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Towards System State Dispatching in High-Variety Manufacturing

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This study proposes a paradigm shift towards system state dispatching in the production control literature on high-variety manufacturing. System state dispatching lets the decision on what order to produce next be driven by system-wide implications while trading of an array of control objectives. This contrasts the current literature that uses hierarchical order review and release methods that control the system at release, whilst myopic priority rules control order dispatching based on local queue information. We develop such a system state dispatching method, called FOCUS, and test it using simulation. The results show that FOCUS enables a big leap forward in production control performance. Specifically, FOCUS reduces the number of orders delivered late by a factor of two to eight and mean tardiness by a factor of two to ten compared to state-of-the-art production control methods. These results are consistent over a wide variety of conditions related to routing direction, routing length, process time variability and due date tightness.

Keywords: High-variety manufacturing, Make-To-Order, Dispatching, Industry 4.0, Simulation, System State

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1 Introduction

This study argues for a paradigm shift towards system state dispatching in the Production Planning and Control (PPC) literature on high-variety manufacturing. System state dispatching is a novel concept that focuses on controlling the manufacturing system at dispatching. High-variety manufacturers are typically Make-To-Order companies that face the challenge of variability in demand, process time and routing (Stevenson, Hendry, & Kingsman, 2005). To ensure that high performance can be achieved despite these challenges, PPC decisions are of vital importance to coordinate complex order flow in real-time. Traditionally, PPC decisions are made using myopic priority rules (i.e. sequence each queue individually, Conway, Maxwell, and Miller 1967) using only local information. Today's literature uses Order Review and Release (ORR) methods that assume a strict decision hierarchy, where centralized release decisions use global information to set boundaries for decentralized priority rules (Chakravorty, 2001; Thürer, Fernandes, & Stevenson, 2020; Thürer, Land, & Stevenson, 2015; Thürer et al., 2014; Thürer, Stevenson, Silva, Land, & Fredendall, 2012). While this was an important advantage in the (not so recent) past, Industry 4.0 developments, including the Internet of Things and novel sensing technologies, increasingly enable decision making based on real-time information from anywhere in the manufacturing process (Chen, Gong, Rahman, Liu, & Qi, 2021; Lee, Azamfar, & Bagheri, 2021; Olsen & Tomlin, 2020; Yao et al., 2019). This questions the need to decompose PPC decisions into strict hierarchies since all system-relevant information can be evaluated in a single decision.

We argue that the current stochastic PPC literature needs a paradigm shift towards system state dispatching whereby dispatching – the decision which order to select next for processing – is driven by system-wide implications. This overcomes myopia, as the value of order characteristics in the local queue is evaluated based on the system state. To our knowledge, there is no prior study in the literature on high-variety manufacturing that includes real-time and system state information into dispatching. We use discrete event simulation to accurately represent the complex dynamics and stochastics of high-variety manufacturing systems as analytical models can only play a minor role in such settings (Sabuncuoglu & Comlekci, 2002). This simulation allows us to include real-time and system state information in dispatching, which is important to realize the potential of Industry 4.0 in practice.

After tracing back academic thought on PPC methods in the next section, we formalize a system state dispatching method called 'FOCUS'. We find that FOCUS considerably outperforms the state-of-the-art ORR method LUMS COR and commonly used priority rules in a wide variety of settings. Both the strength and novelty of FOCUS are captured in the integration of local queue and global system information for various control objectives at dispatching.

2 Literature Review

In reviewing the literature, we confine ourselves to the control decisions release and dispatching and do not consider the planning decisions such as long-term sales and inventory planning. The first section discusses the existing PPC methods – viz. priority rules and ORR methods – to better understand the ideas underlying the state-of-the-art PPC methods in the high-variety manufacturing literature. The second section reviews the underlying control mechanisms that drive performance of existing PPC methods. The last section evaluates the literature and introduces system state dispatching.

2.1 Production Control in High-Variety Manufacturing

Starting in the 1950s and 1960s, the PPC literature had a strong focus on order dispatching using priority rules to control high-variety manufacturing systems. These rules aim to sequence the queue at each work centre following simple priority criteria using solely individual order characteristics. Examples include First-Come-First-Serve (FCFS), Shortest Process Time (SPT) or Earliest Due Date (EDD, see for a comprehensive overviews: Blackstone, Phillips, & Hogg, 1982; Panwalkar & Iskander, 1977; Ramasesh, 1990). The majority of priority rules are developed in the 1960s but some more advanced rules appeared later, such as Modified Operational Due Date (MODD, Baker and Kanet 1983).

While priority rules are easy to apply using local information only, they lead to myopic dispatching decisions by neglecting that the effect of dispatching at one work centre influences the manufacturing system as a whole (Bendul & Blunck, 2019; Branke & Pickard, 2011; Hopp & Spearman, 2004; Melnyk, Tan, Denzler, & Fredendall, 1994). For that reason, multiple scholars concluded that controlling order flow using only priority rules is generally not advisable (Hendry, Kingsman, & Cheung, 1998; Ragatz & Mabert, 1988). It is therefore not surprising that, in the last decades, only a few contributions were made in the priority rule literature.

In the 1970s, scholars increasingly started to realize that control over the entire system was needed to avoid myopic control decisions (Gelders & Kleindorfer, 1974; Hax & Meal, 1975). In response, scholars started to develop hierarchical PPC methods where centralized decisions set the boundaries for decentralized decisions (Bertrand & Muntslag, 1993; Bertrand & Wijngaard, 1986). For high-variety manufacturing systems, the most common approach is to add a central 'release' decision before dispatching (Kingsman, Tatsiopoulos, & Hendry, 1989; Land & Gaalman, 1996; Melnyk & Ragatz, 1989). Release decides to release or withhold an order from the manufacturing system by keeping it in a pre-process order pool until the next release opportunity. This decision is thought to be an important control mechanism to improve on-time delivery performance (Melnyk, Ragatz, & Fredendall, 1990; Thürer, Fernandes, Stevenson, Qu, & Tu, 2019) and allows using simple priority rules for dispatching (Bechte, 1988; Land, Stevenson, & Thürer, 2014). The underlying logic was that limiting the number of orders in the queue through controlled order release reduced the myopic effects of priority rules (Bechte, 1988; Ragatz & Mabert, 1988). Of these hierarchical ORR methods, the concept of Workload Control (WLC) received the most attention. WLC includes a Work-In-Progress (WIP) balancing mechanism to ensure stable but short queue lengths in the entire manufacturing system. Today's most advanced WLC methods combine highly sophisticated ORR methods with relatively simple priority rules (e.g., Fernandes, Thürer, Pinho, Torres, & Carmo-Silva, 2020; Fernandes, Thürer, Silva, & Carmo-Silva, 2017; Haeussler & Netzer, 2020; Kundu, Land, Portioli-Staudacher, & Bokhorst, 2020; Portioli-Staudacher

& Tantardini, 2012; Thürer & Stevenson, 2021). For instance, Fernandes et al. (2020) uses FCFS and MODD as priority rules for dispatching, while using a real-time optimizing ORR method.

2.2 Key Objectives: Average & Dispersion of Lateness

The key control objectives of any PPC method are to ensure high on-time delivery performance and avoid very late deliveries (Kellerer, Rustogi, & Strusevich, 2020; Thürer et al., 2020). This can be achieved by keeping the average lateness and the dispersion of lateness among orders low (Land, 2006; Thürer et al., 2015). Figure 1 shows the distribution of lateness and illustrates the effects of reducing the average lateness (left-hand side) or its dispersion (right-hand side), showing that both lead to a reduction in the number of orders that are late (also known as tardy orders). Throughout the years, a vast array of 'control mechanisms' have been published in the literature that can reduce the average lateness or dispersion of lateness. The best understood control mechanisms are discussed below, starting with the mechanisms associated with average lateness.

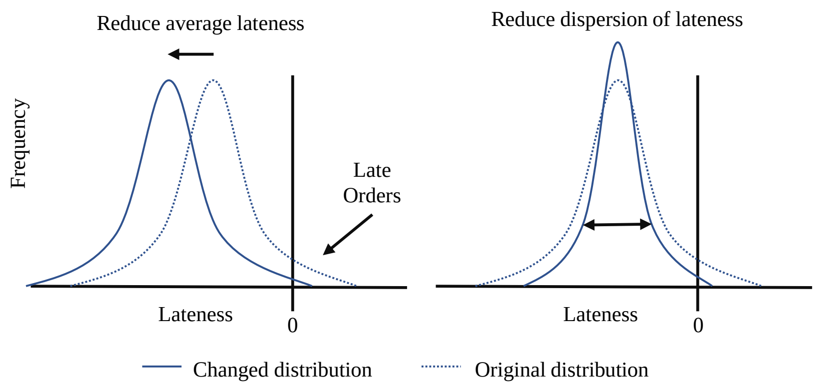

Figure 1: Illustration of reducing the average or dispersion of the lateness distribution (Baker, 1974).

2.2.1 Reduce Average Lateness

In the literature, three control mechanisms can be distinguished to reduce the average lateness; reducing average throughput time using an 'SPT-mechanism', preventing starvation using 'WIP balancing', and responding to starving work centres using a 'starvation response'.

The SPT-mechanism favours orders with a short process time over orders with a long process time (Bai, Tang, & Zhang, 2018). Prioritizing orders with a short process time has the benefit, on a system level, that successive work centres are quickly replenished, which in turn avoids potential throughput losses (Thürer et al., 2015). Besides the priority rule SPT, the ORR literature uses pool sequencing rules that include an SPT-mechanism such as Capacity Slack (Enns, 1995) which implicitly prioritize orders with short process times for release.

WIP balancing can reduce the average throughput time similar to the idea of line balancing or heijunka (Thürer et al., 2012). The aim is to *prevent* starving work centres by distributing WIP equally over the queues (and thus avoiding potential throughput losses). This is typically achieved by ORR methods that fill WIP up to a target – although a pre-defined WIP target is not strictly required (Irastorza, 1974; van Ooijen, 1996). A popular implementation is Kanban, which enforces balance by limiting WIP levels at each work centre (Berkley, 1992; Ohno, 1988). The WLC literature developed ORR methods that balance the workloads – i.e., WIP for each work centre measured in process time units – to account for process time variability (Kundu et al., 2020; Land & Gaalman, 1998; Portioli-Staudacher & Tantardini, 2012; Thürer & Stevenson, 2021; Thürer et al., 2012). Arguably, priority rules such as Work in Next Queue (WINQ) control WIP balance by prioritizing queues with lower WIP levels.

While WIP balancing aims to prevent starving work centres, they can still occur. In such cases, quickly reacting by sending orders using a starvation response mechanism is important (Land & Gaalman, 1998). Various authors include such a starvation response mechanism to complement highly sophisticated WIP balancing mechanisms in ORR methods such as LUMS COR (Fernandes et al., 2017; Land & Gaalman, 1998; Thürer et al., 2012; Yan, Stevenson, & L.C. Hendry, 2016).

2.2.2 Reduce the Dispersion of Lateness

The current literature uses the two distinct control mechanisms 'slack timing' and 'pacing' to reduce the dispersion of lateness.

Slack timing favours orders with less slack time, which is the time left that can be spent on non-processing activities. This idea is integrated into many priority rules (e.g., SLACK or EDD) and pool sequencing rules such as Periodic Release Date (Thürer et al., 2015).

Pacing ensures that orders move through their routing with relatively equal intervals. This avoids orders getting stuck for too long, risking that the order might never be able to complete all its operations before its due date. This is especially important for orders with a longer routing. Pacing is integrated into priority rules such as the Number of Remaining Operations, Operational Due Date (ODD), MODD or Slack for each Operation (Baker & Kanet, 1983; Conway et al., 1967; Kanet & Kayya, 1982).

2.2.3 Evaluation of Control Mechanisms

While multiple control mechanisms have been discussed in isolation, many proposed PPC methods deploy a combination of various control mechanisms. For instance, ORR methods typically evaluate orders in a sequence dictated by slack timing, while the final selection of orders to be released is based on WIP balancing criteria. Also, the priority rule MODD switches between control mechanisms slack timing (using ODD) and the SPT-mechanism (using SPT) in periods of low and high workloads respectively (Land, Stevenson, Thürer, & Gaalman, 2015). Thus, both the dispersion of lateness and average lateness are supposed to be controlled (Thürer et al., 2015).

Furthermore, WIP balancing and a starvation response have been monitored by ORR methods on a manufacturing system level. This is in contrast to the control mechanisms related to the dispersion of lateness which have been used myopically. For instance, ORR methods frequently use an order pool sequence rule to reduce the dispersion of lateness (Thürer et al., 2015) but this rule neglects the urgency of orders in the manufacturing system in comparison with orders in the pre-process order pool. This is in contrast to WIP balancing, where ORR methods make order release dependent on the WIP balance in the entire manufacturing system.

2.3 Discussion: System State Dispatching

To our knowledge, there is no systematic investigation into dispatching based on the state of the full manufacturing system – and thus looking beyond the order queue at dispatching. While hierarchical ORR methods take a system-wide overview when controlling order release, dispatching must correct for order flow disturbances – especially downstream (Land et al., 2014). However, dispatching is controlled by priority rules that base their decision only on local information. To our knowledge, only the priority rule WINQ, and its closely related variants, partly include system information by considering the WIP of the next downstream work centre. Nonetheless, is this rule ineffective in situations where orders all have the same downstream work centre e.g., a pure flow shop. Moreover, it neglects: (i) the system developments beyond the next downstream work centre, (ii) characteristics of orders in the queue and (iii) the need for multiple control mechanisms for effective control of the manufacturing process.

Though not including system state information, another set of priority rules introduce the orders queuing time as real-time information in their decision process (e.g., Chang, 1997; Vepsalainen & Morton, 1987). However, using the order's queuing time faces inherent circularity; queuing time is used as a decision variable but the queuing time depends on the dispatching decision itself. The resulting queuing time is therefore notoriously difficult to predict (Sabuncuoglu & Comlekci, 2002). Therefore, authors have either used constant queueing time estimates (i.e. neither real-time nor system state information) by introducing a constant 'look ahead' scaling parameter (Morton & Pentico, 1993; Vepsalainen & Morton, 1987), which makes the resulting rule again myopic as decisions are solely based on information form orders in the local queue.

The need to avoid local myopia was identified as far back as Conway and Maxwell (1962), who already concluded – regarding dispatching – that *"we still believe that a superior (nonlocal) rule can be advised"*. However, in those years researchers foresaw data availability problems in practice (Bertrand & Wijngaard, 1986; Conway & Maxwell, 1962; Melnyk & Ragatz, 1989). This shifted the literature's attention towards ORR methods to reduce myopia whilst the debates on dispatching dimmed down (one notable exception being Land et al., 2014). Recent developments such as the Internet of Things and sensing technologies allow for more data to be collected and makes system-wide information available at a local level (Chen et al., 2021; Lee et al., 2021; Olsen & Tomlin, 2020; Yao et al., 2019), offering an opportunity to avoid myopia and increase performance. Therefore, we call for a paradigm shift in the stochastic PPC literature on high-variety manufacturing towards system state dispatching.

3 System State Dispatching Method FOCUS

We define a system state dispatching method, referred to as Flow and Order Control Using System state dispatching (FOCUS) to illustrate the effect of our proposed paradigm shift. FOCUS includes all five main control mechanisms that have been discussed in Section 2.2. Each control mechanism is embedded in a 'projected impact function' that returns a 'projected impact' value between $[0, 1]$. For a given order, the projected impact represents the value of a control mechanism, which is obtained by comparing an order characteristic — e.g., process time – with a system state variable – e.g., WIP balance. This comparison is executed by a projected impact function. Whenever selecting an order for dispatching, FOCUS uses the weighted average projected impact of all five functions to trade-off multiple control mechanisms. As this average will be dominated by those mechanisms that have the most impact on either average lateness or the dispersion of lateness given the system state, FOCUS dynamically switches between the mechanisms with the most projected impact over time.

To formalize this, we introduce some notation. Orders are denoted with $i \in I$ and work centres are denoted with $j \in J$. The set of orders in the system are denoted by $O \subset I$ (i.e. orders that arrived but did not yet complete their operations). In turn, orders in the (virtual) queue of j are denoted with $Q_j \subseteq O$ and the orders that are being processed are denoted by $H_j \subseteq O$. Then the orders that are located at work centre j are denoted by $W_j = Q_j \cup H_j$. To accurately represent high-variety manufacturing systems, we treat process times, routing and order inter-arrival time as continuous random variables where process times and routing become known upon order arrival (cf. Thürer et al., 2020). As a consequence, order dispatching takes place in continuous-time t whenever a completed order leaves the work centre while the queue is not empty, or when an order arrives at an idle work centre. Therefore, we can safely assume that two dispatching decisions never take place at *exactly* the same time. FOCUS selects one order for dispatching from all candidate orders in the queue $Q_{j'}$ of work centre j' that awaits a dispatching decision.

The formalization of FOCUS starts by outlining the five projected impact functions. Thereafter, the weighted average projected impact and the order selection process of FOCUS are defined. Since we use FOCUS to illustrate our proposed paradigm swift, we translate existing control mechanisms to the system state dispatching paradigm. As a consequence, since the literature for some control mechanisms (e.g., WIP balancing) is far more developed than other mechanisms (e.g., starvation response), the projected impact functions have varying degrees of complexity.

3.1 Projected Impact Functions

SPT-mechanism π : We consider the process times p_{ij} of all remaining operations from all orders $i \in O$ as the relevant system state, which extends the typical approach in the ORR and priority rule literature of only considering the process times in the queue $Q_{j'}$ of j' where the dispatching decision is taken. We define $P = \{(i,j), \dots\}$ as the set of pairs (i,j) of orders i with remaining operations (thus i is in set O) and work centres j that execute these remaining operations. We evaluate order $i' \in Q_{j'}$ for dispatching using the projected SPT-mechanism impact function $\pi(\cdot)$, which is defined as

$$\pi(i',j') = 1 - \frac{p_{i'j'}}{\max_{(i,j)\in P}\{p_{ij}\}}. \tag{1}$$

The projected impact returned by π is between 0 and 1, and that it is close to 1 if the process time of an order is small relative to the largest process time of some order somewhere in the system. This allows to overcome local myopia since π compares the orders within and beyond the queue. At the same time, π remains versatile to the global system state by comparing the orders in the queue with the order that can better be used to implement a control mechanism – albeit by a dispatching decision in the near future.

WIP balancing $\boldsymbol{\beta}$: Similar to the WLC literature, WIP is measured in process time units – called workload – to account for process time variability. Before the projected WIP balancing impact function can be defined, we must determine how to: (i) measure the workload at each work centre, (ii) compute the change in workload if an order would be dispatched and (iii) evaluate the impact on WIP balance if i' would be dispatched.

(i) We measure workload $l(\cdot)$ that is located at a work centre j as

$$l(j) = \sum_{i\in W_j} p_{ij}. \tag{2}$$

(ii) When considering an order for dispatching, we evaluate the change in workload l^+_{ij} for any $j \in J$ if i would leave its imminent work centre $k^-_i \in J$. Let $k^+_i \in J$ indicate the first downstream work centre to which i moves after leaving k^-_i, then the changed workload l^+_{ij} for i given any j is defined as

$$l^+_{ij} = \begin{cases} l(j) - p_{ij} & j = k^-_i, \\ l(j) + p_{ij} & j = k^+_i, \\ l(j) & \text{else.} \end{cases} \tag{3}$$

(iii) Ideally, the workload is perfectly balanced if a fraction $1/|J|$ of the total workload in the system is located at each work centre $j \in J$ after selecting order i for dispatching. Therefore, we seek a measure that attains the highest value when a perfect WIP balance (i.e. $l^+_{ij}/\sum_{j\in J} l^+_{ij} = 1/|J|$) is achieved by selecting i. In contrast, the measure must return the lowest value whenever a single work centre contains all the workload (i.e. $l^+_{ij}/\sum_{j\in J} l^+_{ij} = 1$) indicating the ultimate WIP imbalance. This is captured by the entropy function $e(\cdot)$, which is defined as (Shannon, 1949)

$$e(i) = -\sum_{j\in J} \frac{l^+_{ij}}{\sum_{j\in J} l^+_{ij}} ln\left(\frac{l^+_{ij}}{\sum_{j\in J} l^+_{ij}}\right), \tag{4}$$

where the maximum entropy $e_{\text{max}} = ln(|J|)$ and the minimum entropy $e_{\text{min}} = 0$ correspond with the perfect WIP balance and the ultimate WIP imbalance, respectively.

At order selection, we want to know the ability of an individual order to change the existing WIP balance. Let e^- be the entropy of the WIP balance before dispatching, then we define the change in entropy $c(\cdot)$ as

$$c(i') = e(i') - e^-. \tag{5}$$

Now we define projected WIP balancing impact function $\beta(\cdot)$ as

$$\beta(i') = \begin{cases} \dfrac{c(i')}{\max_{i\in O}\{c(i)\}} & c(i') > 0, \\ 0 & \text{else.} \end{cases} \tag{6}$$

The projected impact function β gives a positive projected impact to orders that can improve WIP balance whilst the selection amongst orders that cannot improve WIP balance is driven by other criteria.

Starvation Response $\boldsymbol{\xi}$: Work centres that are starving (defined as work centres without waiting orders in the queue) are included in the starvation set $S = \{j \in J \mid Q_j = \emptyset\}$. We define the projected impact equal to projected SPT-mechanism impact π (Equation 1) if an order moves to a starving work centre. Therefore, the projected starvation response impact function $\xi(\cdot)$ is defined as

$$\xi(i', j') = \begin{cases} \pi(i', j') & k^+_{i'} \in S, \\ 0 & \text{else.} \end{cases} \tag{7}$$

Formalizing ξ in such a way, we give the highest impact if the process time of i' is short, so the order can quickly move to a starving work centre.

Slack timing $\boldsymbol{\tau}$: Let $R_i \subseteq J$ be the set of work centres in the remaining routing of i and d_i the due date of i, then the slack $s(\cdot)$ is defined as

$$s(i) = d_i - t - \sum_{j \in R_i} p_{ij}. \tag{8}$$

Slack represents the time an order can still spend on non-processing activities from time t until its due date d_i and is used by the projected slack timing impact function $\tau(\cdot)$, which is defined as

$$\tau(i') = \begin{cases} 1 - \dfrac{s(i')}{\max_{i \in O}\{s(i)\}} & s(i') > 0, \\ 1 & \text{else.} \end{cases} \tag{9}$$

Using τ, we provide an increasingly higher projected impact to orders closer to their due date whilst orders that passed their due date receive the highest projected impact to encourage selection. The ultimate selection amongst these late orders is driven by other criteria than slack timing.

Pacing $\boldsymbol{\delta}$: If $|R_i|$ is the number of remaining routing steps, then the slack per remaining operation $v(\cdot)$ is defined as

$$v(i) = \frac{s(i)}{|R_i|}. \tag{10}$$

Correcting slack for the number of remaining operations allows us to dictate the pace at which the orders' remaining operations need completion. Thus, we define the projected pacing impact function $\delta(\cdot)$ as

$$\delta(i') = \begin{cases} 1 - \dfrac{v(i')}{\max_{i \in O}\{v(i)\}} & v(i') > 0, \\ 1 & \text{else.} \end{cases} \tag{11}$$

Note that the projected impact is higher if the time for each remaining operation becomes shorter. For already late orders, the ultimate selection is driven by other criteria than slack timing by setting the projected impact at one.

3.2 Order Selection

FOCUS selects the order z from the queue $Q_{j'}$ for dispatching that has the highest weighted average projected impact for the five projected impact functions. We denote the weights by $w_1, \dots, w_5$ and define weighted average projected impact $\mathcal{I}(\cdot)$ of each order i at j as

$$\mathcal{I}(i, j) = \pi(i, j)w_1 + \beta(i)w_2 + \xi(i, j)w_3 + \tau(i)w_4 + \delta(i)w_5. \tag{12}$$

Hence, the selected order $z \in Q_{j'}$ is defined as

$$z = \underset{i' \in Q_{j'}}{\operatorname{argmax}}\ \mathcal{I}(i', j'). \tag{13}$$

4 Simulation Model

Similar to existing ORR methods and priority rules, the performance effect of FOCUS in a stochastic high-variety manufacturing system is analytically intractable given the inherent complexity of such systems. Therefore, we use discrete event simulation to obtain a Monte-Carlo estimate of FOCUS' performance. Since system state dispatching is a novel concept, FOCUS is tested in a wide variety of manufacturing systems. The included PPC methods, to which FOCUS is compared, are described after the manufacturing system and order characteristics have been outlined. Thereafter, we discuss the performance measures and experimental design.

4.1 Manufacturing System and Order Characteristics

To aid generalizability, six stylized manufacturing systems are used to test FOCUS in a wide variety of settings. The selected stylized systems have been used extensively in prior literature on PPC decision-making in high-variety manufacturing (Fernandes et al., 2020; Thürer et al., 2020, 2015, 2012). These models are kept as parsimonious as possible to avoid unwanted interaction effects. Therefore, this study assumes no machine breakdowns, infinite raw materials and setups are included in process times. Furthermore, the orders' routing and process times are known upon arrival. An overview of the order and manufacturing system characteristics is provided in Table 1.

MANUFACTURING SYSTEM AND ORDER CHARACTERISTICS	
Manufacturing system	PJS, GFS, PFS with 6 or 12 work centres
Machine capacity	All equal
Inter-arrival times	Exponentially distributed; all systems have 90% utilization
Process times	2-Erlang distributed with mean equals 1 after truncation at 4 time units
Due date setting	Total Work Content

Table 1: Overview manufacturing system and orders characteristics.

The manufacturing systems have six or twelve work centres, each consisting of a single capacity source, to vary the size of the system state. To allow for a wide variety of products to be produced, high-variety manufacturing systems are frequently organized in various layouts. Therefore, the routing length – i.e. the number of operations to be executed – and direction are varied (Oosterman, Land, & Gaalman, 2000). At one extreme is the Pure Flow Shop (PFS) for which the routing length is fixed and directed (i.e. all orders have the same routing). Conversely, the Pure Job Shop (PJS) – also known as a randomly routed job shop (Conway et al., 1967) – has a random routing length and random routing direction (i.e. routing is order specific). In between is the General Flow Shop (GFS), which uses a directed routing but a random routing length. For the PFS, routing length equals the number of work centres (six or twelve) in the manufacturing system. For the PJS and GFS, the routing length is uniformly distributed between one and the number of work centres, whilst each work centre has an equal probability of being included in the routing set. In the case of the GFS, this routing set of work centres is sorted in an ascending manner to create routing direction. Re-entry at the same work centre is allowed for none of the systems. Process times p_{ij} are distributed following a 2-Erlang distribution with a mean of one after truncation (cf. Oosterman et al., 2000; Thürer et al., 2020; Thürer & Stevenson, 2021). The distribution is truncated at four-time units to avoid orders having a process time larger than workload targets of the ORR method discussed below. Orders arrive continuously whilst the inter-arrival times follow an exponential distribution to implement a stochastic process with independent arrivals. Similar to previous works (Thürer et al., 2015, 2012), the mean inter-arrival time is set to achieve an average utilization level of 90%. For the GFS and PJS, this implies a mean inter-arrival time of $1/\lambda = 0.684$ and $1/\lambda = 0.602$ for six and twelve work centres respectively. For the PFS, the mean-inter arrival time is $1/\lambda = 1.111$ for six and twelve work centres. Due dates are obtained using the Total Work Content (TWK) procedure (Enns, 1995; Harrod & Kanet, 2013). Let t_i^a be the time at which order i arrives and K is a constant hyperparameter, then d_i are defined as

$$d_i = t_i^a + K \sum_{j \in R_i} p_{ij}. \tag{14}$$

Recall that R_i is the remaining routing set of i (and thus equal to the full routing set at the time of arrival). Appropriate values of K are highly dependent on the manufacturing system characteristics. To obtain results in the same performance range, hyperparameter K was tuned using pre-tests in such a way that the priority rule ODD achieves a percentage tardy around 15% in an uncontrolled release setting. This allowed obtaining reliable and relevant results across all experimental factors and performance measures discussed below. This implies that K is 8.74, 9.31 and 8.16 for six work centres and 8.08, 8.66 and 7.25 for twelve work centres in the PJS, GFS and PFS respectively.

4.2 Experimental Setup FOCUS

The weights $w_1, \ldots, w_5$ from FOCUS are all set to $1/5$ to make no a-priory assumptions of the importance of one of the control mechanisms. Additionally, we want to study the contribution of each of the five control mechanisms. Therefore, we added five FOCUS configurations where one (of the five) control mechanism was removed. For instance, 'FOCUS - π' implies that FOCUS is used without π by setting its weight $w_1 = 0$ while the other weights $w_2, \ldots, w_5$ are set to $1/4$.

4.3 Benchmark Production Planning and Control methods

FOCUS is compared with an array of PPC methods published in the literature. The priority rules FCFS, ODD, SPT and MODD are used in an immediate release setting. In addition, an ORR method – called LUMS COR – is used to control the manufacturing system hierarchically, as this is the common approach in the state-of-the-art literature (Fernandes et al., 2017; Kundu et al., 2020; Thürer et al., 2020; Thürer & Stevenson, 2021).

4.3.1 Priority rules

While the rules FCFS and SPT are straightforward, multiple versions of ODD are published in the literature. The priority rule ODD uses the operational due date o_{ij} for order i at work centre j. This study uses the best performing and parameter-free version of o_{ij} as outlined by Land et al. (2014). Let t_i^r be the release time and r_{ij} is the routing step number, then ODD is defined as $o_{ij} = t_i^r + r_{ij} \max\{0, (d_i - t_i^r)/|R_i|\}$. Recall the that $|R_i|$ indicates the number of routing steps and equals the total number of routing steps at release. In experiments without controlled release, note that $t_i^r = t_i^a$ as orders are immediately released upon arrival. If o_{ij} is used in conjunction with a ORR method, then generally $t_i^r \neq t_i^a$ since orders remain in the pre-process order pool before release. MODD is defined as $\max\{o_{ij},\ t + p_{ij}\}$ to dynamically switch between ODD ($o_{ij} > t + p_{ij}$) and SPT ($o_{ij} < t + p_{ij}$).

In our experiments, we test the priority rules FCFS, SPT, ODD and MODD without hierarchical control of the system via an ORR method.

4.3.2 ORR method

The hierarchical ORR method LUMS COR (Thürer et al., 2012) is included for two reasons. Firstly, LUMS COR is an established ORR method that is compared to various alternatives using highly similar manufacturing systems as used here (e.g., Fernandes et al., 2017). Therefore, the inner workings and performance explanations of LUMS COR are well documented (Fernandes et al., 2020, 2017; Thürer et al., 2012). Secondly, compared to LUMS COR, no other ORR method in the current literature shows a clear performance advantage for all relevant performance indicators in a wide variety of manufacturing systems (cf. Fernandes et al., 2020).

LUMS COR periodically evaluates orders for release by assessing if the workload contribution of an order fits within the workload target of each work centre. If an order does not fit within the targets of any work centre, then it is withheld in a pre-process order pool until the next release period. Besides periodic release, LUMS COR includes a continuous release trigger which releases an order to an idle work centre, even if it violates workload targets of other work centres. A pool sequence rule is used to determine the sequence in which orders in the pool are evaluated for release. See Thürer et al. (2012) for an elaborate description.

LUMS COR requires setting additional parameters. Since the manufacturing systems studied here are the same or very similar as in previous studies, we adopt the overall best-performing parameters (Thürer et al., 2012). Therefore, the workload targets for each work centre are varied between 4.95, 5.85 and 6.75, whilst the periodic release interval is set to four-time units. The pool sequence rule EDD is used since the due date setting method TWK already includes information on the relative size of the order. The priority rule MODD is used for order dispatching since the current literature generally regards it as the best priority rule for ORR methods (Fernandes et al., 2020; Kundu et al., 2020) as it is adapted or ORR methods.

Throughout the remainder of this study, we refer to LUMS COR as ORR together with the used workload target. For instance, ORR (4.95) refers to LUMS COR using a workload target of 4.95.

4.4 Performance Measures

Delivery performance is the main performance objective in high-variety manufacturing (Sterna, 2021; Teo, Bhatnagar, & Graves, 2012; Thürer et al., 2020). Percentage tardy provides the most general indication of delivery performance. But we include other delivery performance measures based on lateness $\mathcal{L}_i$, which is negative if orders are delivered early, and tardiness $\mathcal{T}_i = \max\{0, \mathcal{L}_i\}$. Previous work used mean tardiness, mean lateness and the standard deviation of lateness as measures for delivery performance (e.g., Haeussler & Netzer, 2020; Sterna, 2021; Yan et al., 2016). However, these measures tend to neglect extreme late deliveries as the tail of the lateness distribution can be very long. Mean squared tardiness $\mathcal{T}_i^2$ is used to capture this form of undesirable delivery performance. Similar to Thürer et al. (2020), we consider the combination of percentage tardiness and mean tardiness as the key criteria, whilst mean throughput time, the standard deviation of throughput times, mean lateness, the standard deviation of lateness and mean squared tardiness are used to support our conclusions.

4.5 Experimental Design

The above model was implemented in `Python` using the `SimPy` module. The full factorial experimental design includes thirteen PPC methods in six manufacturing systems. The included priority rules are FCFS, ODD, MODD, and SPT. The ORR method has three different workload targets. Besides the full FOCUS model, the experimental design includes five FOCUS configurations where one of the five control mechanisms is excluded. All these methods are tested in a PJS, GFS and a PFS with six and twelve work centres. This results into $13 \times 6 = 78$ main experiments.

Besides the main experiments, we added a set of 'sensitivity experiments' with tighter due dates and increased process time variability to check if our conclusions are not unique to specific numerical settings. Tighter due dates were based on a reduction of hyperparameter K that increased the percentage tardy for ODD from 15% to 20%, leading to an additional 78 experiments. For process time variability, the 2-Erlang distribution was replaced with an untruncated Log-normal distribution to be able to vary the coefficient of variation between 0.5 and 1. In these experiments, we had to exclude three ORR methods as these methods cannot handle untruncated distributions, leading to another $10 \times 6 \times 2 = 120$ experiments.

So, we consider 78 main experiments and $78 + 120$ sensitivity experiments, and so 276 in total. Each experiment is carried out over $10,000$ time units and replicated 100 times. For each experiment, an additional warm-up period of $3,000$ time units is used to avoid the initialization bias. This keeps the computational time within reasonable limits while still obtaining an accurate estimate of performance. Common random numbers are used to increase the significance of the performance differences between experiments. These parameters are in line with other studies (Thürer et al., 2012) and were found to be sufficient for our experiments.

5 Results

To obtain a first impression from the results of our 78 main experiments, we use an ANOVA to statistically analyse the impact of our main experimental variable PPC method (PPCM) in all six manufacturing systems (MFS). The statistical results for mean tardiness and percentage tardy can be found in Table 2 whilst the statistical results of our supportive measures can be found in Table 5 in Appendix A.1. For all performance measures, both the main and interaction effects are statistically significant at p-value < 0.05. For percentage tardy and mean tardiness, the main effect PPCM has the highest F-ratio, suggesting that choosing an appropriate PPC method is more influential for on-time delivery than the different characteristics of the six manufacturing systems.

ANOVA Results						
Performance Measure	Source of Variance	Sum of Squares	Degrees of Freedom	Mean Squares	F-ratio	p-value
Mean Tardiness	PPCM	4263.1	7	609.01	492.46	0.00
	MFS	203.51	5	40.7	32.91	0.00
	PPCM × MFS	790.96	35	22.6	18.27	0.00
	error	9,586.81	7,752	1.24		
Percentage Tardy	PPCM	16.3	7	2.33	528.8	0.00
	MFS	1.44	5	0.29	65.25	0.00
	PPCM × MFS	0.51	35	0.01	3.31	0.00
	error	34.13	7,752	0		

Table 2: ANOVA for PPC method (PPCM) and manufacturing systems (MFS).

The averages for our two most important performance measures, mean tardiness $\mu(\mathcal{T}_i)$ and percentage tardy $\%(\mathcal{T}_i)$, are presented in Table 3 for all 78 main experiments. The results of all performance measures can be found in Appendix A.2 (Table 6 and Table 7 for the systems with six and twelve work centres respectively).

Simulation Results												
	Six Work Centres						Twelve Work Centres					
	PJS		GFS		PFS		PJS		GFS		PFS	
Name	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$	$\mu(\mathcal{T}_i)$	$\%(\mathcal{T}_i)$
FCFS	4.18	34.69	3.35	29.54	3.44	25.28	6.02	37.38	4.10	28.73	4.44	24.29
MODD	0.58	6.67	0.57	5.18	0.73	3.53	0.65	5.81	0.65	3.92	0.86	2.74
ODD	1.13	15.04	1.25	15.01	1.66	15.05	1.20	14.99	1.47	15.04	2.29	14.98
SPT	1.92	4.53	1.79	3.91	2.17	3.85	2.55	5.06	2.33	4.09	2.61	3.71
ORR (4.95)	1.27	10.00	1.83	8.57	0.54	4.41	1.52	6.93	3.18	8.19	0.67	3.17
ORR (5.85)	0.88	8.34	1.34	7.47	0.53	4.33	0.94	5.32	2.10	6.41	0.64	3.08
ORR (6.75)	0.68	7.79	0.99	6.90	0.52	4.27	0.66	4.98	1.41	5.47	0.64	3.06
FOCUS	0.44	4.20	0.30	2.85	0.20	1.76	0.35	2.69	0.20	1.44	0.08	0.63
FOCUS - π	1.82	8.40	1.15	6.58	0.87	6.45	1.42	5.62	0.69	3.58	0.61	4.03
FOCUS - β	0.30	2.20	0.26	1.92	0.23	1.80	0.24	1.31	0.18	0.98	0.10	0.73
FOCUS - ξ	0.33	3.12	0.27	2.48	0.21	1.88	0.18	1.51	0.15	1.07	0.08	0.68
FOCUS - τ	1.32	8.40	1.25	6.05	0.84	2.99	1.64	7.34	1.52	5.26	1.10	2.47
FOCUS - δ	0.72	4.92	0.58	3.56	0.36	1.85	0.61	3.32	0.41	2.05	0.18	0.79

Table 3: Simulation results, where mean tardiness is defined as $\mu(\mathcal{T}_i)$ while $\%(\mathcal{T}_i)$ denotes percentage tardy.

5.1 Reducing the Average & Dispersion of Lateness

The results in Table 3 show that FOCUS considerably outperforms all benchmark priority rules and ORR methods on percentage tardy and mean tardiness. To further investigate these results, Figure 2 presents the performance frontier (grey line) between mean tardiness ($x-$axis) and percentage tardy ($y-$axis),

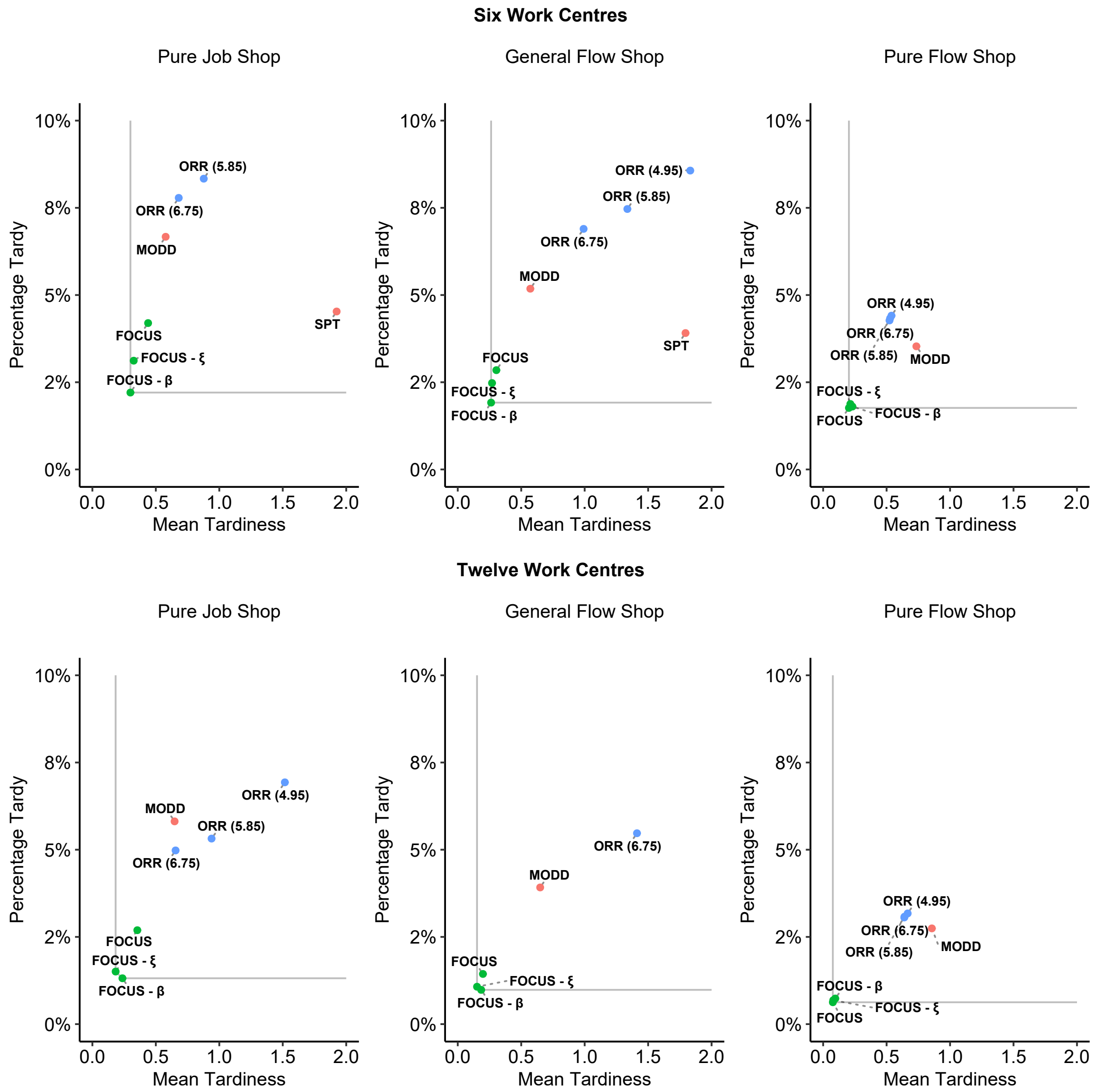

Figure 2: Trade-off frontier percentage tardy and mean tardiness. Grey line is the performance frontier.

where priority rules have red dots, ORR has blue dots, and the FOCUS versions have green dots. We remark that not all PPC methods are depicted in Figure 2 since some – e.g., FCFS – are located too far from the performance frontier or show almost the same results (in the case of the FOCUS versions). When specifically looking at FOCUS, FOCUS - β (FOCUS excluding WIP balancing) and FOCUS - ξ (FOCUS excluding a starvation response), the results indicate that the frontier is fully defined by versions of FOCUS. Compared to SPT (the second-best policy on percentage tardy), FOCUS - β can reduce the percentage tardy by a factor of two in a six work centre PJS up to a factor of ten for twelve work PJS. At the same time, FOCUS also dominates the performance on mean tardiness by realizing reductions compared to ORR (6.75) of at least 63% and compared to MODD of at least 47% in all studied manufacturing systems. These performance improvements are often obtained by FOCUS - β which is consistently best in the six and twelve work centre PJS and GFS.

The performance frontier, shown in Figure 2, suggests that FOCUS is highly effective in adhering both key control objectives. When looking at our supportive performance measures for a reduction in the average lateness, the results in Appendix A.2 indicate that FOCUS can reduce the mean throughput time and mean lateness further compared to ORR and MODD. Only SPT is able to realize a slightly lower mean throughput time and mean lateness. Typically, successfully reducing the average lateness amplifies the dispersion of lateness (Thürer, Stevenson, Land, & Fredendall, 2019), which would result in deteriorated performance on mean tardiness and mean squared tardiness. Compared to FOCUS, all

ORR variants, SPT and MODD have a higher mean squared tardiness. Only ODD has a lower mean squared tardiness than FOCUS in PJS and GFS without a lower mean tardiness. Therefore, the best policy that achieves synergies between both key control objectives is FOCUS by mutually reducing the mean throughput time, mean lateness, mean tardiness and mean squared tardiness.

5.2 Added Value of Projected Impact Functions

Figure 3 presents an overview of all five FOCUS configurations where one control mechanism is removed compared to the full FOCUS configuration. We only show the systems with six work centres, as the twelve work centre systems show the same pattern. The vertical dotted lines show the performance on percentage tardy and mean tardiness of the full FOCUS configuration. If a version of FOCUS is outside the dotted line, this shows that leaving out the indicated control mechanism weakens performance.

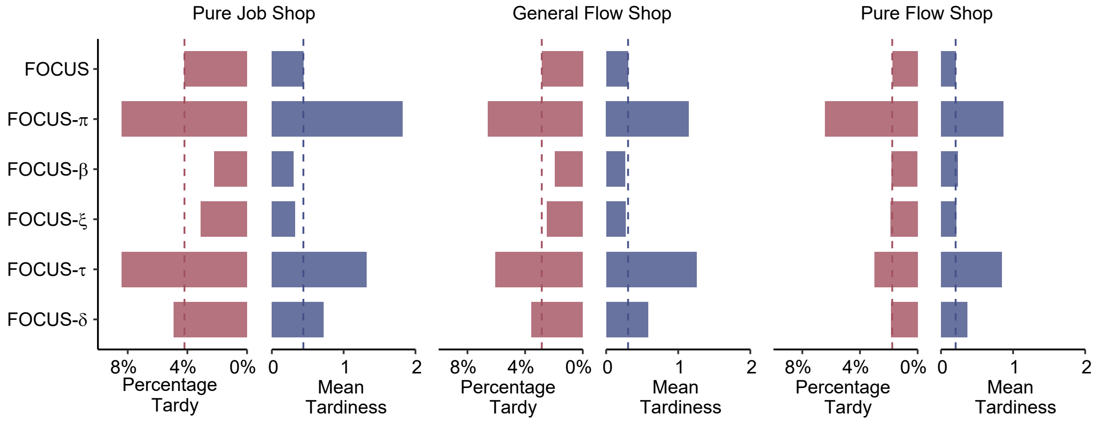

Figure 3: Percentage tardy and mean tardiness. Dotted line is the original version of FOCUS.

The most influential control mechanisms are the SPT-mechanism π and slack timing τ as shown by the results of FOCUS - π and FOCUS - τ, respectively. When one of these two control mechanisms is left out, performance deteriorates on both percentage tardy and mean tardiness. As can be seen by FOCUS - δ, performance also deteriorates when pacing is left out although the effect is less severe. In contrast, WIP balancing (see FOCUS- β) negatively influence performance in a PJS and GFS, whilst its influence in a PFS is minimal. This suggests that pure WIP balancing to *prevent* starvation is not effective at dispatching, especially not if other control mechanisms (such as the SPT-mechanism) can already reduce the mean throughput time and mean lateness. This result contrasts with the WLC literature, which argues that WIP balancing is a key mechanism to reduce throughput times (Thürer et al., 2014) or control the manufacturing system at release (Thürer, Fernandes, et al., 2019). In a similar vein, a starvation response ξ (see FOCUS - ξ) seems to negatively influence performance, especially if routing becomes less directed (i.e. GFS and PJS). In Section 6, we use the above observations to evaluate if we can leave out more control mechanisms.

5.3 Sensitivity Analysis

This section summarizes the results for the sensitivity experiments. Detailed results can be found in Appendix A.3.

Due date tightness: When due dates become tighter, our conclusions remain qualitatively the same as FOCUS keeps outperforming all other PPC methods in all six manufacturing systems. One exception is the result that the control mechanism starvation response ξ starts to contribute positively in both PFS systems.

Process time variability: When process time variability increases, FOCUS - β remains best in all PJS and GFS manufacturing systems. For the PFS systems, FOCUS is Pareto efficient by trading-off a higher percentage tardy for a lower mean tardiness. In these systems, the priority rules SPT (all systems) and

MODD (only PFS) can reduce the percentage tardy further than FOCUS at the cost of increasing – in the case of SPT even doubling – mean tardiness. Similar to increased due date tightness, we find that a starvation response ξ has a positive performance contribution in a PFS. Since the truncation point of the process time distribution is removed in this setting, the results indicate that FOCUS' performance is robust to extremely high process times.

6 Discussion of FOCUS' Performance

To explain FOCUS' performance, we use time series data instead of the steady-state averages (presented earlier), because the latter is important for reliable statistical estimates but fails to show the interaction between control decisions and developments in the system state (Land et al., 2015). We focus on the results of a six work centre GFS, as this system is argued to be most realistic (cf. Enns, 1995) and because our observations are the same in the other systems.

Over time, we collected WIP levels and relate these to lateness performance. Figure 4 illustrates the system state developments under FOCUS - β compared to MODD, ORR (6.75), as these are the most competitive methods from each literature stream. Time is shown on the x-axis whilst the y-axis shows lateness $\mathcal{L}_i$ and the WIP level in terms of load ($\sum_{j \in J} \sum_{i \in W_j} p_{ij}$) in the manufacturing system.

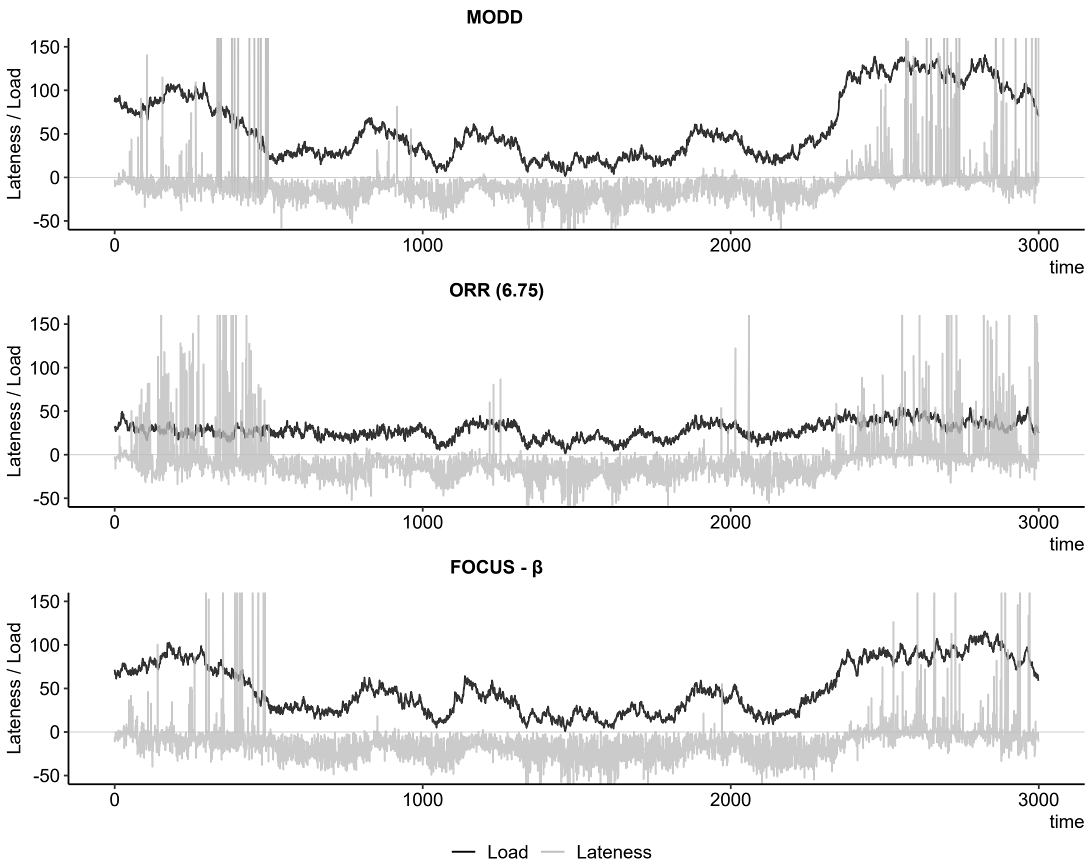

Figure 4: Time-phased projection of the lateness and load in a six work centre GFS.

The results in Figure 4 show that MODD and ORR (6.75) have extreme late deliveries, particularly in periods of peak loads. While this is a known outcome of MODD (Land et al., 2015), we can also see that ORR cannot prevent extreme late deliveries even though peak loads are buffered in the pre-process order pool – explaining the lack of peak loads for ORR (6.75) in the system. FOCUS - β also delivers some orders very late but this is less common and less extreme in comparison with MODD and ORR (6.75). Note how MODD generates higher loads than FOCUS - β, which becomes especially visible during peak loads, for example, at time $2,100$ till $2,500$.

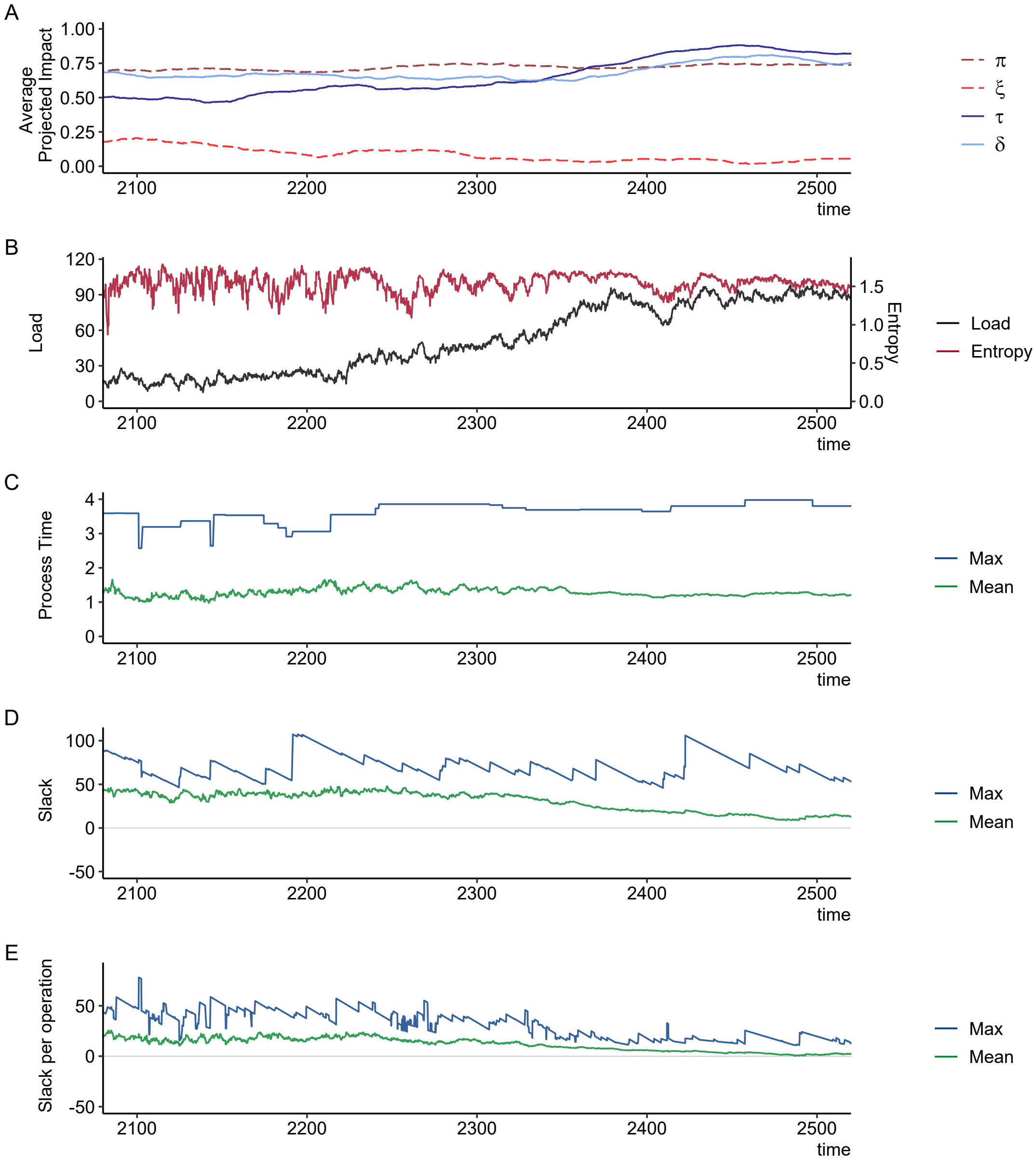

Figure 5: Time-phased projection of system state and projected impact functions at dispatching by FOCUS - β in a six work centre GFS.

To better understand how FOCUS takes decisions over time, we are mainly interested in the decisions of FOCUS - β in low load vs. peak load periods. Therefore, we specifically look at time $2,100$ till $2,500$ and collect additional system state information, which is presented in Figure 5. We gather the output of projected impact functions π, ξ, τ and δ of the selected order (i.e. z) for every dispatching decision. To get a general impression, graph A in Figure 5 shows the moving average of these projected impacts of the imminent and 200 preceding and 200 successive dispatching decisions. At the same time, we collect system state information: the entropy in the system e^{-} (right y-axis, graph B), the load (left y-axis, graph B), the mean and max of process times p_{ij} (graph C), slack $s(\cdot)$ (graph D) and slack per operation $v(\cdot)$ (graph E).

As loads (graph B, Figure 5) increase, we can see that the mean slack (graph D) and mean slack per operation (graph E) decrease, indicating that more orders get close to their due date. At order selection, this leads to a higher projected impact from τ (slack timing) and δ (pacing), as seen in the graph A. However, as – by definition – τ and δ are fixed at (close to) 1 for all (almost) late orders in the queue, this makes selection amongst (almost) late orders increasingly based on the effectiveness of the SPT-mechanism π. This switch to the SPT-mechanism is particularly important in periods of peak loads (Land et al., 2015). Unlike MODD, this switch by FOCUS - β is *not* myopic as it depends on the system state; π is neglected if none of the (almost) late orders in the queue has a short process time, compared to other orders somewhere in the system. In such a manner, FOCUS - β considers the characteristics of orders in the queue but remains versatile to the system state by neglecting a control mechanism if it can better be applied in a near-future dispatching decision.

We found earlier that the role of starvation responding ξ is mixed. Graph A in Figure 5 shows that ξ – on average – becomes less important when loads increase (graph B). We can also see that the entropy values indicate an increasingly balanced system (graph B) as fluctuations in entropy become less frequent and less severe (recall that maximum entropy $e_{max} = 1.79$ for a six work centre GFS). Thus, starvation becomes increasingly unlikely during peak loads, resulting in a minor influence of ξ on mean tardiness and percentage tardy.

When we compare FOCUS logic with ORR logic, a major difference is that ORR assumes a hierarchical sequence of control mechanisms. ORR logic is that the system must be controlled at release using WIP balancing and thereby limiting the ability for priority rules to select non-urgent orders. This logic was primarily discussed at the inception of the ORR literature (Bechte, 1988; Kingsman et al., 1989; Melnyk & Ragatz, 1989; Ragatz & Mabert, 1988) and, to our knowledge, has not been challenged since. For instance, Ragatz and Mabert (1988) mentioned that "*jobs released to the shop floor too early will compete for resources (machine time) with more urgent jobs and may interfere with the progress of those jobs*". As can be seen in Figure 4, ORR's ability to reduce extreme late deliveries is marginal, indicating that ORR's performance is heavily influenced by the ability of priority rules to handle late deliveries. Although not explicitly noted, ORR's dependence on priority rules is also reported by more recent theoretical (Kundu et al., 2020; Land et al., 2014) and empirical work (Soepenberg, Land, & Gaalman, 2012). As we explained above, FOCUS uses projected impact to measure the effectiveness of each control mechanism and adapts to the system state. This overcomes myopic behaviour at dispatching, making the need to use ORR for control of delivery performance limited since non-urgent orders do not compete for resources with urgent ones.

7 Conclusion

This study argues for a paradigm shift in the stochastic production control literature towards system state dispatching. This is in contrast with the existing literature where a hierarchical order review and release (ORR) method controls the system by releasing orders whilst priority rule dispatch orders from the queue. Instead, system state dispatching integrates system-wide information into order dispatching decisions by trading-off an array of control mechanisms. We illustrated the effectiveness of system state dispatching by developing a novel production control method called FOCUS that is comprised of five control mechanisms; Shortest Process Time (SPT) mechanism, Work-In-Progress (WIP) balancing, starvation response, slack timing and pacing. Using a simulation experiment, FOCUS was tested in six different manufacturing systems and considerably outperformed the priority rule SPT, Modified Operational Due Date and ORR method LUMS COR. Compared to these methods, FOCUS reduces the percentage tardy and the mean tardiness with at least a factor of two. These results are robust over all considered manufacturing systems types, regardless of due date tightness or the (maximum) routing length. When assessing FOCUS' excellent performance, we found that not all five control mechanisms of FOCUS are effective. Specifically, WIP balancing – aiming to prevent starving work centres by spreading WIP equally over the work centres – does not or sometimes even negatively influences performance, despite being a key mechanism of the ORR approaches to production control. These findings strongly support our claim that a paradigm shift towards system state dispatching is needed in the PPC literature on high-variety manufacturing.

7.1 Managerial Implications

Under the name of Industry 4.0 or Smart Industries, practitioners advocate the use of advanced data collection and sharing technologies such as sensor networks and autonomous communication via the Internet of Things, enabling the use of system-wide and real-time information (Chen et al., 2021; IBM, 2021; Lee et al., 2021; McKinsey, 2020; Olsen & Tomlin, 2020). In this paper, we show how to make use of system state information in control decisions in specifically high-variety manufacturing. Our results indicate that managers should indeed integrate state information in the deployment of control mechanisms at dispatching to avoid local myopia. More specifically, we found that the combination of control mechanisms needed dependents on the state of the manufacturing system. Therefore, even if system state information is not available, managers should find ways of 'looking beyond the queue' in the deployment of control mechanisms, as this substantially contributes to better delivery performance.

7.2 Limitations & Future Research

A limitation of this study is the character of the stylistic manufacturing systems assumed in our simulation model. We believe this is justified by the explanatory nature of this study and enables us to gain experimental control over important parameters such as capacities, arrivals and process time variability. However, future research can test FOCUS in more complex settings, where e.g., machine failure, capacity changes or seasonal demand changes are considered; as well as empirical settings. A second limitation is that we did not consider controlled release in FOCUS, as release can reduce WIP levels in the system (Thürer et al., 2012). This was done to keep or study focused on the inclusion of state information at dispatching and to evaluate the effect on delivery performance. However, the short mean throughput time of FOCUS already suggest that, even in an uncontrolled release setting, average WIP levels are quite low. This might even become lower if future research adds controlled release to FOCUS by including a trade-off between selecting an order from the pre-process order pool or queue. This potentially allows reducing WIP while maintaining the benefits of system state information at dispatching.

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Data statement

All data and the simulation code are available upon request by the corresponding author.

Appendices

A Detailed Results & Main Experiments

Some tables in the appendix use abbreviations of performance measures which are listed in Table 4, where t_i^a is the arrival time, t_i^c is the completion time and d_i is the due date of order i.

PERFORMANCE MEASURES		
Performance Measure	Notation	Measure Formulation
Mean throughput time	$\mu(T_i)$	$T_i = t_i^c - t_i^a$
Standard deviation throughput time	$\sigma(T_i)$	
Mean lateness	$\mu(\mathcal{L}_i)$	$\mathcal{L}_i = t_i^c - d_i$
Standard deviation lateness	$\sigma(\mathcal{L}_i)$	
Mean tardiness	$\mu(\mathcal{T}_i)$	$\mathcal{T}_i = \max\{0, \mathcal{L}_i\}$
Mean squared tardiness	$\mu(\mathcal{T}_i^2)$	
Percentage tardy	$\%(\mathcal{T}_i)$	

Table 4: Overview abbreviations performance measures.

A.1 ANOVA Results from Supportive Performance Measures

ANOVA RESULTS (SUPPORTIVE PERFORMANCE MEASURES)						
PERFORMANCE MEASURE	SOURCE OF VARIANCE	SUM OF SQUARES	DEGREES OF FREEDOM	MEAN SQUARES	F-RATIO	p-VALUE
Mean Throughput Time	PPCM	16,2521.18	7	23,217.31	954.75	0.00
	MFS	979,912.28	5	195,982.46	8,059.27	
	PPCM × MFS	43,899.6	35	1,254.27	51.58	0.00
	error	188,510.36	7,752	24.32		
Standard Deviation Throughput Time	PPCM	34,732.75	7	4,961.82	364.53	0.00
	MFS	175,538.73	5	35,107.75	2,579.23	0.00
	PPCM × MFS	9,631.76	35	275.19	20.22	0.00
	error	105,517.83	7,752	13.61		
Mean Lateness	PPCM	162,521.39	7	23,217.34	965.59	0.00
	MFS	453,060.02	5	90,612	3,768.48	0.00
	PPCM × MFS	43,906.39	35	1,254.47	52.17	0.00
	error	186,394.59	7,752	24.04		
Standard Deviation Lateness	PPCM	39,798.63	7	5,685.52	277.99	0.00
	MFS	63,149.70	5	12,629.94	617.54	0.00
	PPCM × MFS	20,470.69	35	584.88	28.60	0.00
	error	158,543.52	7,752	20.45		
Mean Squared Tardiness	PPCM	23,716,036.98	7	3,388,005.28	116.48	0.00
	MFS	6,532,247.61	5	1,306,449.52	44.91	0.00
	PPCM × MFS	18,493,953.87	35	528,398.68	18.17	0.00
	error	225,485,803.90	7,752	29,087.44		

Table 5: ANOVA results for PPC method (PPCM) and manufacturing systems (MFS).

A.2 Detailed Results Main Experiments

SIMULATION RESULTS: SIX WORK CENTRES							
PURE JOB SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	25.34	18.11	-5.28	16.99	4.18	96.76	34.69
MODD	19.92	19.47	-10.71	12.65	0.58	64.99	6.67
ODD	21.05	18.17	-9.57	11.37	1.13	16.86	15.04
SPT	13.54	24.50	-17.08	23.25	1.92	309.43	4.53
ORR (4.95)	19.49	18.79	-11.13	13.57	1.27	59.89	10.00
ORR (5.85)	19.49	18.15	-11.13	12.23	0.88	40.80	8.34
ORR (6.75)	19.68	17.85	-10.95	11.51	0.68	29.81	7.79
FOCUS	15.28	16.37	-15.34	13.39	0.44	36.65	4.20
FOCUS - π	17.80	21.75	-12.82	20.06	1.82	247.32	8.40
FOCUS - β	15.31	17.03	-15.31	12.09	0.30	34.34	2.20
FOCUS - ξ	15.43	16.31	-15.20	12.46	0.33	28.93	3.12
FOCUS - τ	15.93	18.80	-14.69	17.68	1.32	109.92	8.40
FOCUS - δ	14.52	16.87	-16.10	15.10	0.72	63.55	4.92
GENERAL FLOW SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	24.40	17.46	-8.23	17.64	3.35	72.30	29.54
MODD	19.61	19.54	-13.01	13.44	0.57	66.35	5.18
ODD	21.54	18.46	-11.08	12.47	1.25	19.26	15.01
SPT	13.12	24.22	-19.50	23.86	1.79	291.91	3.91
ORR (4.95)	19.09	20.66	-13.53	18.20	1.83	170.22	8.57
ORR (5.85)	19.33	19.82	-13.29	16.14	1.34	121.27	7.47
ORR (6.75)	19.58	19.19	-13.04	14.58	0.99	85.29	6.90
FOCUS	14.79	15.96	-17.84	13.53	0.30	25.00	2.78
FOCUS - π	17.67	19.26	-14.96	17.10	1.15	134.39	6.58
FOCUS - β	15.54	17.62	-17.09	12.68	0.26	27.88	1.92
FOCUS - ξ	15.24	16.20	-17.38	12.95	0.27	21.45	2.48
FOCUS - τ	14.35	17.92	-18.27	19.41	1.25	131.69	6.05
FOCUS - δ	14.11	16.55	-18.51	15.52	0.58	57.09	3.56
PURE FLOW SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	36.23	14.84	-12.79	20.08	3.44	82.89	25.28
MODD	29.62	19.24	-19.40	15.61	0.73	105.44	3.53
ODD	33.24	18.01	-15.77	15.04	1.66	33.49	15.05
SPT	20.02	26.65	-28.99	25.22	2.17	371.21	3.85
ORR (4.95)	30.01	18.51	-19.01	14.29	0.54	63.61	4.41
ORR (5.85)	30.01	18.35	-19.00	14.21	0.53	61.92	4.33
ORR (6.75)	30.08	18.25	-18.94	14.18	0.52	61.23	4.27
FOCUS	22.82	15.53	-26.20	12.66	0.20	19.95	1.76
FOCUS - π	28.18	17.51	-20.84	15.36	0.87	74.06	6.45
FOCUS - β	23.54	16.92	-25.48	12.80	0.23	26.31	1.80
FOCUS - ξ	23.16	15.65	-25.86	12.66	0.21	20.59	1.88
FOCUS - τ	21.02	18.13	-28.00	17.49	0.84	111.02	2.99
FOCUS - δ	21.44	15.98	-27.58	13.94	0.36	45.04	1.85

Table 6: Simulation results for six work centre manufacturing systems.

Simulation Results: Twelve Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	46.71	30.75	-5.84	22.59	6.02	182.95	37.38
MODD	38.57	31.45	-13.99	14.94	0.65	77.00	5.81
ODD	40.11	30.52	-12.45	13.60	1.20	17.54	14.99
SPT	24.70	33.25	-27.85	31.76	2.55	433.45	5.06
ORR (4.95)	36.95	31.24	-15.60	17.78	1.52	134.10	6.93
ORR (5.85)	37.24	30.62	-15.31	15.73	0.94	91.95	5.32
ORR (6.75)	37.75	30.26	-14.80	14.47	0.66	63.04	4.98
FOCUS	26.83	24.62	-25.72	18.93	0.35	31.58	2.69
FOCUS - π	30.14	29.22	-22.41	23.89	1.42	224.68	5.62
FOCUS - β	27.27	26.11	-25.29	16.76	0.24	33.14	1.31
FOCUS - ξ	26.86	24.68	-25.70	17.29	0.18	17.34	1.51
FOCUS - τ	27.76	27.30	-24.79	26.23	1.64	178.21	7.34
FOCUS - δ	25.37	24.30	-27.18	20.72	0.61	62.17	3.32
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	44.22	29.04	-12.10	23.64	4.10	112.91	28.73
MODD	37.90	31.96	-18.43	17.15	0.65	103.82	3.92
ODD	41.17	31.23	-15.16	15.96	1.47	26.73	15.04
SPT	23.44	33.21	-32.89	34.09	2.33	447.41	4.09
ORR (4.95)	37.70	34.76	-18.63	28.04	3.18	492.60	8.19
ORR (5.85)	37.55	33.16	-18.77	23.69	2.10	319.99	6.41
ORR (6.75)	37.89	32.21	-18.44	20.49	1.41	208.26	5.47
FOCUS	25.52	24.16	-30.81	19.82	0.20	27.61	1.44
FOCUS - π	30.43	27.81	-25.90	20.72	0.69	116.00	3.58
FOCUS - β	26.93	27.01	-29.40	18.41	0.18	32.90	0.98
FOCUS - ξ	25.90	24.46	-30.42	18.98	0.15	21.47	1.07
FOCUS - τ	24.26	25.04	-32.07	29.37	1.52	222.81	5.26
FOCUS - δ	24.43	24.36	-31.89	21.78	0.41	60.72	2.05
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	68.76	20.56	-18.32	26.83	4.44	142.74	24.29
MODD	58.56	25.92	-28.53	20.33	0.86	156.78	2.74
ODD	65.37	25.46	-21.71	20.46	2.29	65.22	14.98
SPT	37.35	34.81	-49.74	33.21	2.61	521.12	3.71
ORR (4.95)	59.60	25.35	-27.48	19.20	0.67	107.26	3.17
ORR (5.85)	59.48	25.17	-27.61	19.04	0.64	104.69	3.08
ORR (6.75)	59.56	25.10	-27.53	19.05	0.64	105.25	3.06
FOCUS	40.34	20.20	-46.74	15.93	0.08	6.12	0.63
FOCUS - π	52.15	22.95	-34.93	19.00	0.61	53.32	4.03
FOCUS - β	41.42	22.18	-45.67	16.06	0.10	8.79	0.73
FOCUS - ξ	40.84	20.30	-46.24	15.87	0.08	6.02	0.68
FOCUS - τ	37.84	24.78	-49.25	24.50	1.10	175.48	2.47
FOCUS - δ	38.88	20.42	-48.20	17.07	0.18	21.65	0.79

Table 7: Simulation results for twelve work centre manufacturing systems.

A.3 Details & Results Sensitivity Analysis

Due Date Tightness: The results from the main experiments might be unique to our due date allowance and, therefore, we increase due date tightness by decreasing the due date hyperparameter K such that the percentage tardy for ODD increases from 15% to 20%. Detailed results can be found in Table 8 and Table 9.

TIGHT DUE DATE: SIX WORK CENTRES							
PURE JOB SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	25.34	18.11	-2.94	16.33	4.86	115.38	39.16
MODD	19.61	19.25	-8.66	12.62	0.76	82.94	8.68
ODD	21.10	17.53	-7.18	10.87	1.55	23.52	19.97
SPT	13.54	24.50	-14.73	22.80	2.08	325.70	5.19
ORR (4.95)	19.51	18.52	-8.77	13.17	1.54	70.41	12.48
ORR (5.85)	19.48	17.81	-8.80	11.78	1.11	48.84	10.93
ORR (6.75)	19.61	17.46	-8.67	11.04	0.90	36.96	10.55
FOCUS	15.26	16.19	-13.02	12.76	0.57	45.29	5.59
FOCUS - π	17.92	22.19	-10.36	20.36	2.19	289.04	10.34
FOCUS - β	15.34	16.91	-12.94	11.64	0.40	44.87	3.10
FOCUS - ξ	15.44	16.14	-12.84	11.87	0.44	37.92	4.36
FOCUS - τ	15.85	18.65	-12.43	17.06	1.50	122.39	9.88
FOCUS - δ	14.55	16.92	-13.73	14.64	0.90	77.35	6.25
GENERAL FLOW SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	24.40	17.46	-5.53	16.74	3.99	88.67	34.04
MODD	19.30	19.40	-10.62	13.36	0.74	86.05	6.85
ODD	21.67	17.95	-8.26	11.96	1.74	27.90	20.08
SPT	13.12	24.22	-16.80	23.24	1.95	309.33	4.53
ORR (4.95)	19.14	20.39	-10.78	17.61	2.01	180.30	10.24
ORR (5.85)	19.33	19.48	-10.59	15.56	1.49	129.61	9.29
ORR (6.75)	19.54	18.79	-10.38	13.97	1.15	92.71	9.05
FOCUS	15.00	15.87	-14.93	12.72	0.43	33.43	4.08
FOCUS - π	17.92	19.82	-12.01	17.50	1.54	178.72	8.95
FOCUS - β	15.62	17.51	-14.30	12.14	0.37	39.70	2.81
FOCUS - ξ	15.39	16.11	-14.54	12.23	0.39	30.68	3.72
FOCUS - τ	14.38	17.89	-15.54	18.51	1.39	142.13	7.08
FOCUS - δ	14.18	16.56	-15.75	14.84	0.73	69.22	4.64
PURE FLOW SHOP							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	36.23	14.84	-9.12	19.40	4.27	104.90	30.39
MODD	29.19	19.28	-16.17	15.83	0.93	130.43	4.85
ODD	33.40	17.66	-11.95	14.92	2.32	48.36	20.07
SPT	20.02	26.65	-25.33	25.06	2.36	393.31	4.41
ORR (4.95)	29.67	18.38	-15.69	14.41	0.74	84.68	6.17
ORR (5.85)	29.65	18.20	-15.70	14.29	0.73	81.78	6.09
ORR (6.75)	29.72	18.11	-15.63	14.27	0.72	81.40	6.05
FOCUS	23.08	15.47	-22.27	12.59	0.32	30.57	2.97
FOCUS - π	28.47	17.92	-16.89	16.01	1.30	112.68	9.53
FOCUS - β	23.78	16.80	-21.57	12.81	0.35	38.88	2.90
FOCUS - ξ	23.45	15.58	-21.90	12.59	0.33	30.66	3.16
FOCUS - τ	21.12	17.89	-24.23	16.98	0.93	117.38	3.69
FOCUS - δ	21.57	15.95	-23.78	13.79	0.48	56.12	2.64

Table 8: Tight due dates for six work centre manufacturing systems.

Tight Due Date: Twelve Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	46.71	30.75	-2.98	21.98	6.98	219.23	41.68
MODD	38.06	30.86	-11.63	15.03	0.86	103.32	7.56
ODD	40.09	29.52	-9.60	13.09	1.69	25.84	20.00
SPT	24.70	33.25	-24.99	31.03	2.73	455.69	5.65
ORR (4.95)	36.90	30.65	-12.79	17.41	1.78	148.00	8.59
ORR (5.85)	37.13	29.97	-12.57	15.36	1.16	104.61	7.04
ORR (6.75)	37.55	29.54	-12.15	14.03	0.84	73.28	6.92
FOCUS	26.78	24.32	-22.91	17.90	0.44	39.34	3.37
FOCUS - π	30.13	29.18	-19.56	23.52	1.66	257.34	6.73
FOCUS - β	27.27	25.72	-22.42	15.80	0.30	39.08	1.72
FOCUS - ξ	26.81	24.27	-22.88	16.19	0.24	22.37	1.99
FOCUS - τ	27.65	27.08	-22.04	25.25	1.81	192.21	8.29
FOCUS - δ	25.39	24.21	-24.30	19.83	0.73	73.90	4.05
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	44.22	29.04	-8.65	22.61	4.94	140.72	33.09
MODD	37.34	31.35	-15.54	17.03	0.83	129.28	5.23
ODD	41.22	30.38	-11.66	15.42	2.07	39.25	20.00
SPT	23.44	33.21	-29.44	33.07	2.51	471.84	4.59
ORR (4.95)	37.58	34.20	-15.30	27.40	3.35	510.97	9.26
ORR (5.85)	37.45	32.49	-15.43	23.01	2.25	330.39	7.60
ORR (6.75)	37.67	31.48	-15.21	19.87	1.55	219.74	6.91
FOCUS	25.65	23.91	-27.23	18.42	0.26	33.38	1.89
FOCUS - π	30.66	27.84	-22.22	20.27	0.92	148.14	4.86
FOCUS - β	27.09	26.70	-25.79	17.26	0.25	41.83	1.38
FOCUS - ξ	26.06	24.20	-26.81	17.59	0.21	27.06	1.48
FOCUS - τ	24.27	24.91	-28.61	27.87	1.62	230.38	5.92
FOCUS - δ	24.51	24.24	-28.37	20.56	0.51	72.99	2.58
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	68.76	20.56	-13.76	26.26	5.50	180.88	29.10
MODD	57.82	25.73	-24.70	20.48	1.05	185.64	3.67
ODD	65.53	25.04	-16.99	20.43	3.11	90.24	20.00
SPT	37.34	34.81	-45.17	33.07	2.81	550.08	4.16
ORR (4.95)	58.87	25.05	-23.65	19.27	0.86	135.69	4.31
ORR (5.85)	58.78	24.81	-23.74	19.06	0.83	129.02	4.19
ORR (6.75)	58.85	24.70	-23.67	19.01	0.81	127.95	4.18
FOCUS	40.65	19.95	-41.87	15.69	0.12	9.38	1.00
FOCUS - π	52.53	23.07	-29.99	19.41	0.93	82.48	5.92
FOCUS - β	41.77	21.88	-40.75	15.97	0.15	14.32	1.18
FOCUS - ξ	41.18	20.04	-41.34	15.63	0.12	9.48	1.08
FOCUS - τ	37.88	24.56	-44.64	24.02	1.19	184.05	2.83
FOCUS - δ	39.03	20.25	-43.49	16.81	0.24	28.63	1.12

Table 9: Tight due dates for twelve work centre manufacturing systems.

Process Time Distribution: We replace the truncated 2-Erlang distribution (used in our main experiments) with an untruncated Log-normal distribution and varied the coefficient of variation ($CV = \sigma/\mu$) between 0.5 and 1 to increase from moderate to high variability, respectively, while keeping the mean at 1 time unit. The results are presented in Table 10 and Table 11 for moderate variability while the results for high variability are shown in Table 12 and Table 13.

Moderate Variability ($CV = 0.5$): Six Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	20.96	15.15	-9.63	14.32	1.94	35.22	21.56
MODD	18.08	16.78	-12.51	11.21	0.36	31.73	4.93
ODD	18.54	16.02	-12.05	10.48	0.55	6.95	8.69
SPT	13.04	21.76	-17.55	20.81	1.70	228.34	4.43
FOCUS	14.31	14.46	-16.28	12.29	0.33	21.74	3.11
FOCUS - π	15.51	16.72	-15.08	15.13	0.87	90.36	4.98
FOCUS - β	14.40	14.78	-16.19	10.81	0.17	15.70	1.38
FOCUS - ξ	14.48	14.37	-16.11	11.38	0.22	14.75	2.17
FOCUS - τ	15.16	16.80	-15.43	16.18	1.10	78.48	6.98
FOCUS - δ	13.67	14.86	-16.92	13.66	0.57	41.38	3.84
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	19.64	14.25	-12.95	14.98	1.33	22.08	16.12
MODD	17.32	16.47	-15.26	12.19	0.36	36.78	3.53
ODD	18.22	15.67	-14.37	11.50	0.56	7.68	7.92
SPT	12.31	21.28	-20.28	21.41	1.54	212.02	3.69
FOCUS	13.74	14.02	-18.84	12.69	0.24	18.08	2.05
FOCUS - π	15.22	15.71	-17.37	14.35	0.59	67.97	3.60
FOCUS - β	14.39	15.38	-18.19	11.73	0.15	17.43	1.14
FOCUS - ξ	14.12	14.26	-18.46	12.10	0.20	15.16	1.66
FOCUS - τ	13.33	16.08	-19.26	18.45	1.17	114.79	5.23
FOCUS - δ	13.16	14.60	-19.43	14.39	0.50	44.37	2.72
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	26.19	11.69	-22.77	15.23	0.68	11.30	7.59
MODD	23.33	14.45	-25.63	12.67	0.33	41.28	1.37
ODD	24.59	13.45	-24.37	12.05	0.32	4.73	4.01
SPT	17.44	21.84	-31.52	20.51	1.53	217.53	3.09
FOCUS	19.47	12.41	-29.49	10.53	0.07	3.90	0.78
FOCUS - π	22.21	12.95	-26.75	11.56	0.19	10.04	2.08
FOCUS - β	19.80	13.19	-29.16	10.60	0.07	4.69	0.82
FOCUS - ξ	19.71	12.50	-29.25	10.55	0.07	4.30	0.80
FOCUS - τ	18.29	14.17	-30.67	13.48	0.40	37.54	1.79
FOCUS - δ	18.70	12.63	-30.26	11.05	0.14	11.22	0.84

Table 10: Moderate variability ($CV = 0.5$) for six work centre manufacturing systems.

Moderate Variability ($CV = 0.5$): Twelve Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	38.63	25.56	-13.87	19.59	2.38	53.12	21.33
MODD	34.23	27.90	-18.26	13.76	0.27	24.67	3.08
ODD	34.70	27.58	-17.80	13.33	0.38	4.55	5.99
SPT	23.72	29.03	-28.78	28.32	2.02	277.10	4.80
FOCUS	24.92	22.11	-27.58	18.26	0.22	15.70	1.73
FOCUS - π	26.42	23.90	-26.08	19.91	0.57	67.03	2.82
FOCUS - β	25.49	23.18	-27.01	15.89	0.10	9.44	0.58
FOCUS - ξ	25.12	22.32	-27.38	16.73	0.09	5.81	0.80
FOCUS - τ	26.18	24.23	-26.31	24.30	1.21	105.39	6.04
FOCUS - δ	23.65	21.48	-28.85	19.25	0.38	29.83	2.21
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	34.70	23.01	-21.56	21.32	1.16	21.83	12.56
MODD	32.09	27.00	-24.18	16.16	0.30	40.52	1.78
ODD	33.35	26.53	-22.92	15.52	0.37	5.35	5.05
SPT	21.60	27.99	-34.66	30.54	1.75	260.43	3.62
FOCUS	23.20	20.99	-33.07	19.18	0.10	6.81	0.84
FOCUS - π	25.76	22.71	-30.50	18.74	0.23	24.32	1.53
FOCUS - β	24.62	23.57	-31.65	17.64	0.07	7.90	0.39
FOCUS - ξ	23.68	21.48	-32.59	18.28	0.06	4.45	0.51
FOCUS - τ	22.18	21.02	-34.09	27.72	1.21	134.44	4.50
FOCUS - δ	22.46	21.05	-33.81	20.33	0.23	21.56	1.26
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	47.07	15.41	-39.93	19.82	0.33	6.10	3.21
MODD	43.62	19.03	-43.38	16.09	0.27	39.29	0.64
ODD	45.32	18.37	-41.67	15.63	0.15	2.27	1.63
SPT	31.63	26.56	-55.37	25.29	1.46	227.68	2.43
FOCUS	33.70	15.87	-53.30	13.21	0.01	0.26	0.08
FOCUS - π	39.38	16.68	-47.61	14.27	0.03	1.48	0.41
FOCUS - β	34.08	17.11	-52.91	13.30	0.01	0.32	0.10
FOCUS - ξ	34.08	15.94	-52.91	13.15	0.01	0.20	0.08
FOCUS - τ	32.14	18.82	-54.86	18.65	0.45	51.97	1.30
FOCUS - δ	32.96	15.95	-54.04	13.69	0.03	2.18	0.18

Table 11: Moderate variability ($CV = 0.5$) for twelve work centre manufacturing systems.

High Variability ($CV = 1.0$): Six Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	35.47	25.80	4.87	24.31	11.45	429.30	55.71
MODD	22.26	24.44	-8.34	14.80	0.85	123.26	9.01
ODD	26.80	23.33	-3.80	14.65	3.80	88.63	31.44
SPT	14.30	25.30	-16.30	22.90	1.51	268.07	4.94
FOCUS	18.88	22.35	-11.72	18.44	1.67	148.18	11.38
FOCUS - π	24.11	37.74	-6.49	36.34	5.80	1234.68	17.31
FOCUS - β	18.07	21.75	-12.53	14.34	0.61	69.66	5.99
FOCUS - ξ	19.06	22.00	-11.53	16.34	1.30	107.76	9.77
FOCUS - τ	19.83	25.57	-10.76	23.94	3.07	315.04	15.08
FOCUS - δ	18.42	23.49	-12.18	21.26	2.26	224.67	12.07
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	35.35	25.61	2.76	25.10	10.59	389.73	52.50
MODD	22.22	24.60	-10.38	15.06	0.74	111.88	7.09
ODD	28.47	24.91	-4.13	16.38	4.45	115.17	32.08
SPT	14.11	24.64	-18.48	23.08	1.34	230.09	4.22
FOCUS	19.02	22.16	-13.57	17.48	1.22	111.28	8.84
FOCUS - π	24.60	34.10	-7.99	31.76	4.59	898.88	16.64
FOCUS - β	18.88	23.52	-13.71	14.87	0.55	76.10	4.67
FOCUS - ξ	19.40	22.34	-13.19	16.72	1.16	99.49	8.43
FOCUS - τ	18.41	23.91	-14.18	24.32	2.47	299.30	11.24
FOCUS - δ	18.15	22.77	-14.44	20.74	1.74	190.94	9.21
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	61.04	23.11	12.07	30.34	19.06	869.42	65.57
MODD	37.28	26.96	-11.69	18.59	1.33	210.18	8.22
ODD	52.99	27.99	4.02	22.56	11.29	419.66	51.45
SPT	23.67	29.90	-25.30	26.50	2.11	371.31	4.49
FOCUS	33.95	24.48	-15.02	18.60	1.82	130.64	13.88
FOCUS - π	46.51	40.74	-2.46	39.03	8.90	1623.96	31.22
FOCUS - β	33.68	26.51	-15.29	17.60	1.13	128.94	10.14
FOCUS - ξ	34.43	24.71	-14.54	18.80	1.93	137.56	14.48
FOCUS - τ	30.50	23.20	-18.47	21.67	2.03	163.75	10.95
FOCUS - δ	31.14	24.09	-17.83	20.58	1.95	173.86	10.43

Table 12: High variability ($CV = 1.0$) for six work centre manufacturing systems.

High Variability ($CV = 1.0$): Twelve Work Centres							
Pure Job Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	65.31	43.07	12.81	32.31	19.26	1015.98	63.85
MODD	43.92	37.99	-8.58	17.63	1.29	201.49	10.04
ODD	52.52	36.73	0.01	16.75	6.53	169.01	44.83
SPT	26.10	34.24	-26.40	30.81	2.02	373.83	4.99
FOCUS	34.38	33.34	-18.13	24.92	2.14	237.72	10.28
FOCUS - π	39.74	44.09	-12.76	37.93	5.46	1078.22	15.46
FOCUS - β	34.27	32.79	-18.23	17.99	0.72	76.40	5.95
FOCUS - ξ	34.28	32.31	-18.22	20.20	1.25	118.56	7.46
FOCUS - τ	35.47	37.17	-17.03	34.35	4.36	586.51	15.29
FOCUS - δ	33.05	33.84	-19.45	28.09	2.72	334.67	10.84
General Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	65.27	42.68	9.01	32.96	17.21	877.02	59.59
MODD	44.32	38.90	-11.95	18.27	1.10	189.01	7.32
ODD	57.27	40.25	1.00	20.18	8.50	275.13	46.42
SPT	25.72	33.88	-30.55	32.25	1.81	339.61	4.20
FOCUS	35.07	33.48	-21.20	21.96	1.18	133.84	7.26
FOCUS - π	43.37	43.09	-12.90	32.55	4.42	839.98	16.10
FOCUS - β	36.40	36.34	-19.87	18.53	0.64	91.57	4.69
FOCUS - ξ	35.52	33.64	-20.75	20.83	1.07	114.64	6.80
FOCUS - τ	32.53	32.61	-23.73	33.35	3.08	432.06	10.78
FOCUS - δ	33.24	33.39	-23.03	25.33	1.65	217.89	7.55
Pure Flow Shop							
Name	$\mu(T_i)$	$\sigma(T_i)$	$\mu(\mathcal{L}_i)$	$\sigma(\mathcal{L}_i)$	$\mu(\mathcal{T}_i)$	$\mu(\mathcal{T}_i^2)$	$\%(\mathcal{T}_i)$
FCFS	123.31	31.75	36.30	40.44	40.83	2981.84	80.75
MODD	76.43	36.07	-10.57	23.81	2.32	402.70	11.04
ODD	115.06	39.14	28.05	31.06	31.28	1904.73	78.18
SPT	46.16	40.07	-40.85	35.44	2.96	575.05	4.94
FOCUS	68.75	33.38	-18.25	24.56	2.99	206.38	19.51
FOCUS - π	92.99	53.57	5.98	50.53	16.06	2803.93	46.51
FOCUS - β	68.34	35.68	-18.66	23.41	2.02	193.89	18.00
FOCUS - ξ	69.60	33.60	-17.40	24.75	3.18	224.37	20.57
FOCUS - τ	60.62	31.13	-26.38	29.68	2.96	253.98	12.91
FOCUS - δ	62.95	32.56	-24.05	26.16	2.63	231.82	12.24

Table 13: High variability ($CV = 1.0$) for twelve work centre manufacturing systems.

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