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Analysing the impact of uncertainty reduction on WLC methods in MTO flow shops

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ABSTRACT

With more and more demanding customers, make-to-order (MTO) companies are becoming more important. Workload control (WLC) is specifically developed for MTO companies. Most previous studies have proposed solutions assuming no mismatch between planned and actual production time. However, in real situations, inaccurate estimation of processing time is a daily routine. This study focuses on processing time estimation error and evaluates performance of two different WLC order review and release (ORR) methods through simulation of a pure flow shop. Simulation results demonstrate that balancing workload is more effective than limiting workload at different error levels. However, with decrease in errors, difference in performance between limiting and balancing methods becomes wider. Further investigation shows that improving processing time estimation heavily affects the order selection process in balancing method, which is the main reason for performance improvement. Finally, aspects of Industry 4.0 are discussed in context of ORR methods in MTO flow shops.

1. Introduction

An increase in item variety, a reduction in life cycles, and mass customisation are becoming competitive weapons in today's manufacturing world. Therefore, make-to-order (MTO) companies are becoming extremely important. However, high customisation increases the complexity of production processes.

Workload control (WLC), a production planning and control approach, is one of the most effective methods to manage production in MTO companies (Silva, Stevenson, & Thürer, 2015; Stevenson & Vanharanta, 2015).

Although input control may be exercised at several points within WLC, a focus on order review and release (ORR) is considered since it is the most widely applied approach in the literature (Thürer, Stevenson, & Protzman, 2015; Yan, Stevenson, Hendry, & Land, 2016). ORR decouples the shop floor from higher level planning. Orders are not released onto the shop floor immediately but enter into a pre-shop pool from which they are released to meet due dates while also keeping work-in-process within limits, or norms. The pre-shop pool buffer protects/defends the shop floor

against variance in the incoming order stream (Melnyk & Ragatz, 1989; Thürer, Stevenson, Silva, Land, & Fredendall, 2012). Thus, ORR is very useful in dealing with the variability that affects processing times and demand, shifting variability from the shop floor to the pre-shop pool.

However, most of the literature makes a strong assumption: actual processing times are known/given when an order release decision is made.

This assumption is valid for stable environments where demand and processes are very repetitive and stable for a long period, and hence, processing data of orders can be considered as deterministically known in advance.

However, most MTO companies are very dynamic environments, where customisation, innovation and high variety are the main competitive drivers. Therefore, there are continuous changes in products and production processes (Prakash & Chin, 2015). On one hand, a shorter product life cycle leads to continuous innovation of products and thereby continuous renovation of processes (Madonsela, Mukwakungu, & Mbohwa, 2017). On the other hand, an increase in customisation requests leads to an enlargement of options, and hence, related activities necessary for making product differentiation increase too (Yu, Mou, Ji, Xu, & Gu, 2018).

In this environment, job processes data are definitely not stable and need to be estimated, but factors such as customisation, innovation, and variety make the estimation very difficult (Haddadzade, Razfar, & Zarandi, 2014).

As a consequence, companies operate in uncertain conditions. They have great difficulties in precisely predicting the actual workload of orders in the pre-shop pool. They build datasets where expected processing times are used and apply WLC methods using such estimated data. Those data are more or less different from the actual data, depending on the degree of uncertainty, which appears to be one of the main causes leading to WLC failures (Huang, 2017).

However, in the Industry 4.0 (IND 4.0) era and with all the opportunities for gathering more data and making a better use of available information, it is possible to make investments and reduce uncertainty. Therefore, the main objective of this research study is to analyse the impact on WLC performance of reducing uncertainty through improving processing time estimation accuracy.

In particular, this study addresses two research questions:

Is reducing processing time estimation error beneficial to the overall production system performance in a WLC environment?

Does reducing processing time estimation error affect different ORR methods in the same way?

There are different methodological approaches such as case studies, surveys, simulation, etc., that can be used to answer these research questions. However, different levels of complexity required to study processing time estimation error (PTEE) are difficult to create in a real company. Simulation can capture the complexities involved in a real company (Javahernia & Sunmola, 2017) and help to run multiple scenarios within a short period of time. Therefore, this study remains confined to a simulation study by carrying out simulations of shop floor environments under different levels of PTEE. With a rapid increase in the requirement for different products from different customers, many companies have started looking at the flow rather than single resources (Botti et al., 2017), thus streamlining their production processes. Moreover, smart

manufacturing will lead to increased flexibility of systems (Theorin et al., 2017), so products can be manufactured adopting a fixed sequence of flexible resources. Therefore, MTO companies are moving forward to adopt a flow shop configuration rather than traditional job shops. Following the current trend, a pure flow shop is used for simulation in this research.

The remainder of this paper is organised as follows. Since this study is different to earlier flow shop research in considering uncertainty, Section 2 starts with workload studies under uncertainty. Section 3 then outlines the experimental design of the simulation study that investigates: (i) the effect of uncertainty on the order release method; and (ii) a comparison between two ORR methods under uncertainty. The results of the simulation study are presented in Section 4. Finally, the paper concludes with Section 5, where a discussion of future research directions is provided.

2. Research background

Section 2.1 provides a brief overview of how uncertainty has been considered in WLC literature. WLC's load-limiting order release methods are then outlined in Section 2.2 to identify the release methods to be considered in this study.

2.1. *Workload control and uncertainty*

Processing time can be defined as 'the time needed to produce one good item (manufacturing time plus handling time plus rework time etc.)' (Bertrand & Van Ooijen, 2002). It helps the manager to have a proper plan regarding the identification of the machines, tools, and fixtures required to perform the operation. It also makes it easier to allocate suitable resources to perform a set of activities in a period of time. Traditionally, in WLC and more generally in production planning and scheduling approaches, processing time is assumed as a parameter, and it is known beforehand. However, in MTO companies, the orders differ from each other, which creates uncertainty in processing times. Therefore, it is hard to predict accurate processing time at the planning stage. Uncertainty of processing time means that processing time is unknown by the company or rather that the expected processing time of a job in a determined workstation is different from the actual time (Thürer, Stevenson, Silva, & Qu, 2017). In other words, uncertainty is the phenomenon that explains the error between the processing time estimation of a job and the actual value, which is not caused by the process instability.

PTEE is an underestimated phenomenon and has rarely been considered in the literature (Thürer et al., 2017).

PTEE happens because of the difficulty in precisely predicting processing times of new activities (Haddadzade et al., 2014). This factor is a real disturbance observed in the shop floor and it is not known in advance while making ORR decisions.

ORR methods first evaluate the status of the shop floor and the pre-shop pool. Based on that information, orders are selected for release to the shop floor. PTEEs are not known beforehand, which creates deviations in scheduling and shop status over time.

Therefore, the processing time in the shop floor becomes different to the planned time, based on which release decision is made (Cigolini, Perona, & Portioli, 1998).

Few researchers have tried to investigate the most appropriate way to overcome the PTEE issue. Some of those instances in MTO companies are presented here.

Matsuura, Tsubone, and Kataoka (1995) used uncertainty in job processing times and determined the robustness of two loading ORR approaches. It was found that the loading method that considers workload status over infinite loading is the best, but its performance deteriorates wherever there is disturbance in processing times. Hatchuel, Saidi-Kabeche, and Sardas (1997) proposed a new planning and scheduling approach for MTO companies that are characterised by a complex production process, small order quantities, and complex products. With the assumption that the planned processing times are rarely equal to the actual ones, they suggested adding some slack to the lead time in order to avoid any schedule delay from the product to the customer. In their simulation model, they used a uniform distribution between 1 and 99 in order to calculate the standard processing time, and, in order to determine the real time, they multiplied the former by a coefficient 'a' ($a = 0.8, 1, 1.5, 2.5, 3$).

Cigolini et al. (1998) considered different sources of uncertainty in processing time while comparing different ORR methods in a job shop environment. They confirmed that uncertainty in processing time and disturbances have a great impact on determining the best ORR method.

The robustness of ORR methods facing the environmental conditions plays a major role in determining the performance in a dynamically changing shop floor and should be considered as key features of ORR methods (Cigolini et al., 1998).

Kouvelis, Daniels, and Vairaktarakis (2000) also addressed about uncertain processing times. They developed two alternative frameworks to define processing time uncertainty. In the first framework, the processing times are defined using discrete values. In the second framework, the processing times are defined using certain intervals, and they are continuous in nature. For the computational performance of the frameworks, they set processing time considering uniform distribution of the integer on the interval $[10\text{ß}j, (10 + 40\alpha)\text{ß}j]$, where $\alpha (= 0.2, 0.6, 1.0)$ allows variability of processing time across jobs, and ß represents the processing time requirements of machine j. They first formulated the robust scheduling problem and then applied optimisation and heuristic solution approaches. Their solutions showed more effective results against uncertain processing time.

Haddadzade et al. (2014) highlighted the importance of integration of process planning and scheduling. They proposed a process planning algorithm for job shop plants by taking into consideration the sources of uncertainty. In the simulation model, they added to the mean processing time a uniform distribution with ± 10% variance. Their algorithm gave more robust results with stochastic processing time rather than in a deterministic situation. Thürer, Land, and Stevenson (2014) addressed the difficulty in estimating processing time precisely at the planning stage in high-variety job shops. They proposed a method in which orders are grouped into simple classes (e.g. small, medium and large) based on the workload contributions. Their objective was to minimise the deviation between expected processing times and actual processing times in the shop floor. Their algorithm showed better results for large-scale problems.

It is quite clear from this literature review the relevance of uncertainty and of PTEE in MTO companies. Nonetheless, there is still little work on uncertainty in WLC and its impact on ORR methods and virtually no work on how to reduce PTEE in MTO companies.

2.2. Workload control order release method

WLC literature proposes many order release methods, most of which are presented in reviews from Wisner (1995), Land and Gaalman (1996), Bergamaschi, Cigolini, Perona, and Portioli (1997), Perona and Portioli (1998), Sabuncuoglu and Karapinar (1999), Breithaupt, Land, and Nyhuis (2002), and Fredendall, Ojha, and Patterson (2010).

In this paper, two approaches are analysed: limiting and balancing.

Limiting is recognised by practitioners and academics as the seminal order release method for workload implementation (see Bechte, 1988), and it has been proven to lead to significant performance improvement (Land & Gaalman, 1998). The limiting method used in this research is adopted from the articles by Cigolini and Portioli-Staudacher (2002) and Portioli-Staudacher and Tantardini (2012).

The balancing release method is used because it is a new ORR method that has been shown to give significantly better performance than limiting in flow shops (Portioli-Staudacher & Tantardini, 2012). It uses a periodic release procedure, executed at fixed intervals, to control and balance the shop floor workload. This method explicitly aims to balance workload at each workstation, minimising the sum of the deviations from the target workload. It prevents the workstations from remaining inactive (Thürer et al., 2015) and improves the predictability of the processing times in the system (Land & Gaalman, 1996). Moreover, it helps to achieve improvements in throughput times and timeliness (Van Ooijen, 1998). Apart from this method, there are very few other ORR methods directly aimed at balancing (Irastorza & Deane, 1974; Onur & Fabrycky, 1987; Shimoyashiro, Isoda, & Awane, 1984; Van Ooijen, 1998).

The main purpose of the balancing method is to balance the workload to be released for each workstation, irrespective of the workload already on the shop floor. Its objective is to minimise the total overload and underload over a period of time. It is shown as follows:

$$min \sum_{k=1}^{K} \sum_{p=1}^{TL} w(p)(UL(p,k) + r.OL(p,k)) \tag{1}$$

Underload and overload are calculated as follows:

$$UL(p,k) = \begin{cases} max\left(\left(\frac{TWL-IL}{K}\right) - RL(p,k); 0\right) & p=1, \ k=1,\ldots,K \\ max(cap - RL(p,k); 0) \forall p>1, \ k=1,\ldots,K \end{cases} \tag{2}$$

$$OL(p,k) = \begin{cases} max\left(RL(p,k) - \left(\frac{TWL-IL}{K}\right); 0\right) & p=1, \ k=1,\ldots,K \\ max(RL(p,k) - cap; 0) \forall p>1, \ k=1,\ldots,K \end{cases} \tag{3}$$

The workload that is to be released for every release period on each workstation is as follows:

$$RL(p, k) = \sum_{i=1}^{N} t(i, k). \, x(i, p) \forall p, \forall k \tag{4}$$

where K is the total number of workstations,

N is the total number of orders in the pre-shop pool,

$t(i,k)$ is the processing time of order i on workstation k,

TWL is the target workload for the shop after a release,

cap is the capacity of a single workstation,

$W(p)$ is the penalty with the workload unbalancing in release period p,

r is the penalty of the overload for every workstation, compared with underload,

$TIME\ LIMIT\ (TL)$ represents the number of release periods that are considered in the pre-shop pool planning,

$x(i,p)$ is 1 if order i is planned to be released in period p, otherwise 0,

$RL(p,k)$ is the workload on workstation k resulting from orders that are to be released in period p,

IL is the initial load already in the system before the release procedure,

$UL(p,k)$ is the under-load, on workstation k in period p,

$OL(p,k)$ is the over-load, on workstation k in period p.

There are other constraints ensuring that the orders are released within their latest release dates. In this way, the method ensures that the orders in the pre-shop pool are not postponed too much in order to avoid missing the due dates, thereby adding value to the customers. This method is in line with the lean approach and can be used to make the system lean, as it absorbs the external variability and balances the workload within the flow. The details of the mathematical model and other relevant information are presented in the article by Portioli-Staudacher and Tantardini (2012). This method is named released workload balancing (RB) in this paper.

3. Simulation model

A simulation model was built to test the influence of processing time error on the performance of ORR methods for pure flow shops. It was developed using the Python 3.4 SimPy module. Gurobi 6.5 was used to solve the optimisation model incorporated to realise balancing. The pure flow shop model and the parameters of different ORR methods are first described in Section 3.1. Then, the experimental design is outlined in Section 3.2. Finally, the measures used to evaluate performance are presented in Section 3.3.

3.1. *Simulation model and parameters of the ORR methods*

The model represents a pure flow shop with five workstations, each consisting of a single resource, as shown in Figure 1.

The maximum capacity of each workstation per day is 8 h. The choice of the random distribution plays an important role while designing a manufacturing planning and control system (Melnyk, Tan, Denzler, & Fredendall, 1994). In this research, standard distributions are used to determine the arrival rate and processing time of each order. The orders are assumed to follow a Poisson distribution of mean 15 and enter the pre-shop
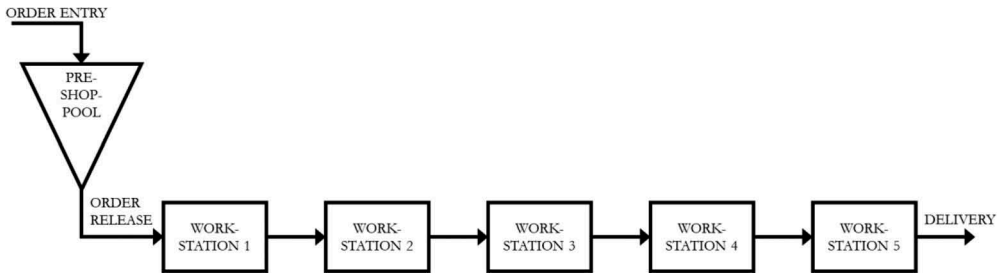
Figure 1. Pure flow shop configuration.

pool once per day just before each release decision. The processing time of each order at each workstation is assumed to follow a lognormal distribution with a mean of half an hour and a coefficient of variation of 0.8. Thus, the average service rate is 16 orders every day, which leads to an average utilisation of 93.75% in combination with the arrival rate of 15 orders per day. Set-ups are assumed to be sequence independent and hence are enclosed in the processing time. This is preferred in order to avoid unexpected interactions between the release mechanism and the shop floor due to workload fluctuations caused by sequence-dependent set-ups.

The PTEE is determined by

$$d_i = e^{Uni\left(\log\left(\frac{1}{n}\right),\log(n)\right)} \tag{5}$$

where n is varied to get different levels of estimation error. Here, $n = 1, 2, 3, 5$ is used to create four levels of PTEE. Then, the PTEE factors are multiplied with the real processing time in order to have four different estimated scenarios (zero, low, medium and high). Therefore, the new estimated processing time is denoted by:

$$p(i, k) = t(i, k) * d_i \tag{6}$$

where $t(i,k)$ is the real processing time of order i at workstation k.

It is very difficult to set a due date (Thürer, Stevenson, Silva, & Land, 2013), and many different methods can be adopted. Therefore, in order to keep the due date assignment method simple with a reasonable percentage of tardy orders, a constant delivery time allowance of 7 working days (56 h, assuming 8 h for each working day) is added to the order arrival date to calculate the due date.

Based on tests in preliminary simulation runs, the planned shop floor time (SFT) is set to three working days. Then, the latest released dates are calculated as the difference between due date and planned SFT. In case of RB, the orders exceeding the latest release dates are forced into the shop floor. Following Portioli-Staudacher and Tantardini (2012), an infinite time limit and a release period length of one day are adopted in this paper. The release method RB includes a ratio (r) between the penalty associated with the overload and underload for workstation k. These penalties are set equally ($r = 1$), as in Cigolini and Portioli-Staudacher (2002) and Portioli-Staudacher and Tantardini (2012). All the parameters are shown in Table 1.

Table 1. Parameters and their values.

Parameters	Values
Due date	Arrival day +7 working days
Planned shop floor time	3 working days
Latest release date	Due date − 3 working days
Release period length	1 working day
Time limit	Infinite
Penalty (r)	1

Table 2. Experimental factors and their ranges.

Experimental factors	Levels
Release rules	Limiting, Balancing
Workload norms	9 levels leading to 9 shop floor times
Processing time estimation error	ρφ (zero PTEE), ρ1 (low PTEE), ρ2 (medium PTEE), ρ3 (high PTEE)
Release frequency	8 h

3.2. *Experimental design*

The aggregate workload limiting (AL) and released workload balancing (RB) form the basis of the experimental design. Initial experiments have been executed to keep the final experimental design sufficiently compact. Particularly the balancing method requires long simulation times, since after every successive release period, an optimisation model must be solved. Therefore, based on initial test experiments, the extended schedule visibility is excluded from the full factorial design. As is common in studies that focus on controlled release, the simulations are run with different workload norms, which depend on the ORR method that is used. Based on this and the findings in initial experiments, four experimental factors are considered in the basic experimental design, which are summarised in Table 2.

Both release rules and workload aggregation have two specific levels, whereas workload norms have nine levels and PTEE factors have four levels. This results in a full factorial design with 72 experiments.

It is necessary to compare the ORR methods at a certain level of norm tightness. However, it is not possible to define norm tightness in terms of the workload norm levels themselves. This is because the workload norms that lead to similar average SFTs will depend on the specific combination of release rule and workload aggregation method applied. Instead, the average SFT is used as an intermediate variable, and two norms in different settings are equally tight if they result in the same average SFT.

Each experiment is replicated 50 times. Based on the initial experiments, the warm-up period is set to 200 days (Welch, 1983), and the length of the simulation run is set to 500 days. Paired *t*-tests are performed whenever differences in performance are discussed.

3.3. *Performance measures*

Four performance measures are used in this study. Those measures can be grouped in two types. The performance measures are shown in Table 3.

The average SFT is used as an intermediate variable to represent the level of workload reduction realised by the different norm types and their levels.

Table 3. Performance measures.

Shop-oriented measures	Order-oriented measures
Average gross throughput time (GTT)	Standard deviation of lateness (SD_L)
Average shop floor time (SFT)	Percentage of tardy orders (% Tardy)

4. Results

The results of this study are organised around the two research questions. The first question is addressed in Section 4.1, where it is investigated how delivery performance for a shop managed with WLC is affected by PTEE.

In line with the second research question, Section 4.2 then compares the performance of two order release methods and suggests possible impacts of implementing IND 4.0 tools.

Figures 2 and 4 provide overviews of the results of the main experiments.

4.1. Performance assessment: PTEE impact

In Figure 2, the SFT is taken as the basis and plotted along the x-axis, whereas the other performance measures, gross throughput time (GTT), standard deviation of lateness (SD_L), and percentage tardy (% Tardy), are plotted along the y-axis for the AL order release method.

The results are presented in the form of performance curves, where the left-hand starting point of the curves represents the tightest workload norm of 27 h. The case of processing time with no error ($\rho\phi$) is represented by the solid blue curve, whereas the cases of processing time with errors is represented by the dotted curves. The points for each workload norm are represented by circles. The workload norm increases step-wise by moving from left to right in each graph, with each data point representing one workload norm (from 27 h to 110 h). Loosening the norms (towards a norm of 110 h) increases the workload on the shop floor, and as a result, the SFT increases.

The effect of reducing PTEE can be observed from the performances curves. With the decrease in PTEE level, the performance improves. An interesting insight is that according to these results, the effect of reducing PTEE on shop performance is stronger when the norm is tight.

Figure 3 illustrates how PTEE impacts on the order release choices at two different levels of norms (low and high). The number of orders released in each period (N_{op}) is plotted along the y-axis, and the number of days along the simulation run (D_s) is plotted along the x-axis. The curves measure the difference between order release choices done without PTEE and choices done under high PTEE ($\rho3$), counting every day's differences in the list of released orders. AL at a low workload norm is represented by a green curve, whereas AL at a high workload norm is represented by a violet curve.

Figure 3 demonstrates that the curve with a tighter norm (low SFT) has a greater difference than the curve with a looser norm (high SFT). This means that the tight norm curve is further away from the ideal decision made with no PTEE. The looser norm leads to higher levels of jobs in the shop floor, and the high number of jobs leads to a balancing of different PTEEs in the computation of workload.
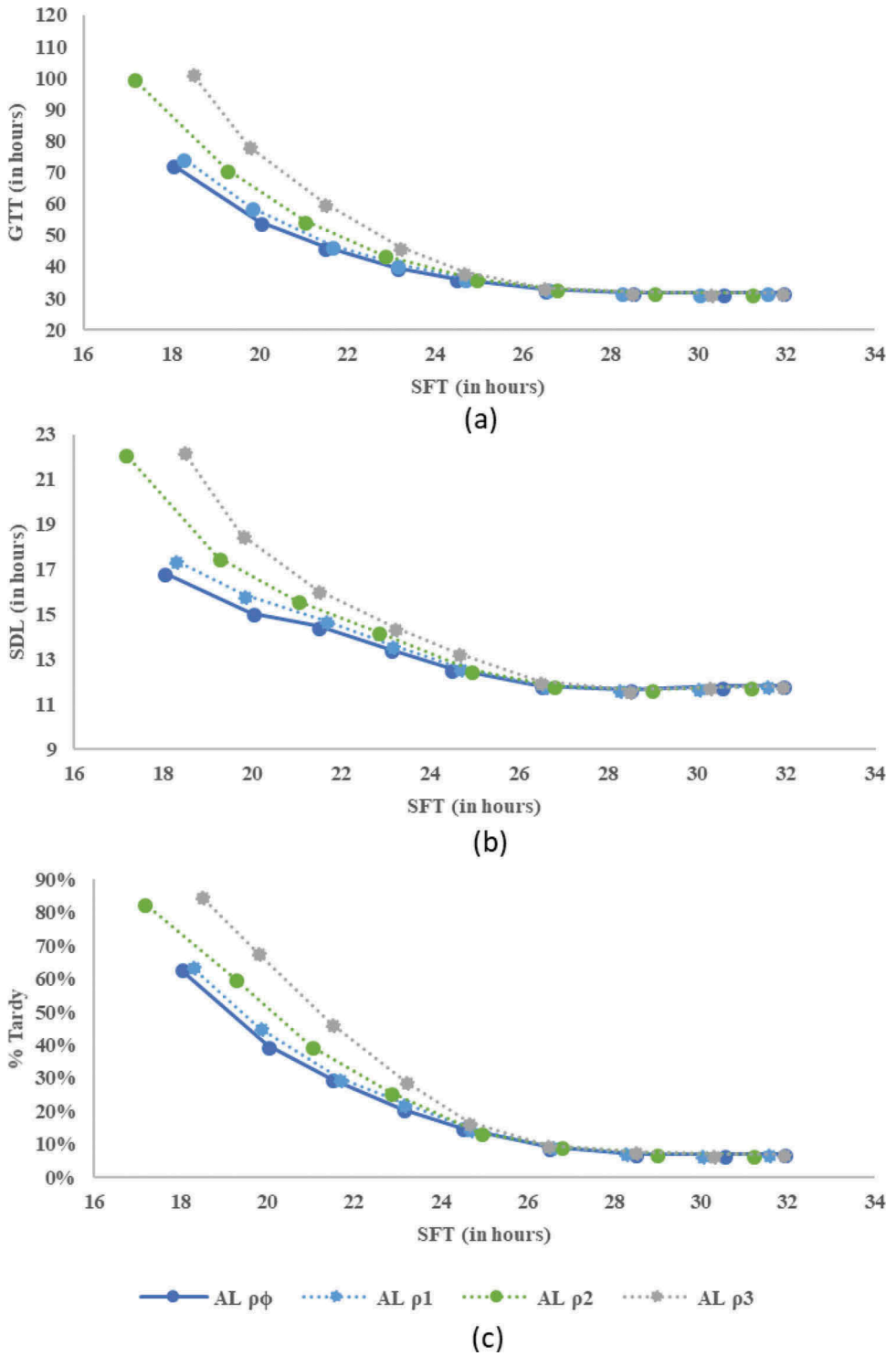
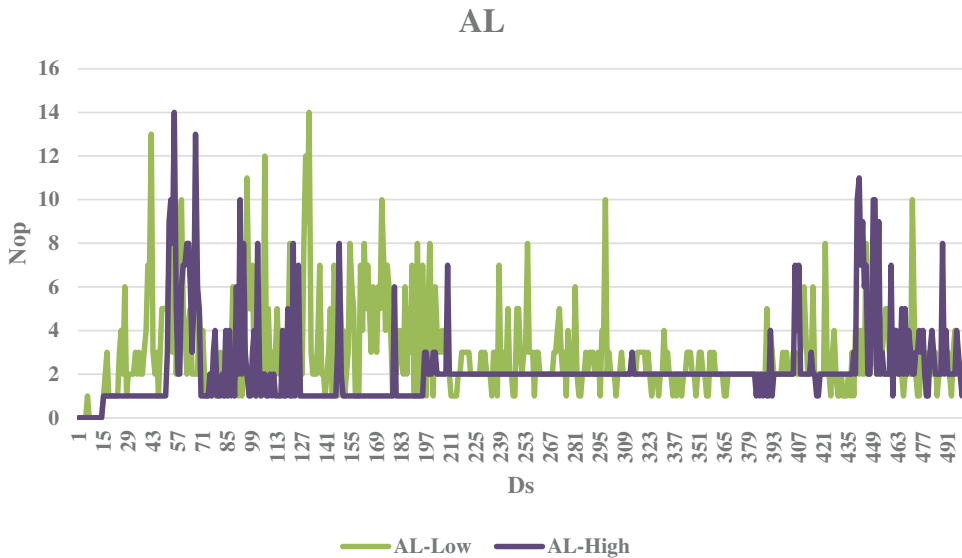Figure 2. Performance of AL under different PTEE levels.

Figure 3. Day-wise errors for AL at low and high workload norms.

Overall, the above results confirm that input control (as introduced by Portioli-Staudacher & Tantardini, 2012) and PTEE reduction (improving the capability of predicting and understanding job workload as proposed by Cigolini et al., 1998) should play complementary roles within WLC.

4.2. WLC release methods

In Figure 4, the SFT is taken as the basis and plotted along the x-axis, whereas the other performance measures, GTT, SD_L and percentage tardy (% Tardy), are plotted along the y-axis for AL and RB order release methods for different norms.

The processing time with no error ($\rho\phi$) is represented by the solid blue curve, whereas the processing time with errors is represented by the dotted curves. The workload norm points for AL scenarios are represented by circles, whereas the workload norm points for RB scenarios are represented by cross marks. Figure 4 indicates that the benefits of using a complex rule, such as RB, instead of a simple one, such as AL, exist even in the presence of PTEE.

However, improving estimation accuracy has an interesting insight for RB. Generally, GTT, SD_L, and percentage tardy worsen as norms are tightened. However, with RB, when PTEE is reduced, GTT and percentage tardy improve as norms are tightened, at least until SFT is near 18 h. Moreover, in general, it is evident that PTEE reduction brings larger improvement to RB than AL.

From the curves in Figure 4, it can be observed that RB is also affected by PTEE in all performance measures, and, as for AL, the benefit of reducing PTEE increases with a decrease in workload norms.

In Figure 5, the number of orders released in each period (N_{op}) is plotted along the y-axis, and the number of days along the simulation run (D_s) is plotted along the x-axis. AL at a low workload norm is represented by a green curve, whereas RB at a low
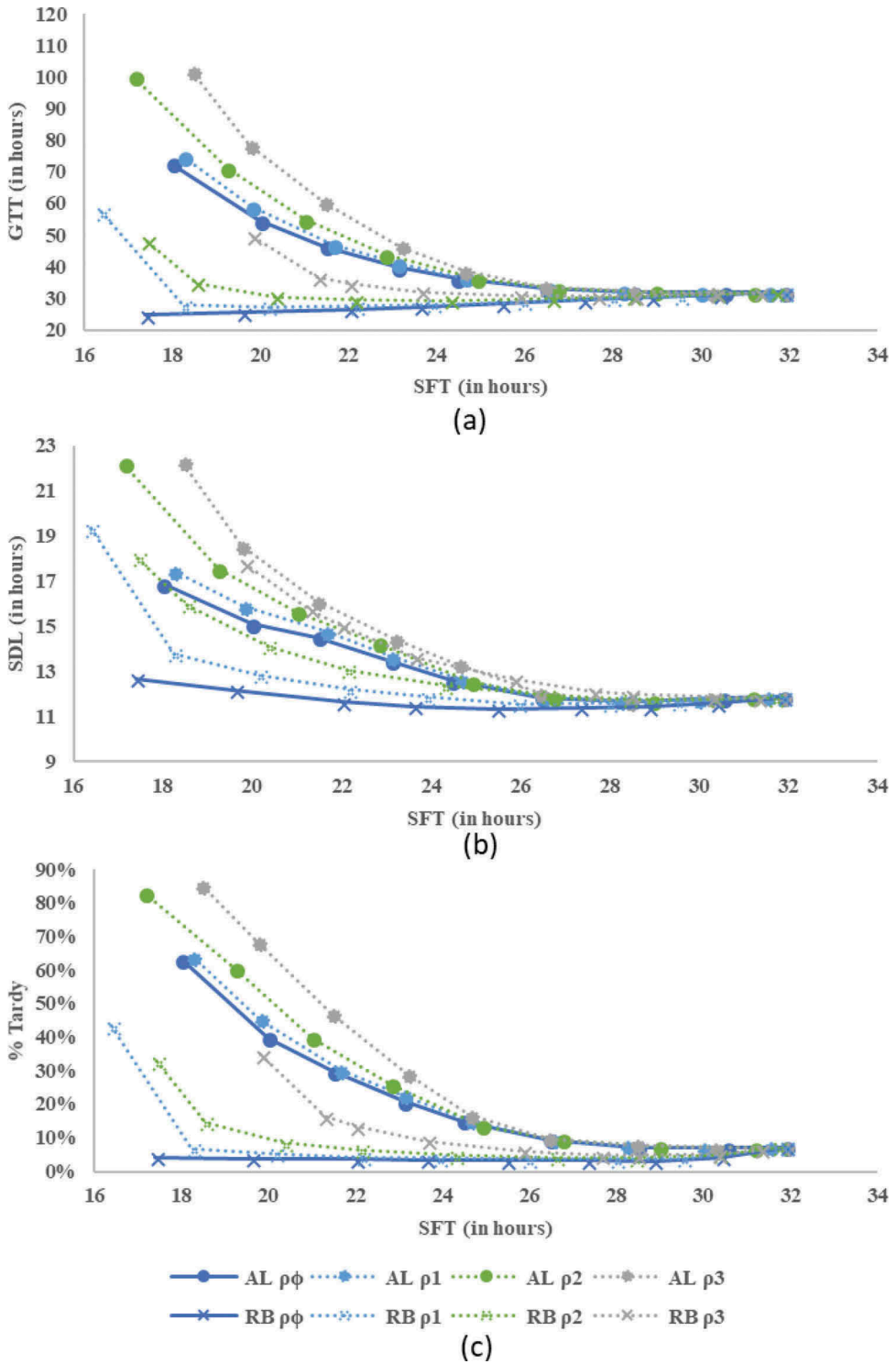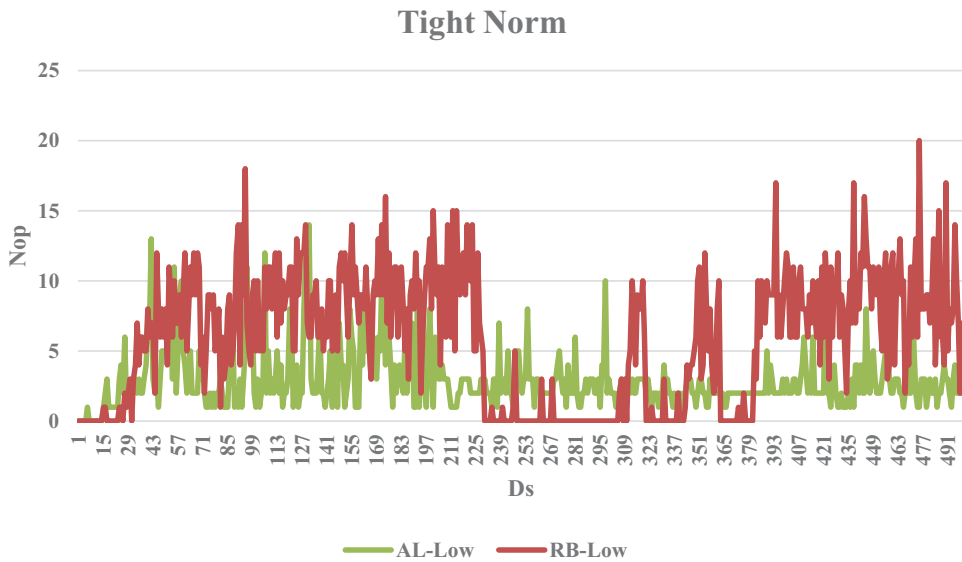
Figure 4. Different performance measures for AL and RB.

Tight Norm

Figure 5. Day-wise errors for AL and RB at a tight workload norm.

workload norm is represented by a grey curve. It seems that RB is more affected than AL by a reduction in PTEE. In fact, from Figure 5, it can be observed that at a low (tight) workload norm, the number of differences in released orders with RB is greater than the number of differences in released orders with AL.

In order to investigate why RB is improving more than AL, the deviation of estimated processing time and actual processing time is calculated at the time just after selection of orders. The same SFT, around 21 h, is taken as a reference for both limiting and balancing methods. It is found that for the limiting method, the percentage of orders that are different in the case with zero PTEE compared to the case with high PTEE is 19.48%. For the balancing method, the percentage of orders that are different for zero and high PTEEs is 34.13%.

The reduction in PTEE affects the selection of orders for the balancing method more than the limiting method. In the limiting method, the orders are selected one by one based on the sequence of the release dates. The first selected orders are the first in the queue (pre-shop pool). Limiting uses a specified workload norm for each workstation. Hence, the first orders released at the beginning of the release procedure will not be affected by PTEE because the limitation effect is not effective when the workload is far away from the limit. It is only when the workload norm is getting close to the full limit that the selection of orders will be affected. It may happen to very few orders depending on the size of the order. Therefore, there is minimal impact of estimation error on the performance of the limiting method.

On the other hand, the balancing method selects a group of orders based on their estimated processing time. Its objective is to minimise the overload and underload of the whole shop floor. As a result, it selects some orders that are presumed to have low processing time but actually have high processing time in the real shop floor. Those orders pass on quickly from the pre-shop pool to the shop floor but get stuck in the shop floor for a long time. Hence, the difference in performance measures, particularly

for SD_L, between zero and high PTEE becomes much larger compared to the limiting method. Therefore, the performance of the balancing method is highly improved when the gap between estimated and actual processing time decreases.

In traditional MTO companies, it is difficult to predict the accurate processing time required for each order. However, IND 4.0 provides the chance for companies to change their working conditions by enhancing their control over the system. It also improves the reliability of information used for ORR by enhancing the capability of predicting/knowing the exact workload necessary for a job. Therefore, IND 4.0 could support companies in fighting uncertainty either by reducing the effect of uncertainty by increasing the control over the system (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014) or decreasing the uncertainty level.

Nowadays, practitioners and researchers are trying to focus on how to exploit the huge amount of data collected from the system. Optimization works better if sufficient information about the system is available. However, if the information is not so reliable, and the algorithm is not robust enough, the result could be quite far from being a success. The benefit of reducing PTEE has been shown in Section 4.1 above.

Therefore, in order to minimise the estimation error and enhance performance measures, full implementation of IND 4.0 is desirable. Some of the properties for full implementation of IND 4.0 are mentioned below.

First, there should be production automation as a tool in order to increase manufacturing flexibility (Ivanov, Dolgui, Sokolov, Werner, & Ivanova, 2016). Second, every physical component of the shop floor and manufacturing process should have a particular 'cyber' representation (Molina & Bell, 1999) embedded in the informational system. Third, a series of sensors should be installed to supervise and control the state of the physical components, manufacturing processes, and production orders. Fourth, there should be a proper network that facilitates communication among all the physical components themselves as well as with the manufacturing processes and production orders (Lasi et al., 2014).

Although there are several benefits of adopting IND 4.0 in manufacturing industries, it will require huge investment to implement IND 4.0, and there are several other challenges, as addressed in the articles by Leonhardt and Wiedemann (2015), Wuest, Weimer, Irgens, and Thoben (2016), and Kiel, Müller, Arnold, and Voigt (2017). Therefore, all the challenges should be addressed before final implementation of IND 4.0 in MTO flow shops.

5. Conclusion

Previous studies on WLC in MTO companies have mainly focused on the assumption that the planned processing time for each order is the same as the real processing time in the shop floor. In contrast, this study tries to evaluate how WLC performs in the case of a mismatch in processing time between the planning stage and the shop floor. Following the current trend, pure flow shops are considered instead of traditional job shops for a simulation study. Two different WLC ORR (limiting and balancing) methods are used for the study.

The results of the simulation runs help to answer the two research questions defined in this paper. First, it is observed that PTEE has a major impact on the performance of the order release method. With a decrease in PTEE, the performance of the limiting

method (AL in this case) improves substantially at a lower SFT (tighter workload norms). When the queue is shorter (tighter workload norms), even a small error can cause starvation of resources. However, at looser workload norms, the impact of PTEE almost disappears, and there is no difference in the AL method's performance with or without PTEE. With tighter workload norms, a reduction in PTEE improves all AL performance measures.

Second, with a reduction in PTEE, all the performance measures of the balancing method improve, similar to the limiting method. However, the balancing method has a significant advantage compared to the limiting method in terms of the SD_L and a slight advantage in terms of other performance measures. Further investigation shows that estimation error heavily affects the order selection process in the balancing method, which is the main reason for performance improvement in ideal conditions (zero PTEE).

In the end, the potential of IND 4.0 to improve performance in an uncertain flow shop environment is discussed. IND 4.0 could enhance the production control and improve reliability of process parameters, such as the decrease in distortion between the expected workload of a job and the actual workload.

In order to reduce the estimation error and enhance system performance, full implementation of IND 4.0 is desirable. However, implementation of IND 4.0 requires a huge investment. In addition, there may be some challenges in changing the current situation in the companies. Therefore, managers of the companies should address all possible challenges and carry out a cost benefit analysis before final implementation.

This work suggests promising future research directions in flow shop production planning. Firstly, the simulation indicates that reducing processing time error significantly improves the performance of WLC methods in MTO flow shops, especially for balancing methods. However, it would be interesting to test ORR methods in a real MTO company where different aspects of IND 4.0 are implemented.

In companies, there may not always be a flow shop. Due to changes in product specifications or to accelerate the process, some changes must be adopted. Therefore, it would be beneficial to investigate the same phenomena in other shop configurations like divergent/convergent flow shops, a general flow shop, or multiple production cells.

Disclosure statement

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