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Visual charts produced by simulation to correlate service rate, resource utilization and DDMRP parameters

Guillaume Dessevre [a], Pierre Baptiste [a], Jacques Lamothe [b] and Robert Pellerin [a]

[a]Département de Mathématiques et de Génie Industriel, Polytechnique Montréal, Montréal, Canada; [b]Centre Génie Industriel, IMT Mines Albi, Albi, France

ABSTRACT

Demand Driven Material Requirements Planning (DDMRP) is a recent method mixing push and pull flow management. Although it claims to be the solution to traditional methods' limitations, the DDMRP method works at infinite capacity: manufacturing or supply orders are launched according to a logic of replenishment of stocks defined as buffers. This article proposes an evaluation of capacity management using visual charts developed by simulation. These charts correlate the bottleneck resource's loading rate to a service rate by considering one of the DDMRP method parameters, the Decoupled Lead Time (DLT). The charts are a decision support tool. They allow identifying to which loading rate the DLTs are representative of the flow times of manufacturing orders and which capacity level to use. We study different workshops, including a real industrial case. Our results show that it is better to control the flow times by adjusting capacity rather than adjust the DLT parameter.

KEYWORDS

Decision support; capacity management; decoupled lead time; DDMRP; simulation

Introduction

Demand Driven Material Requirements Planning (DDMRP) is a production planning and management method introduced by Ptak and Smith (2011). In integrating push and pull flows, this method is based on buffers' strategic positioning along the Bill of Material (BOM). DDMRP is one of the production control systems that emerged recently (Bagni et al. 2021).

As shown in Figure 1, each stock buffer is sized according to the Average Daily Demand (ADU), which can change over time, and several parameters, including the Decoupled Lead Time (DLT), which is defined as the longest upstream lead time not protected by a buffer, the Lead Time Factor (LTF), the Variability Factor (VF) and the Minimum Order Quantity (MOQ).

A replenishment order to the TopOfGreen level is placed anytime a TopOfYellow threshold is exceeded (Equation 1):

$$\text{Physical inventory} + \text{Work - in - process} - (\text{Day demand} + \text{Peak demand}) \leq \text{TopOfYellow} \quad (1)$$

A peak is an original concept of DDMRP. It corresponds to an exceptionally large demand in the backlog over a given time horizon (Ptak and Smith 2016). It generates a replenishment on demand instead of on consumption.

Dessevre et al. (2019) have shown that the choice of DLT can influence shop floor performance, including customer service rate. However, the 'DLT - service rate' relationship still deserves to be clarified. Hopp and Spearman (1996) define a shop floor's service rate as the probability that the order flow times are less than or equal to the allocated lead time. In a DDMRP context, the shop service rate can be defined as the probability that these flow times are less than or equal to the DLT (Equation 2).

$$\text{Workshop Service Rate} = P\{\text{Flow Time} \leq \text{DLT}\} \quad (2)$$

Therefore, the DLT is an important parameter linked to both the service rate and the stock level (because it determines the buffer's zones): a too small DLT will not absorb all the flow times and may cause shortages, degrading both customer service rate and workshop service rate, and a too larger DLT will increase stock levels and the associated costs.

Also, queuing theory shows that flow times in production lines increase drastically when the loading rate increases (Kingman 1962). However, DDMRP operates at infinite capacity, suggesting that scrolling times in a DDMRP managed shop can increase rapidly as the loading rate increases. To answer the capacity issue,

CONTACT Guillaume Dessevre guillaume.dessevre@polymtl.ca Département de Mathématiques et de Génie Industriel, Polytechnique Montréal, Montréal, Canada

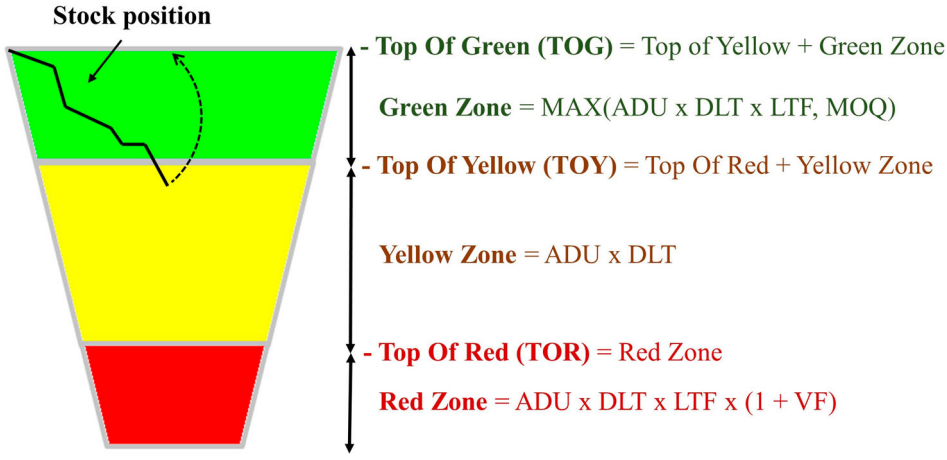

Figure 1. The three zones of a DDMRP stock buffer.

Ptak and Smith (2011) propose a capacity buffer defined as 'the protective capacity at both constraint and unconstraint resources that allows these resources to catch up when Murphy strikes', referring to Murphy's law: what can go wrong will go wrong. Unfortunately, a capacity buffer is just an additional amount of capacity to protect the system: it gives no recommendation, and it may be incorrectly sized.

This paper aims to create visual charts that correlate the bottleneck resource loading rate, the workshop service rate, and the DLT parameter by simulating different DDMRP managed workshops, including an industrial case.

The created charts will help to answer the following questions:

- Up to what loading rate of the bottleneck resource can the DLT absorb flow times?
- What percentage of flow time is less than or equal to this DLT?
- How does the service rate behave according to the loading rate?
- What can a production manager do to get under control the flow times and so the service rate?

Answering these questions will allow a better parameterisation of the DDMRP method, as it will provide an assessment of the sizing of the DLT, with a visualisation of the parameterisation choices' consequences. Moreover, our charts can be used to determine the size of the capacity buffer. This paper is an extension of a previous one Dessevre, Baptiste, and Lamothe (2020), where we go further in the reasoning: we study here a real industrial case, we compare it with our fictional workshop, we answer another management problem (the choice of the number of shifts that the production manager must decide, explaining how to use the charts) and we show limits of the charts. The two papers are complementary in this research project.

This article is organised as follows. First, Section 2 presents a review of the literature on publications related to the topic. Section 3 then describes the research methodology (the workshops studied, the experimental design, and the simulation parameters). Section 4 presents the results, and finally, Section 5 concludes and proposes avenues for further research.

Literature review

First, The DDMRP method is a controversial subject. Often restricted to a 'consultants' method', it has made its way into the academic world with an increasing number of research articles dedicated to it. The first publications have demonstrated the method's relevance by comparing it to other traditional MRPII and Kanban methods, showing the force of the DDMRP: a better compromise between stock level and service rate, the anticipation of peak demand, dynamic adjustment of buffer sizing, and the ability to work with high product diversity (Ihme and Stratton 2015; Miclo et al. 2016; Shofa and Widyarto 2017; Miclo et al. 2018). Today, the field of research on DDMRP has expanded. While some are interested in its strategic perspective, like Vidal et al. (2020) studying the Adaptive Sales & Operations Planning, others focus on the mechanics and operational parameters. For instance, Martin et al. (2018) propose a decision tree allowing a better parameterisation of buffers. Dessevre et al. (2019) are interested in DLT and LTF parameters by putting them under control. Recently Lee and Rim (2019) propose an alternative to the safety stock calculation model. The comparison of DDMRP with other methods is still up to date, as Thürer, Fernandes, and Stevenson (2020)

compare four production control systems, showing the potential of DDMRP in multi-stage assembly systems. Nowadays, studies on DDMRP are both axiomatic and empirical (Bagni et al. 2021). However, there are still many issues to be addressed scientifically, while more and more companies are developing DDMRP in many industrial sectors (Bahu, Bironneau, and Hovelaque 2019). Therefore, researchers aim to study the method in more complex environments (Acosta et al. 2019), raising new questioning from particular industrial sectors (Dessevre et al. 2020), and bringing the need of a standardised implementation process for the method DDMRP (Orue, Lizarralde, and Kortabarria 2020).

Then, we focus on the role of lead time in a workshop in literature. Hopp and Spearman (1996) define 'the lead time of a given routine or line is the time allotted for production of a part on that routeing or line'. They clearly explain that lead time is different from flow time, as the former is a management choice, and the latter is generally random. A good lead time must absorb flow times and their variations, hence Equation 2, but it must but as small as possible to limit stocks: in a DDMRP context for example, the greater the lead time, the greater the DLT, and therefore the greater the stock buffers (Figure 1). Moreover, Christensen, Germain, and Birou (2007) show that lead time is linked to financial performance. That is why a branch in the literature is about 'controllable' times, where these studies focus on reducing lead times in procurement (preparation and transport time) and/or in production (changeover time, production time, speed, batch size, etc.). For example, Sarkar, Mandal, and Sarkar (2015) studied two models with different demand distributions, Jha and Shanker (2013) included a constraint on the service rate in their model, Glock (2012) proposed methods for reducing lead time in a single-vendor-single-buyer model, and many others (Pan and Yang 2002; Ouyang, Wu, and Ho 2004; Hidayat and Simatupang 2018; Shin et al. 2016). Thus, many scientists consider lead times as a decision variable and try to size it as best as possible.

Finally, the factor $\rho/(1\text{-}\rho)$, where ρ represents the loading rate, is present in the formulas for calculating average flow times from the queue theory of 1-server systems: Kingman (1962), Marchal (1976) or Krämer and Langenbach-Belz (1976). Therefore, the higher the loading rate, the more drastically the times increase. To avoid this issue, it is important to control the loading rate, especially for the bottleneck resource. Ptak and Smith (2011) introduce a capacity buffer, which is an additional amount of capacity in order to absorb variability. They explain that 'capacity buffers are not being used […] to maximise a resource's utilisation or efficiency. [They] require that a resource maintain a bank a capacity that goes unused' (Ptak and Smith 2016). But how to determine the size of that bank? And if it is not enough? They answer the former by analyzing the demand variability, and the latter by proposing different long-term methods such as reengineering the products to manipulate the load or raising price to manipulate the demand. Thereby, there is no answer for short-term capacity issues.

As a conclusion of this review, it is known that (i) flow times are correlated with the loading rate (by the queue theory), that (ii) lead time is a decision variable that can be reduced at a certain cost (controllable times), that (iii) the DLT parameter of the DDMRP method is used in the dimensioning of buffers and that (iv) it is an important parameter related to the service rate of the workshop. One question thus arises: How can we control a service rate in a DDMRP-managed shop subject to load variations? To answer this question, we propose to create charts correlating the service rate, the loading rate, and the DLT parameter.

Methodology

Our research strategy is based on the study of two simulated cases: a fictional flowshop and an industrial case. Both cases are similar: products are buffered and manufactured in a workshop where components are buffered too. In this way, there is always a flowshop with a bottleneck station between two buffers. If both cases give similar results, we might work on the fictional case in future research between two buffers, as it is easier to change fictional parameters (number of stages, products, etc.). Simulation has been chosen because it easily allows to model and analyze complex environments with several sources of variability (Mourtzis 2020). Furthermore, the objective is not to optimise but to observe a phenomenon, it is therefore not necessary to develop more 'fine' tools.

This section describes the workshops studied as well as the simulation parameters used.

The ictional lowshop

Workshop parameters

The workshop studied is a production line composed of 6 workstations (one machine per workstation) with DDMRP stock buffers at the beginning and end of the line (for components and finished products, as shown in Figure 2). This type of workshop was chosen since it corresponds to what can be found between two DDMRP stock buffers in the industry.

Since DDMRP performs well in highly variable environments, several sources of variability were introduced into the system (demand, production, etc.). The first machine is subject to 4-hour outages every 36 h and the

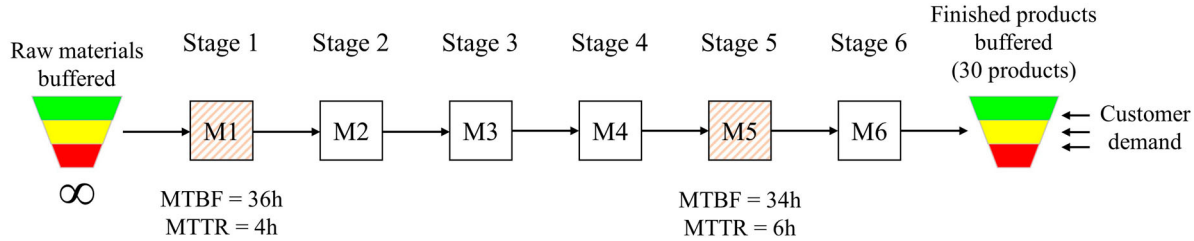

Figure 2. Diagram of the studied production line and positioning of the DDMRP stock buffers.

Table 1. Changeover time (in hours) for each product.

Products	M1	M2	M3	M4	M5	M6
1–10	0.25	0.25	0.5	0.5	0.25	1
11–20	0.5	0.5	0.5	0.5	0.5	0.5
21–30	1	1	0.5	0.5	1	0.25

Table 2. Production time (in seconds per part) for each product.

Products	M1	M2	M3	M4	M5	M6
1–10	5	5	5	10	15	5
11–20	5	10	10	10	10	10
21–30	5	15	15	10	5	15

Table 3. Average order size for each product.

Products	1	2	3	4	5
ADU	65	23	55	63	19
Products	6	7	8	9	10
ADU	38	29	33	61	34
Products	11	12	13	14	15
ADU	61	62	57	32	52
Products	16	17	18	19	20
ADU	21	61	42	48	44
Products	21	22	23	24	25
ADU	35	52	23	56	55
Products	26	27	28	29	30
ADU	37	32	51	55	52

fifth machine to 6-hour outages every 34 h, representing 10% and 15% of the time respectively. These values arbitrarily follow exponential laws to model a non-negligible but not excessive variability in production, close to reality.

Thirty products are manufactured in the workshop. Series changeover times (in hours) and production times (in seconds per part) per machine are presented in Tables 1 and 2. To simulate variability in production times, the changeover times are multiplied by a variable following a triangular law (0.75, 1, 1.25) and the production times by a variable following a triangular law (0.8, 1, 1.2). An operator is required during changeover and production operations for a machine to operate.

Each product has a different average order size, and this order size follows a uniform law of ±20% around the average as an arbitrary choice after observing demand signals from the industrial case. The delay between each order of the same product follows an exponential law of expectation of 1 d. Therefore, the Average Daily Usage (ADU) of each product equals the average order size, shown in Table 3.

The DLT, LTF, and VF are equal for each product and are valid for 10 days, 50%, and 50%, respectively. This choice of parameterisation comes from previous research conclusions (Dessevre et al. 2019).

The workshop and operators work 8 h a day, 5 days a week. Since the components are themselves managed on DDMRP stock buffers, they are considered available at all times in sufficient quantities. Finished product stocks are randomly initialised between 50% and 100% of the Top Green of each buffer.

Because of breakdowns and product mix, the bottleneck is globally located on the M5 machine but can temporarily shift to other machines. Moreover, when the number of operators is reduced, the bottleneck resource becomes the operators.

The workshop manages partial orders: when a customer order arrives, it is delivered in full if possible. Otherwise, it enters a queue and will be given priority when the product's stock in question is available again.

Design of experiments and simulation parameters For the fictional case, the goals of the design of experiments are:

- To verify the average flow time of all production orders represents the average flow time of productions orders for each finished product;
- To compare a case where the bottleneck resource is a machine and the one where it is the operators; and
- To create flow charts that will be compared with the industrial case.

The input and output variables of the design of experiments are presented here. There are two input variables: the average customer demand and the number of operators.

To generate a progressive scale-up, the average size of each order has been uniformly increased step by step. The aim is to have a load/capacity ratio between 70% and

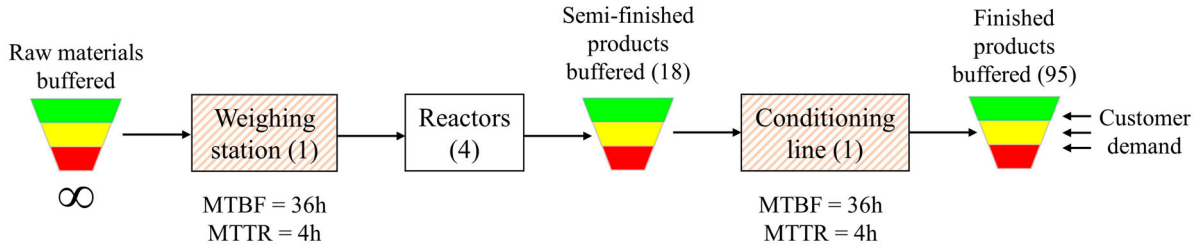

Figure 3. Diagram of the studied industrial case composed of two workshops and positioning of the DDMRP stock buffers.

100% (in all demand scenarios, below this ratio, the workshop has overcapacity, above this ratio, it is overused and saturates very quickly).

Also, two cases are studied to test two different types of critical resources:

- Case 1: the bottleneck is a machine (the fifth on the line) and 6 operators are present in the workshop; and
- Case 2: 5 operators are present in the workshop and represent the bottleneck resource.

The output variables of the experimental design are:

- The loading rate of the bottleneck resource;
- The workshop service rate, defined according to Hopp and Spearman (1996) as the ratio between the number of production orders with flow times less than or equal to the allotted time (*i.e.* the DLT), and the total number of production orders (Equation 2);
- The customer service rate, defined as the ratio of the number of orders filled on time to the total number of orders;
- Flow time distribution, defined as the value where X% of the production orders have flow times less than or equal to this value (where X is 50, 60, 70, 80, 90, and 100); and
- The average flow times.

These variables will allow us to plot the desired charts presented in the results section. 120 scenarios were simulated for each case. Each scenario is simulated 100 times and each replication lasts 110 weeks (550 days), including a 10-week warm-up period (not included in the results). The modelling and simulation were performed on Arena version 15.10 software.

The industrial case

Workshop parameters for the industrial case

The industrial case is made of two consecutive workshops. In the first one, the raw materials are weighed, then mixed, and heated up in a reactor to manufacture semi-finished products in a tank. In the second one, the semi-finished products are packed on a conditioning line to manufactured finished products, which are shampoo bottles filled up by the semi-finished products (Figure 3).

The raw materials (plant extracts) are buffered and considered available at all times in sufficient quantities. The semi-finished products (shampoos) are buffered, and there are 18 different ones (almond, mint, quinine, etc.). To produce them, the raw materials are weighed at the weighing station, mixed and heated in a reactor, and finally transferred in a tank. There are one weighing station, out of order 10% of the time, and four reactors. The weighing station is the bottleneck resource in this workshop, working 24 h a day (3 shifts of 8 h).

The 95 finished products are buffered. They are made of semi-finished products by being operated on a conditioning line. A semi-finished product can make between 2 and 8 different finished products: The differentiation between finished products from the same semi-finished products comes from the bottle size and the linguistic version. The link between semi-finished products and finished products is shown in Table 4.

The conditioning line is out of order 10% of the time. There are six types of finished products, two according to the bottles' size (200 and 400 mL) and up to 3 different linguistic versions. About half of the finished products of the same semi-finished products is made of 200 mL bottles. The time to change the size of bottles on the conditioning line is about four times the time to change the semi-finished product. Therefore, the decision to change the bottle size is taken the first day of the week only: on Monday, the conditioning line is set to satisfy the longest queue of conditioning orders between those in 200 mL and those in 400 mL.

The DLTs are fixed to 10 days for the first workshop (weighing station and reactors) and 15 days for the second (conditioning line). The LTFs are set to 10% for the semi-finished products buffers and 50% for the finished products buffers. The VF are set to 10% for the semi-finished products buffers and 20% for the finished products buffers. The size of a production order for the semi-finished products are predetermined, depending on

Table 4. Links between semi-finished products and finished products.

Semi-finished product	Bottle size	Finished products	Semi-finished product	Bottle size	Finished products
1	200	1–3	10	200	50–52
	400	4–5		400	53–55
2	200	6–8	11	200	56–58
	400	9–11		400	59–60
3	200	12–14	12	200	61–62
	400	15–17		400	63–64
4	200	18–20	13	200	65–67
				400	68–70
5	200	21–23	14	200	71–73
	400	24–26		400	74–75
6	200	27–29	15	200	76–77
	400	30–31		400	78–79
7	200	32–34	16	200	80–82
	400	35–37		400	83–85
8	200	38–40	17	200	86–88
	400	41–43		400	89–93
9	200	44–46	18	200	94–95
	400	47–49			

the formula and the reactor size (6 or 10 tons). Therefore, we cannot launch orders of 4 tons or 13 tons, for example. The finished products buffers have a MOQ of 5 000 bottles (this is a psychological threshold below which operators and managers do not see the point of launching an order). The workshop manages partial orders the same way as the fictional case.

The second workshop can work 16 h a day (2 shifts of 8 h per week), 20 h a day (1 week with 2 shifts and 1 week with 3 shifts, resulting in an average of 2.5 shifts per week), or 24 h a day (3 shifts). The production manager's goal is to find the best number of shifts to deal with the customer demand. Thus, we will create visual charts to help decide between the three possibilities of the number of shifts (2, 2.5, and 3).

Design of experiments and simulation parameters for the industrial case

For the industrial case, the design of experiments has different goals:

- To compare and validate the fictional case study (the charts must look like the same);
- To help the production manager to find the number of shifts with the visual charts, depending on an expected demand; and
- To compare the average flow times of the same resource (the conditioning line) between the three capacity possibilities (number of shifts), depending on the resource's loading rate.

To do so, we generate a progressive scale-up to have a load/capacity ratio between 70% and 100% for both workshops and for each capacity possibility for the second workshop. For the chart with the three shifts, we simulate the workshop with an average weekly demand from 75 000 bottles a week to 300 000 bottles a week for each shift.

The outputs variables are the same as the ones for the fictional case: the loading rates of the bottleneck resources, the workshop service rates, the customer service rates (named 'customer service rate' for the second workshop because it serves customers, and 'buffer service rate' for the first workshop because the second one is the customer of the first one), the average flow times and their distributions.

300 scenarios were simulated (60 for the first workshop and 240 for the second one), each of them is simulated 100 times, and each replication lasts 60 weeks, including a 10-week war-up period.

Results and discussion

T his section presents the results of the above scenario s For space reasons, only the visual charts are presented.

The ictional lowshop

First, we verify the average flow time of all Production Orders (PO) represents the average flow time of PO for each finished product. Figure 4 illustrates the average flow times of PO for six different finished products (finished products 5, 10, 15, 20, 25, and 30 in different blues) and the average flow time for all PO (in black) depending on three loading rates of the bottleneck resource (70%, 85%, and 95%). It shows an unsubstantial difference between flow times of different finished products. The average flow time all of POs can be used to represent the flow time of POs for all finished products, independently of the loading rate of the resource. We explain it because most of the flow time is

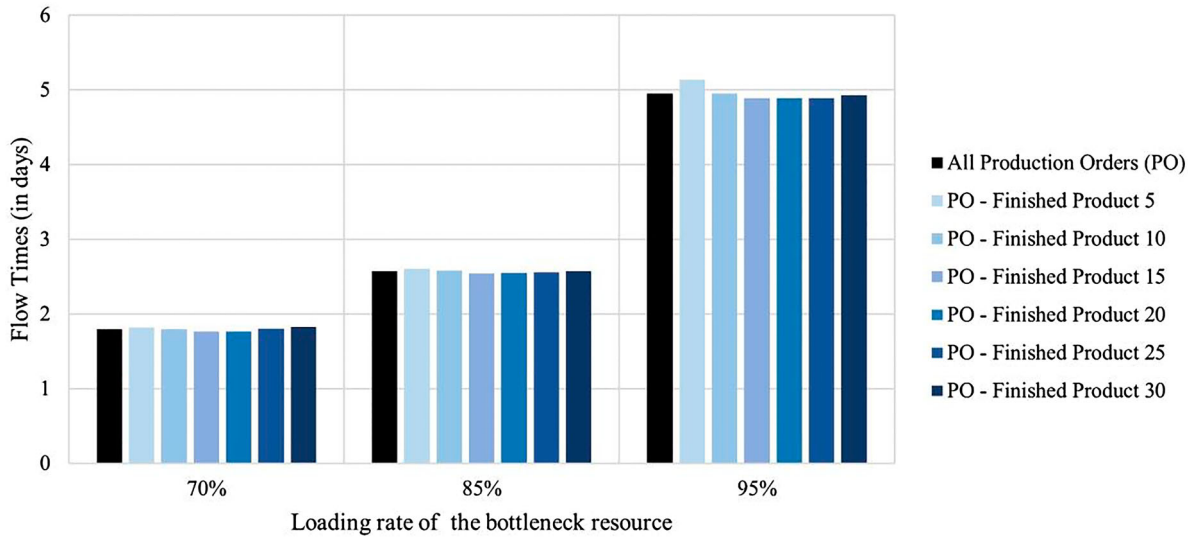

Figure 4. Average Flow Times of Production Orders for different Finished Products depending on the Loading Rate of the Bottleneck Resource.

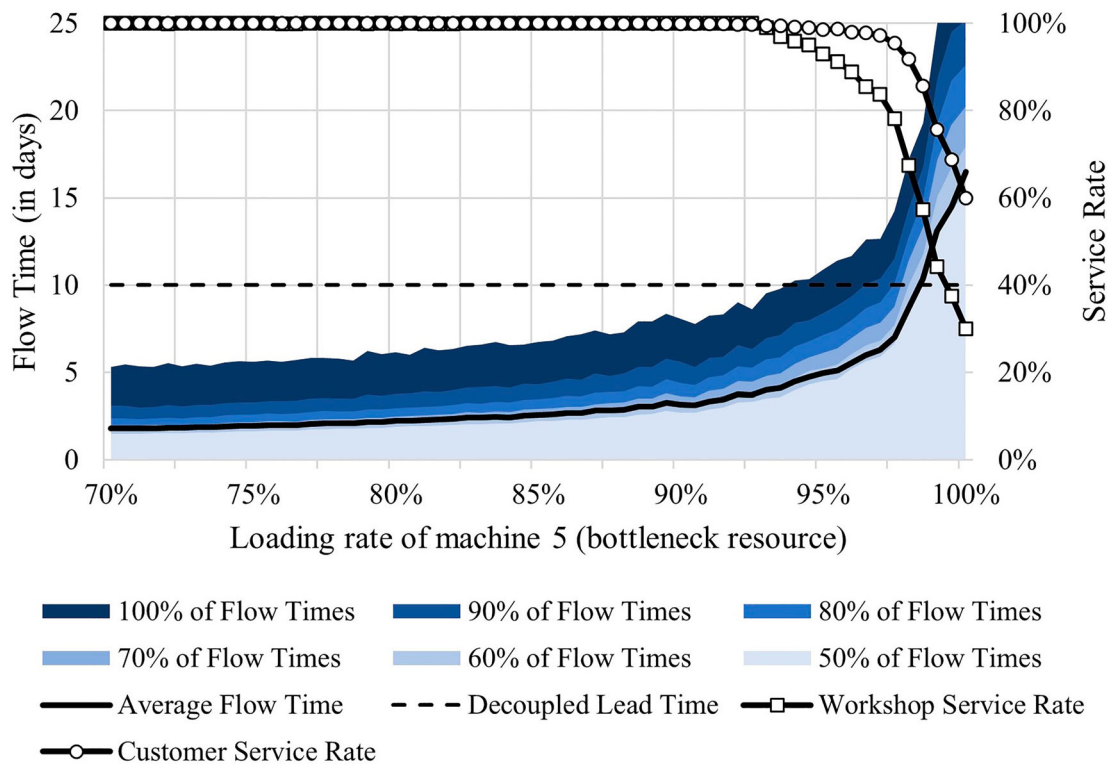

Figure 5. Flow Times (average and distribution) and Service Rates (workshop and customer) depending on the loading rate of machine 5.

queue time in front of each stage (Hopp and Spearman 1996), then differences of changeover time and production time between products do not affect the average flow times.

Now we can create charts using the average flow time to represent all finished products. Both charts in Figures 5 et 6 have the same axes and legend:

- On the abscissa is the loading rate of the bottleneck resource (machine 5 for Figure 5 and the operators for Figure 6), ranging from about 70% to 100%;
- On the left y-axis is the flow times in days. The black curve represents the average flow time. The dotted horizontal line represents the DLT of the workshop. The areas correspond to the distribution of

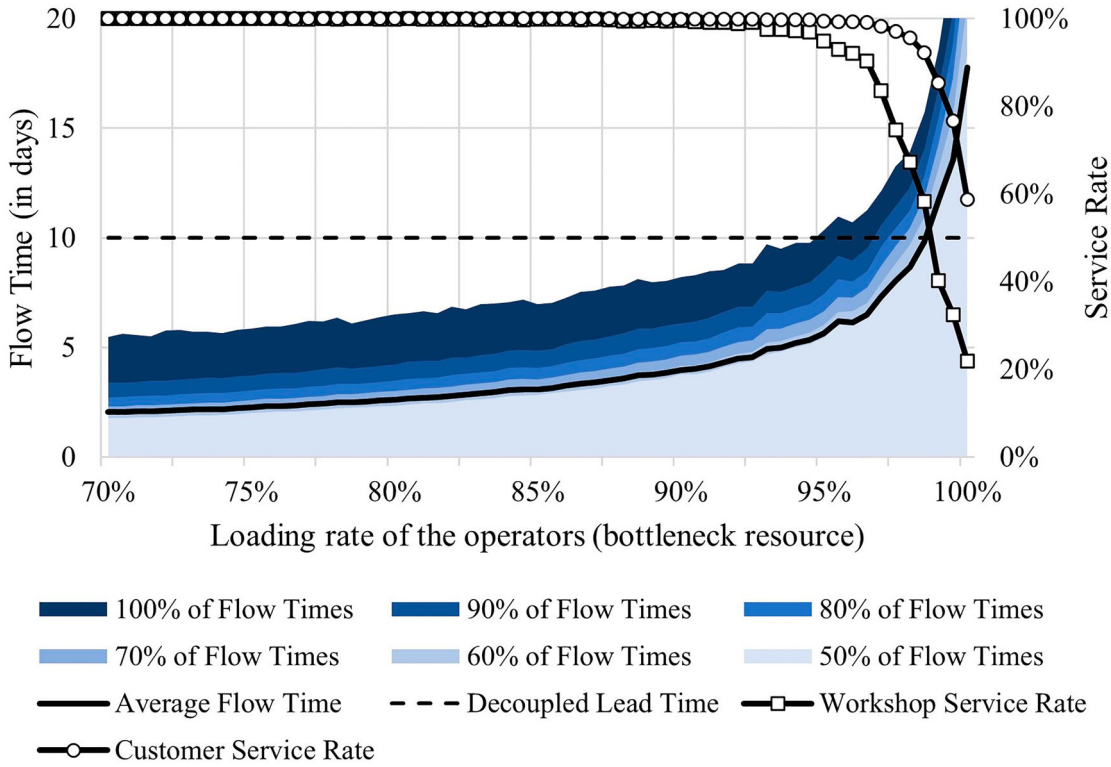

Figure 6. Flow Times (average and distribution) and Service Rates (workshop and customer) depending on the loading rate of the operators.

flow times (from 50% in light blue to 100% in dark blue); and

- On the right y-axis is the service rate scale, between 0 and 100%. The curve represents the workshop service rate at the square marks and the customer service rate by the curve at the circular marks.

From these graphs, it follows that the more the loading rate of the bottleneck resource increases, the more the average flow time increases hyperbolically in the workshop (conclusion known by the queue theory (Hopp and Spearman 1996)) but also its dispersion. The average flow time coincides with the area representing 50% of all flow time in the workshop (*i.e.* the distribution median). Therefore, taking a DLT equal to the average flow time represents only half of the manufacturing orders.

The workshop service rate begins to deteriorate sharply when the DLT line crosses the different flow time distribution areas. The customer service rate is slightly out of line with the workshop service rate due to each stock buffer's red zone, acting as a safety stock.

There is not much difference between the two charts (Figures 5 and 6), meaning that machines and operators behave the same way as the bottleneck resource.

These charts help answer the first three research questions. In our example, the DLT set at 10 days can absorb 100% of the flow times up to a load rate of about 91%, 90% of the times up to a rate of 94%. This shows that the average remaining flow time of around 3–5 days should not be relied upon as long as the load rate is below 94%. A 5-day DLT would not even absorb all the flow time for a 70% charge rate.

Then, for example, for a 97% loading rate in Figure 4, the DLT would only absorb 80% of the flow times. As a result, the workshop service rate drops to 80%, and the customer service rate also deteriorates to around 92%. The production manager, anticipating a ramp-up (or ramp-down) on the shop floor, might then choose to adjust the DLT accordingly, or seek to reduce the loading rate by adapting capacity to control flow times (with a target service rate), or increase/decrease safety stocks to absorb flow time variations.

The industrial case

In this case, we verify that the chart looks like the fictional case (to validate our assumptions), and we show how to use the visual charts to help decide on the number of shifts.

Figure 7 has the same axes and legend as the previous charts. It represents the average flow time, dispersion, and service rates depending on the weighing station's loading rate (the bottleneck of the first workshop).

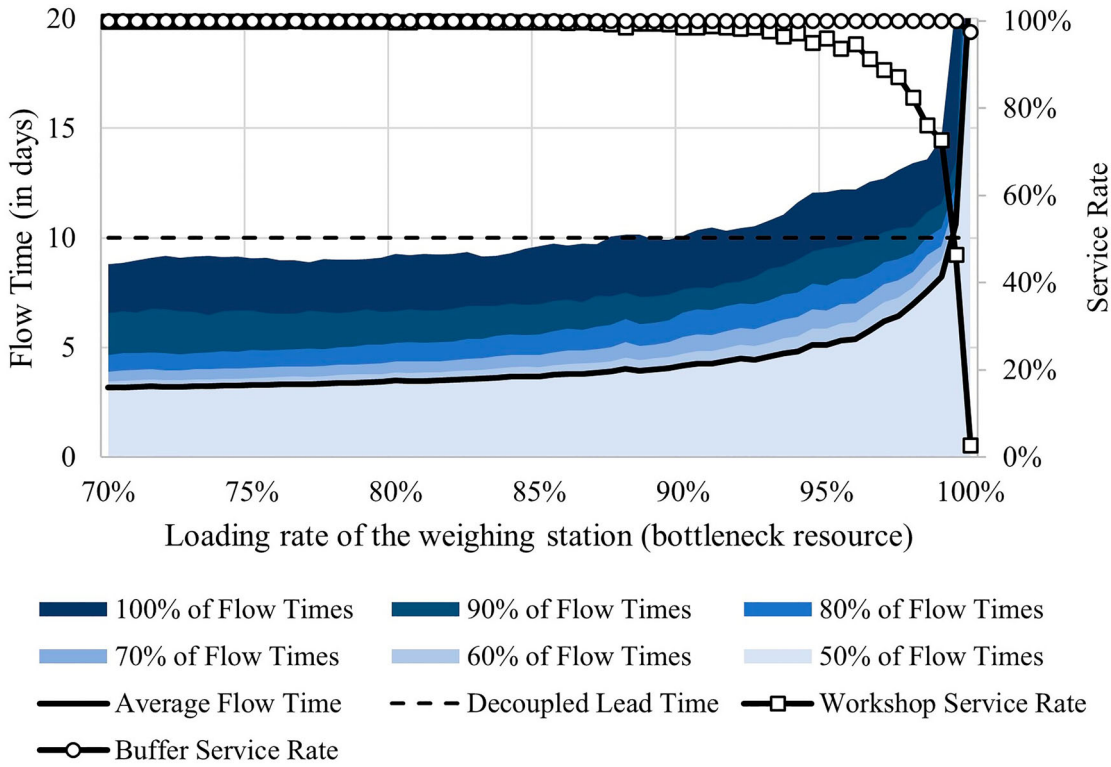

Figure 7. Flow Times (average and distribution) and Service Rates (workshop and buffer) depending on the loading rate of the weighing station.

The chart is closer to the ones made with the fictional workshop: when the bottleneck resource's loading rate increases, flow times increase too, and service rate decreases. In this case, a DLT set to 10 days covers 100% of the flow times until around 85% of the loading rate. Above this value, the production manager might increase the DLT or seek to reduce the loading rate. To visualise the effect of reducing loading rate, we created a chart for the conditioning line of the second workshop.

In Figure 8, the average weekly customer demand of the workshop is represented in abscissa, and the curves represent the average flow times (full curves), 80% of flow times (dashed curves), and 100% of flow times (dotted curves), when the conditioning line works with 2 shifts (black curves), 2.5 shifts (blue curves) and 3 shifts (green curves). The red dashed line is the Decoupled Lead Time.

As the flow times increases drastically when the demand increases, it seems better to seek to reduce the loading rate (by changing the number of shifts) rather than changing the DLT (what increases the buffer sizing and reduces the shop's reactivity): for example, with a demand of 150 000 bottles a week, a DLT of 15 days absorbs all the flow times with 2.5 shifts while it needs a DLT of 30 days to absorb only the average flow times.

When the average demand increases, the loading rate of the conditioning line increases too, so does the average flow time (and its dispersion). As a result, the production manager could use this chart: if the average demand is not higher than 100 000 bottles a week, 2 shifts and a DLT of 15 days are enough to absorb at least 90% of flow times. If we forecast more than 100 000 bottles a week, the production manager has to increase the DLT, or set 2.5 shifts. Above 200 000 bottles a week, 2.5 shifts are not enough, and we need 3 shifts. Figure 9 represents the average flow times depending on the conditioning line's loading rate for the three sets of shifts.

Firstly, under 98% of loading rate, the three curves are very close, meaning that the average flow times is nearly the same with 2, 2.5, or 3 shifts when the resource is used at the same loading rate (for example, the average flow time is around 5 days at 95% of the loading rate, regardless of the number of shifts).

Secondly, the green curve (3 shifts) turns around when it reaches 98%. The conditioning line set with 3 shifts never get a loading rate above 98%, because the first workshop (weighing station and reactors) becomes the bottleneck workshop. Consequently, as demand increases, conditioning orders are waiting for semi-finished products availability, which increases the flow-time while reducing the loading rate of the conditioning stage. To better understand, Figure 10 represents the loading rate of the weighing station (black curve), the weighing workshop buffer service rate (blue curve), and

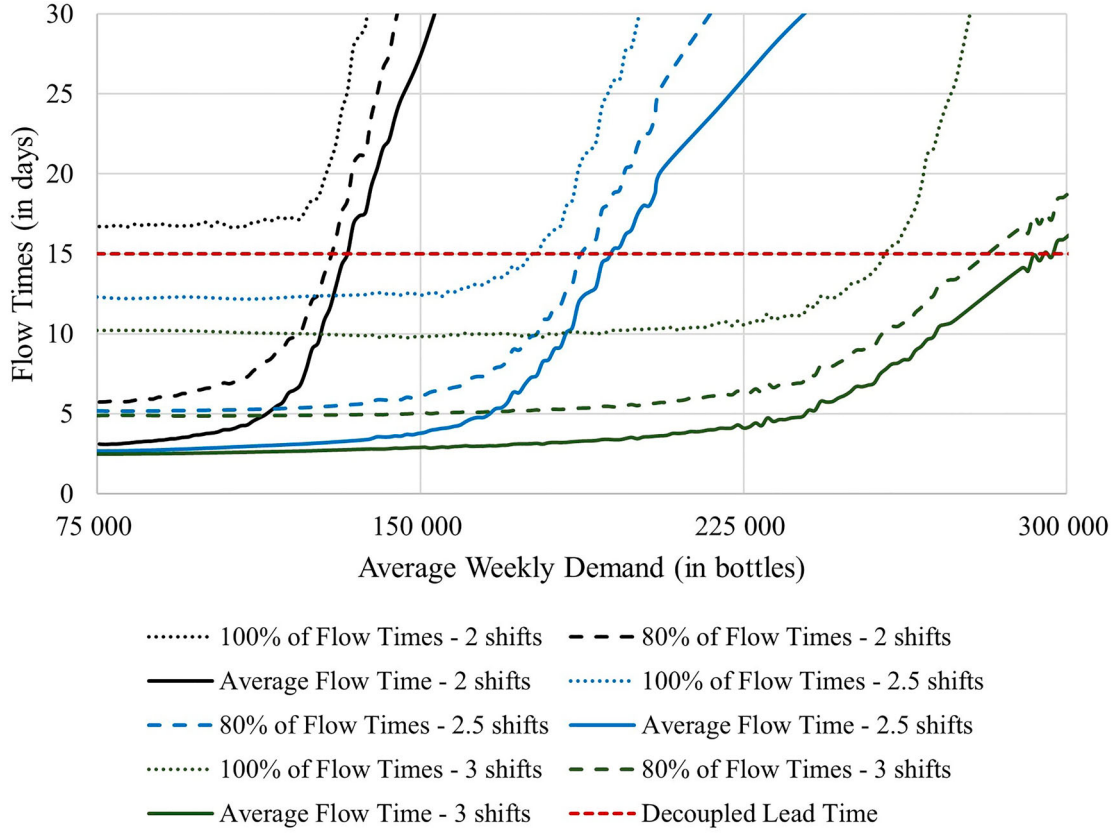

Figure 8. Flow Times (average, 80%, and 100%) depending on the Average Weekly Demand (in bottles) and the number of shifts (2, 2.5, 3).

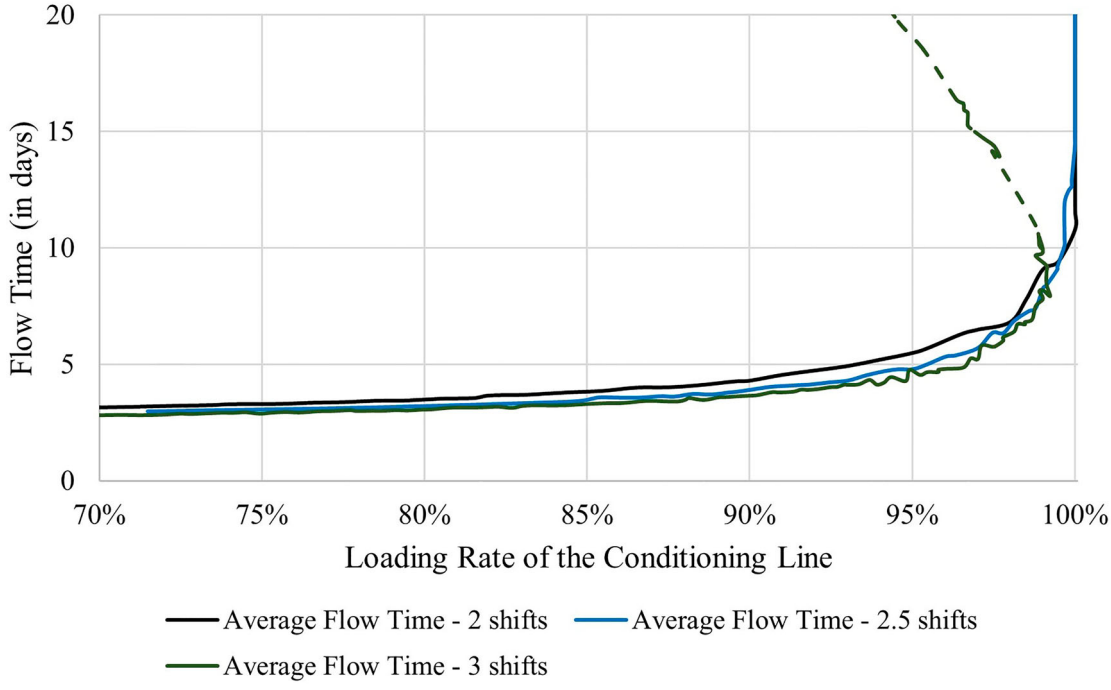

Figure 9. Average Flow Time depending on the Loading Rate of the Conditioning Line and the number of shifts (2, 2.5, 3).

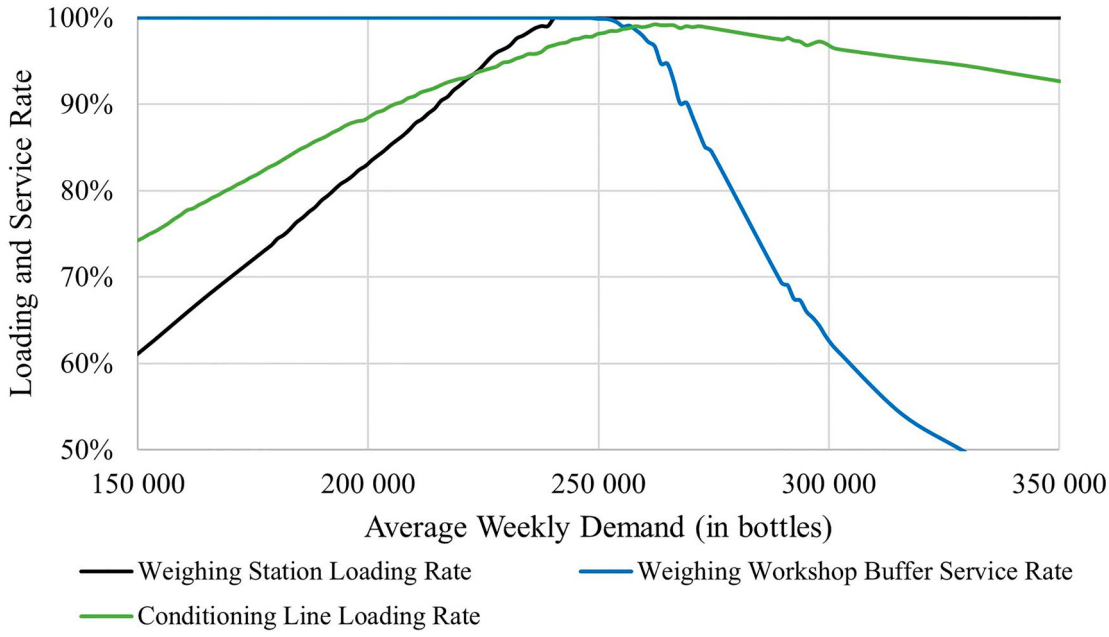

Figure 10. Loading Rates of the Weighing Station and the Conditioning Line, and Service Rate of the Weighing Workshop Buffer depending on the Average Weekly Demand (in bottles).

the loading rate of the conditioning line (green curve). Above 250 000 bottles a week, the weighing station loading rate reaches 100%. This is why its service rate begins to decrease (as we saw in Figure 7 previously). Therefore, the semi-finished products are slow to arrive, delaying the production orders of finished products. As a result, the conditioning line is waiting, and its loading rate decreases. This last chart represents the relation between the two workshops, depending on the demand. Above 250 000 bottles a week, the average flow times increase because both the loading rates of the conditioning line are near 98%, and the loading rate of the weighing station reached 100%.

Conclusion

This paper proposes charts to visually correlate bottleneck resources load rate, flow time distribution, and service rates. They are realised by simulating DDMRP-managed production workshops, including an industrial case. Using the workshop service rate definition as the probability that the flow times are less than or equal to the DLT parameter, we have two choices to improve the workshop service rate: Control the flow times by adjusting the capacity and/or adjust the DLT parameter.

The graphs we have created help deciding based on the expected loading rate or the expected customer weekly demand. It enables mid-term management of capacity as demand trend changes. These experimental results are essentially very contextual. That is why we simulated an industrial case to validate our fictional one. However, it will be necessary to verify their sensitivity to key workshop parameters: product mix, workshop variability, and technical data. In this study, charts show similar behaviour between the fictional case with bottleneck machine, the fictional case with bottleneck operators, and the industrial case with different numbers of shifts.

The customer service rate is then shifted from the workshop service rate due to the safety stock represented by the DDMRP red zone. Therefore, it is possible to keep a correct customer service rate by playing on this safety stock. However, it requires a strong control of the loading rate. The slightest error induces a drastic drop in the service rate. Consequently, it is more interesting to try to control the flow times rather than to adapt the DLT parameter or to play with the safety stock: a minor capacity adjustment (from 95% to 90%, for example) is equivalent to significantly increasing the DLT (from 25% to 50%) without impacting the average stock. This remark supports the implementation of capacity buffers as suggested by Ptak and Smith (2011), and our charts can be used to determine the size of the capacity buffer.

In our industrial case, the production manager's concern is to find which number of shifts is required to face the demand (the decision is made weekly or monthly). The charts correlate the flow time dispersion depending on the forecasted customer demand and the number of shifts working. They help to decide if 2 shifts are good enough, or if more working hours are needed.

Therefore, it remains up to the production manager to choose which capacity adjustment to implement in the workshop, depending on the available levers (increasing

the number of operators, working overtime, working several shifts (switching to 3 shifts for example), capacity subcontracting, etc.). Thus, we can imagine different charts similar to those presented here. Each curve would propose a different scenario (6 operators with 2 shifts or 4 operators with 3 shifts, for example, or even a scenario with an increase in DLT and comparing average in-process and finished product stocks). These graphs would be used as a decision aid for capacity adjustments when forecasting a load increase (or decrease), by setting a customer and/or workshop service rate objective. They could thus be used for tactical or even strategic decisions.

Finally, we showed that the average flow time is not suitable to size the DLT, and it is better to know the dispersion of flow times. By coupling the DDMRP method with a tool reducing the variability of flow times, we could reduce the dispersion, and therefore reduce the DLT, thus reducing stocks while maintaining a high loading rate. Moreover, other types of workshops could also be processed (job shop, open shop, production lines crossovers, etc.) to verify that the same phenomena are identified.

Data availability statement

The data that support the findings of this study are available from the corresponding author, Guillaume Dessevre, upon reasonable request. Restrictions apply to the availability of these data, which are available with the permission of the industrial partner.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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