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Research Article

Analysis of a support method for offering delivery promises in environments managed by S-DBR system

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Abstract

Paper aims: The objective of this paper is to investigate the effectiveness of a method, here denominated the due date promise by slack time rule (DDPSTR), to evaluate its feasibility and effectiveness for accepting urgent orders in make-to-order (MTO) environments managed by the Simplified Drum-Buffer-Rope (S-DBR) system.

Originality: Evaluating alternative methods for dealing with urgent orders in MTO environments managed and controlled by the S-DBR system is a subject that has received little attention from academia. This study contributes to the field of knowledge by identifying and comparing three alternatives.

Research method: To evaluate its feasibility and effectiveness, the DDPSTR was compared with variations of a method based on prior reserve capacity when dealing with regular and urgent orders. Computer simulation was used to model a theoretical production line that emulated the S-DBR system in different scenarios, using average delay and percentage of late orders as performance indicators.

Main findings: The DDPSTR method achieved optimal results for both indicators, enabling reliable delivery dates and, at the same time, flexibility in accepting urgent orders.

Implications for theory and practice: This work has verified the effectiveness of the DDPSTR method as a means of dealing with urgent orders without compromising the reliability of previously promised order deadlines. It has additionally proposed the means by which future research can evaluate adaptations, such as offering the shortest feasible delivery times to customers when those initially requested by them prove unworkable.

Keywords

Production planning and control. Theory of Constraints. Make to order. Simulation.

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1. Introduction

Make-to-order (MTO) environments are characterized by low volume, high variety, less predictable futures, greater flexibility, greater variety of flow on the shop floor and longer response times for customers. Although MTO environments avoid problems such as low inventory turnover, high investment, stock shortages and obsolescence, there are also challenges, such as promising and fulfilling deadlines reliably and competitively (equal to or lower than those required by the market) and offering flexibility (Kingsman et al., 1996; Stevenson et al., 2005; Schragenheim et al., 2009; Souza & Pires, 2014; Girotti & Mesquita, 2015; Ghalehkhondabi & Suer, 2018; Borges et al., 2020). In terms of dealing with these challenges, the Theory of Constraints (TOC) establishes that flow must be the main objective of operations and that production planning must be carried out based on the identification of a system constraint, one which other resources should submit to (Souza, 2005; Schragenheim et al., 2009; Goldratt, 2009; Schragenheim, 2010; Souza & Baptista, 2010; Santos & Alves, 2014; Pacheco, 2014; Ikeziri et al., 2019; Telles et al., 2020; Orue et al., 2021; Telles et al., 2022).

For a company to have flexibility and offer low customer response times, it is essential that there is some level of excess (Hopp & Spearman, 2011) or, according to TOC terminology, protective capacity. That is, there should be no active capacity constraints in a system. Another factor that encourages the choice of demand as a main constraint of a system is that, in competitive markets, customers can opt for other suppliers who accept urgent orders and offer shorter delivery times and greater flexibility (Schragenheim et al., 2009; Schragenheim, 2010).

When a system constraint is demand, having protective capacity allows companies to operate with competitive advantages in terms of speed, reliability in meeting deadlines and greater flexibility, potentially resulting in increased sales. With a reduction in production lead time, provided by maintaining protective capacity in production resources, companies now have the possibility of offering shorter delivery times than those generally expected in the sector, while additionally being able to accept urgent orders (Schragenheim, 2006; Goldratt, 2009; Schragenheim et al., 2009; Schragenheim, 2010; Souza & Baptista, 2010; Ikeziri et al., 2019; Orue et al., 2021).

TOC proposes that planning should be carried out in order to identify the constraint of a system, elaborate a set of decisions that enable it to be exploited in the best way (drum), establish a buffer mechanism to protect it, and subordinate the other resources to the drum (rope). When applied in demand constraint environments, this so-named Drum-Buffer-Rope (DBR) system undergoes changes and simplifications, reflected in a new denomination by which it is increasingly known: the Simplified Drum-Buffer-Rope (S-DBR).

Considering MTO environments with demand constraints and planning managed by S-DBR, Schragenheim (2006) established a method based on subdividing the available capacity of a system so that part of it is used to meet regular orders and the other part to meet urgent orders. Despite the simplicity of their method, urgent orders are accepted without a precise verification of available capacity, therefore demanding greater attention during the production control stage (Souza & Baptista, 2010).

Although dealing with urgent orders in MTO environments managed by the S-DBR system is a relevant and challenging issue, there is a paucity of studies in the area. Souza & Baptista (2010) were unique in studying this topic. Using a search string based on Ikeziri et al. (2019) and restricting studies to 2010 onwards, we identified that only Souza & Baptista (2010) studied this theme. They proposed an approach based on the following principle: when an urgent order is accepted, orders with longer deadlines are shifted forward in time, delaying their initiation and completion. Therefore, an urgent order can only be accepted if its consignment does not wholly consume the slack time of orders already accepted.

Although the method proposed by Souza & Baptista (2010) is logically structured and apparently more robust than that proposed by Schragenheim (2006), no other study has sought to model it as a way of further evaluating its effectiveness. This, therefore, is the aim of the present work: to model, simulate and analyze the performance of the method proposed by Souza & Baptista (2010). To this end, the research question presented here is "what are the advantages and disadvantages that the Souza & Baptista (2010) method brings in relation to the method initially proposed by Schragenheim (2006)?"

Using the AnyLogic software, different scenarios of a simulated production line operating in an MTO environment, whose production management is based on the S-DBR system, were studied. To evaluate the performance of the simulated scenarios, average delay and percentage of late orders were used as performance indicators.

The remainder of this paper is structured as follows. Section 2 presents a theoretical grounding of the concepts addressed in the study. Section 3 describes the methodology applied, and the results are presented and discussed in Sections 4 and 5, respectively. Finally, Section 6 concludes the article and suggests future research opportunities.

2. Theoretical grounding

This section aims to provide a theoretical grounding as justification for conducting the research, by presenting a brief explanation of the DBR and Buffer Management (BM) system, the S-DBR, the commitment to urgent orders and the research methods explored.

2.1. Drum-Buffer-Rope and Buffer Management

Classic DBR is one of the production planning methods proposed by TOC. It assumes that a system's main constraint is an internal resource of the production system (capacity constraint resource – CCR) that, if not programmed in detail, can become a bottleneck, that is, an active CCR. In DBR, therefore, the drum refers to the detailed programming of the CCR, which is carried out by the production load imposed by the customer orders, and the number of setups to be performed and their sequence (Souza, 2005; Schragenheim et al., 2009; Srikanth, 2010; Souza & Baptista, 2010; Santos & Alves, 2014; Pacheco, 2014).

TOC proposes a protection in the form of time, called a buffer (Srikanth, 2010; Cox III et al., 2012). The buffer can also be understood as a liberal estimate of the manufacturing lead time between two control points (Schragenheim et al., 2009). There are three types of buffer: constraint buffer (located between CCR and the raw material release), assembly buffer (between release and assembly), and shipping buffer (between CCR and market) (Souza, 2005; Schragenheim et al., 2009; Srikanth, 2010; Souza & Baptista, 2010; Santos & Alves, 2014).

Finally, the rope is the mechanism by which all resources are subordinated to the decision of how best to exploit the constraint of a system. The rope “ties” all resources to a few points of control and releases material to the factory floor, avoiding the accumulation of unnecessary work-in-process (WIP) and, therefore, offering a faster flow of products through a system (Souza, 2005; Schragenheim et al., 2009; Srikanth, 2010; Souza & Baptista, 2010; Santos & Alves, 2014).

Production control and sequencing are carried out using the BM method. BM works with the buffer status (BS) concept, which basically calculates how much a certain production order has consumed from its buffer and, based on that, establishes three attention zones or prioritization colors. In the green zone are the orders that consumed less than 1/3 of the buffer and, therefore, do not yet require management attention. In the yellow zone, penetration of orders is between 1/3 and 2/3 of the buffer, giving a warning signal. In the red zone, the penetration is greater than 2/3, and such orders must be expedited if late delivery is to be avoided (Souza, 2005; Schragenheim et al., 2009; Srikanth, 2010; Schragenheim, 2010).

2.2. Simplified Drum-Buffer-Rope (S-DBR)

The main difference between the DBR and S-DBR methods lies in the fact that DBR admits that, and even encourages, the main constraint of the system is its CCR, with consequent methodological needs as presented in the previous section.

The S-DBR, on the other hand, admits that, for a considerable number of companies, the constraint of a system is on its demand; that is, the resources (including the CCR) have capacity to meet demand with a certain slack, most of the time. In this scenario, therefore, all of a company’s resources have protective capacity. In this way, production initiates with only one buffer, called production buffer (PB), whose objective is to protect the delivery dates of orders. The PB must encompass the entire production flow, from the release of raw materials to delivery. Another important difference is that in S-DBR, the detailed CCR schedule is replaced by a method which monitors the load on available resources – called the planned load – which aims to ensure the delivery of products within a certain time interval, and to monitor whether a CCR is becoming active (a bottleneck). Mathematically, considering $tccr_{it}$ and Q_{it} to be, respectively, the unit processing time of the CCR and the quantity of product i planned to be processed by the CCR in a time horizon T, the planned load can be expressed by (Schragenheim et al., 2009; Souza & Baptista, 2010; Schragenheim, 2010) (Equation 1):

$$planned\ load\left(T\right)=\sum_{i=1}^{I} trrc_{it}\ x\,Q_{it}, \forall t \leq T \tag{1}$$

Another important factor in planned load is assessing the safe completion dates for orders. These are established by the planned load (including the order processing time in the CCR) plus ½ PB. The release of materials for a specific production order must be carried out ½ PB before the projected planned load, matching the acceptance of the order. That is, the production order must be released to the shop floor when there is one PB time left for completion. This mechanism aims to reduce WIP and avoid overloading the CCR with unnecessary work over a given timeframe (Schragenheim et al., 2009; Souza & Baptista, 2010; Schragenheim, 2010). Figure 1 illustrates these calculations.

Figure 1 shows a synthesis of the S-DBR concept applied in MTO environments. The histogram at the bottom of the figure represents the CCR planned load. Adding the order processing time and half a PB gives a safe date that can be promised to a customer. Subtracting a PB from this date logically gives the release date of production material to the shop floor.

To clarify this concept, consider the following example adapted from Souza & Baptista (2010): a company works eight hours a day, five days a week, with a BP of 5 days (40 hours of work). The industry standard term is 20 days or 160 hours of work. On a given day, an order from one of its customers is received. To accept this order, the company calculates the planned load on the CCR, which includes the order under review, resulting in 90 hours. The promised delivery time for this order should be the planned load plus half a production buffer.

Therefore, a reliable delivery date would be around 14 days (90 + 0.5x40 = 110 hours ≅ 14 days) and the release of the material for this order would take approximately 9 days (90 -0.5x40 = 70 hours ≅ 9 days). Therefore, any period stipulated above 14 days constitutes a safe delivery date for the customer. It is noteworthy that, based on this calculation, the company is able to offer a shorter delivery term than that expected by the sector.

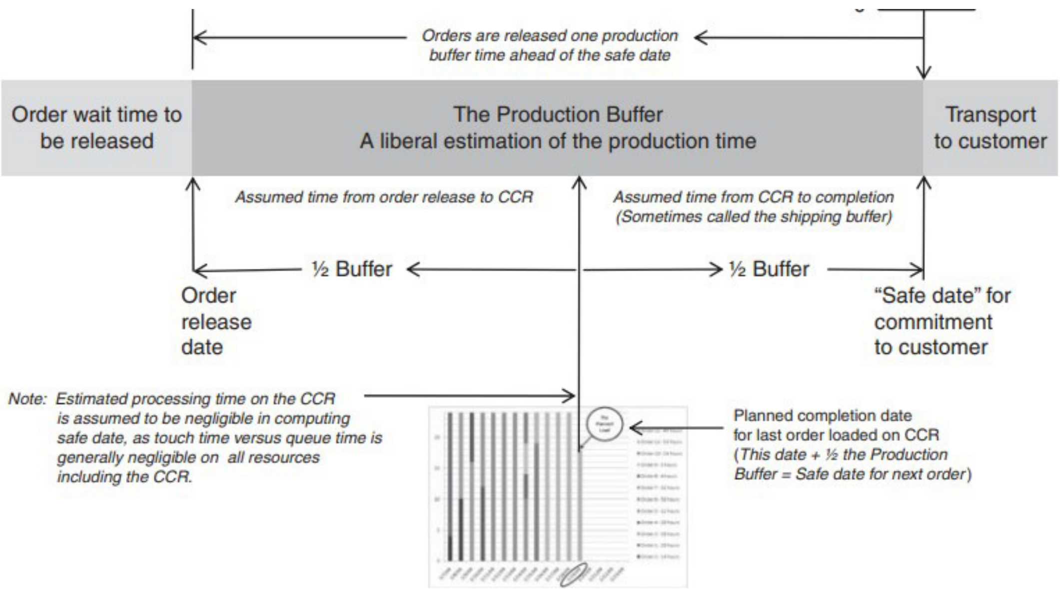

Figure 1. Planned load and calculation logic for the release of an order and promised delivery dates. Source: Schragenheim (2010).

2.2.1. Recent studies

Relying on Ikeziri et al. (2019), a search for studies focused on the S-DBR method was carried out on the Scopus database. Among the studies found were those that showed production system improvements with S-DBR, which permitted greater flow (Buestán Benavides & Van Landeghem, 2015; Hales & Chakravorty, 2016) and reductions in response times (Hales & Chakravorty, 2016).

Some obstacles to the effectiveness of the S-DBR were identified, such as the assumption that the CCR is located in the middle of the flow (or close to such a position) and that, in some cases, a lack of reliability causes a drop in system performance (Lee et al., 2010; Buestán Benavides & Van Landeghem, 2015). Notably, interactive CCRs constitute an obstacle to the implementation of S-DBR (Lee et al., 2010). Other studies suggested adaptations and modifications as a means of working with planned load to improve S-DBR performance (Chang & Huang, 2014), while Govoni et al. (2021) evaluated a number of improvement methods and highlighted that different production line configurations require different improvement approaches.

Another prominent S-DBR theme is the definition of target level (TL) in make-to-stock environments. Parsaei et al. (2012) suggested the importance of TL in the sequencing of production orders and the subsequent release of materials. Narita et al. (2021) and Ikeziri et al. (2023) investigated the performance of the Dymanic Buffer Management (DBM) method in different scenarios, while Castro et al. (2022) focused on an evaluation of sequencing rules.

Souza & Baptista (2010) suggested a way of dealing with urgent orders in MTO environments managed by S-DBR, whose approach is referred to in this paper as "due date promise by slack time rule" (DDPSTR). Such an approach verifies, on the acceptance of an urgent order for rapid delivery, the consumption of the slack of orders with longer deadlines, which are shifted forward in time, delaying their start and completion. Therefore, an urgent order can only be accepted if the load imposed on the CCR does not totally consume the slack time of prior accepted orders that have longer delivery times.

2.3. Dealing with urgent orders

S-DBR implementations allow lead time reduction and increased delivery performance, potentially providing an increase in demand. In addition, a company's sales force will be less burdened by following up on orders and dealing with dissatisfied customers, which in turn allows them to focus on increasing sales. With a reduction in production lead time, many companies reach a PB smaller than the lead time of the sector, with a consequent protective capacity and the possibility of accepting urgent orders without compromising those previously accepted.

That is, if a given order is committed to a delivery time equal to or greater than one PB, an order buffer is created, as shown in Figure 2. This order will remain in the green region of the order buffer for a longer period of time, allowing other more urgent orders to pass in front of it, without compromising on-time delivery. This mechanism has two advantages: i) it does not waste CCR capacity, since, if there are no new urgent requests, a prior request will be processed without leaving the resource idle and ii) the correct priorities are maintained on the shop floor (Schragenheim, 2006; Goldratt, 2009; Schragenheim et al., 2009; Souza & Baptista, 2010; Schragenheim, 2010).

2.3.1. Method proposed by Schragenheim (2006)

One way of dealing with urgent requests is offered by Schragenheim (2006), who proposes that the planned load calculated for regular requests should correspond to a percentage of the total available capacity of a CCR (for example, 70% to 80%), leaving the remaining capacity available for urgent requests. Henceforth, this method will be here called Rapid Response (RR).

To illustrate this concept, let us return to the example adapted from Souza & Baptista (2010). As seen, the planned load on the CCR was 90 hours of work. The company realized that the application of S-DBR meant it could work with shorter lead times than the industry standard. Using the concept proposed by Schragenheim (2006), it reserved 70% of CCR capacity for its regular orders and 30% for urgent orders. Therefore, the new planned load for regular orders was approximately 128 hours (90/0.70), so the company could deliver a new order in 18.5 days (128+20=148 hours), a period even shorter than that commonly practiced within the sector, of 20 days. As this is a regular request, the author recommends offering a period equivalent to 20 days, releasing protective capacity for the CCR.

In this case, the material should be released 13.5 days (128-20=108 hours) from now on. Urgent orders, offered with delivery times of, for example, 15, 10 or 5 days, will be accepted with confidence knowing that sufficient capacity (30%) is dedicated to them. The materials for orders placed within 15 days will be released after 10 days (15 days for delivery minus 5 days of PB). Similarly, the materials for orders placed within 10 days will be released within 5 days and material for orders to be delivered within 5 days released from the factory floor immediately.

It is worth mentioning that the feasibility of rapid response (RR) orders already accepted or under analysis, can be verified by the planned load on the CCR calculated over a time horizon equivalent to the corresponding delivery period. If the planned loads for each of the three deadlines suggested above (15, 10 and 5 days) are lower than the delivery date minus half a PB, an order will probably not be delayed. If a delay is inevitable, it may be necessary to take short-term capacity enhancement actions, such as working extra hours and shifts or even denying the request. This procedure requires simulations of planned load calculations for each new order under analysis.

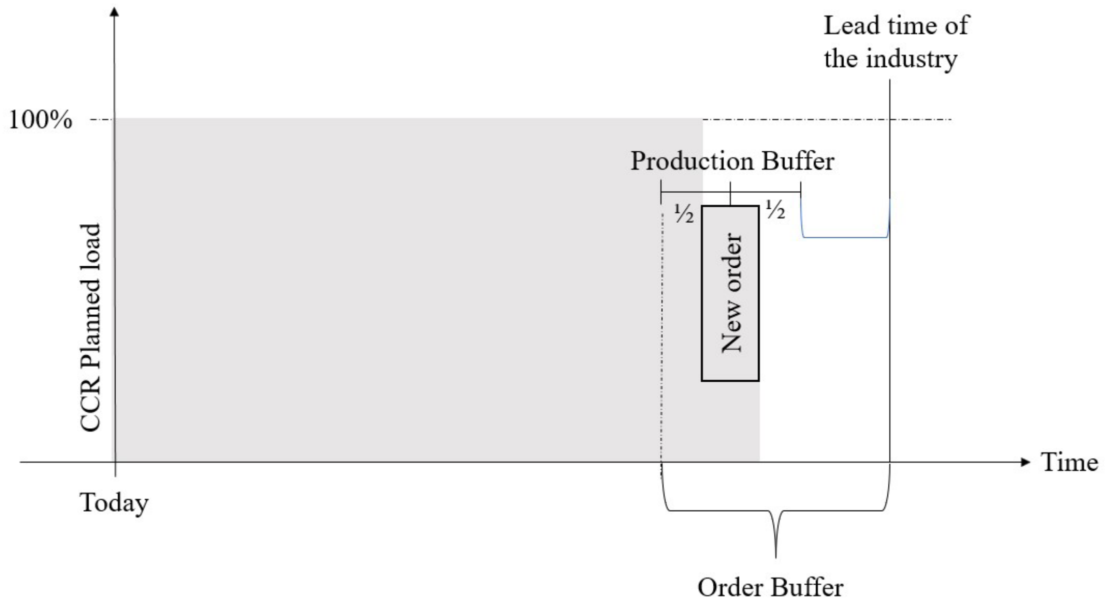

Figure 2. Representation of the order buffer. Source: Adapted from Souza & Baptista (2010).

In the present study, when urgent orders are processed without prior verification of the reserved planned load, - that is, RRC capacity is partitioned and incoming orders are automatically accepted - the method will be referred to as "capacity reserve without load verification" (CRWoLV). If the CCR load is checked whenever urgent orders are received - and, if it exceeds the reserved amount, such requests are refused -, the method will be referred to as "capacity reserve with load verification" (CRWLV).

2.3.2. Method proposed by Souza & Baptista (2010)

Although the method proposed by Schragenheim (2006) deals with RR orders and is simple, the acceptance of such orders requires load simulations, greater control of the shop floor and increased short-term capacity management effort (Souza & Baptista, 2010).

Souza & Baptista (2010), on the other hand, suggest an approach based on the principle that acceptance of RR requests postpones the initiation and completion of requests with later deadlines. By the DDPSTR method, an order can be accepted if and only if its payload does not totally consume the slack time of previously accepted orders. Therefore, the algorithm should start with the calculation of the slack time of regular orders, given by the following formula (Equation 2):

$$ST_i = DD_i - PL - \frac{1}{2}PB \tag{2}$$

Where PB is the production buffer, ST_i is the slack time of the order i, DD_i is its promised due date and PL is the planned load on the CCR. Thus, whenever a regular order i is accepted, its slack time (ST_i) must be calculated.

Based on this calculation, whenever the sales team receives an RR-type order (RR_j), the load that this order imposes on the CCR (L_j) should be verified and subtracted from the slacks of all the orders already accepted and with prior deadlines (ST_k). Mathematically, the slack of the urgent delivery order j in relation to m previously accepted orders with prior deadlines k $(STRR_{jk})$ can be expressed by the following formula (Equation 3):

$$STRR_{jk} = ST_k - L_j, \forall 1 \le k \le m \tag{3}$$

Assuming $STRR_{jk} \ge 0$, then the urgent delivery order j can be accepted and the slack of all existing orders updated, taking the value of the prior slack minus the load which the order RR_j imposes on the CCR. The slack of order RR_j is given by

$$STRR_j = DD_j - PLH_j - \frac{1}{2}PB \tag{4}$$

Where DD_j and PLH_j are, respectively, the delivery date and the planned load on the CCR to be delivered on a time horizon H inferior to DD_j.

Souza & Baptista (2010) reinforce the view that the shortest promised deadline for an order must be limited by the PB, guaranteeing protection and high reliability for the delivery date. However, given that the DBR method (proposed by Goldratt) implies that it is possible to deliver orders when there is only half of the dispatch buffer available, the S-DBR method declares that delivering orders in ¼ of the PB is possible. Therefore, it is necessary that less than 10% of the production orders are in this situation, that there is short-term capacity management and that the customer and the company are aware of the risks. Finally, once the delivery dates have been defined for a given customer, the material is released one PB before the promised deadline.

To illustrate the DDPSTR method, we return once more to the example adapted from Souza & Baptista (2010). The planned load on the CCR is 90 hours of work and an urgent order was received, here called the RR Order, whose processing time through the CCR is 2 hours, with delivery promised in 80 hours (or 10 days). By the proposed method, the first step is to list all the orders whose delivery times are greater than 80 hours, since this new order will shift prior orders forward in time. Among

these requests, five had a relatively small slack time: Order X – slack of 0.25 hours; Order Y – slack of 0.5 hours; Order Z – slack of 1.5 hours; Order W – slack of 2.0 hours; and Order T – slack of 3.0 hours. Following this, the impact of the eventual acceptance of the RR order was evaluated. To do this, the slack time of each of the prior orders was subtracted from the processing time of the RR Order in the CCR, whereby the slacks of orders X, Y and Z become negative and order W equal to zero. Thus, the urgent order should not be accepted, as it would delay the shipment of orders X, Y and Z. However, in this scenario the production manager then realizes that the slack times of orders X, Y and Z were wrong and their real values were 2.25 hours, 3.5 hours and 4.0 hours, respectively. Under such conditions, the new request can be accepted, since $STRR_{jk} \ge 0$ for all of the orders $(ST_w = 0, ST_x = 0.25\,hours, \ldots)$.

With the new order accepted, the slack for all orders whose deadlines were longer than 80 hours are updated, subtracting the load of the RR Order on the CCR. To calculate the slack time of the RR Order itself, the planned load for orders to be delivered within 80 hours (10 days) must be obtained. This load must be subtracted from the 80 hours of the order period, as well as half a PB (in this case, ½ x 40 hours = 20 hours). Assuming that the load on the CCR is 58 hours, the RR Order slack would assume a value of 2 hours (80 - 58 - 20 = 2 hours).

3. Methodological procedures

To ensure that analysis of the proposed model takes into account the variability and uncertainties typical of productive environments, simulation was chosen as a research method, allowing new theories to be developed and knowledge about existing theories expanded (Davis et al., 2007; Banks et al., 2004; Borges et al., 2020). A further point that justifies the choice of simulation is that it has already been used to analyze the DBR, S-DBR and BM methods (Ok & Park, 2014; Millstein & Martinich, 2014; Lee & Seo, 2016; Thürer & Stevenson, 2018; Castro et al., 2022; Narita et al., 2021; Govoni et al., 2021; Thürer et al., 2022; Costa et al., 2023; Ikeziri et al., 2023).

The software chosen was AnyLogic, whose modeling is based on agents, which enables the creation, testing and analysis of various complex models that interact with each other. In addition, the software is versatile, providing both highly-detailed analysis of the behavior of the system over time in addition to the more summarized information; that is, while having "native" software elements such as agent, delay, source and sink, it also allows various functions and events to be programmed within the model. Furthermore, the 2D and 3D visualizations offered by AnyLogic provide verification and validation, thus avoiding bugs and other data inaccuracies due to programming and/or modeling failures (Taylor, 2014; Avdeeva et al., 2020; Borges et al., 2020; Chasanah & Sakakibara, 2022).

3.1. Construction of the model

The model built in the present work is axiomatic, that is, directed to idealized models of the problem, since the main objective was to evaluate and compare the methods proposed in the literature (Suh et al., 1998; Bertrand & Fransoo, 2002; Kulak et al., 2010). The first step of constructing the computational model was to define the production line. Thürer & Stevenson (2018) comment that in simulations of the DBR method, a direct flow is normally used. For our model, we chose linear and direct flow, with the CCR located in the middle of the flow, since, as pointed out by Lee et al. (2010), when a CCR is in other positions, the assumption of the ½ buffer rule may not be valid. Our simulated theoretical production line involved seven machines, with machine number 4 (in the middle of the production flow) being the CCR of the model. Orders were generated daily; that is, at the end of each day the demands for each product were computed and production orders generated for the following day. Three different delivery times were defined for three different products, P1, P2 and P3, whose demands were stochastic (see section 3.2) and equally different. The model built in the Anylogic software is shown in Figure 3. The flowchart in Figure 4 illustrates the system logic of the computational model.

For comparison purposes, three different ways of accepting urgent orders were evaluated: capacity reserve method proposed by Schragenheim (2006), with (CRWLV) or without load verification (CRWoLV) for accepting orders, and the DDPSTR method developed by Souza & Baptista (2010).

The method for accepting orders with capacity reserve allocates part of the CCR load to regular orders and the remainder to urgent orders. Therefore, for simulation purposes, the procedure was as follows:

- Load on the CCR equal to 85%: approximately 59% (70% of 85%) of the available capacity of the CCR was allocated to meet regular orders and 26% (30% of 85%) to meet urgent orders;
- Load on the CCR equal to 95%: approximately 67% (70% of 95%) of the available capacity of the CCR was allocated to meet regular orders and 28% (30% of 95%) for urgent orders.

To clarify the difference between the methods, the following example was considered: a given urgent order is received and its deadline must be evaluated. The DDPSTR method calculates the slack for orders with later dates and checks if there is a possibility that this urgent order will be accepted, by analyzing the consumption that the order will impose on the slack of all prior orders with later delivery dates. In the CRWoLV method, however, the percentage of capacity allocated for regular and urgent order requests is trusted; that is 30% and 70%, respectively. The CRWLV method, on the other hand, checks whether urgent order requests are exceeding the reserve of 30% of the capacity intended, and new urgent requests are refused if they are.

The performance measures used in the simulation were: average delay (obtained as an average of order delays in relation to the total number of orders generated) and percentage of late orders (obtained from the number of late orders in relation to the total number of orders generated). For verification purposes, a 2D visual model was built in the software, with information regarding the stock, machines and production orders, such as sequence, product, delivery date, quantity and value of buffer penetration displayed on the screen (to check the BM). The simulation was interrupted at each event of interest, visually checking the system. The first verification concerned the generation of production orders, according to which, at the end of the day, demands should be generated for products P1, P2 and P3 with regular, fast (shorter than the regular) and super-fast (shorter than the fast) deadline delivery dates.

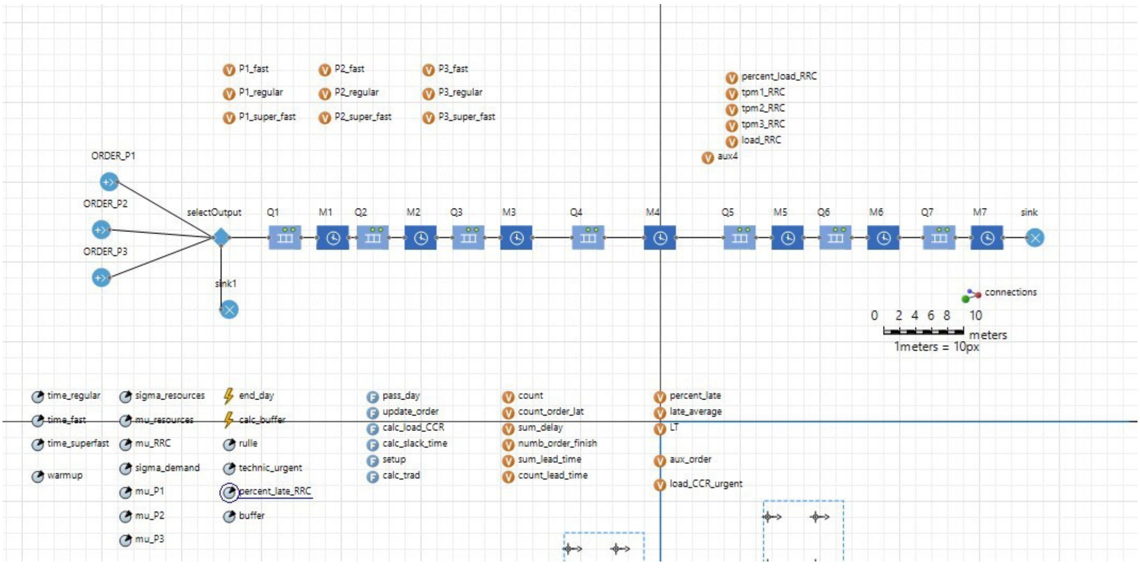

Figure 3. Representation of the model in Anylogic.

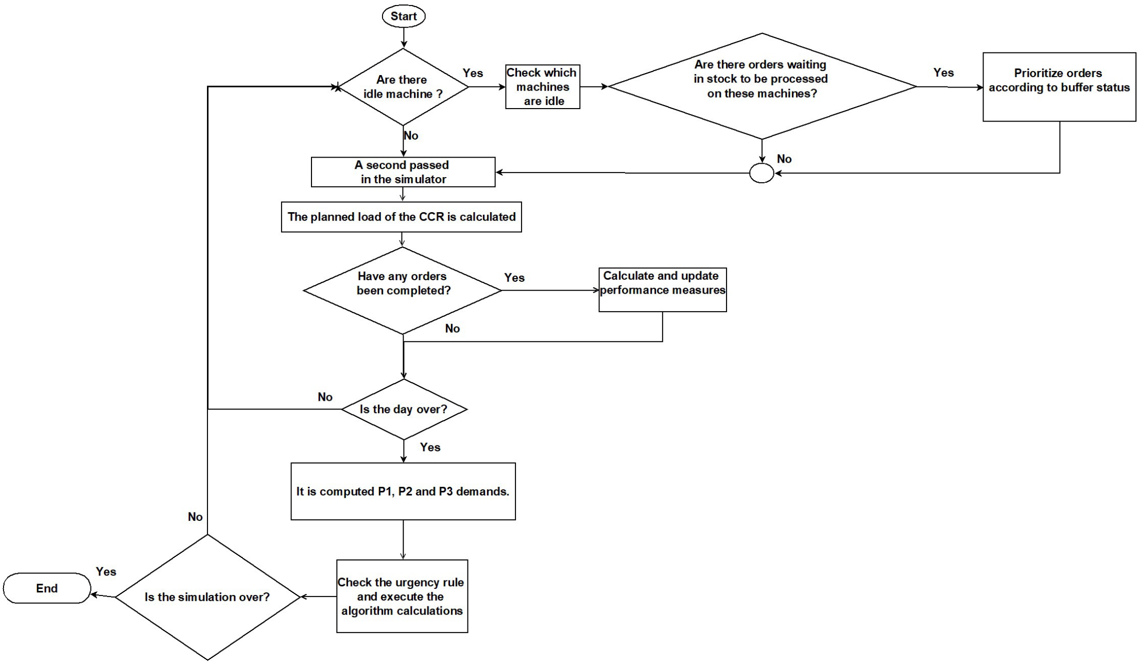

Figure 4. Representation of the logic of the model.

Order completion dates were kept constant. For example, in the same scenario, all fast deliveries have the same completion deadline, achieved by varying the order quantity using a lognormal probability distribution. The second verification was BM function, evaluating the remaining time for completing the orders, the buffer, the calculation of the associated numerical values, which orders were loaded in the machines and if they were compatible with the BM. Finally, the two methods of assessing the feasibility of delivering orders on time were compared.

3.2. Experiment planning

Loads of 85% and 95% occupation of the capacity of the theoretical line CCR (machine 4 of the model) were simulated. The loads of the other resources were also established in two levels, 70% and 85%, respectively. By this method, an average daily demand was defined for P1 of 15 units, P2 of 20 and P3 of 10 units, with 70% of this demand referring to regular orders, 20% to fast orders and 10% to super-fast orders. Once the average demand was defined, it was divided by the daily available time to obtain the average resource processing times. To simulate variability in demand and internal resources, the lognormal probability distribution was chosen (Diglio et al., 2021; Gonzalez-Neira et al., 2021). Based on Hopp & Spearman (2011), two levels of coefficient of variation (CV) were established: high (CV=1.5) and low (CV=0.5). Such levels were defined both for the demand and for the processing times of resources, in such a way that the standard deviations varied and the averages of the processing times and the quantities demanded remained the same. Table 1 summarizes the scenarios.

Delivery times were obtained as follows: for each of the proposed scenarios, a prior simulation was performed, obtaining the average lead time for that period. In the odd-numbered scenarios, the PB was obtained by adding a 50% protection to the lead time, and in the even-numbered scenarios, a 25% protection was added. Values were rounded to an integer number of days. For example, in scenario 1, after simulation, the PB was calculated as 1.5 times the average production lead time, that is, 1.5 times 0.75 which, rounded up, corresponds to two days. In scenario 2, the PB was calculated as 1.25 times 0.75 which, rounded up, corresponds to one day.

In this research, and based on Schragenheim (2006) and Souza & Baptista (2010), were defined three delivery times: super-fast, fast and regular. The super-fast delivery is the shortest practicable production lead time, which is one PB. Fast delivery was chosen to have a delivery time 50% longer than super-fast, and regular delivery, in turn, twice as long as super-fast.

Finally, two important parameters were defined: the number of replications to be performed and the simulation time. Each scenario was replicated 150 times and each simulation covered a period of one year and six months. The warm-up time was set to 180 days, representing half a year of simulation. The warm-up time and the minimum number of replications were obtained, respectively, by applying the Marginal Standard Error Rule and confidence interval methods, in accordance with Robinson (2004).

4. Results and discussions

The results obtained from the simulations can be seen in Table 2.

With the aim of verifying data normality, the Shapiro-Wilk test was performed. Where the data of the 150 simulation replications are identical, the cell is filled with "IDENT DATA". Thus, considering a significance level of 5%, in all situations, at least one of the methods did not meet the data normality condition. It was necessary, therefore, to perform non-parametric tests to compare the methods. The Friedman test was applied, for this purpose, to identify whether there were significant differences between at least two rules.

Table 1. Summary of the simulation scenarios.

Scenario	Load	CV of the processing times	CV demand	Normal deadline (days)	Fast deadline (days)	Super-fast deadline (days)	Lead time (days)
1	85/70	0.5	0.5	4	3	2	0.75
2	85/70	0.5	0.5	3	2	1	0.75
3	85/70	1.5	1.5	6	5	3	1.47
4	85/70	1.5	1.5	4	3	2	1.47
5	95/85	0.5	0.5	6	5	2	1.53
6	95/85	0.5	0.5	4	3	2	1.53
7	95/85	1.5	1.5	16	12	8	4.75
8	95/85	1.5	1.5	12	9	6	4.75

The results of the tests are shown in Tables 3 and 4. Considering a significance level of 5%, there was a rule that was not normal in all scenarios; in addition, there was a significant difference in all scenarios except in 1. Therefore, the Nemenyi test with Bonferroni correction was performed to identify which rules had significant differences at the 5% significance level. These results are given in Tables 5 and 6.

Looking at Table 1, we can observe that increases in resource utilization led to increases in lead time, being in line with the utilization law proposed by Hopp & Spearman (2011) that increases in utilization without any other changes to the system, causes increases in WIP and lead time). This fact can be observed by comparing scenarios 1 and 2 with 5 and 6 and scenarios 3 and 4 with 7 and 8.

In addition, increases in variability also caused increases in lead time. Hopp & Spearman (2011) show that, in a production system, variability forms safety reserves as a combination of stock, capacity, and time, and increases in variability cause safety reserves to increase. As in the simulated environment, we do not work with finished product inventory, because it is an MTO system, as soon as there was no increase in capacity on the line, increases in variability increased the lead time, as can be seen by comparing scenarios 1 and 2 with 3 and 4 and scenarios 5 and 6 with 7 and 8.

Table 2. Average delay and percentage of orders delayed per scenario.

SCENARIO	DDPSTR		CRWoLV		CRWLV	
	AVERAGE DELAY (days)	% DELAYED	AVERAGE DELAY (days)	% DELAYED	AVERAGE DELAY (days)	% DELAYED
1	0.00000	0.000%	0.00015	0.007%	0.00002	0.001%
2	0.03621	3.298%	0.05011	4.441%	0.04871	4.161%
3	0.09071	1.079%	0.64800	8.456%	0.43718	6.097%
4	0.11977	1.626%	0.97330	14.313%	0.71463	11.131%
5	0.00000	0.000%	0.11171	1.798%	0.00323	0.078%
6	0.00000	0.000%	0.30401	5.413%	0.03518	1.299%
7	0.00799	0.045%	2.91971	13.998%	0.65273	3.595%
8	0.03036	0.217%	4.22031	25.087%	1.01432	8.058%

Table 3. Normality and Friedman tests for the average delay.

AVERAGE DELAY				
SHAPIRO WILK (NORMALITY)				Friedman Test
SCENARIO	DDPSTR	CRWoLV	CRWLV	
1	IDENT DATA	2.2E-16	2.2E-16	0.8317
2	0.0007392	2.2E-16	1.55E-14	2.2E-16
3	2.2E-16	4.78E-14	2.83E-14	2.2E-16
4	2.2E-16	6.948E-16	2.61E-09	2.2E-16
5	IDENT DATA	2.2E-16	2.2E-16	3.76E-11
6	IDENT DATA	2.2E-16	2.2E-16	2.2E-16
7	2.2E-16	2.2E-16	2.2E-16	2.2E-16
8	2.2E-16	1.468E-13	1.12E-14	2.2E-16

Table 4. Normality and Friedman tests for the percentage of late orders.

PERCENTAGE OF LATE ORDERS				
SHAPIRO WILK (NORMALITY)				Friedman Test
SCENARIO	DDPSTR	CRWoLV	CRWLV	
1	IDENT DATA	2.2E-16	2.2E-16	0.9275
2	0.0002679	7.292E-08	2.943E-10	2.2E-16
3	3.097E-16	1.702E-10	1.733E-10	2.2E-16
4	3.156E-14	2.692E-09	0.00001235	2.2E-16
5	IDENT DATA	2.2E-16	2.2E-16	1.842E-10
6	IDENT DATA	2.2E-16	5.838E-16	2.2E-16
7	2.2E-16	9.995E-17	2.2E-16	2.2E-16
8	2.2E-16	3.965E-10	2.86E-13	2.2E-16

Because the delivery times had adjusted according to the variations in lead time, comparisons between scenarios were compromised. However, by analyzing Tables 1 and 2, we can conclude that reductions in lead time decreased system performance since the protection (in the form of time) of the system was decreased. In addition, increases in resource variability, even with a better offered delivery times, worse the performance.

The results reveal that reductions in delivery times and increases in variability worsened system performance, as well as illustrate the relationship between the presence of protective capacity and the ability to offend short deadlines, while also compromising the output of the production line. These facts are in line with both Hopp & Spearman (2011) and Schragenheim et al. (2009). In particular, however, as already stated, the models developed have the characteristic of adjusting delivery deadlines according to variations in the system loads and variability, which makes sensitivity analysis difficult from these factors. It is worth mentioning that although the AnyLogic software allows, in its professional version, to perform sensitivity testing of the parameters, the authors did not have access to this version.

Regarding the performance of the methods, DDPSTR performed better than CRWoLV and CRWLV in all scenarios, with a significant statistical difference in all of them, except for scenario 1. It is worth noting that scenario 1 – as well as scenario 2 – have the bigger protective capacity in resources with the lowest levels of variability in demand and processing time. This allows the system to handle practically all order requests, reducing the relevance of having a rejection rule.

Table 5. Nemenyi test for the average delay.

	SCENARIO 1			SCENARIO 2	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	0.66	-	CRWoLV	2.00E-16	-
CRWLV	0.71	1	CRWLV	2.00E-16	0.62
	SCENARIO 3			SCENARIO 4	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	2.80E-14	-	CRWoLV	2.00E-16	-
CRWLV	2.30E-14	0.15	CRWLV	2.90E-14	0.11
	SCENARIO 5			SCENARIO 6	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	0.00017	-	CRWoLV	2.30E-14	-
CRWLV	0.03406	0.27446	CRWLV	2.00E-16	0.11
	SCENARIO 7			SCENARIO 8	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	2.20E-14	-	CRWoLV	2.00E-16	-
CRWLV	1.20E-05	6.10E-05	CRWLV	2.80E-14	2.10E-05

Table 6. Nemenyi test for the percentage of late orders.

	SCENARIO 1			SCENARIO 2	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	0.55	-	CRWoLV	2.00E-16	-
CRWLV	0.62	0.95	CRWLV	2.00E-16	0.59
	SCENARIO 3			SCENARIO 4	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	2.50E-14	-	CRWoLV	2.00E-16	-
CRWLV	3.90E-14	0.15	CRWLV	1.10E-14	0.35
	SCENARIO 5			SCENARIO 6	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	0.00014	-	CRWoLV	2.70E-14	-
CRWLV	0.01201	0.27446	CRWLV	4.00E-15	0.35
	SCENARIO 7			SCENARIO 8	
	DDPSTR	CRWoLV		DDPSTR	CRWoLV
CRWoLV	2.30E-14	-	CRWoLV	2.00E-16	-
CRWLV	2.10E-05	4.70E-05	CRWLV	2.90E-14	2.40E-05

In addition, it is worth noting that CRWLV outperformed CRWoLV in all scenarios. However, it only showed significant statistical difference in scenarios 7 and 8. Therefore, checking whether urgent requests will exceed the load assigned to them can generate benefits for the company. However, it should analyze whether the choice of this method is justified. Because, the CRWLV generates good benefits in determined scenarios, especially where there is high resource utilization and high variability. In other scenarios, such as those with low variability and utilization, your choice wasn't justified, as it is more sophisticated and requires more calculations.

Therefore, the results indicate that the DDPSTR is the best option, among the alternatives tested and within the research scope, in working with urgent orders, by reducing the average delay and the percentage of late orders. However, using the rule also implies rejecting urgent orders when the slack from prior regular orders does not provide sufficient processing time for urgent order, and resulting in a drop in the number of accepted orders. Such a characteristic can decrease profitability in the short term, but in the long term can help sustain a company's image and protect future sales. It is worth noting that the rejection of an urgent order does not necessarily imply its loss, as the sales team may be able to negotiate a deadline change with the customer. For this purpose, the DDPSTR method can verify which production orders have slack times that would not initially support a given urgent request and then make the necessary adjustments to promise a delivery date immediately superior to the longest term of such prior orders.

Furthermore, DDPSTR and CRWLV do not "choose" the rejection of requests; that is, they are performed according to input order and algorithmic calculation. In real situations, a company may choose to prioritize urgent orders from certain customers over others. This would be done as a determination that orders from specific customers are evaluated in order of "importance". For example, orders from one day can be accumulated and later checked for viability, with customers kept informed of order delivery changes.

Another point that should be highlighted is that the methods under analysis are not "stand alone"; that is, they must be judged in the context of the presence of a production planning and control system acting along the lines of the S-DBR. This assumes the presence and exploitation of an order buffer and the suppression of the release of material due to the speed being limited by the demand constraint. It also means that production orders, having been released, are prioritized by the BM method.

In practical terms, the method proposed by Souza & Baptista (2010) offers greater calculation complexity, as it requires the slack time for both regular and urgent orders to be calculated and updated, even if already released to the factory floor. With the computational advances and available technologies, such as sensors and labels based on Radio-Frequency Identification (RFID), orders can easily be identified and their position in the production route checked. In addition, big data and cloud computing technologies can aid with calculations and information storage.

In summary, the present worked allowed i) to expand knowledge boundaries in S-DBR methods in MTO environments, since we analyzed some proposed methods for dealing with urgent requests, highlighting the good performance of DDPSTR in relation to the forms recommended by the literature and, ii) in practical terms, it offers an alternative method of checking and offering delivery times - regular and urgent - to customers, as well as it points to some potential difficulties in its application.

5. Conclusions

From a computational model constructed in the AnyLogic software, a theoretical production line composed of seven machines producing three different types of products was simulated. Eight different scenarios were created, with two levels of load on the factory, two levels of variability (high for demand and processing times simultaneously or low for both) and two levels of PB.

We could conclude from the results that the DDPSTR method proposed by Souza & Baptista (2010) performed significantly better in all scenarios, except 1, which had low levels of variability and resource utilization.

We recognize that the simplicity of the scenarios simulated and not applying the research object algorithm in a real factory are limitations of the research. Future research could be dedicated to the simulation of more complex production environments, involving assemblies, re-entrant flows and a larger number of products and machines. In addition, investigations could be carried out into the use of the DDPSTR method to promise urgent orders deadlines other than those originally demanded by the customers. Furthermore, future research could be dedicated to the implementation of these algorithms in companies that use the S-DBR system in MTO environments, identifying cultural aspects, the challenges to implementation and the daily effort required to implement the DDPSTR, verifying to what extent its use is feasible in comparison with those methods proposed by Schragenheim (2006).

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