Dynamic Planned Lead Times in Production Planning and Control Systems: Does the Lead Time Syndrome Matter?

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Keywords: *MRP; Drum Buffer Rope; Workload Control; Dynamic Production Control; Lead Time Syndrome.*

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Abstract

Many companies in practice want to dynamically adjust planned lead times in their production planning and control systems in response to demand fluctuations. But for decades it has been recognized that this can lead to escalating planned lead times and realized throughput times. Authors have highlighted the negative impact of this "lead time syndrome", especially in the context of Material Requirements Planning systems, prompting the development of alternative concepts intended to overcome its vicious cycle, such as Workload Control. Yet some authors have shown that increasing planned lead times has advantages – it can improve end-item service levels. To resolve this paradox, we conjecture that the effects of the lead time syndrome are limited when demand is independent of internally planned lead times, such as in make-to-order companies, and subsequently use simulation to prove this conjecture. We show that although dynamic planned lead times have a detrimental effect on performance in make-to-order systems, it is not an increase in planned lead times that leads to a performance loss. Rather, it is the decrease of lead times in low load periods that increases workloads in upcoming periods of high load. This questions the use of upper bounds (WIP-cap) in these contexts.

Keywords: *MRP; Drum Buffer Rope; Workload Control; Dynamic Production Control; Lead Time Syndrome.*

1. Introduction

Production planning and control systems such as Material Requirements Planning (MRP; see, e.g., Orlicky, 1975; Gelders & Van Wassenhove, 1981; Guide & Srivastava, 2000) and the Theory of Constraints' Optimized Production Technology (OPT; Goldratt & Cox, 1984; Goldratt, 1990; Watson *et al*., 2007; Ikeziri *et al*., 2019) are widely applied in practice. Both MRP and OPT use planned lead times to explode the bill of materials backwards from a customer due date to determine production start dates, either for all or a subset of parts (Thürer *et al*., 2021). Production start dates are then used to exercise material flow control, i.e. to decide whether a job should be released onto the shop floor and whether a station should be authorized to produce at a production stage (Graves *et al*. 1995). Traditional MRP systems assume infinite capacity and constant planned lead times (Milne *et al*., 2015); but realized throughput times may vary in practice due to the influence of several external (e.g. unplanned demand) and internal factors (e.g. capacity constraints). If planned lead times become inaccurate, performance is likely to deteriorate (Ioannou & Dimitriou, 2012) or additional safety stock will be needed, which can be costly (Dolgui & Ould-Louly, 2002). As a result, a key managerial challenge concerns both the initial setting of appropriate planned lead times and the dynamic adjustment of these lead times if demand fluctuates (Schneckenreither *et al*., 2021). A broad literature has consequently emerged on stochastic and deterministic methods for both make-to-order and make-to-stock environments, including based on analytical modeling, mathematical programming, simulation models and machine learning (e.g. Enns, 2001; Dolgui & Ould-Louly 2002; Teo *et al*., 2012; Ben-Ammar & Dolgui 2018; Haeussler *et al*. 2019; Missbauer, 2020).

Graves (2021) recently subdivided the literature on planned lead times into: literature that focuses on how to understand and manage the dynamics that planned lead times can induce within a planning system (e.g. Selçuk *et al*., 2006; Schneckenreither *et al*., 2021; Haeussler *et al*., 2021); literature that takes realized throughput times as exogenous random variables and then prescribes how to set the planned lead times, thereby ignoring any dependence between the throughput time and planned lead times (e.g. Dolgui & Ould-Louly, 2002; Jansen *et al*., 2019; Ben-Ammar *et al*., 2020a,b); and literature that treats throughput times as endogenous (due to constrained resources) and seeks to determine planned lead times from the solution of a deterministic constrained optimization model (e.g., Missbauer & Uzsoy, 2020; Missbauer, 2020). This study contributes to the first stream of the literature. It focusses on contexts where planned lead times are dependent on the realized lead time. An important phenomenon in this context is the vicious cycle of lead times, or the so-called "lead time syndrome" (Wight, 1970; Mather & Plossl, 1977; Plossl, 1988).

The lead time syndrome reflects the way in which planners behave in practice and how their planning interventions impact the behavior of the planning and control function (Haeussler *et al*., 2021). It explains that if discrepancies between the realized throughput times and planned lead times result in the late completion of parts or orders then planners will increase planned lead times. This leads to work being started earlier, which will increase workloads and realized throughput times in the production system, thereby creating a vicious and escalating cycle (Zäpfel & Missbauer, 1993; Graves, 2021). In other words, dynamic planned lead times that are based on the workload in the system can create a "self-reinforcing" feedback loop (Sterman, 1989, 2000; Knollmann & Windt, 2013) that causes an unavoidable increase in throughput times and contributes to unstable and inefficient decision-making (Herer & Masin, 1997; Selçuk *et al*., 2006). A similar phenomenon has been described by recent literature in the context of supply chains (Disney & Lambrecht, 2008, Fransoo & Lee, 2013, Cannella *et al*. 2018). While the lead time syndrome is a behavioral phenomenon that has been known for decades, it is likely to become even more important in the era of smart manufacturing due to new technologies that enable the continuous tracking and tracing of throughput and transportation times (Gaukler *et al*., 2008). Managerial biases are not resolved via the use of new technology, rather they can easily be embedded into new technologies (Land *et al*., 2021).

The lead time syndrome has received significant research interest (e.g. Selçuk *et al*., 2006 and 2009; Moscoso *et al*., 2010; Bendul & Knollman, 2016; Haeussler *et al*., 2021) since the first reference was made to the phenomenon back in 1970 (Wight, 1970). Further, production control systems such as Workload Control have been developed specifically to overcome its negative performance effects (Kingsman *et al*., 1989; Breithaupt *et al*., 2002; Stevenson & Hendry, 2006; Thürer *et al*., 2011). Despite this attention in the academic literature, we often find that the lead time syndrome is not a phenomenon that is of major concern to managers in practice. Further, Hoyt (1978) and Melnyk & Piper (1985) found that increases in planned lead times consistently improve, rather than diminish, end-item service levels. This runs counter to what would be expected from the lead time syndrome and its vicious cycle of increasing planned lead times and realized throughput times. To resolve this paradox, this study asks – under what conditions does the lead time syndrome matter?

A first indication of a solution was provided by Kanet (1986) who considered the lead time syndrome to be a transient phenomenon. In other words, the logical assumption that the long-term utilization rate of a system or resource is less than 100% guarantees that, at some point in time, the effects of an increase in planned lead times will disappear. Yet, in the same paper, Kanet (1986, p. 311) weakened this argument by stating that although his analysis appeared to contradict the lead time syndrome, it is really no contradiction at all because, in the lead time syndrome's explanation, an additional assumption is made that management reacts to every backlog surge by increasing planned lead times. Similarly, Bendul & Knollman (2016) stated that the main trigger for the lead time syndrome is a discrepancy between the latency period and the update frequency of the lead time.

In this study, we argue that there is a further condition that must be met before management behavior and the update frequency start to play a role. That is, the assumption that the workload can increase. In a make-to-stock context, production precedes actual demand and, therefore, increasing the planning period can lead to an increase in (anticipated or forecasted) demand. But in a make-to-order context, production only starts – and therefore backlogs can only begin to build up – after demand is placed. This means the maximum workload that can be in the production system is given by the existing demand. We consequently conjecture that the effects of the lead time syndrome are only limited in contexts where customer demand is independent from planned lead times, as is typically the case in make-to-order production environments. Discrete event simulation will be used to validate our conjecture. From a practical perspective, it is anticipated that this will provide an important contingency factor, restricting the lead time syndrome to make-to-stock production contexts. From a theoretical perspective, the paper seeks to further our understanding of the reinforcing feedback loop underpinning the vicious cycle of lead times that characterizes the lead time syndrome.

2. Background and Literature Review

There are two major shortcomings of production planning and control systems such as MRP and OPT that use planned lead times to schedule production – especially when demand fluctuates over time, either in terms of the type or quantity of demand. First, these systems assume that work-orders can be combined and that the same planned lead times can be used for all types of parts or products (Pahl *et al*., 2007; Ioannou & Dimitriou, 2012; Rossi *et al*., 2017). In practice however, different types of products may require different parts or processes, where each incurs a different throughput time. Second, these systems assume that predetermined lead times can be used when calculating release dates. In practice however, fluctuations in demand can impact both the workload and realized throughput times. The literature on dynamic planned lead times has consequently focused on how to set planned lead times for different products (e.g. Riezebos & Zhu, 2015; Haeussler *et al*., 2019) and on how to set planned lead times in accordance with capacity constraints and/or the current workload situation at a station or for the shop as a whole (e.g. Enns & Suwanruji, 2004; Jodlbauer &

Reiter, 2012; Teo *et al*., 2012; Missbauer, 2020; Schneckenreither *et al*., 2021). If dynamic planned lead times are based on realized throughput times, then the lead time syndrome, which is a reinforcing feedback loop, may occur.

The lead time syndrome occurs over time when planned lead times are dependent on realized throughput times. This means that there should be fluctuations in demand and any model that seeks to assess its impact should be a multi-period model. Meanwhile, the lead time syndrome occurs at all control levels for which planned lead times are estimated. This means it relates to the control system and its structure, not the production system. For example, in a multi-stage production system it may occur at each stage if a planned lead time is used for each stage, as in MRP, or at a single stage if a single planned lead time for the shop floor throughput time is used. Since it is a dynamic phenomenon that evolves over time, the system cannot be optimized towards certain criteria. In fact, it is argued that the lead side syndrome will lead to work-in-process escalation and a system that never reaches a stable state. Literature on the lead time syndrome will be discussed next.

2.1 Literature Review: The Lead Time Syndrome

The phenomenon of a vicious cycle of planned lead times was first mentioned by Wight (1970), but the term "lead time syndrome" was only introduced in 1977 by Mather & Plossl (1977). The logical argument underpinning the syndrome can be described as follows:

(1) The planned lead times for jobs, which are used to backward schedule from due dates to find production start dates, turn out to be inaccurate and, as a consequence, due dates are not met;

(2) Planners respond to poor due date adherence by increasing the planned lead times in order to provide jobs with more time on the shop floor to complete the necessary production steps;

(3) In accordance with longer planned lead times, orders are released earlier. This increases workloads on the shop floor (i.e. the levels of work-in-process) and leads to even longer-than-planned lead times. Now cycle back to (1) and repeat the steps, resulting in an escalating problem and a revolving sequence of ineffective interventions.

The lead time syndrome was observed, for example, by Selçuk *et al*. (2006), who using discrete event simulation found that, under realistic high-variety conditions, dynamic planned lead times cause an unavoidable increase in throughput times and, as a result, contribute to unstable and inefficient decision-making. However, Selçuk *et al*. (2006) did not backward schedule from the due date, as would be expected for an MRP or OPT system. Rather, the authors used an optimization-based order release model (an integer linear program) based on De Kok & Fransoo (2003) to control the flow of goods between different production stages. Similarly, although Selçuk *et al*. (2009) included an extensive discussion on the lead time syndrome in the context of MRP, the authors only modelled the production process as a single-server queue controlled by a Constant Work-in-Process (ConWIP, Spearman *et al*., 1990) system with a continuous arrival and processing rate for production orders. In their simulations, orders could be added in or cancelled by a higher-level planning system based on the planned lead time.

Few studies have used backward scheduling to evaluate the lead time syndrome, and these studies have first increased customer lead times (or due dates) before scheduling new release dates (Knollmann & Windt, 2013; Knollmann *et al*., 2014; Windt & Knollmann, 2014). It has been argued that it is the interaction between due date setting and subsequent order release that amplifies the control feedback loop (Windt & Knollmann, 2014). Note that there also exists a broad literature on dynamic planned lead times in the context of due date estimations. But in due date setting we face a fundamentally different problem specification compared to the order release problem, and a longer due date will not lead to an increase in workload if it is not followed by earlier releases. The vicious cycle of the lead time syndrome and its effects on the production system do not exists if only due dates are increased in response to increases in workload. In this study, we assume that the order release mechanism is predetermined and independent of the assignment of due dates.

Finally, Haeussler *et al*. (2021) used behavioral experiments with deterministic demand and given due dates where participants had to estimate lead times to determine release dates. But it remains unknown how each participant estimated or calculated the planned release dates and whether they used backward scheduling or some alternative heuristic.

2.2 Discussion of the Literature

A major shortcoming of the above literature is its focus on planned lead times and realized throughput times. This neglects the important role of the workload. In fact, the lead time syndrome argues that increases in planned lead times expand the workload, which in turn lengthens realized throughput times. Thus, the existing workload sets a limit on any increase in throughput times. In a make-to-stock environment, however, there is theoretically no limit on the workload because production precedes demand. That is, for production to commence it is irrelevant whether or not forecasted demand actually materializes. In contrast, in a make-to-order system, particularly customized production contexts, demand and thus the workload is limited since production can only commence once an order has been placed. This means that the maximum workload in the system is determined by existing demand, and the resulting maximum throughput time is typically referred to as the range (Nyhuis & Wiendahl, 2008) or the planned backlog length (Hendry & Kingsman, 1993).

In this study, we consequently conjecture that the lead time syndrome is only of limited relevance in make-to-order companies. In the worst-case scenario, all orders are released immediately as and when they arrive at the production system. To further prove our conjecture, we assess the performance of MRP and OPT using a discrete event simulation model of a multi-stage assembly system where demand for components or product parts depends on the market-driven demand for end products.

3. Simulation Model

We use SIMIO software to implement two discrete event simulation models, one for MRP and one for OPT. The use of commercial software such as SIMIO with common random numbers ensures comparability across models. The models can be requested from the corresponding author. Both simulation models follow Thürer *et al.*'s (2021) adaptation to Jodlbauer & Huber's (2008) model of a multi-stage assembly system. The two models differ in terms of the implemented control structure. The shop contains six stations or production stages, where each is a single, constant capacity resource. There are eight different end products, with the structure of the products summarized in Table 1. For example, Product 1 requires two units of item B1 to be assembled at Station 1 (the final station). B1 is produced at Station 2 and requires three units of item C1. In total, each end product needs six assembly operations to be completed across stations 1 to 6. Raw materials for Station 6 (the gateway station) are always available and there is an output buffer after each station. Since we consider OPT, there should be a bottleneck station, and this will be Station 3.

[Take in Table 1]

Operation processing times before the adjustment made to create the bottleneck follow a 2-Erlang distribution with a mean of 0.5 time units at stations 1 and 2 and a mean of 1.0 time units at the remaining four stations. The 2-Erlang distribution was chosen since it better approaches processing times in real-life shops than, for example, an exponential distribution (Oosterman *et al*., 2000). Given the part quantities in Table 1, this results in a balanced shop. The shop has one bottleneck station – Station 3 – which is created by reducing the processing times at non-bottleneck stations by 5%. The arrival of demand is a stochastic process where the demand rate follows a Poisson distribution, and all end products have the same probability of arriving. We chose a Poisson distribution since it is arguably the most commonly used distribution to model customer arrival rates (Law & Kelton, 2000, pp. 289). There are fixed periods (e.g. weeks) in which demand occurs. In our study, the average demand arrival rate is 9 end products per period of 10 time units. The average demand has been set such that it deliberately results in a utilization level of 90% at bottleneck Station 3. Finally, three levels of due date tightness are considered, which are created by adding 50 (loose), 45 (medium) or 40 (tight) time units to the order entry date.

3.1 Production Planning and Control

Two different production planning and control systems are implemented as follows:

- *MRP*: Production start dates for each station are calculated for each part by backward scheduling using planned lead times. Planned lead times will be described in Section 3.2 below. Production is then executed at each station according to the calculated start date (i.e. production cannot start if this start date is not reached). If the scheduled production start date of a station is reached but not all parts are yet available from the upstream station, then and only then is safety stock used, if indeed it is available. We use safety stock for all parts and for the end products. The safety stock level or buffer size at each stage is set to 8 items, based on Thürer *et al*. (2021). The total stock level is distributed equally over the number of part types.
- *OPT (or Drum-Buffer-Rope)*: In contrast to MRP, where components are planned and released on a level-by-level basis (Steele *et al*., 2005), OPT schedules only the resource(s) that constrain(s) the system (later called the "Drum"). In our models, this is Station 3. We therefore use two buffers – an output buffer at Station 4, to protect Station 3, and an output buffer at Station 1. Products from Station 1's output buffer can be moved into the finished goods inventory immediately, which means demand is satisfied from this buffer (although the product is still not delivered to the customer before the due date). Production start dates are then calculated for each part at Station 3 (our bottleneck) and at Station 6 (our gateway station) using the planned lead times described in Section 3.2. Identical buffer sizes are considered at both the finished goods buffer and at Station 4. Both buffers are set to 16 items to limit their effect. The total buffer level is equally distributed across the number of part types. Again, all parameters are based on Thürer *et al*. (2021) who assessed the impact of different parameter settings.

Note that MRP buffers all production stages whereas OPT only buffers a subset, which leads to lower work-in-process levels for OPT systems. Finally, priority dispatching on the shop floor is based on the calculated production start dates for MRP. Meanwhile, for OPT, production start dates are calculated for each part by backward scheduling from the due date using the same planned lead times as for the release calculations.

3.2 Dynamic Lead Times

This study focusses on contexts where the planned lead time is dependent on the realized throughput time, i.e. the processing time plus the queue waiting time. An estimate of the lead time *b* at production stage *i* is calculated using the same exponential smoothing technique as in Selçuk *et al*. (2006):

$$b_{i,t} = \alpha L_{i,t-1} + (1-\alpha) b_{i,t-1} \tag{1}$$

where $L_{i,t-1}$ is the realized average throughput time in period $t-1$, and α is a smoothing constant, which is set to 0.1, 0.5 and 0.9. The update frequency is set to 10, 20 and 30 time units (i.e. 1, 2 and 3 times the demand period). We do not round to the next integer since we model continuous time. As a baseline, we also execute experiments with a constant lead time set to 6 time units for the bottleneck station and 4 time units for each non-bottleneck station. These values are based on the realized operation throughput times in preliminary simulation experiments.

3.3 Experimental Design and Performance Measures

Our study considers: (i) two production control systems (MRP and OPT); (ii) three different levels of due date tightness (loose, medium and tight); (iii) three levels of the smoothing constant α (0.1, 0.5 and 0.9); and, (iv) three levels of the update frequency (10, 20 and 30 time units). We used a full factorial design with 54 (2x3x3x3) scenarios, each of which was replicated 100 times. Results were collected over 13,000 time units following a warm-up period of 3,000 time units. These simulation conditions allow us to obtain stable results while keeping the simulation run time to a reasonable level. As in previous literature comparing this type of production planning and control system (e.g. Steele *et al*., 2005; Jodlbauer & Huber, 2008; Thürer *et al*., 2021), three main performance measures are considered: (1) the *Service Level (SL)*, referring to the fraction of the number of customer orders delivered on time; (2) the *Finished Goods Inventory (FGI)*, which is the number of end products completed and assigned to a customer order; and, (3) the *Work-In-Process (WIP) inventory*, which is the number of parts (and end products) in the production system that have departed from raw material inventory but have not yet entered into the FGI. The work-in-process includes buffers, which will lead to higher values for MRP. This however is not considered an issue since we are not interested in comparing MRP and OPT, but rather we want to assess the impact of dynamic planned lead times for each production planning and control system.

4. Results and Analysis

To obtain a first indication of the relative impact of the experimental factors, statistical analysis has been conducted by applying ANOVA. The results for MRP and OPT are summarized in Table 2 and Table 3, respectively. All main effects for the two factors influencing the dynamic planned lead time – the smoothing constant α and the update frequency – are statistically significant. The main effect of due date tightness is significant at 0.05 for MRP in terms of the service level and work-in-process inventory. There are some significant two-way interactions, and no significant three-way interactions.

[Take in Table 2 & Table 3]

Detailed performance results for MRP and OPT are given in Table 4 together with the 95% confidence interval for dynamic and constant planned lead times. In addition, the significance of the differences between the outcomes of individual experiments for dynamic and constant lead times have been verified by paired t-tests, which comply with the use of common random number streams to reduce variation across experiments. Whenever we discuss a difference in outcomes between two experiments, the significance can be proven by a paired t-test at a level of 97.5%.

[Take in Table 4]

From the table we can observe that the service level improves with the stability of the planned lead time, i.e. with decreases in α and the update frequency. Constant planned lead times result in the best performance, but this is at the cost of a higher finished goods inventory. Meanwhile, work-in-process inventories increase with dynamic planned lead times for MRP but remain relatively constant for OPT. In general, these results appear to contradict our conjecture – particularly the results for the service rate – because there is a negative performance effect for dynamic planned lead times. But is this due to the lead time syndrome? This question requires further analysis.

4.1 Performance Analysis

To better understand how performance is realized, we monitored the following for the MRP system: (i) the planned lead time; (ii) the realized throughput time; and, (iii) the work-in-process of our bottleneck station (Station 3). Results for 5,000 time units of an arbitrary simulation run are given in Figure 1. We only present results for a due date of 45 time units (medium) and an update frequency of 10 time units, given patterns where similar across these factors.

[Take in Figure 1]

By comparing the results for a constant planned lead time with the results for a dynamic planned lead time, we can observe a much higher work-in-process when dynamic planned lead times are used, specifically around 4,000 and 5,500 time units. We can also see that the higher the α value, the higher the update magnitude of the planned lead time. In fact, dynamic planned lead times create a reinforcing feedback loop. Further, increases in work-in-process precede increases in realized throughput times, which in turn precede increases in planned lead times. In other words, fluctuations in the workload appear to trigger the lead time syndrome. This somewhat deviates from the commonly held explanation, which starts with inappropriate planned lead times triggering the reinforcement cycle, and it links the lead time syndrome to MRP nervousness, as will be discussed in Section 5. But first we analyze the reinforcing feedback loop.

4.2 Analysis of the Reinforcing Feedback Loop

Demand, and consequently the workload, follow a stochastic process in our simulations. They are independent from the planned lead time, i.e. the planned lead time does not impact the size of the workload increase. Rather, the planned lead time only affects the workload distribution over time. We would therefore expect work-in-process to rise faster for dynamic planned lead times compared to constant lead times, but we did not expect the amplitude of the increase observed. There must be some other effect explaining at least part of this work-in-process increase.

Taking a closer look at the results for dynamic planned lead times we can observe that there are periods when dynamic planned lead times are lower than constant lead times. At the same time, and as assumed by MRP, jobs do adhere to planned release dates in our simulations. This is required because otherwise the production planning and control system would not exercise any material flow control, i.e. it would not determine whether a job should be released to the system or whether it should be authorized to be produced at a station (Graves *et al*., 1996). If the planned lead time does not determine whether a job should be released or produced, then its effect is restricted to the impact of sequencing deviations, as was discussed, for example, in Lödding & Piontek (2017). In our simulations sequencing would have no effect since the priority ordering of parts is not affected.

We consequently argue that the deterioration in performance observed for dynamic planned lead times is not due to an artificial inflation of planned lead times but rather due to planned lead times that are too short, i.e. the production planning and control system does not release enough work to the system. When planned lead times are too short, it means that parts are released tardy during low load periods, which further restricts the workload in the system, resulting in lower throughput times, and so on. This cycle may result in low service levels in periods of low load, and in an artificial backlog, which then increases the workload in an upcoming high load period. To confirm this argument, we executed additional experiments in which we set a lower bound of 6 time units for the estimated dynamic planned lead time at the bottleneck station and a lower bound of 4 time units at all other non-bottleneck stations. The results are provided in Table 5. To facilitate the interpretation and comparison of the results for the three approaches to setting planned lead times (constant, dynamic, and dynamic with lower bound), Figure 2 also provides a bar chart of the results with medium due date tightness, a smoothing constant of 0.5, and an update frequency of 10. The latter parameters for the dynamic approaches were selected since they represent the middle level.

[Take in Table 5 & Figure 2]

The results in Figure 2 and Table 5 confirm that, with an appropriate lower bound, the service levels clearly improve for dynamic planned lead times when compared to those for constant lead times. This is achieved by increasing the workload in high load periods to avoid starvation that is otherwise caused by there being no orders authorized to be produced. The same effect also explains the increase in finished goods inventory for dynamic planned lead times with a lower bound. Meanwhile, work-in-process levels for dynamic lead times remain higher when compared to constant planned lead times. But rather counter-intuitively, a lower bound reduces the work-in-process inventory. This gives further support to our performance analysis above, since it can be explained by the avoidance of artificial backlogs. Note that performance differences in terms of work-in-process are less pronounced for OPT, which in general operates at lower levels when compared to MRP since it uses less inventory as safety stock or as a buffer.

5. Discussion and Managerial Implications

Planned lead times are one of the few parameters that are under the direct control of management; but for managers to exercise this control effectively, it is important that they have a good understanding of how performance outcomes are affected by the way in which they set and adjust planned lead times (Kanet, 1986). This need is even greater in the context of smart manufacturing where decisions are often delegated to algorithms or some form of artificial intelligence (Kusiak, 2018). In this context, new technologies can draw on timely order progress information provided through radio frequency identification (RFID) and the Internet of Things (IoT) to estimate appropriate planned lead times (Gaukler *et al*., 2008; Olsen & Tomlin, 2020). However, managers still need to be aware of phenomena such as the lead time syndrome and its consequences, not only to overcome their own cognitive biases but also to ensure they do not introduce these biases into implementations of new technologies (Bendul, 2019). In fact, new technology and the abundance of real-time data allows for an increase in the update frequency, which makes reinforcing control cycles even more relevant.

5.1 Contribution to Theory

The lead time syndrome is typically related to how management determines planned lead times. It is distinguished or separated out from MRP nervousness, which arises when changes in the workload (gross requirements) or the production start dates (scheduled receipts) at one stage of the system propagate to another stage, making it necessary to reschedule on a frequent basis (see e.g., Whybark & Williams, 1976; Ho, 1989; Murthy & Ma, 1991; Dolgui & Prodhon, 2007; Blackburn *et al*., 1985, 1986; Kadipasaoglu & Sridharan, 1995). In this study, we have shown that changes in the workload trigger changes in production start dates if dynamic planned lead times are used. This links the lead time syndrome to the literature on MRP nervousness. First, it highlights that the lead time syndrome may be triggered by similar factors to MRP nervousness, such as lot sizes, demand uncertainties, etc. Second, the effects of the lead time syndrome may propagate through the whole production system as part of MRP nervousness. This kind of interaction was referred to as the planning bullwhip in Moscoso *et al*.'s (2010) empirical investigation of planning instabilities in advanced planning and scheduling systems. Our study contributes by further disentangling the effects of the lead time syndrome and MRP nervousness.

Further, we found that the negative performance effect in our simulations is not due to planned lead times being artificially inflated, but rather due to planned lead times being too short, which leads to artificial backlogs. Note that this could not be evaluated by simply measuring the difference between planned lead times and realized throughput times, as has been common practice in prior studies (e.g., Selçuk *et al*., 2006; Knollmann & Windt, 2013; Knollmann *et al*., 2014; Windt & Knollmann, 2014). This requires us to rethink the lead time syndrome. More specifically, if we understand the lead time syndrome as a reinforcing feedback loop then this can lead to either an increase or a decrease in workloads, throughput times and lead times. While previous literature on the lead time syndrome has emphasized the impact of an increase, this study highlights the impact of a decrease. This also extends the results presented in Land *et al*. (2015), which showed that shop performance is largely determined by high load periods. We expand on this by showing that this is dependent on the control mechanism being implemented – low load periods may have a larger-than-expected impact if, for example, material flow control systems such as MRP or OPT are applied. This result also questions the usefulness of a Work-in-Process cap (Hopp & Spearman, 2004) in the context of these material flow control systems. Avoiding so-called premature station idleness (Land *et al*., 1998) appears to be more important than limiting the workload.

5.2 Managerial Implications

From a practical perspective, the results presented in this paper support our initial conjecture. That is, the effects of the lead time syndrome are limited in contexts where customer demand is independent from planned lead times, as is typically the case in make-to-order production environments. We have also shown that a simple lower bound overcomes the negative performance effect that occurs when dynamic planned lead times are too short. Thus, rather than using an upper bound to overcome the lead time syndrome, as in Schneckenreither *et al*. (2021), a lower bound should be used in make-to-order contexts. If a lower bound is applied, then dynamic planned lead times can outperform constant lead times. This provides an important contingency factor – the lead time syndrome needs only to be considered in make-to-stock contexts, where increases in the planning period often increase internal demand (i.e. stock to be sold in the future).

Finally, while demand in make order-to-order contexts is not dependent on the planned lead times used for production planning and control, we recognize that demand may be dependent on the planned lead times used for quoting due dates to prospective customers. Make-to-order companies often have to take part in a competitive bidding process for every order they 'win', where the criterion considered by customers when awarding tenders can vary and may depend on a blend of outcomes, including responsiveness and price (Melnyk *et al*., 2010). In this context, longer planned lead times create later customer due dates. This will increase the likelihood of a customer rejecting the bid or awarding the tender to another company. Rather than leading to greater demand and workloads, as would be assumed by the lead time syndrome, increasing dynamic planned lead times will lead to lower demand and workloads. In fact, Thürer *et al*. (2014) showed how load-dependent dynamic planned lead times used as part of the quotation process during customer enquiry management can stabilize workloads either by increasing demand if planned lead times decrease or by decreasing demand if planned lead times increase.

6. Conclusions

Ever since it was first mentioned in 1970, the lead time syndrome and its vicious cycle of planned lead times has divided opinions. On the one hand, some scholars have argued that the lead time syndrome may significantly impact the performance of production planning and control systems such as MRP and OPT that use planned lead times to backward schedule to find both release and production start dates. Meanwhile, the Workload Control concept, which limits the level of work-in-process in the system to stabilize realized throughput times, was designed specifically to overcome the lead time syndrome. On the other hand, practitioners appear to be less concerned with the phenomenon while other scholars have been unable to observe the phenomenon in their studies.

To resolve this paradox, this study has used discrete event simulation to assess the performance of an MRP and an OPT production planning and control system with dynamic planned lead times in a multi-stage assembly system in which the demand for components or product parts depends on the market-driven demand for end products. The results confirm our conjecture that the lead time syndrome has only a limited effect in shops where demand is independent from planned lead times, such as is typical of make-to-order shops. In this context, the effect of the lead time syndrome is limited by the use of immediate release and immediate authorization at all stations, i.e. by no material flow control being exercised. This provides an important contingency factor that determines the impact of the lead time syndrome for managers in practice. The negative consequences of the lead time syndrome are restricted to make-to-stock contexts where increases in the planning period may affect the workload in the system. Finally, the study highlights the direct, negative effect of underestimating planned lead times in low load periods, which may lead to artificial backlogs. This requires us to rethink the lead time syndrome. Reinforcing feedback loops may not only lead to lead times that are too long but also to lead times that are too short.

6.1 Limitations and Future Research

A main limitation of our study is its focus on just two production planning and control systems. While MRP and OPT are arguably the most commonly applied systems in practice, future research could investigate other production planning and controls systems that use backward scheduling, such as Demand-Driven MRP. Another major limitation is our focus on a context with externally set due dates, i.e. due dates that are determined by the customer. We posit that also in a context where due dates are dependent on planned lead times, and thus internally set by the company, the worst case will be immediate release and that there will be no effect on realized throughput times. The main effect will be an increase in the finished goods inventory if jobs are not directly delivered to the customer after completion. Future research could however be conducted to confirm this conjecture.

In addition, the overall performance of a production system may be determined by low load periods and high load periods, depending on the control mechanism applied. This warrants further research to better explain how performance is actually realized through production planning and control whilst also taking into account interactions between behavior in low and high load periods. Finally, future research is also needed to further disentangle the interaction between the lead time syndrome and MRP nervousness. More generally, the way in which several overlapping feedback loops influence production planning and control warrants further exploration. It is currently underrepresented in the literature but is likely to become even more important in the new digital manufacturing era that enables more regular feedback from the shop floor.

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Table 1: Product Structure

Station 1 (Final)			Station 2			Station 3			Station 4			Station 5			Station 6
Output	Input		Output	Input		Output	Input		Output	Input		Output	Input		Output
	Type	Q[1)]		Type	Q		Type	Q		Type	Q		Type	Q	
Product 1	B1	2	B1	C1	3	C1	D1	1	D1	E1	1	E1	F1	1	F1
Product 2	B2	2	B2	C1	1	C1	D1	1	D1	E1	1	E1	F1	1	F1
Product 3	B3	2	B3	C2	2	C2	D2	1	D2	E2	1	E2	F2	1	F2
Product 4	B4	2	B4	C2	2	C2	D2	1	D2	E2	1	E2	F2	1	F2
Product 5	B1	2	B1	C1	3	C1	D1	1	D1	E1	1	E1	F1	1	F1
Product 6	B2	2	B2	C1	1	C1	D1	1	D1	E1	1	E1	F1	1	F1
Product 7	B3	2	B3	C2	2	C2	D2	1	D2	E2	1	E2	F2	1	F2
Product 8	B4	2	B4	C2	2	C2	D2	1	D2	E2	1	E2	F2	1	F2

Q[1)] – Quantity

Table 2: ANOVA Results – MRP

	Source of Variance	Sum of Squares	Degrees of freedom	Mean Squares	F-Ratio	p-Value
Service Level	DD Tightness (DD)	352.39	2	176.19	4.10	0.02
	Smoothing Constant (α)	73122.58	2	36561.29	850.49	0.00
	Update Frequency (U)	20042.87	2	10021.44	233.12	0.00
	DD x α	309.55	4	77.39	1.80	0.13
	DD x U	620.17	4	155.04	3.61	0.01
	α x U	10663.49	4	2665.87	62.01	0.00
	DD x α x U	497.49	8	62.19	1.45	0.17
	Error	114908.65	2673	42.99		
Finished Goods Inventory	DD Tightness (DD)	3.00	2	1.50	1.94	0.14
	Smoothing Constant (α)	1285.77	2	642.88	834.08	0.00
	Update Frequency (U)	351.86	2	175.93	228.25	0.00
	DD x α	4.66	4	1.17	1.51	0.20
	DD x U	10.64	4	2.66	3.45	0.01
	α x U	227.44	4	56.86	73.77	0.00
	DD x α x U	7.81	8	0.98	1.27	0.26
	Error	2060.27	2673	0.77		
Work-In-Process Inventory	DD Tightness (DD)	9713.13	2	4856.57	67.24	0.00
	Smoothing Constant (α)	54274.75	2	27137.37	375.71	0.00
	Update Frequency (U)	6462.36	2	3231.18	44.74	0.00
	DD x α	608.81	4	152.20	2.11	0.08
	DD x U	1152.22	4	288.06	3.99	0.00
	α x U	6853.31	4	1713.33	23.72	0.00
	DD x α x U	670.03	8	83.75	1.16	0.32
	Error	193067.29	2673	72.23		

Table 3: ANOVA Results – OPT

	Source of Variance	Sum of Squares	Degrees of freedom	Mean Squares	F-Ratio	p-Value
Service Level	DD Tightness (DD)	10.66	2	5.33	0.07	0.93
	Smoothing Constant (α)	6377.39	2	3188.69	43.30	0.00
	Update Frequency (U)	38785.22	2	19392.61	263.31	0.00
	DD x α	480.15	4	120.04	1.63	0.16
	DD x U	112.15	4	28.04	0.38	0.82
	α x U	291.31	4	72.83	0.99	0.41
	DD x α x U	120.67	8	15.08	0.20	0.99
	Error	196862.28	2673	73.65		
Finished Goods Inventory	DD Tightness (DD)	0.80	2	0.40	0.17	0.84
	Smoothing Constant (α)	290.98	2	145.49	62.72	0.00
	Update Frequency (U)	1568.28	2	784.14	338.02	0.00
	DD x α	15.89	4	3.97	1.71	0.14
	DD x U	7.13	4	1.78	0.77	0.55
	α x U	11.06	4	2.77	1.19	0.31
	DD x α x U	8.45	8	1.06	0.46	0.89
	Error	6200.89	2673	2.32		
Work-In-Process Inventory	DD Tightness (DD)	0.28	2	0.14	1.21	0.30
	Smoothing Constant (α)	1.53	2	0.77	6.54	0.00
	Update Frequency (U)	16.79	2	8.40	71.75	0.00
	DD x α	0.71	4	0.18	1.52	0.19
	DD x U	1.53	4	0.38	3.26	0.01
	α x U	0.28	4	0.07	0.60	0.66
	DD x α x U	1.05	8	0.13	1.12	0.34
	Error	312.84	2673	0.12		

Table 4: Simulation Results – MRP & OPT

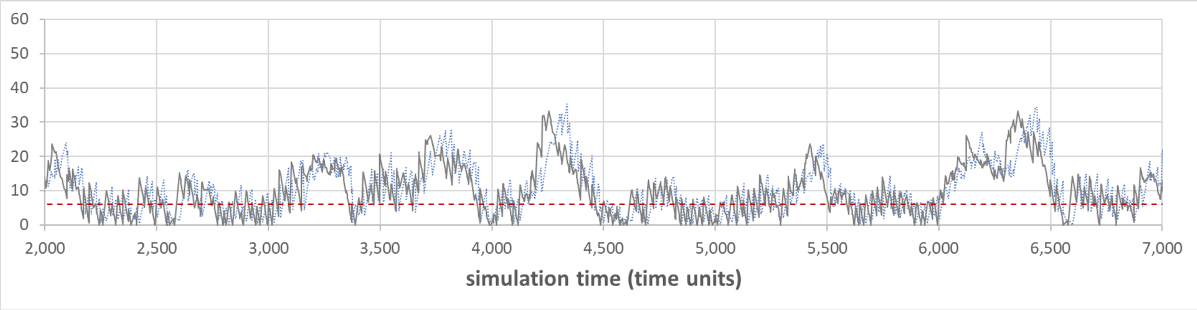
	Due Date	α	UF[1]	MRP			OPT		
				SL (%)[2]	FGI[3]	WIP[4]	SL (%)	FGI	WIP
Constant Lead Time	Loose	n/a	n/a	69.4±0.47	6.1±0.05	66.8±0.16	69.7±1.88	11.0±0.38	21.5±0.07
	Medium	n/a	n/a	69.3±0.51	6.1±0.05	66.7±0.18	70.0±1.67	10.8±0.39	21.4±0.06
	Tight	n/a	n/a	69.6±0.42	6.1±0.04	66.7±0.14	72.1±1.59	11.3±0.37	21.4±0.07
Dynamic Lead Time	Loose	0.10	10	53.5±1.61	4.6±0.22	85.6±2.09	58.2±1.95	7.9±0.35	21.5±0.06
	Medium	0.10	10	57.8±1.43	5.1±0.19	79.5±1.62	58.7±1.92	8.0±0.35	21.5±0.08
	Tight	0.10	10	56.1±1.53	4.9±0.21	79.6±1.65	58.6±1.74	8.0±0.32	21.6±0.07
	Loose	0.50	10	50.9±1.20	4.3±0.16	92.3±2.31	53.2±1.72	6.9±0.30	21.6±0.07
	Medium	0.50	10	51.8±1.15	4.4±0.15	88.2±1.72	53.2±1.70	6.9±0.30	21.7±0.07
	Tight	0.50	10	52.5±1.06	4.4±0.14	85.1±1.77	53.5±1.60	6.9±0.27	21.7±0.07
	Loose	0.90	10	48.3±1.04	4.0±0.14	89.3±1.70	49.9±1.64	6.2±0.27	21.8±0.07
	Medium	0.90	10	49.6±1.05	4.2±0.14	85.6±1.58	50.3±1.56	6.3±0.27	21.7±0.07
	Tight	0.90	10	49.1±1.07	4.1±0.15	84.1±1.83	49.8±1.64	6.2±0.29	21.7±0.06
	Loose	0.10	20	63.4±1.97	6.0±0.27	78.0±2.01	60.5±2.24	8.4±0.40	21.5±0.68
	Medium	0.10	20	63.1±1.52	5.9±0.21	76.2±1.54	60.5±1.67	8.4±0.33	21.5±0.06
	Tight	0.10	20	64.2±1.48	6.1±0.21	73.7±0.94	62.1±1.51	8.7±0.29	21.5±0.07
	Loose	0.50	20	53.5±1.23	4.6±0.16	87.6±1.81	54.5±1.72	7.3±0.29	21.6±0.07
	Medium	0.50	20	52.8±1.22	4.5±0.16	87.1±1.76	54.2±1.82	7.0±0.32	21.7±0.07
	Tight	0.50	20	54.6±1.29	4.7±6.70	83.2±1.79	55.3±1.79	7.3±0.32	21.6±0.07
	Loose	0.90	20	51.6±1.25	4.4±0.17	88.8±1.83	51.7±1.70	6.6±0.30	21.7±0.07
	Medium	0.90	20	50.6±1.23	4.2±0.16	88.4±1.87	52.0±1.71	6.7±0.27	21.7±0.07
	Tight	0.90	20	50.8±1.36	4.3±0.18	86.3±2.19	52.7±1.65	6.9±0.29	21.7±0.07
	Loose	0.10	30	69.5±1.20	6.8±0.17	75.2±0.69	64.1±1.63	9.1±0.32	21.5±0.07
	Medium	0.10	30	68.9±1.55	6.7±0.21	74.2±0.69	62.9±1.75	8.9±0.30	21.5±0.07
	Tight	0.10	30	69.5±1.47	6.7±0.20	72.7±0.84	62.9±1.80	9.0±0.31	21.5±0.08
	Loose	0.50	30	54.7±1.24	4.7±0.16	85.3±1.64	56.3±1.95	7.6±0.33	21.6±0.06
	Medium	0.50	30	54.2±1.17	4.6±0.16	84.8±1.70	56.5±1.74	7.5±0.31	21.7±0.07
	Tight	0.50	30	55.6±1.14	4.8±0.15	80.5±1.65	56.3±1.65	7.5±0.31	21.6±0.07
	Loose	0.90	30	51.3±1.23	4.4±0.16	90.7±1.82	54.5±1.45	7.2±0.25	21.6±0.06
	Medium	0.90	30	53.6±1.18	4.6±0.15	86.1±1.79	53.7±1.66	7.1±0.28	21.6±0.06
	Tight	0.90	30	52.1±1.26	4.4±0.17	85.8±2.00	52.1±1.58	6.7±0.26	21.7±0.07

UF[1] – Update Frequency; SL[2] – Service Level; FGI[3] – Finished Goods Inventory; WIP[4] – Work-In-Process Inventory

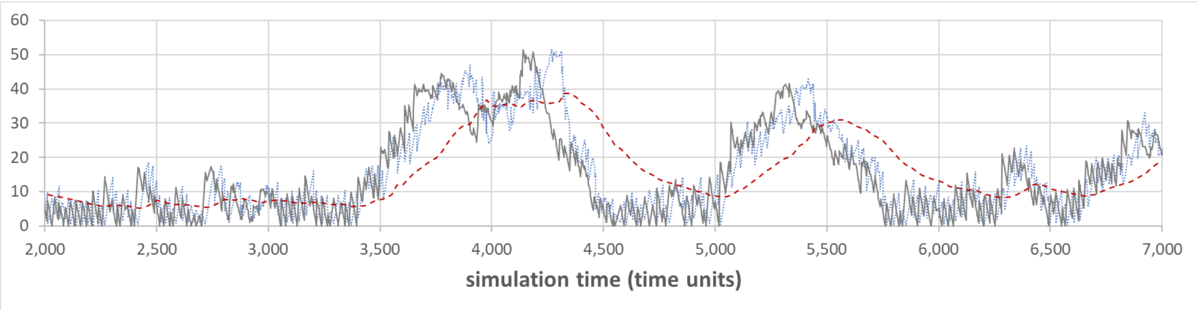
Table 5: Simulation Results – MRP & OPT with Lower Bound

Due Date	α	UF[1)]	MRP			OPT		
			SL (%)[2)]	FGI[3)]	WIP[4)]	SL (%)	FGI	WIP
Loose	0.10	10	78.4±0.39	8.2±0.06	79.8±0.32	72.2±1.97	12.1±0.47	21.5±0.07
Medium	0.10	10	78.2±0.43	8.1±0.07	77.5±0.26	71.9±1.92	12.1±0.42	21.5±0.07
Tight	0.10	10	78.4±0.44	8.1±0.07	74.9±0.20	73.1±2.03	12.3±0.46	21.5±0.07
Loose	0.50	10	76.5±0.43	7.9±0.07	81.6±0.27	77.2±1.72	14.0±0.44	21.5±0.06
Medium	0.50	10	76.6±0.40	7.9±0.06	78.3±0.22	77.5±1.61	14.2±0.43	21.5±0.06
Tight	0.50	10	76.2±0.42	7.7±0.07	75.5±0.20	78.5±1.87	14.4±0.44	21.4±0.07
Loose	0.90	10	76.0±0.40	7.9±0.06	83.3±0.27	77.7±1.85	14.1±0.45	21.5±0.08
Medium	0.90	10	76.0±0.49	7.8±0.07	79.9±0.27	77.8±1.51	14.0±0.36	21.4±0.05
Tight	0.90	10	75.9±0.43	7.7±0.06	76.3±0.20	78.7±1.59	14.3±0.41	21.4±0.06
Loose	0.10	20	79.2±0.48	8.3±0.08	79.8±0.32	72.2±1.97	12.3±0.42	21.5±0.06
Medium	0.10	20	79.2±0.46	8.3±0.07	77.7±0.25	74.2±1.70	12.6±0.33	21.5±0.06
Tight	0.10	20	79.4±0.44	8.3±0.07	75.1±0.19	73.3±1.79	12.4±0.44	21.5±0.07
Loose	0.50	20	76.9±0.45	7.9±0.07	80.5±0.27	76.4±2.08	13.7±0.50	21.5±0.06
Medium	0.50	20	77.1±0.45	7.9±0.07	77.7±0.27	77.9±1.65	14.1±0.41	21.4±0.07
Tight	0.50	20	76.9±0.39	7.9±0.07	74.8±0.22	77.0±1.78	13.7±0.42	21.5±0.06
Loose	0.90	20	76.3±0.38	7.9±0.07	81.7±0.24	78.7±1.61	14.2±0.42	21.4±0.07
Medium	0.90	20	76.3±0.49	7.8±0.07	78.4±0.26	79.2±1.69	14.5±0.40	21.4±0.06
Tight	0.90	20	76.1±0.43	7.8±0.06	75.4±0.19	76.7±1.84	13.8±0.42	21.5±0.07
Loose	0.10	30	79.8±0.43	8.3±0.07	80.3±0.40	72.8±1.96	12.3±0.43	21.4±0.06
Medium	0.10	30	80.3±0.41	8.3±0.07	78.2±0.23	74.0±1.63	12.4±0.38	21.4±0.07
Tight	0.10	30	80.0±0.46	8.3±0.07	75.3±0.20	72.7±1.75	12.0±0.40	21.5±0.06
Loose	0.50	30	77.4±0.50	8.0±0.08	79.9±0.33	76.7±1.85	13.9±0.48	21.5±0.07
Medium	0.50	30	77.5±0.45	8.0±0.06	77.2±0.26	78.1±1.60	14.0±0.42	21.5±0.07
Tight	0.50	30	77.5±0.38	8.0±0.07	74.6±0.20	77.9±1.67	14.0±0.44	21.5±0.06
Loose	0.90	30	76.3±0.44	7.9±0.08	81.0±0.27	78.0±1.58	14.1±0.41	21.5±0.06
Medium	0.90	30	76.4±0.50	7.8±0.08	78.1±0.29	76.5±1.57	13.8±0.40	21.5±0.07
Tight	0.90	30	76.4±0.43	7.8±0.06	75.0±0.22	77.1±1.95	13.9±0.46	21.4±0.06

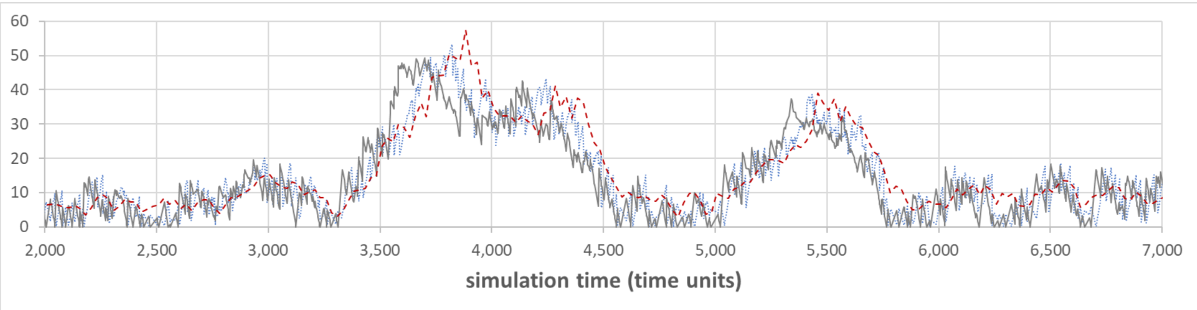
UF[1)] – Update Frequency; SL[2)] – Service Level; FGI[3)] – Finished Goods Inventory; WIP[4)] – Work-In-Process Inventory



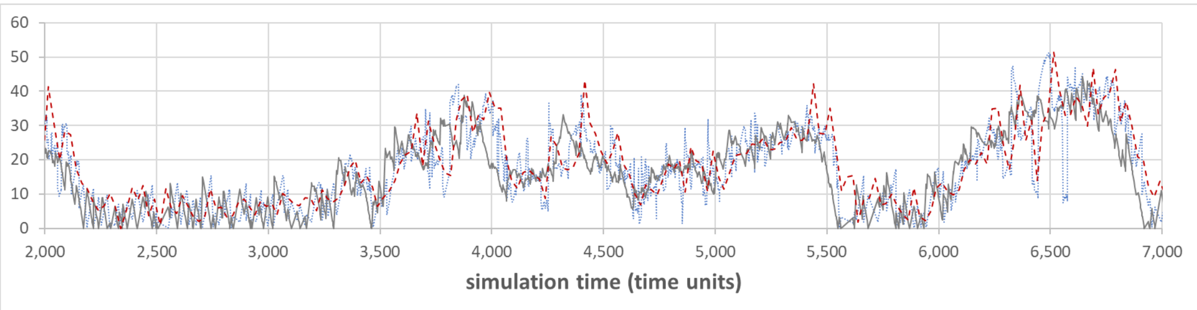
(a) constant



(b) smoothing constant α = 0.1



(c) smoothing constant α = 0.5



(d) smoothing constant α = 0.9

Throughput Time — Work-In-Process - - - - Planned Lead Time

Figure 1: Overtime Results for the Planned Lead Time, the Realized Throughput Time, and the Work-In-Process: MRP, Medium Due Date Tightness, and Update Frequency of 10 Time Units

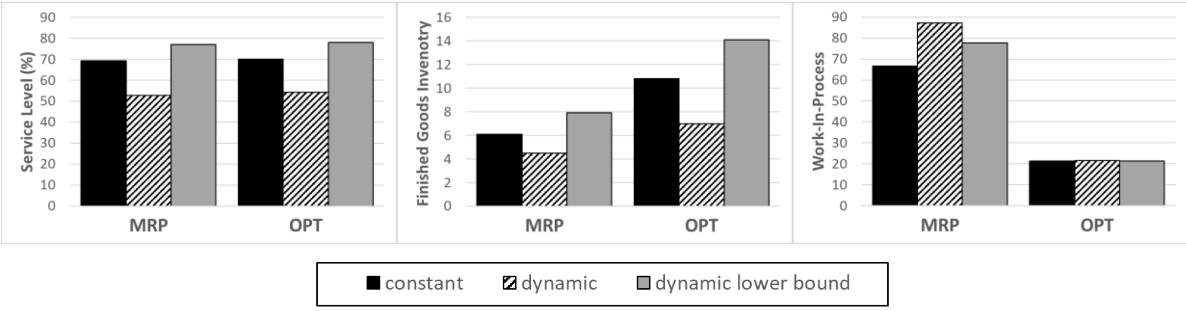


Figure 2: Graphical Representation of Results for Medium Due Date Tightness, Smoothing Constant of 0.5, and Update Frequency of 10 Time Units