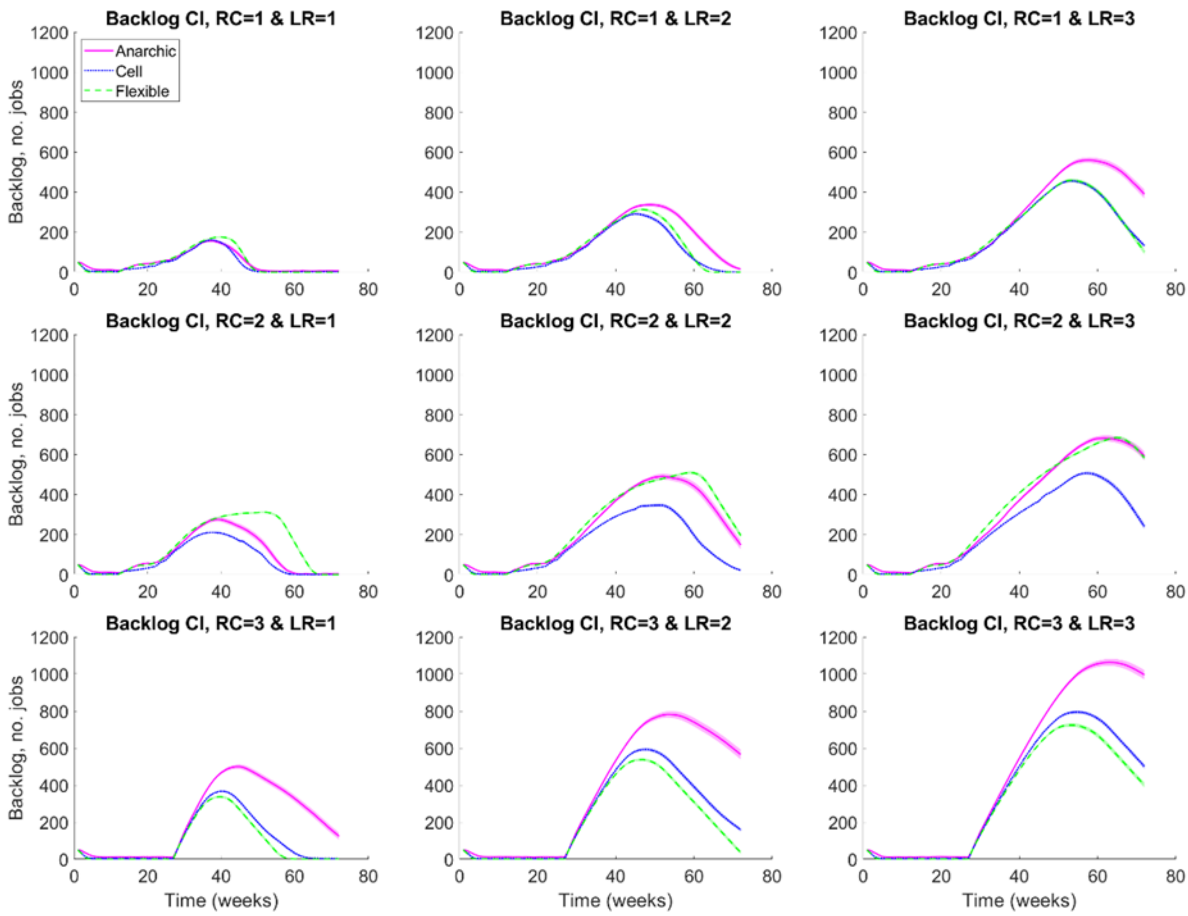

Figure 6-1: Experiment 1 learning rates confidence interval backlog plots

6.1.2 Experiment 2, failure severity

The second experiment evaluating an increasing failure severity by increasing repair time (RT) maintained the gradual transition ramp up curve (RC = 1), these backlog plots at the 95% confidence interval are displayed in Figure 6-2. As the impact of failure becomes more severe, by increasing repair time, it is evident that the anarchic system becomes superior as it less sensitive to the disruption and can flexibly manage the scenario; adapting to disruptions and exploiting available flexibility. This is particularly apparent at the most severe parameter level, RT=3, where there is clear separation between 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 increases, however the fixed hierarchical cell system performs very poorly as the parameter level increases. Highlighting the rigidity and lack of flexibility in the cell structured system.

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

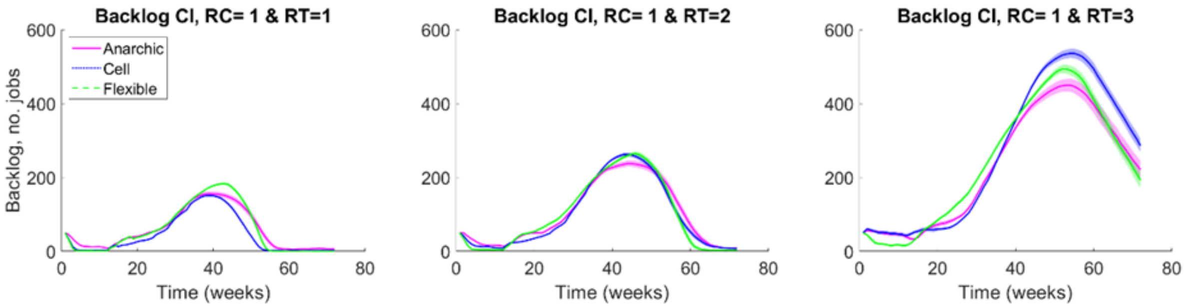

Figure 6-2: Experiment 2 failure severity confidence interval backlog plots

6.1.3 Experiment 3, structural flexibility

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 6-3 displays the backlog confidence interval plots for all parameter settings, directly comparing the three systems. Figure 6-4 to Figure 6-6 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 is a significant degradation in performance for most systems and ramp up curves. The anarchic is very poor at the direct changeover scenario, RC=3. During concurrent production, RC=2, the cell system significantly reduces performance as 1 resource is shared. Generally, the centralised systems perform similarly whilst the anarchic is worse for all scenarios.

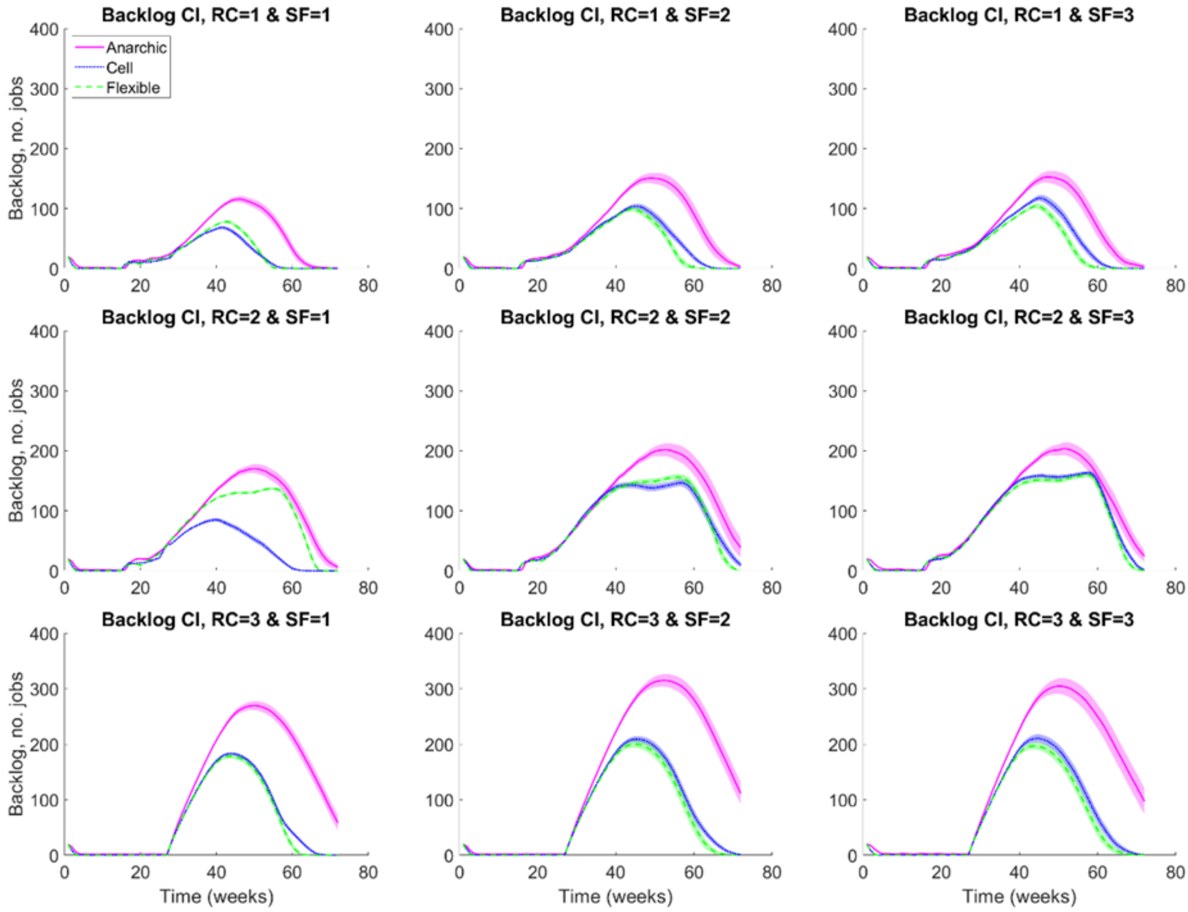

Figure 6-3: Experiment 3 failure severity confidence interval backlog plots

On evaluating the performance differences between parameter levels more closely, shown in Figure 6-4 to Figure 6-6, further characterisation can be elicited. Comparing the system performance as the number of shared resources increases directly, using the 95% confidence interval, indicates 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) does not have a significant difference in performance at the 95% confidence interval; observed through overlapping confidence interval ranges. This is in contrast to the hierarchical cell system, displayed in Figure 6-5, which shows a significant difference, at the 95% confidence interval, between each level of shared resources. Performance reduces as there are more shared resources. This indicates that the hierarchical cell system degrades at a faster rate and is less robust to this structural change. The hierarchical system is less effective at adapting to a more constrained system, reducing the effectiveness of the hierarchical cell structure. The centralised flexible system adapts similarly to the anarchic system, with little difference when at least one resource is shared.

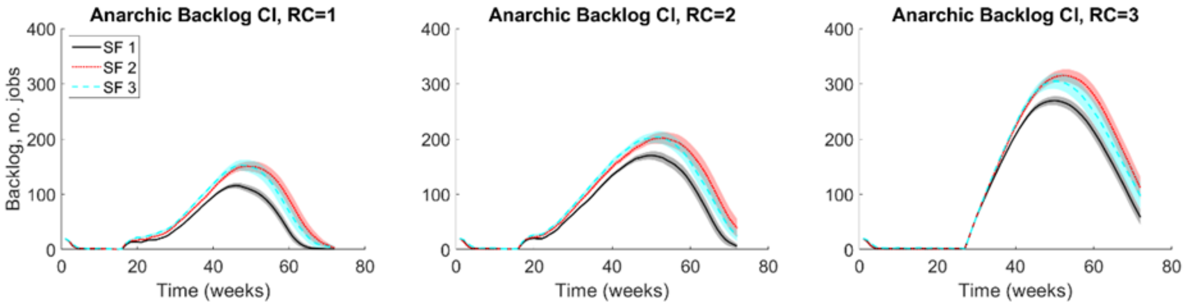

Figure 6-4: Experiment 3 anarchic system confidence interval backlog plots

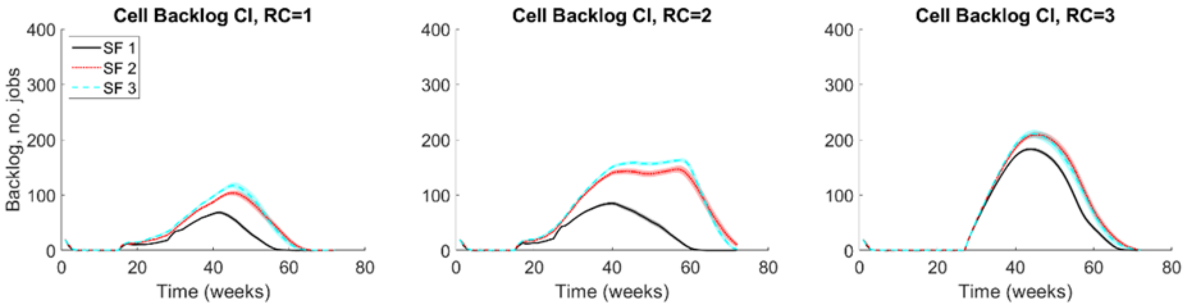

Figure 6-5: Experiment 3 centralised cell system confidence interval backlog plots

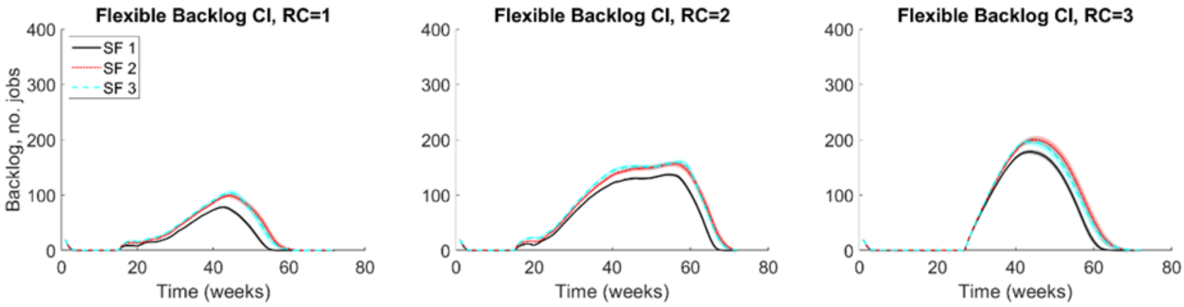

Figure 6-6: Experiment 3 centralised flexible system confidence interval backlog plots

6.2 Case study 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 6-7 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. This metric provided some insight, with a lower WIP indicating a better performance.

For the gradual and concurrent changeovers, RC=1 and 2, all systems can manage the scenario and have zero backlog. For the direct changeover scenario, RC=3, the anarchic system performs very poorly and cannot overcome the sharp change at high demand levels; a large backlog is created. This is due to the anarchic system being influenced by the recent past, its perception of the current market conditions is very different to the current and future reality. The market conditions are 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 is unable to effectively price according to new market conditions, impacting allocative efficiency.

For gradual and concurrent changeovers, the anarchic system performs worse during the changeover period but manages the scenario and maintains WIP at a manageable 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 performs better than the fixed centralised system. This highlights the anarchic system's flexibility as demand and high utilisation stress the system.

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

This automotive case study provides real world validation to the previous simulation experiments, as observed by similar outcomes and zero backlog for most scenarios. It can be concluded that the anarchic manufacturing system is functional against a real-world case study, but not the best performing. Flexible dispatch heuristics perform well, and for most scenarios the anarchic manufacturing system can maintain a good performance, which at times of high stress exceeds the hierarchical structure. Due to the lack of backlogs and instead a WIP metric being used for this experiment, further analysis and insight is cautioned against beyond stating the anarchic manufacturing system is functional in this real-world scenario.

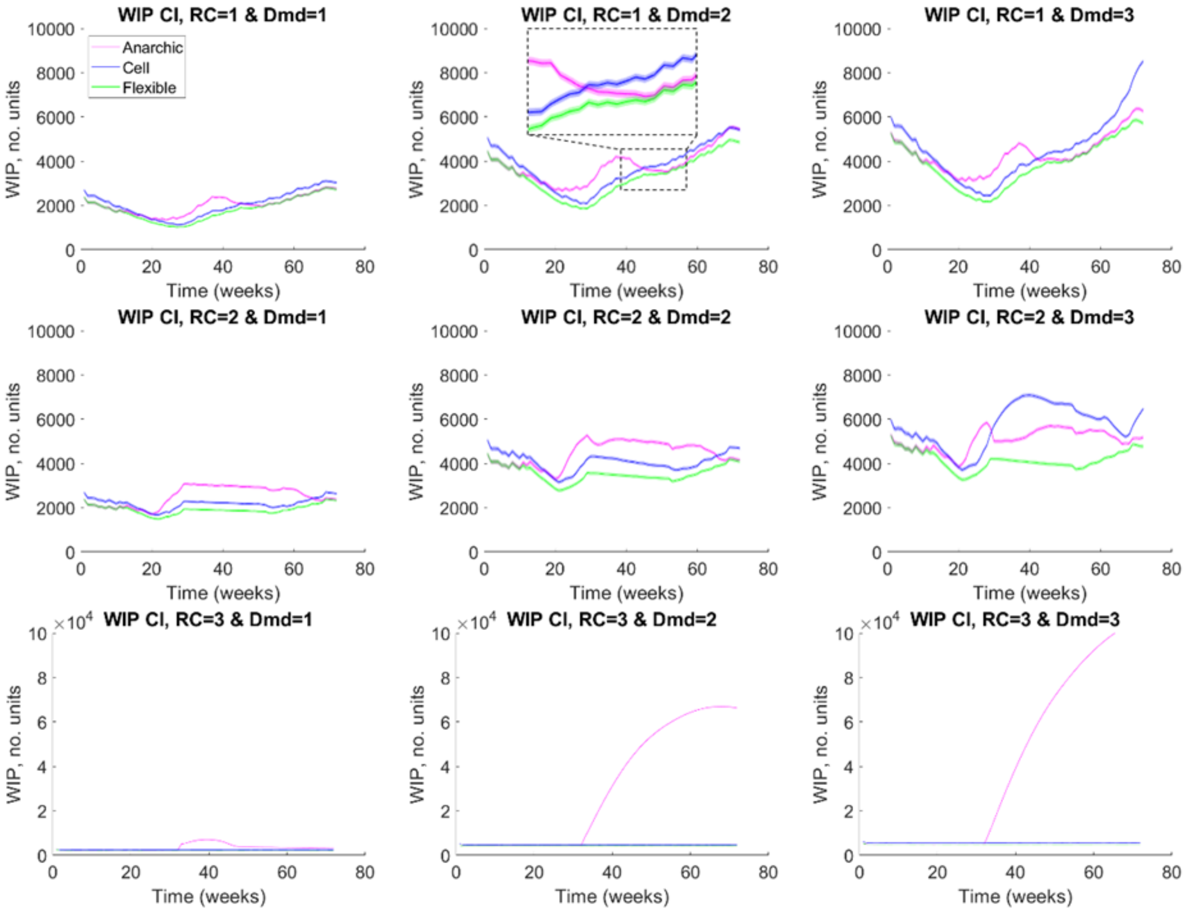

Figure 6-7: Automotive case study WIP with confidence interval plots

7 Conclusion

The research presented in this paper evaluates whether a distributed system can perform in a product transition scenario. The anarchic manufacturing system, using a free market architecture, was evaluated against two simple centralised systems; with a flexible and a hierarchical cell structure.

From the four experiments conducted, there was no overall best performing 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 provided, particularly for the second experiment which increased failure severity. However, when there was a direct changeover transition, without concurrent production of products, the anarchic system performed relatively worse and for some scenarios very poorly. This was due to a latency in the agent's interpretation of the environment in a shock change. The speed of reaction is managed to reduce volatility, however, due to a lack of forecasting the distributed agents cannot react appropriately.

The automotive case study validated the anarchic system's performance in a real-world context for concurrent production scenarios; showing comparable performance, which in high demand and high stress scenarios could outperform the hierarchical manufacturing system. The dynamic batching mechanism maintains distributed decision making and anarchic freedom. It leverages economies of scale and enables effective decision making by directly evaluating the profitability of a changeover and processing a batch of alternate products. This profitability assessment is relatable to the overall environment and an agent's individual circumstance, this in turn reduces system myopia; whilst aligning to the free market paradigm and individual decision-making autonomy.

The anarchic manufacturing system was shown to manage the product transition scenario effectively and warrants further investigation as to whether the benefits of distributed systems can be leveraged in the volatile transition scenario. This paper used an industrial case study to validate simulation experiments. However, all scenarios assumed flexible routing and ignored transportation issues and safety stock levels. Further work to evaluate the benefits of distributed systems in product transition will compare the anarchic to advanced centralised systems, as well as the anarchic system's ability to incorporate pilot production and advanced learning methodologies.

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9 Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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