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Analysis of a Dynamic Capacity Management Approach in DDMRP: Application on A Real Industrial Case

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Abstract:

Purpose: Although the authors of the Demand Driven Material Requirements Planning (DDMRP) argue that the method DDMRP is the solution to the limitations of traditional production management methods, its capacity management system remains unclear. Since DDMRP operates at infinite capacity, it is important to consider a capacity management approach to avoid under- or overloading production workshops.

Design/methodology/approach: We propose a new dynamic capacity management approach for the DDMRP method. Our approach is based on the calculation of the anticipated workload, using DDMRP stock buffers and considering customer order spikes. Considering a real industrial case, we compare the proposed approach to a static one and a dynamic approach from the literature.

Findings: The analysis of the results, supported by a two-way ANOVA, indicates that the proposed capacity management approach outperforms the performance of the other two approaches by maximizing the resource loading rate while ensuring a high customer service level.

Originality/value: The originality of the article comes on the one hand from the capacity adjustment module by calculating the anticipated workload, and on the other hand from the comparison of this approach with two others, one of which comes from the literature.

Keywords: capacity management, DDMRP, dynamic adjustment, simulation, industrial case

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1. Introduction

Capacity management is defined by Yu-Lee (2002) as "managing the amount of what the organization has and uses to perform work". Capacity management can be done at different decision-making levels, corresponding to different horizons: the strategic level (e.g., the purchase of a new machine or a warehouse), the tactical level (e.g., load smoothing over periods of low activity or subcontracting), and the operational level (e.g., the number of operators required and overtime). In this paper, we are interested in capacity management at the operational level, over the short-term horizon, in a pull production context.

The research for this paper is motivated by the need for an industrial partner to move from a push flow approach to a pull flow one, by deploying the Demand Driven Material Requirements Planning (DDMRP) as a method for pulling production. One of the main obstacles to switching from push to pull production is capacity management for the short-term horizon. This has been underlined by the case study of Dessevre, Baptiste, Lamothe and Pellerin (2021). The partner is a manufacturer and a distributor of dermo-cosmetic products, and its bottling line can work two or three shifts a day. In push production, production orders are created several weeks in advance, therefore it is easy to determine the number of shifts needed to satisfy the demand. In pull production, where production orders are created at the last moment, it is difficult to anticipate whether the bottling line should work two or three shifts a day. A capacity management approach is therefore needed to help the production manager to decide how many shifts are required for the coming weeks in the workshop.

To understand the source of the probleme, a brief reminder of how DDMRP work is presented and illustrated: the DDMRP is a demand planning method mixing push and pull production management, which is based on buffers' strategic positioning along the bill of material (Ptak & Smith, 2011). As illustrated on the left of Figure 1, each buffer is composed of three zones (a safety zone in red, a cover stock in yellow, and a minimum lot size in green) and is replenished when its net flow position reaches a threshold called Top of Yellow (ToY). Every time the net flow position, which is the sum of the stock level and the work-in-process minus the qualified demand, reaches the ToY a supply or production order is created to replenish the buffer to the Top of Green (ToG). The qualified demand is defined as the sum of daily demand, unsatisfied demand, and the detected order spikes (i.e., the sum of the customer orders exceeding the Order Spike Threshold (OST) over the Order Spike Horizon (OSH) as represented on the right of Figure 1).

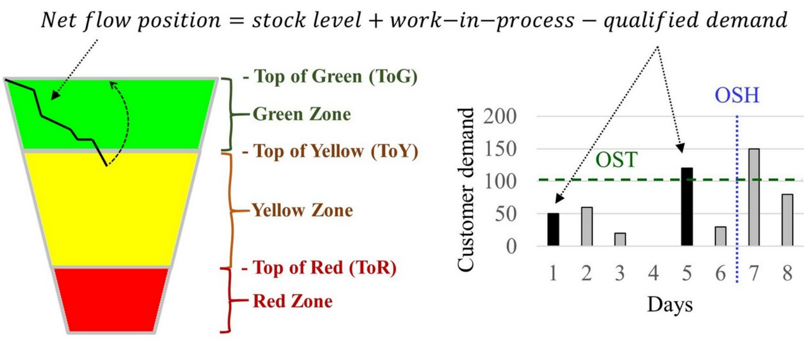

Figure 1. The three zones of a DDMRP stock buffer, the formula of the net flow position, and an example of qualified demand

Therefore, with this threshold-based replenishment logic, and since all the products manufactured on the workshop can be managed by a stock buffer, there is a risk of under or overloading the production floor if demand is too low or too high.

This paper aims to contribute to the research in capacity management for DDMRP production systems and to propose a new approach to adjust dynamically the capacity of a demand-driven production system facing various demand scenarios (square signal, demand with spikes, etc.). For these purposes, we propose a workload calculation approach based on the stock position of DDMRP buffers. The approach is able to anticipate the demand (including order spikes), and is compared using discrete event simulation with two others capacity management approaches: a static approach corresponding to classic DDMRP operation (without conscious capacity management), and an approach from literature based on visual charts developed by simulation. To the best of our knowledge, our study is the only one which deals with dynamically adjusting the capacity based on external information (such as order customer order spikes) and intrinsic DDMRP parameters.

The paper is organized as follows. Section 2 is dedicated to related literature. Section 3 describes the industrial case, the research methodology, and the design of experiments. Section 4 presents the results and analysis. Finally, Section 5 concludes and proposes further research.

2. Literature Review

This literature review focuses on capacity management, publications about DDMRP, and capacity management within the DDMRP method.

2.1. Capacity Management

Capacity management is a crucial process that should not be underestimated by companies: it is known, by queueing theory, that the higher the loading rate of a bottleneck resource, the more drastically the waiting times increase (Kingman, 1962; Wu, Srivathsan & Shen, 2018). The literature on short and medium-term capacity issues seeks to fulfill forecasted demand with available capacity (Vollmann & Berry, 1997). Unfortunately, customer demand is less and less easy to predict, and push flow management methods such as Material Requirements Planning (MRP) are limited: its synchronization strength becomes its weakness (Ptak & Smith, 2011). Conversely, it is difficult to anticipate the required short-term capacity with pull flow management methods since the creation of production orders is done at the last moment. Therefore, the capacity flexibility of the workshops is a major asset for countering forecast errors and adapting to real demand. Bish, Muriel and Biller (2005) outline the benefits of flexible capacity, such as improved sales, but warn of the effects of fluctuations in production and supply.

The main solutions to overcome capacity issues are (Jodlbauer & Reitner, 2012; Taal & Wortmann, 1997): considering alternative resources, applying lot summarization to reduce the number of set-ups, adjusting available capacity (with overtime, more staff, etc.), postponing gross requirements, considering anticipated production over periods of underactivity (leading to temporary storage), and accepting tardiness (subsequent residual capacities leading to backlogs and extended delivery).

Since many production systems operate in infinite capacity (e.g. production systems driven by MRP), many researchers propose different ways to consider the workload of production systems and to deal with capacity adjustment. For example, Rossi and Pero (2011) propose an MRP method that considers capacity constraints and lead times, while Sun, Heragu, Chen and Spearman (2012) compare MRP and dynamic risk-based scheduling (a tool that creates a set of policies leading to a more robust production system). Hu, Guan, Han and Wen (2017) propose a mathematical model to solve the capacity adjustment problem where workstations can be adjusted differently depending on the desired production level. Recently, Jodlbauer and Strasser (2019) develop a production planning approach considering limited capacities of production resources where lead times are dynamically calculated according to capacity adjustment. Moreover, Ou and Feng (2019) present a capacity adjustment algorithm considering production costs and capacity adjustment costs. Prior literature on the subject is summarized by the reviews of Beach, Muhlemann, Price, Paterson and Sharp (2000) and De Toni and Tonchia (1998).

2.2. Publications About DDMRP

The DDMRP from Ptak and Smith (2016) is a more and more well-known material management method, both in the academic world with the number of research articles increasing, and in this industrial world where many companies implement it. In the literature, two main research topics are found. The first one is the comparison of DDMRP to other traditional methods such as MRP and Kanban. A series of studies have thus proven the relevance of the DDMRP: a better compromise between stock level and service rate, customer order spike anticipation, dynamic adjustment of buffer sizing, and the ability to work in highly variable environments (Franco-Quispe, Yauri-Tito, Cabel-Pozo & Raymundo, 2022; Ihme & Stratton, 2015; Kortabarria, Apaolaza, Lizarralde & Amorrortu, 2018; Miclo, Lauras, Fontanili, Lamothe & Melnyk, 2019; Shofa & Widyarto, 2017; Thürer, Fernandes & Stevenson, 2022). The second topic is the study and improvement of the method itself. For example, Martin, Lauras, Baptiste, Lamothe, Fouqu and Miclo (2019) develop a process control and a decision-making tool to adjust buffer parameters, Lee and Rim (2019) propose an alternative model for the safety stock calculation, while Achergui, Allaoui and Hsu (2020) develop an algorithm to solve the optimization problem of minimizing storing costs for uncapacitated buffer positioning and (Damand, Lahrichi & Barth, 2023) propose a multi-objective genetic algorithm to determine a set of parameters related to DDMRP. Recently, Dessevre et al. (2021) propose a visual tool to correlate service rate, resource utilization and DDMRP parameters, that helps to choose a capacity solution among others and Azzamouri, Baptiste, Pellerin and Dessevre (2022) analyze the impact of a periodic review of DDMRP stock buffers, while Cuartas and Aguilar (2023) develop a hybrid algorithm based on reinforcement learning to determine the optimal time and quantity to buy a product and Martin, Lauras and Baptiste (2023) propose an experimental design to compare different multi-parameter sizing policies.

Studies on DDMRP are both axiomatic and empirical (Bagni, Godinho-Filho, Thürer & Stevenson, 2021), but many issues remain to be tackled scientifically, especially from complex environments (Velasco Acosta, Mascle & Baptiste, 2020), industrial sectors (Dessevre, Lamothe, Pellerin, Ali, Baptiste & Pomponne, 2023), and about the implementation process (Orue, Lizarralde & Kortabarria, 2020). Azzamouri, Baptiste, Dessevre and Pellerin (2021) present more details in a systematic review.

This paper deals with the capacity management for DDMRP systems, which has been rarely addressed in DDMRP literature, especially at the operational level.

2.3. Capacity Management within the DDMRP Method

For the DDMRP systems, capacity management is considered as a tactical issue mainly managed by the Demand Driven Sales & Operations Planning (DDS&OP). DDS&OP is a tactical process used to match the evolving business plan through the operational model master settings (Ptak & Smith, 2016): "a significant part of the DDS&OP process is to determine if sufficient capacity exists to support the proposed future". This level of decision-making, between strategic and operational, proposes for example to smooth the workload by using a planned adjustment factor that will adjust the sizing of buffers, in order to outsource part of the production to reduce workload, or to raise the price of certain items if the business is incapable of meeting all the demand (Ptak & Smith, 2016). These capacity adjustments seem appropriate for a medium-term vision, but not for a short-term operational point of view as proposed in this paper. Another alternative proposed by Ptak and Smith (2011) is to introduce a capacity buffer, which is an additional amount of capacity in order to absorb variability. However, there is no recommendation on the size of this buffer or its limits (e.g. unnecessary costs).

In conclusion of the literature review, we note that: (1) a flexible capacity management approach is essential to work well with pull production management methods; (2) the DDMRP method has been in the spotlight recently with numerous scientific articles, in particular comparisons between production management methods; and (3) there is no recommendation from the DDMRP authors on short-term capacity management, and only Dessevre et al. (2021) propose a solution in the scientific literature. Moreover, short-term capacity management is one of the concerns of manufacturers wishing to deploy the DDMRP method.

This paper contributes simultaneously to the capacity management literature and the DDMRP literature by proposing a new approach to adjust capacity over a short-term horizon using DDMRP buffers.

3. Methods

In this paper, we propose to deal with the same real industrial case considered by Dessevre et al. (2021) since the industrial partner is facing problems related to the deployment of the DDMRP method on a production line. The production process is too complex to be evaluated analytically, and so has to be studied using simulation. Discrete event simulation is used because it enables us to compare the performance of different systems considering several sources of variability (Mourtzis, 2020). Next, we describe the industrial case, as well as the design of experiments.

3.1. Industrial Case

We consider an industrial unit producing shampoo bottles composed of two consecutive workshops (see Figure 2): the shampoo manufacturing workshop and the bottling line.

The raw materials are buffered and considered available at all times in sufficient quantities. They are weighed at the weighing station, which is out of order 10% of the time: the Mean Time Between Failure (MTBF) is equal to 36 hours and the Mean Time To Repair (MTTR) is 4 hours. Raw materials are then mixed and heated in a reactor (there are four of them) to produce one of 18 varieties of shampoo (almond, mint, quinine, etc.). These shampoo varieties are considered as different Semi-Finished Products (SFP) and are managed using DDMRP buffers. The shampoo manufacturing workshop works 24 hours a day (three shifts of eight hours) all the time.

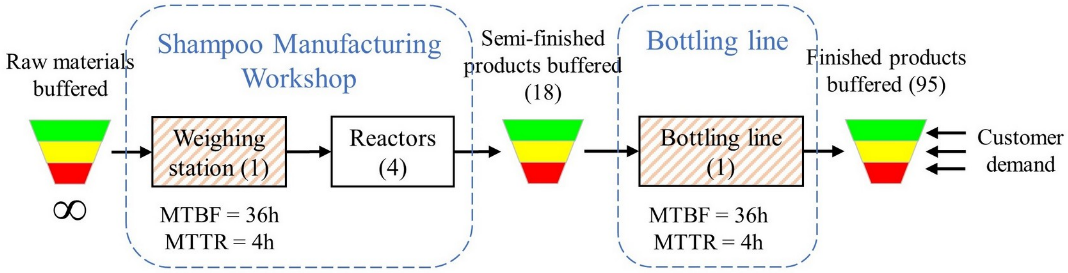

Figure 2. The production process of shampoo bottles and the positioning of the DDMRP stock buffers

There are 95 different Finished Products (FP, shampoo bottles characterized by a shampoo variety, a bottle size, and a language), all driven by DDMRP buffers. FP are made from SFP by being operated on the bottling line, which is out of order 10% of the time (MTBF of 36 hours and MTTR of 4 hours). As shown in Appendix 1, each SFP can make between two and eight different FP: the differentiation between FP from the same shampoo comes from the bottle size (200mL or 400mL) and the linguistic version of the bottle. The time required to change the size of bottles on the bottling line is about four times the time to change the SFP, therefore the decision to change the bottle size is taken only on the first day of the week: on Monday, the bottling line is set to satisfy the longest queue of bottling orders between those in 200mL and those in 400mL.

The Decoupled Lead Time (DLT) of FP, as well as the OSH, are fixed to 15 days (three weeks). The OST is set to five times the Average Daily Usage (ADU), which is one of the three ways recommended by Ptak and Smith (2016) to define an OST. The Lead Time Factor (LTF) is set to 50% and the Variability Factor (VF) to 20%. The industrial partner imposes for FP buffers a minimum order quantity of 5 000 bottles. All these parameters are illustrated in Figure 3. The size of a production order for the SFP is predetermined, depending on the formula and the reactor size (six or ten tons). Partial fulfillment is allowed: 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.

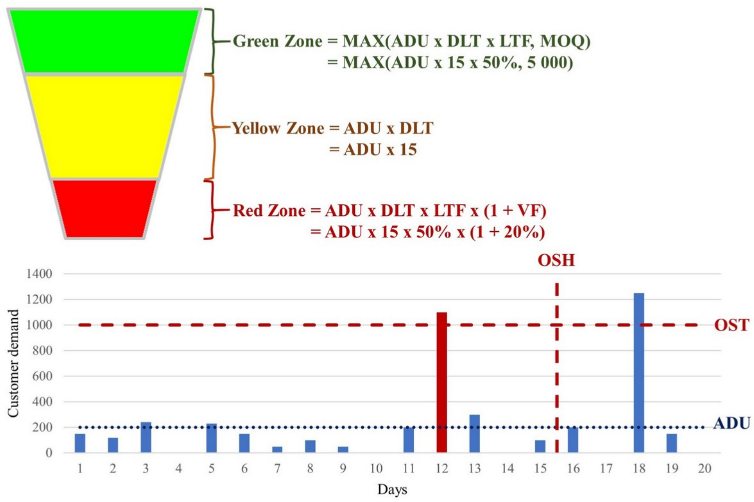

Figure 3. Illustration of the parameters established to size the DDMRP stock buffers and to detect order spikes

The industrial partner has the possibility to operate the bottling line 16 hours a day (two shifts) or 24 hours a day (three shifts). The production manager's goal is to find the best number of shifts to deal with customer demand: an overloaded workshop will increase flow times and degrade the customer service rate (Dessevre et al., 2021), while an overcapacity workshop will generate unnecessary costs. A capacity management approach is therefore needed, and its stake is the compromise between a high loading rate of the bottling line and a high customer service rate (see Figure 4). In addition, for union reasons, the number of shifts must be known two weeks in advance. In other words, each week the bottling line capacity is frozen for the next two weeks of production, and the manager must find the number of shifts (two or three) for the third week.

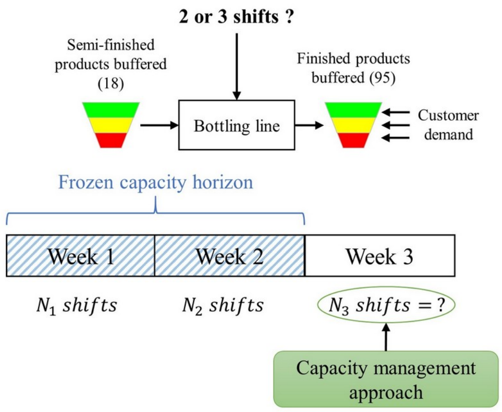

Figure 4. Frozen capacity horizon and the need for a capacity management approach

3.2. Experiments

In this study, we follow the procedure recommended by Montgomery (2017) for designing and analyzing experiments (see Figure 5). The objectives of the experiments are to compare and analyze different capacity management approaches dealing with different demand scenarios.

Considering the industrial partner objectives, we choose to analyze results regarding two performance measures: the customer service rate and the loading rate of the bottling line. We intend to maximize the loading rate of the bottling line (targeting between 80% and 85%) while ensuring a high customer service rate (close to 100%). In this study, we examine different capacity management approaches (decision factors in the design of experiments) facing various demand scenarios.

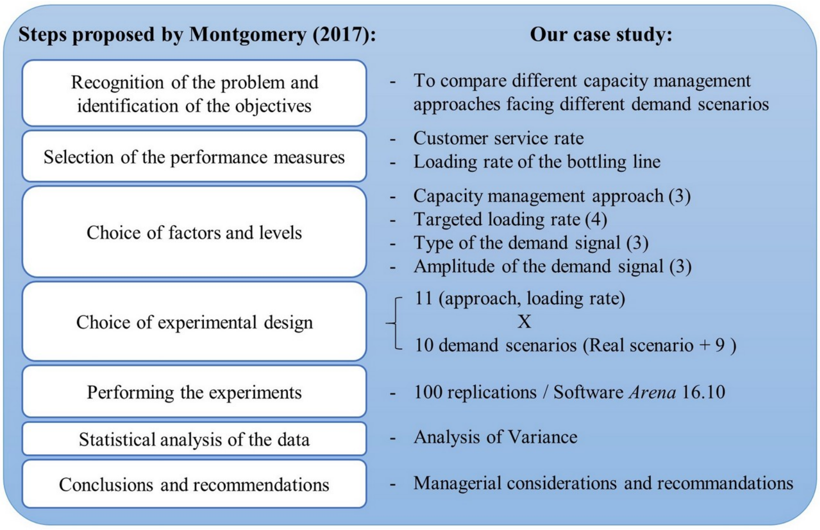

Figure 5. Experimentation procedure inspired by Montgomery (2017)

3.3. Capacity Management Approaches

We propose to evaluate the performance of various dynamic approaches, compared to a static approach considered as a baseline.

3.3.1. Static Approach (Baseline)

We consider an intuitive approach that determines the fixed number of shifts for the entire experiment among three capacity possibilities: two shifts, three shifts, and 2.5 shifts (modeled as two shifts one week, followed by three shifts one week, on a loop).

3.3.2. Dynamic Approach Based on the Anticipated Workload Calculation (DAAWC)

Since there is no explicit capacity management in the DDMRP method, we developed an approach to adapt production line capacity as closely as possible to customer demand (which will trigger production orders according to the replenishment logic of DDMRP stock buffers). In this way, we propose to use the operation of the buffers to anticipate the workload on the production line, in order to align the number of shifts required.

We propose a new approach that anticipates the workload calculation, through four main steps (see Figure 6):

1. **Estimation of the number of bottles to be bottled**: as explained in Figure 1, for each FP (shampoo bottle), the net flow position is calculated as the sum of the physical stock and the work-in-process, from which the qualified demand (considering customer order spikes) is subtracted (Step 1.1 in Figure 6). Then, the projected net flow position is calculated by subtracting the projected demand over the short-term horizon (i.e. fifteen times the average daily usage ADU considering a three-week horizon, five days a week, and a linear demand over the three weeks) as illustrated by Step 1.2 in Figure 6. The number of FP to be bottled is first deducted as the difference between the projected net flow position and the Top of Green level (i.e., the quantity that needs to be available in the DDMRP buffer over the short-term horizon). Second, the number of production orders is calculated by dividing the number of products by the Green Zone (Step 1.3 in Figure 6). For example, 40 000 bottles to be bottled with a Green Zone of 20 000 bottles will generate two production orders, because the Top of Yellow level (i.e., the replenishment level) will be reached two times. The estimation of the number of production orders and the number of FP to be bottled is done for all the 95 FP (Figure 6, Step 1);
2. **Calculation of the short-term workload**: knowing the average changeover time, the average unit bottling time, the number of production orders, and the number of products to be bottled, the workload in hours is calculated (Figure 6, Step 2);

3. **Deduction of the required capacity**: the required capacity depends on the target loading rate. According to Dessevre et al. (2021), a loading rate between 80% and 85% is a good compromise between high use of the resource and a high customer service rate. In this study, four target loading rates are experimented: 75%, 80%, 85%, and 90% (Figure 6, Step 3). By knowing the target loading rate and the estimated workload, the required capacity can be deduced;
4. **Determination of the number of shifts for the third week**: the capacity required for the third week is calculated as the total capacity required for the short-term horizon minus the capacity of the frozen two weeks. The number of shifts for the third week is then deducted by dividing by 40 (assuming that one shift accumulates 40 hours of production per week). In the case of a decimal number, it is always rounded up to the next integer to avoid a loading rate higher than the targeted one (Figure 6, Step 4).

The four steps are explained with the following example (presented at the bottom of Figure 6), considering a target loading rate of 80%:

1. The number of FP to be bottled is estimated at 500 000 for the next three weeks, corresponding to 60 production orders.
2. Knowing the different production times, a workload of 240 hours is calculated.
3. For a target loading rate of 80%, the required capacity is 300 hours.
4. The number of shifts for the next two weeks is set at 2 and 3, corresponding to 200 hours of work. There are 100 hours of production left, i.e., 100/40 = 2.5 shifts, rounded to three shifts (Figure 6, 4). Thereby, the actual loading rate will be closer to 75% (240/320 = 75%) than to 80%.

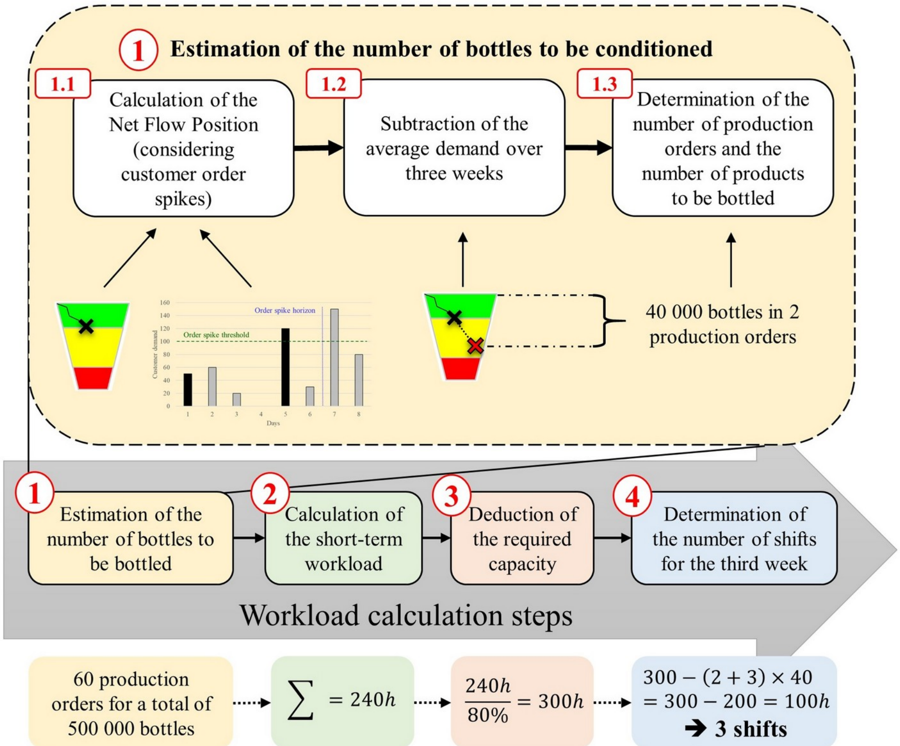

Figure 6. The four main steps of the workload calculation with an illustrated example

3.3.3. Dynamic Approach Based On Visual Charts (DAVC)

In addition to the DAAWC approach which is the main contribution of this paper, we propose to exploit the visual charts proposed by Dessevre et al. (2021). These charts are developed by simulation and correlate the bottleneck resource's loading rate to a specific customer service rate. They enable to identify which capacity level is required to fulfill the short-term projected demand. In this study, we aim to evaluate the capacity of visual charts to compete with the DAAWC.

In this case study, there are two capacity levels: two or three shifts per week. Considering the capacity of the two frozen weeks, a visual chart can be used to determine the number of shifts for the third week. Thus, four capacity scenarios are possible: six shifts (two shifts per week for three weeks), seven shifts (two shifts one week and three shifts for two weeks), eight shifts, and nine shifts. Figure 7 illustrates the visual charts created by simulating a progressive scale-up in the demand, which will affect the loading rate and then the customer service rate.

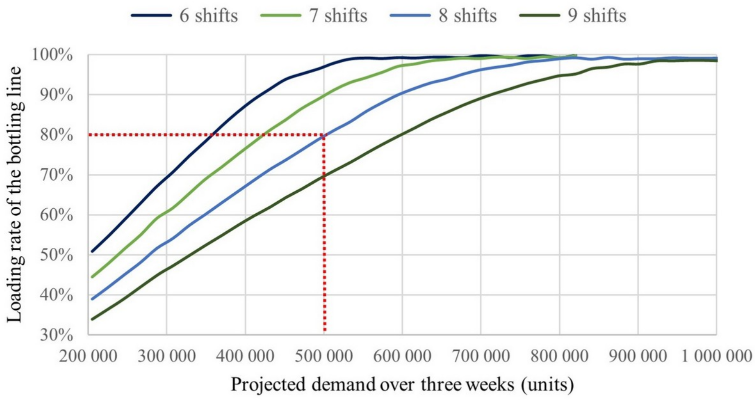

Figure 7. Visual charts correlating the projected demand and the loading rate of the bottling line

Depending on the projected demand and the target loading rate, we can determine the appropriate capacity thresholds. For example (red points in Figure 7), with a demand of 500 000 bottles over three weeks, eight shifts are needed to reach a loading rate of 80%. The capacity manager can then estimate the number of shifts required for the third week of production (knowing that the first two are fixed): if there are 3 shifts for the next week and 3 for the following week, then 8 - 3 - 3 = 2 shifts are required for the third week. Beyond 500 000 bottles, nine shifts are needed. Below 350 000 bottles, only six shifts are needed. Once the capacity thresholds are determined, the choice of the number of shifts can be automated.

As with the DAAWC approach described in Section 3.3.2, four target loading rates are tested with visual charts: 75%, 80%, 85%, and 90%. Similar to what is done in Step 4 of Figure 6, for a specific target loading rate, the capacity required for the third week is calculated as the total capacity required for the short-term horizon minus the capacity of the frozen two weeks. Then, we can deduct the number of shifts needed for the third week. For example, for a target loading rate of 80% and a projected demand of 500 000 bottles for the next three weeks, the visual charts suggest that eight shifts are needed. Thus, if we assume that there are three shifts in week 1 and two shifts in week 2, it takes three shifts in week 3 to get to eight shifts over the three-week horizon.

3.4. Demand Scenarios

In order to evaluate the limits of the capacity management approaches in different environments, we propose to evaluate ten different demand scenarios. The first scenario corresponds to the real customer demand experienced by the industrial case between January and September 2019. For example, customer demand signals for products FP1, FP64, and FP86 are represented in Figure 8.

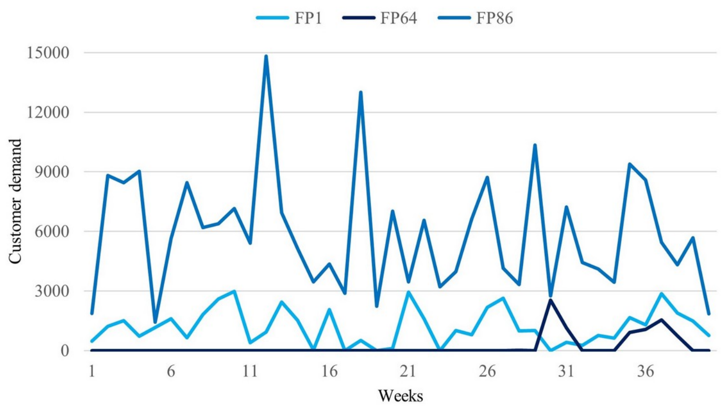

Figure 8. Real customer demand for the products FP1, FP64, and FP86

Figure 8 clearly shows that there is a real difference in customer demand, with distinct demand profiles: FP1 has fairly stable, low demand (around 1,500 bottles on average). FP86 has very punctual demand (around weeks 30-31 and 35 to 37 only). FP86 has fairly stable high demand (6,000 bottles on average) but with order peaks (almost 15,000 bottles ordered in week 12, for example).

In addition to the real scenario, we generate nine demand scenarios. We consider three types of demand scenarios, as represented in Figure 9 (in this figure, only the demand signals for FP1 are represented): a stable signal, a square signal, and a signal with customer order spikes. For each of these scenario types, three demand amplitudes (which correspond to the average customer order) are considered: a Low (L) one, a Medium (M) one, and a High (H) amplitude. To conclude, for each FP, nine demand signals are experimented, in addition to the real demand (so a total of 10 different demand signals), in order to compare capacity management approaches in different likely demand scenarios to assess which approaches work best in which contexts.

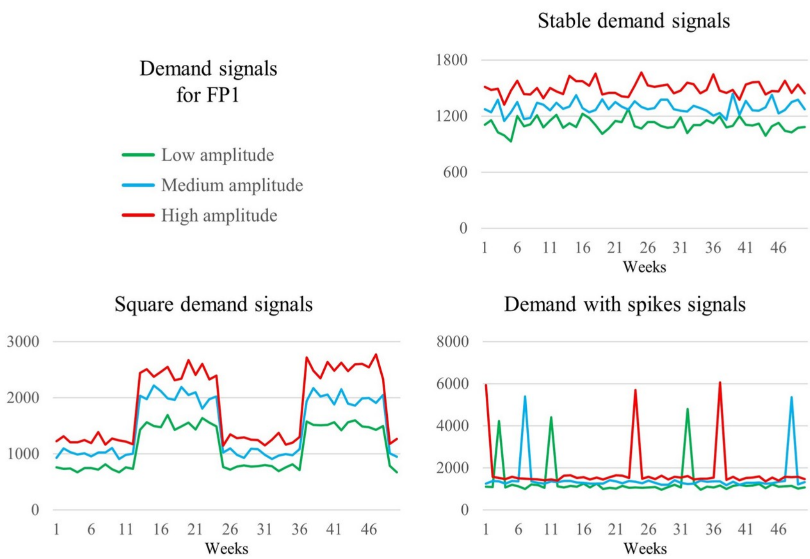

Figure 9. Representation of the nine demand signals experimented for FP1, other than the real demand

3.5. Design of Experiments

Table 1 illustrates the design of experiments. The objective is to evaluate the performance of the proposed workload calculation approach (the DAAWC), compared to the static approach and the DAVC in different demand scenarios.

For the three capacity management approaches, different settings are possible:

- For the static approach, the number of shifts can be: 2, 2.5, or 3.
- For the DAAWC, different levels of the target loading rate can be considered. In order to explore the impact of the target loading rate, we propose to test four levels: 75%, 80%, 85%, and 90%.
- For the DAVC, we also consider four levels for the target loading rate: 75%, 80%, 85%, and 90%.

			Capacity management approach										
			Static			DAAWC				DAVC			
			Number of shifts			Target loading rates				Target loading rates			
			2	2.5	3	75%	80%	85%	90%	75%	80%	85%	90%
Demand scenarios	Real customer demand												
	Stable signal	L											
		M											
		H											
	Square signal	L											
		M											
		H											
	Signal with spikes	L											
		M											
		H											

Table 1. Design of experiments (amplitude: L = Low, M = Medium, H = High)

There are thus 3 + 4 + 4 = 11 approaches to simulate with 10 demand scenarios, making a total of 11 x 10 = 110 experiments. Each experiment is composed of 100 replications of a simulation that lasts 40 weeks (corresponding to the data extracted from the company's enterprise resource planning). In the initial state, the bottling line is set to two shifts a day for the first two weeks (corresponding to the default status), and the products' stock levels are initialized between 90% and 130% of the Top of Yellow level according to a uniform law. Modeling and simulations are carried out with the software *Arena*, version 16.10.

4. Results

Our results are analyzed regarding two performance measures:

- The loading rate of the bottling line: the objective is to obtain a loading rate as close as possible to 80-85% in order to maximize the utilization of the bottleneck resource without compromising production by overloading it or generating unnecessary costs by underloading it.
- The customer service rate: the goal is the maximize it to satisfy customers.

4.1. Real Customer Demand Scenario

Figure 10 presents the results for the real customer demand scenario. While on the abscissa is the loading rate of the bottling line, between 60% and 90%, on the ordinate is the customer service level, between 99.5% and 100%. The different capacity approaches are represented by the shapes and colors: for example, the white square represents the Dynamic Approach based on the Anticipated Workload Calculation (DAAWC) with a loading rate of 75%, while the black square represents the Dynamic Approach based on the Visual Charts (DAVC) with the same loading rate. The static approach is represented by a "plus" for 2.5 shifts and a "cross" for 3 shifts (note that the capacity scenario with 2 shifts is not represented because the customer service level is below 99.5%). The target area (a loading rate of around 80% and a customer service rate of 100%) is represented by a green zone, and the further one moves away from this circle, the more the performance decreases.

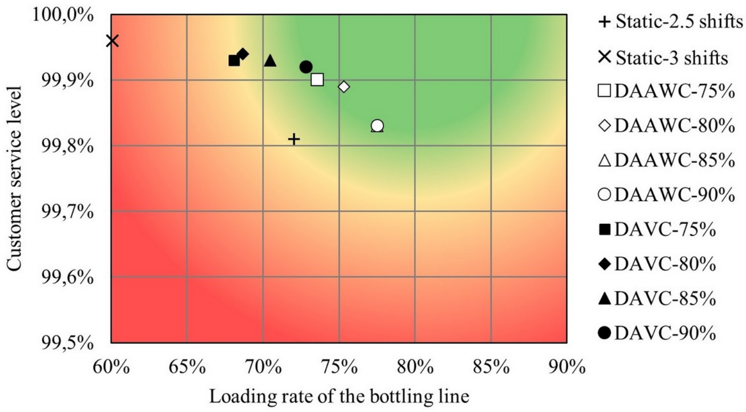

Figure 10. The performance reached by the capacity management approaches for different target loading rates with the real customer demand scenario

First, we note that performance measures reached by the static approach scenarios are the worst: either the loading rate of the bottling line is too low (60% with 3 shifts), or the customer service level is too low (99.8% with 2.5 shifts). Both the dynamic approaches (DAAWC and DAVC) outperform the static ones.

Then, we notice that the points corresponding to the four target loading rates with our proposed approach (DAAWC) are all inside the green zone, in contrast to the approach DAVC proposed by Dessevre et al. (2021). The customer service level reached by the DAAWC is a little lower than the one with the DAVC, but the loading rate is closer to the target. We conclude that the DAVC offers a better customer service level, but the DAAWC offers a more precise workload calculation.

This statement is confirmed in Figure 11, which illustrates the dynamic adjustment of the number of shifts over time proposed by the DAAWC and the DAVC, according to the real customer demand (and therefore to the bottling line workload). Note that in this scenario, the average number of shifts is 2.275 for the DAAWC (in blue), and 2.525 for the DAVC (in red), which explains the difference in loading rates. We observe that the DAVC is more "cautious" (going up to 3 shifts faster), explaining why it offers of better customer service level than the DAAWC which, on the other hand, is more precise.

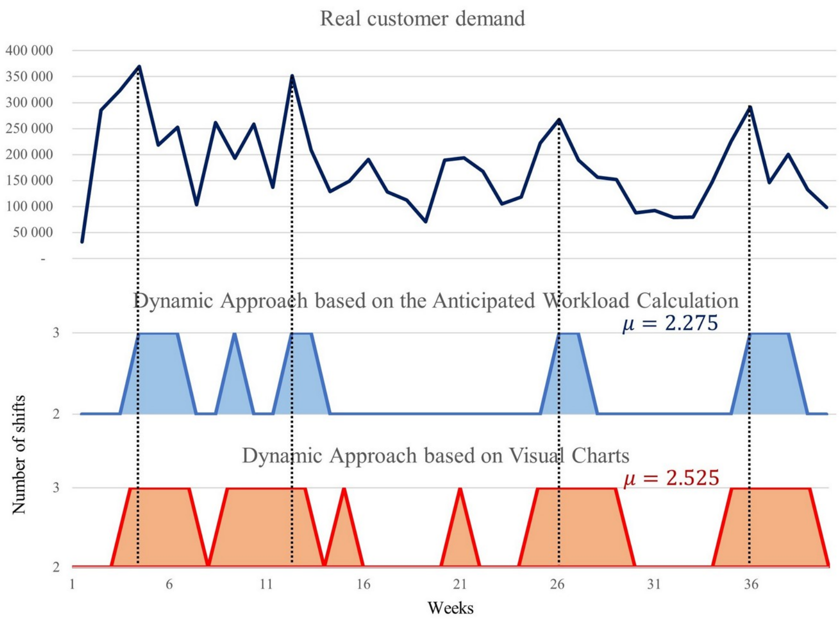

Figure 11. Illustration of the dynamic adjustment of the number of shifts for the real customer demand scenario with a target loading rate of 85%

4.2. Two-Way ANOVA

An ANOVA is a statistical test used to measure the effect of two categorical variables on quantitative variables, by estimating how the mean of the quantitative variable changes according to the levels of the categorical variables. In our case, categorical variables are the Capacity Management Approach (CMA) and the Workload Target (WT), which is the parameter used to set the CMAs. We try to measure the effect of the WT, taking values between 75% and 90%, and the CMA, taking DAAWC or DAVC, on two quantitative performance measures: the loading rate of the bottling line and the customer service rate.

Considering the real customer demand scenario, the two-way ANOVA has been performed, first, on the workload rate of the bottling line. Table 2 presents the means calculation for the workload rate of the bottling line, while the variance and *F*-value calculations are summarized in Table 3.

Workload rate of the bottling line		Workload Target (WT)				
		75%	80%	85%	90%	Mean
Capacity Management Approach (CMA)	DAAWC	73.59%	75.31%	77.51%	77.52%	75.98%
	DAVC	68.09%	68.68%	70.46%	72.86%	70.02%
	Mean	70.84%	71.99%	73.98%	75.19%	73.00%

Table 2. Workload rates for the bottling line with the real customer demand scenario

Source of variability	Sum of Squares (SS)	SS / SS (Total)	Degrees of freedom	Mean SS	*F*-value	F_3^x (99%)
WT	0.229%	24%	3	0.076%	12.93	34.12
CMA	0.711%	74%	1	0.711%	120.64	29.46
Residual	0.018%	2%	3	0.006%		
Total	0.958%					

Table 3. Variance and *F*-value calculation for the workload rate of the bottling line

Since the F-value related to the WT is lower than the value of the F-test with 3 degrees of freedom F_3^3 for the significance level alpha = 0.01, we cannot conclude that the effect of WT on the workload rate is statistically significant. However, the F-value related to the CMA is greater than the F_3^1 (alpha = 0.01), thereby, we can affirm that the CMA has a statistically significant effect on the workload rate of the bottling line. Therefore, to improve the workload rate of the bottling line, we recommend choosing the best capacity management approach rather than rising the workload target.

A two-way ANOVA was also performed on the customer service level, but for both the WT and the CMA, F-values are lower than their respective F_3^x (alpha = 0.01). Thus, we reject the hypothesis that these two factors have a significant effect on the customer service level.

4.3. Results for the Other Scenarios

The results for the other scenarios are presented in Figure 12 where the static approach is represented by the gray squares, the DAAWC is represented by the white circles, and the DAVC is represented by the black triangles. The detail of each value is present in Appendix 2 where each line corresponds to a demand scenario, and where the two best capacity scenarios (a compromise between a high customer service rate and a bottling loading rate close to 80-85%) are in bold for each demand scenario.

Results in the appendices, represented in Figure 12, underline that the DAAWC has more often the best performances than the DAVC or the static approach.

Finally, as managerial insights, we recommend using the DAAWC as it maximizes both the customer service level and the loading rate of the bottling line. However, if the maximization of the loading rate is not a priority, the DAVC offers a better customer service level. As shown with the ANOVA analysis, the choice of capacity management approach has a greater impact than the setting of the approach itself.

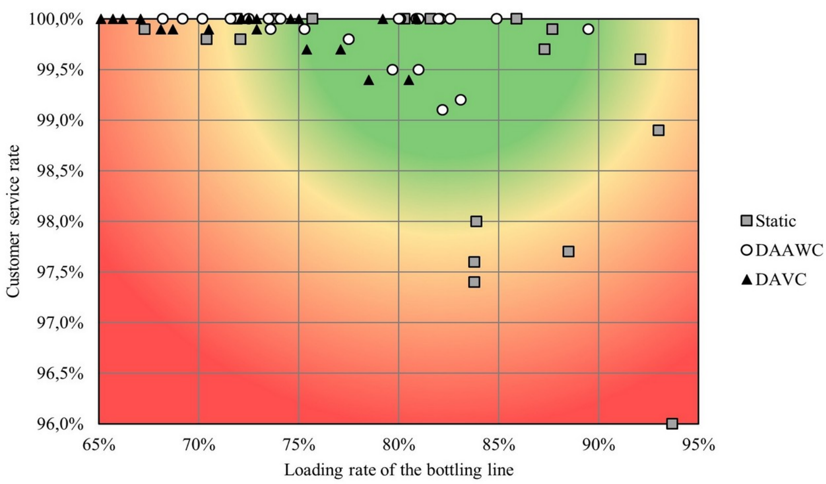

Figure 12. The performance reached by the capacity management approaches for all scenarios

5. Conclusions, Recommendations, and Opening

In this paper, we propose a new dynamic capacity management approach for the DDMRP method, based on an anticipated workload calculation. This approach is compared to a static one and a dynamic approach proposed by Dessevre et al. (2021), on a real industrial case composed of a bottling line operating with two or three shifts.

Different demand scenarios, in addition to a real customer demand scenario, are simulated to compare approaches in several environments. The analysis of the results supported by a two-way ANOVA indicates that the proposed capacity management approach better maximizes the workload of the bottling line while ensuring a high customer service level for the different demand scenarios. The ANOVA underlines that the choice of capacity management approach has a greater impact than the setting of the approach itself.

In real life, contrary to our model, some customers are in reality international distributors (belonging to the industrial partner) who deliver the local customers (shops) worldwide. The FP are also buffered in the distributors' warehouses: a service rate a little lower than 100% can be accepted because the local buffers will absorb variability to satisfy the end customers. Thus, the proposed approach increases the loading rate of the bottling line without necessarily reducing the end customers' service rate.

To go further, it would be interesting to add a calculation of costs in the capacity management approach. Thus, we could compare if is it better to maximize the customer service level in favor of a lower resource loading rate or to reduce the customer service level a little bit and maximize the utilization of resources. It should be noted that, unlike the approach of Dessevre et al. (2021) where the visual charts must be recreated by simulation when a major change occurs in the production line, the approach proposed in this paper automatically adapts to the production line and the size of the DDMRP stock buffers. Therefore, as future research, including time and cost considerations may be of theoretical and practical interest.

Declaration of Conflicting Interests

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Appendices

Appendix A

Links between semi-finished products SFP (shampoo), finished products FP (shampoo bottles), and bottle size.

SFP	Bottle size (mL)	FP	SFP	Bottle size (mL)	FP
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			

Appendix B

Results of the design of experiments for each demand scenario.

Demand signal and amplitude		Performance measures (%)	Static			DAAWC				DAVC			
			2x8	2.5x8	3x8	75%	80%	85%	90%	75%	80%	85%	90%
Real customer demand		CSR	97.7	99.8	100	99.9	99.9	99.8	99.8	99.9	99.9	99.9	99.9
		LR	88.5	72.1	60.1	73.6	75.3	77.5	77.5	68.1	68.7	70.5	72.9
Stable signal	Low	CSR	99.6	100	100	100	100	100	100	100	100	100	100
		LR	92.1	75.7	63.2	72.0	74.1	80.1	82.1	63.8	64.1	66.2	72.1
	Medium	CSR	85.4	100	100	100	100	100	100	100	100	100	100
		LR	97.2	85.9	71.9	72.5	73.5	80	82.1	72.5	72.5	72.5	72.9
	High	CSR	68.3	98.9	100	100	100	100	100	100	100	100	100
		LR	97.6	93.0	80.3	80.9	80.9	81.0	82.0	80.9	80.9	80.9	80.9
Square signal	Low	CSR	98.0	99.9	100	100	100	100	100	100	100	100	100
		LR	83.9	67.3	56.3	68.2	69.2	70.2	71.6	63.7	65.1	65.7	67.1
	Medium	CSR	78.7	97.6	99.8	99.5	99.5	99.1	99.2	99.7	99.7	99.4	99.4
		LR	95.5	83.8	70.4	79.7	81.0	82.2	83.1	75.4	77.1	78.5	80.5
	High	CSR	53.2	82.8	97.4	93.7	93.3	92.8	90.0	95.5	94.6	94.2	93.2
		LR	97.5	93.9	83.8	88.7	90.3	90.9	91.5	85.7	86.9	88.0	89.1
Signal with spikes	Low	CSR	81.0	99.9	100	100	100	99.9	98.6	100	100	100	100
		LR	97.9	87.7	73.9	82.6	84.9	89.5	92.1	74.6	75.0	79.2	84.1
	Medium	CSR	65.6	96.0	100	100	99.8	99.1	95.9	100	100	99.9	99.5
		LR	99.1	93.7	81.6	85.7	90.4	91.9	94.6	82.5	83.9	88.8	91.8
	High	CSR	51.3	85.7	99.7	99.7	97.4	94.0	89.0	99.9	99.4	96.5	91.1
		LR	99.5	96.8	87.3	90.3	93.2	94.7	95.6	88.6	90.6	93.9	95.5