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Comparison of pull management policies for a divergent process with DDMRP buffers: an industrial case study

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ABSTRACT

Production planning and scheduling for companies with divergent processes, where a single component can be transformed into several finished products, are challenging as planners might face material misallocation issues. In this paper, we address the problem of managing a divergent process with DDMRP stock buffers, where different finished products are bottled with the same component having a fixed batch size. An allocation decision needs to be made to determine the quantities of finished products to be bottled. This study is motivated by a real-life problem faced by a dermo-cosmetic company. We compare and analyze by simulation nine different policies triggering allocation decisions. The first policy is the classic DDMRP rule, while the others are new policies, including a virtual buffer of a generic finished product and ConWIP loops, delaying the allocation decision. Our results show that the policy combining the classic DDMRP rule and a ConWIP loop surrounding a part of the process reduces the work-in-process by 34% compared to the classic DDMRP while ensuring high customer service rates and control of flow times.

1. Introduction

A divergent production process, or a V-plants process, is characterised by diverging points throughout the production process (Umble 1992). For several industries, such as the forest industry, the textile industry, the agro-food industry, and the petroleum industry, a single raw material can be transformed into several different finished products. The three main characteristics of a divergent process are the following (Umble 1992): (i) the number of finished products is larger than the number of raw materials; (ii) all finished products are generally processed in the same way; and (iii) the equipment is capital intensive and highly specialised. Moreover, V-plants face misallocation problems and excess stocks (Umble and Srikanth 1995): due to minimum batch-sizing policies, batches larger than required are processed to satisfy customer demand, leading to a surplus of Work-In-Process (WIP) and Finished Goods Inventory (FGI). In the worst case, raw materials are misallocated from one product to another, leading to shortages for some finished products and large FGI for others. Due to many constraints such as production campaigns (Grunow, Günther, and Lehmann 2002), divergent processes are usually piloted with a push approach (Fumero et al. 2016). However, the review of Panwar et al. (2015) demonstrates the potential application of pull production and more generally, lean manufacturing in process industries. A trend toward pull production in process industries is confirmed by Bähner, Prado-Rubio, and Huusom (2021).

The research for this paper was motivated by the need of 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 throughout its entire supply chain (Dessevre et al. 2020). As a manufacturer and distributor of dermo-cosmetic products, the partner is dealing with a divergent production process composed of two major steps: (i) the raw material is manufactured into shampoo batches which (ii) can be bottled into various Finished Products (FP). All FPs are monitored by DDMRP buffers. In addition, the replenishment decisions of the different buffers are dependent since the batch size set by the shampoo manufacturing is larger than the need for a single FP. Allocation decisions need to be made to determine how many products will be bottled per FP and the quantities to be processed for each order.

The Demand Driven Material Requirements Planning (DDMRP) is a recent material management method

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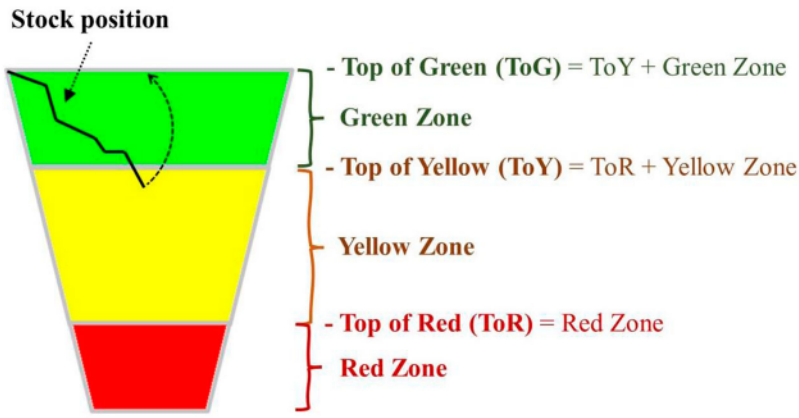

Figure 1. The three zones of a DDMRP stock buffer.

introduced by Ptak and Smith (2016), claimed as the solution to traditional methods' limitations. The main idea is to place stock buffers on strategic positions and replenish them with the following rule: when the stock position of a buffer reaches the threshold called "Top of Yellow" (ToY), it must be replenished up to the level called "Top of Green" (ToG), as illustrated in Figure 1. This inventory policy is similar to a reorder point policy, except that ToY and ToG are dynamically adapted according to several parameters. The equation to calculate the stock position considers order spikes.

The three zones are determined by the following equations of Ptak and Smith (2016), where the Average Daily Usage (ADU) corresponds to the demand forecast (that changes dynamically), the Decoupled Lead Time (DLT) is a "qualified cumulative lead time defined as the longest unprotected sequence in a bill of material" (*i.e.* the allotted time to replenish the buffer), and the Lead Time Factor (LTF) and Variability Factor (VF) are linked to both the minimum order quantity and the safety stock sizing.

$$Red\ Zone = ADU \times DLT \times LTF \times (1 + VF) \quad (1)$$

$$Yellow\ Zone = ADU \times DLT \quad (2)$$

$$Green\ Zone = ADU \times DLT \times LTF \quad (3)$$

The mechanism works very well in many cases, and therefore the DDMRP method is increasingly successful, especially in the industrial world (Bahu, Bironneau, and Hovelaque 2019; Kortabarria et al. 2018). However, the application of DDMRP to the divergent process industries has not been documented (Azzamouri et al. 2021; Dessevre et al. 2020).

This paper proposes to delay allocation decisions until the last moment, where we have access to precise information about the quantities of FPs to bottle. One of the best ways to do that is to use a Constant Work-In-Process (ConWIP) system. The ConWIP is a control system using a single card type, called a ticket, to control the amount of WIP in a production loop (Spearman, Woodruff, and Hopp 1990). Based on Little's Law (Little 1961), this method aims to control the amount of work by limiting it to control the cycle time in the ConWIP loop. The ConWIP tickets limit the waiting times in different queues in the loop by moving these times before the loop.

In this paper, three hypotheses are questioned:

(1) The classic DDMRP policy, where a production order is triggered when a buffer reaches its ToY, leads to an increase in stocks (WIP and FGI) in a divergent process;
(2) Considering simultaneously all the buffers of finished products processed by the same component can avoid this increase in stock; and
(3) A ConWIP loop coupled with DDMRP delays the creation of production orders until the last possible moment and makes the quantities of finished products to be processed more relevant.

To validate the three hypotheses, nine policies that trigger the allocation decision when the FPs are monitored by DDMRP buffers are compared. The design of experiments also includes the impact of the sizing of the Decoupled Lead Time parameter (from the DDMRP method) and the bottling line capacity on the service rates and stocks. We analyze the performance of the different policies by comparing service rates, WIP, FGI, and flow times and their decomposition.

The paper is organised as follows. Section 2 is dedicated to the review of literature on publications related to the topic. Then, Section 3 describes the industrial case. Section 4 details the research methodology and the design of experiments, while Section 5 presents the results and analysis. Finally, Section 6 concludes and proposes avenues for further research.

2. Literature review

This section depicts some models and approaches used in the literature to deal with production planning problems for divergent processes. Then, we present some literature related to DDMRP and the ConWIP deployment.

2.1. Production planning problems for divergent processes

Most researchers use mathematical programming models to solve this kind of problem in the literature. Vila, Martel, and Beauregard (2006) propose a methodology to design the production-distribution network of divergent process industry companies with an application in the lumber industry. Rizk, Martel, and D'Amours (2006) use a tight mixed-integer programming model to resolve a multi-item dynamic production-distribution planning problem, where the issue is to plan the production, the shipments, and the inventory levels of finished and intermediate products over a finite planning horizon. Gaudreault et al. (2011) evaluate two alternative formulations to simultaneously perform process planning and scheduling in a divergent production system with coproduction, using mixed-integer programming and constraint programming. Simulation is also used in literature, especially where there are many variability sources to consider. Farnoush and Wiktorsson (2013) present four different production control mechanisms derived from the POLCA and ConWIP system in an automotive company with a high variety of products and a divergent line. Recently, Dumetz et al. (2021) compared different tactical-operational coordination approaches to optimise production planning of a divergent production system with coproduction.

The literature dealing with divergent production processes includes studies in different sectors. For example, Luo et al. (2012) propose to solve the scheduling problem of a divergent production system in an aluminum manufacturing company. Ahumada and Villalobos (2009) reviewed more than 50 models developed to plan the food supply chain activities. While Joly, Moro, and Pinto (2002) propose a nonlinear model to support planning and scheduling applications for refinery operations, Taşkın and Ünal (2009) investigate tactical-level planning problems faced by a float glass manufacturing in Turkey. Kallrath (2002) presents a state-of-the-art of planning and scheduling problems in the chemical process industry, where production processes combine divergent and convergent product flows.

Although a lot of tools and policies were proposed in the literature to schedule and allocate resources in production systems with divergent processes, there is no research related to the management policies of a divergent process with a pull approach. In particular, no study has proposed stock buffers, like those in DDMRP, replenished with production orders for different finished products linked together by a fixed common lot.

2.2. Publications on DDMRP

The increase in the number of papers on DDMRP in recent years confirms it is a subject increasingly studied scientifically, as the method is deployed in many industries (Bahu, Bironneau, and Hovelaque 2019).

The first stream of literature focuses on comparing the DDMRP to other traditional material management methods, such as MRPII and Kanban, demonstrating the method's relevance and showing its force: a better compromise between stock level and service rate, the anticipation of spike 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; Thürer, Fernandes, and Stevenson 2020).

Recent publications focused on the operation of the method itself to complete or improve it. Martin et al. (2018) propose a decision tree to adjust the buffers' parameters over time, Dessevre et al. (2019) propose a feedback loop approach to control the DLT parameter. Vidal et al. (2020) study the Adaptive Sales & Operations Planning process, the strategic level of the DDMRP. Lee and Rim (2019) propose an alternative way to calculate the safety stock of the DDMRP buffers. Achergui, Allaoui, and Hsu (2020) develop an algorithm to solve the optimisation problem of minimising storing costs for uncapacitated buffer positioning.

Although studies on DDMRP are both axiomatic and empirical (Bagni et al. 2021), many issues remain to be scientifically addressed, like questioning its applicability to specific industrial sectors or complex environments (Velasco Acosta, Mascle, and Baptiste 2019) and its implementation process (Orue, Lizarralde, and Kortabarria 2020). More details can be found in the systematic review of Azzamouri et al. (2021). This paper contributes to compensating for this gap by providing a real case in the dermo-cosmetic industry.

2.3. ConWIP

According to Jaegler et al. (2018), the research on ConWIP is divided into four fields. The first field is related to the sizing characteristics, corresponding to the number of tickets inside the loop and the lot sizing (Spearman, Woodruff, and Hopp 1990; Hopp and Roof 1998). These parameters determine the targeted average cycle

time or throughput: the amount of WIP in the loop is determined by the number of tickets, which is a compromise between throughput, lowering cost, and cycle time. In the literature, two approaches are used to determine these parameters: static ticket count calculations (Hopp and Spearman 1996; Marek, Elkins, and Smith 2001) and adaptive WIP level methodology (Hopp and Roof 1998; Tardif and Maaseidvaag 2001; Belisário and Pierreval 2015). The second field concerns the implementation of ConWIP loops. The choice of a Production Control System (PCS) depends on the demand context and workshop configuration, as Stevenson, Hendry, and Kingsman (2005) explain. Make-to-Stock demand and flow shops are the most studied environment on ConWIP (Jaegler et al. 2018). The third field of research is the comparison of ConWIP with other PCS. For example, it has been compared to push methods (Bahaji and Kuhl 2008; Lavoie, Gharbi, and Kenne 2010), Kanban system (Marek, Elkins, and Smith 2001), adaptive or modified ConWIP (Takahashi and Nakamura 2002; Prakash and Chin 2015), Base-stock (Khojasteh 2015), POLCA (Harrod and Kanet 2013), COBACABANA (Land 2009), etc. In conclusion, although the ConWIP system is not always the best solution, especially in a complex environment, it is the easiest to implement and maintain. Moreover, some researchers combined the ConWIP with other methods: Bonvik, Couch, and Gershwin (1997) a hybrid Kanban/ConWIP system to reduce inventories. This system was analyzed later by Leonardo et al. (2017) in a case study. Takahashi and Hirotani (2005) compare ConWIP and synchronised ConWIP in an assembly line. More recently, the studies of (Onyeocha et al. 2015; Al-Hawari, Qasem, and Smadi 2018) have compared a Hybrid Kanban ConWIP system, a Base-stock ConWIP model, and a Base-stock Kanban ConWIP system in terms of service rate and WIP level. More details may be found in the literature review of Prakash and Chin (2015) with fifteen modified ConWIP systems and González-r, Framinan, and Pierreval (2012) about token-based pull production control systems. Finally, the last field is the research approach used to study ConWIP, where simulation is the most frequently used (Jaegler et al. 2018; Framinan, González, and Ruiz-Usano 2003).

This paper contributes to the literature on DDMRP and proposes new approaches to trigger allocation decisions in divergent production systems by combining DDMRP and ConWIP systems. In particular, we aim to evaluate and compare by simulation different management policies for a divergent process with DDMRP stock buffers.

3. Industrial case

In this study, we consider a case study in the dermo-cosmetic industry. The supply chain of the industrial use case is presented in Figure 2.

Unlike other industries operating with divergent production processes, dermo-cosmetic companies choose to have divergent processes for economic reasons. When creating hydrogen by electrolysis, for example, the production of dioxygen is inevitable. The divergent process is more technical than economic. In the wood or food industry, cutting a trunk or an animal is optimised to meet demand while creating the best co-products. In our case, it is possible to produce exactly the desired product. Still, due to minimum lot sizing rules, forcing the bottling of orders larger than required, it is more economical to share the component among the possible finished products.

The production process of FP (shampoo bottles) is divided into two steps: the manufacture of the Semi-Finished Products (SFP), shampoo batch, and the bottling of shampoo in bottles to make the FPs (shampoo bottles). The raw materials (shampoo ingredients and bottles) are buffered and considered available at all times in sufficient quantities in our model. First, the shampoo batch is made in the *Shampoo manufacturing workshop*, where the ingredients are weighed at a weighing station, then mixed and heated in a reactor, and finally transferred in a tank. There are two parallel weighing stations and four parallel reactors (one of six tons and three of ten tens). There are 18 different SFPs, depending on the fragrance. The total production time of SFP is on average 16 hours without considering waiting times: 2 hours of preparation, 12 hours of manufacture, and 2 hours of transfer. Then, the shampoo is bottled in bottles of 200 mL or 400 mL on the *Bottling line*. There are 95 different FPs: the differentiation is made by the type of shampoo, the size of the bottle, and the label language. The total production time of FP is around 6 hours without considering waiting times: 2 hours of preparation and 4 hours of bottling. The 95 FPs (which are buffered with DDMRP stock buffers) are stored in a distribution centre that delivers to direct customers and international distributors. There are 19 international distributors, corresponding to 19 different countries (France, China, Canada, etc.), and each has FP buffers, for a total variety of 477 pairs (country, product). Shipping times vary from country to country: from a few days for European countries to several weeks for Mexico and China.

For the bottling line, the set-up times to change the format (switch from 200 mL to 400 mL or conversely) is

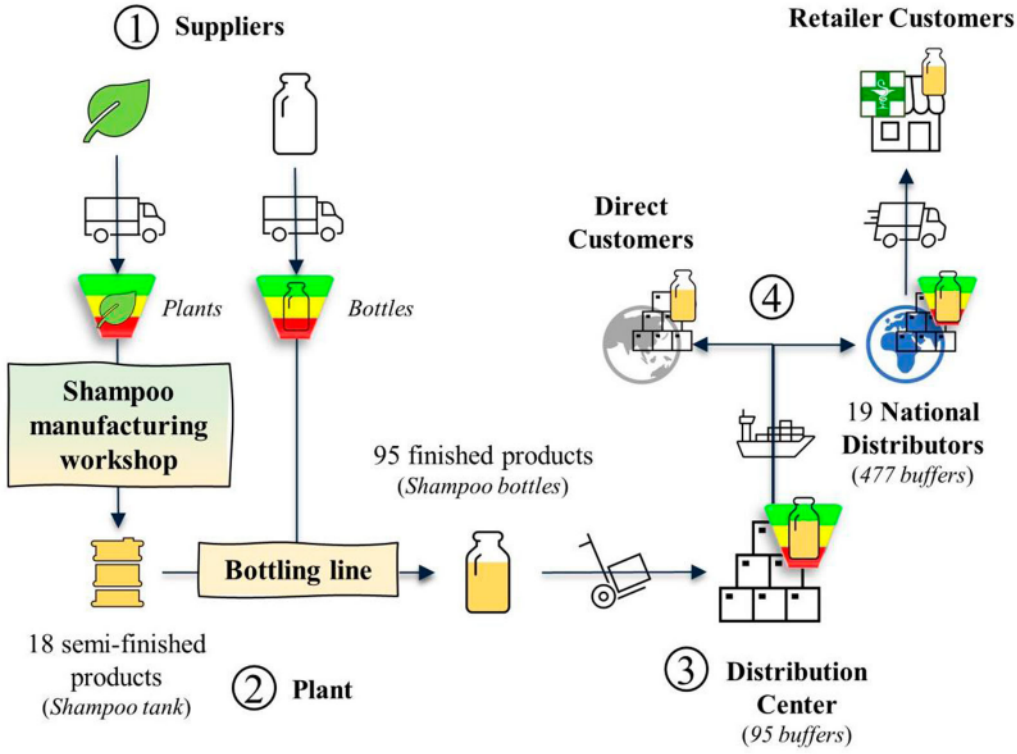

Figure 2. Supply chain of the industrial case.

four times longer than to change SFP: about 4 hours to change the format and 1 hour to clean the pipes between two different shampoos. Thereby, the bottling line works in a campaign: when the line is set for a format (200 mL or 400 mL), it stays at least one week. Production campaign issues are widely studied in the literature, especially for scheduling (Grunow, Günther, and Lehmann 2002; Bérard et al. 2003). In our case, every week, the number of bottling orders ready to be bottled (*i.e.* their components are ready) in each of the two queues (200 and 400 mL) are compared, and the campaign is decided according to the largest queue (the one with the most orders ready).

For example, in Figure 3, although it is possible to make a single batch of SFP1 to bottle the five FPs, in reality, a production order of SFP1 is for a given format because of production campaigns and batch conservation constraints. Thus, when the batch of SFP1 is finished, it will be consumed as soon as possible. This is where there are the divergence points since a batch of shampoo can be bottled to manufacture different FPs. The term Generic Finished Product (GFP) is therefore used to designate the FPs having the same SFP (shampoo) and the same format (Figure 3).

The only difference between the FPs of the same GFP is the language written on the bottle. There are 34 different GFPs in the model, and the links between SFPs, GFPs, and FPs are presented in Table 1.

The most important constraint is the fixed batch size of the SFP: the SFPs are manufactured in reactors containing six or ten tons of shampoo. The size depends on the reactor used, which itself depends on the recipe, and therefore on the SFPs. For example, the SFP2 (in the right in Figure 3) will always be heated in ten tons reactors, and thus we will always manufacture ten tons of SFP2 when required, even if less is needed. For reasons of conservation and space, when an SFP is produced, it must be consumed as quickly as possible (*i.e.* bottled in bottles).

Let us illustrate with the example presented by Figure 4. After checking the buffers at the distribution centre, 15 000 bottles of FP6 need to be bottled (1), but manufacturing ten tons of SFP2 represents about 42 500 bottles of 200 mL (2). What to do with the remaining 27 500 bottles? FP6 is part of GFP3, which encompasses FP6, FP7, and FP8. The 42 500 bottles must therefore be allocated to these three products. In example (3), the allocation decision determined the following allocation: 25 000 FP6, 10 000 FP7, and 7 500 FP8. Therefore, the manufacturing order of SFP2 and the three bottling orders are sent respectively to the shampoo manufacturing workshop and to the bottling line. The allocation decision must be made as soon as the SFP is started in production because, during this time, the bottles are routed from the supplier to the bottling line.

Another constraint is the minimum lot size on the bottling line, which is set at 5 000 bottles. In other words, a

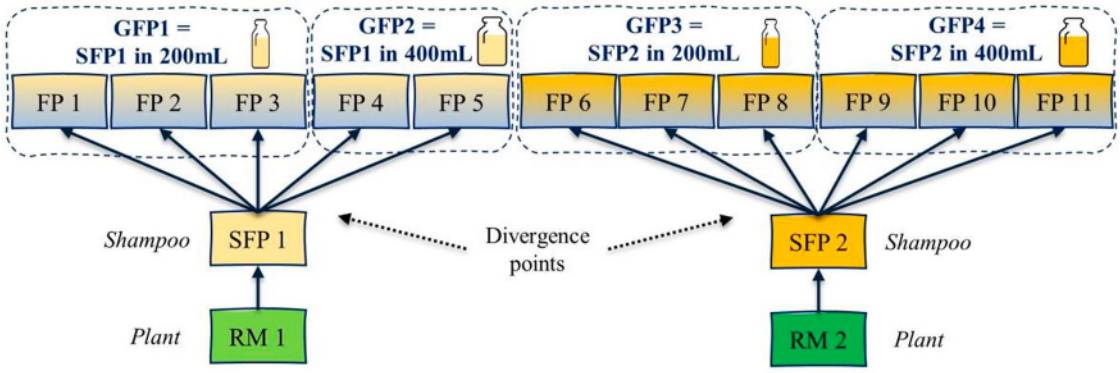

Figure 3. The divergence points and the Generic Finished Product.

Table 1. Links between Semi-Finished Products, Generic Finished Products, and Finished Products.

Semi-Finished Product	Bottle size (ml)	Generic Finished Product	Finished Product	Semi-Finished Product	Bottle Size (ml)	Generic Finished Product	Finished Product
1	200	1	1–3	10	200	18	50–52
	400	2	4–5		400	19	53–55
2	200	3	6–8	11	200	20	56–58
	400	4	9–11		400	21	59–60
3	200	5	12–14	12	200	22	61–62
	400	6	15–17		400	23	63–64
4	400	7	18–20	13	200	24	65–67
					400	25	68–70
5	200	8	21–23	14	200	26	71–73
	400	9	24–26		400	27	74–75
6	200	10	27–29	15	200	28	76–77
	400	11	30–31		400	29	78–79
7	200	12	32–34	16	200	30	80–82
	400	13	35–37		400	31	83–85
8	200	14	38–40	17	200	32	86–88
	400	15	41–43		400	33	89–93
9	200	16	44–46	18	400	34	94–95
	400	17	47–49				

bottling order of fewer than 5 000 bottles cannot pass on the line due to the long set-up times and the high required throughput.

In a pull flow management strategy, two questions remain: (i) when and how are created the SFP orders, and (ii) how are allocated the quantities to bottling orders of FPs. To answer these two questions, we propose different management policies based on DDMRP concepts and evaluate their performance in a divergent production context.

4. Methodology

Discrete events simulation is widely used to model, evaluate, and compare different policies for a complex system with great variability (Mourtzis 2020), like our industrial use case. The main steps are (i) to gather information and data from our industrial partner; (ii) to model the entire process and feed it with real data; (iii) to validate the model; (iv) to define a design of experiments and the simulation parameters; and finally (v) to analyze the results.

4.1. From preparation to model validation

The first three steps are developed here. First, the scope of the study (the manufacture of shampoo and its bottling line, from the supply of raw materials to the distribution in the international distributors to satisfy customer demand) was defined, and data was gathered to understand the supply chain, the production process and to build scenarios. Then, the model was developed and fed with the scenario data extracted from real data (the company's Enterprise Resource Planning (ERP)): bill of materials, customer demand, set-up time, shampoo production time, cleaning time, campaign changeover time, bottling time, transfer time, delivery time, workshop opening times, number of resources, and initial stock levels. After creating a close-to-reality model, the model output data was compared with real data to validate it, such

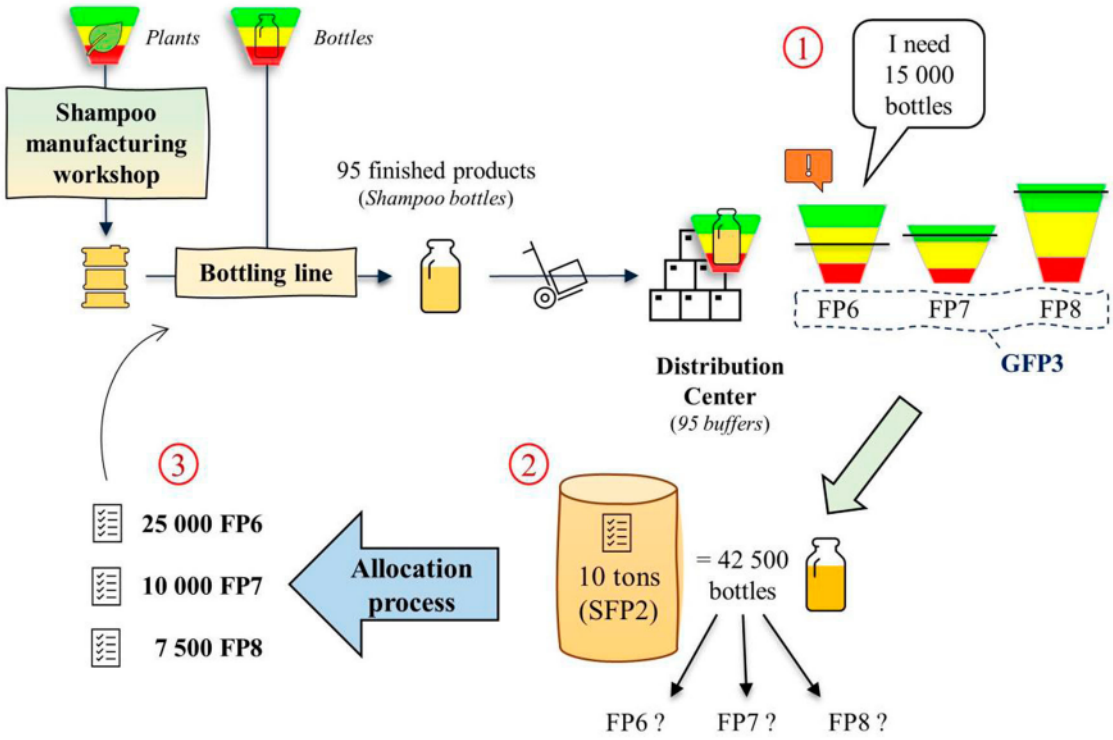

Figure 4. Example of the fixed quantity of SFP2 and the allocation decision.

as the number of products bottled on the line, the number of products shipped to the distributors, resources' utilisation, stock levels, average flow times, production hours, and average service rate.

4.2. Design of experiments

For each production order, the quantity of FPs to be produced and at what time the production will take place must be specified. These decisions can be taken differently depending on the allocation policy. In this study, an allocation decision has to be made to determine the quantities to bottle for each FP. To do so, we follow the different steps illustrated in Figure 5 for the example of Figure 4:

- Step 1: when the allocation decision is triggered, the lot size is initialised to be equal to the stock position minus the threshold ToY for each FP buffer of the same GFP;
- Step 2: the lot size of each bottling order is gradually increased by one percent of the green buffer zone;
- Step 3: when the sum of the lot sizes reaches the number of bottles that can be made with the SFP tank, we stop (42 500 bottles in the example); and
- Step 4: if a bottling order is under the minimum order quantity fixed at 5 000 bottles, it is cancelled and distributed among the other orders.

In this way, FP stocks are replenished fairly to the same level to ensure that the next time one product is needed, the others will be too (or nearly so). The remaining question is when to trigger the allocation decision?

Motivated by the needs of our industrial partner, the objectives of the Design of Experiments (DoE) are to identify how to pull flows in the divergent process with DDMRP buffers, to analyze the impact of the sizing of the DLT parameter on service rates and inventory levels, and to understand the impact of the bottling line capacity on flow times. To meet these objectives, we propose to model and simulate nine different policies to control the divergent process with DDMRP buffers, three different DLT values, and three capacity possibilities. The three dimensions (policy, DLT, capacity) involved in the DoE are presented in the next subsections. The DoE is then composed of $9 \times 3 \times 3 = 81$ scenarios. Each scenario is made of 100 replications (determined from a pilot analysis and the half-width of the performance criteria to obtain consistent results) of a simulation that lasts 40 weeks (duration corresponding to the data collected). In the model, set-up, manufacturing, bottling, transfer and quality control, and transportation times are stochastic. The distribution laws are the result of a preliminary study on the data extracted from the company's ERP as well as an analysis of the interviews with several actors in the supply chain. For example, the set-up time on the bottling line when switching format follows a triangular

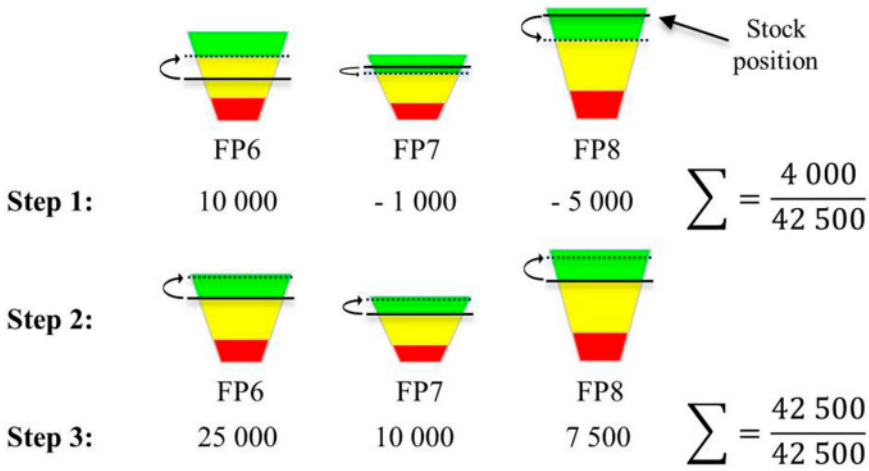

Figure 5. Calculation of lot sizes during the allocation decision.

distribution between 1.84 and 5.32 hours with a mean of 3.58 hours. The rest of the model is considered deterministic (there is no scrap, for example), and the customer demand corresponds exactly to what was requested over the 40 weeks. In addition, the initial stocks are randomly generated at ±20% around the average between the ToY and the ToG for each buffer to model different possible initial states. Modelling and simulations are carried out with the software *Arena*, version 16.10.

4.2.1. Pull management policies

The nine different policies to trigger the allocation decision are detailed in the following paragraphs. The first three policies are presented in Figure 6.

The first policy, which is the one of reference and the easiest to implement, is the basic rule of DDMRP: when the stock position of one FP buffer reaches the threshold called ToY (FP2 in Figure 6), the allocation decision for the products that are parts of the same GFP is triggered, hence the name (FP-ToY). We assume this policy reduces flow times and ensures a high customer service rate because the production orders are made as soon as a need arises, but it increases FGI, because product buffers for the other products of the GFP are replenished long before it was necessary.

In a second policy, the idea is to trigger the allocation decision when there is a common need between the FPs of the same GFP. This second policy, called (GFP-ToY), introduces the virtual buffer of the GFP. The GFP stock position is the sum of its FP buffers. It is a virtual one because there is no real GFP stock (WIP or FGI). When the stock position reaches the ToY of the GFP buffer, the allocation decision is triggered, hence the name (GFP-ToY). The GFP buffer behaves like a stock buffer weighted by the volume of its FPs. We assume this policy reduces FGI, because the production orders are created only when the average stock position reaches the average ToY, but it might increase the flow times because the time between the recognition of a need (when a FP stock position reaches the ToY) and the creation of the order (when the GFP stock position reaches its ToY) will increase. Moreover, when the volume distribution is not equal among the FPs of the same GFP, the risk is as follows: if the stock position is high for the FP buffer with the highest proportion, the total stock position of the GFP buffer will be high as well, obscuring the other FPs buffers. This may end up in shortages for the low-volume products.

Thereby, a third policy called (GFP-ToY || FP-ToR) is introduced: if the stock position of the GFP buffer reaches its ToY level, OR if a FP buffer reaches its ToR level (*i.e.* its safety zone), then the allocation decision is triggered, hence the name (GFP-ToY || FP-ToR). We assume it will combine the advantages of the two previous policies, namely stock reduction and a high customer service rate.

The six other policies are a combination of the first three with a ConWIP loop. The triggering of the allocation decision for each policy is illustrated in Figure 7.

Policies 4, 5, and 6, respectively named (FP-ToY)-ConWIP(SFP), (GFP-ToY)-ConWIP(SFP), and (GFP-ToY || FP-ToR)-ConWIP(SFP), combine the three previous policies with a ConWIP loop on the manufacture of SFP (shampoo). The allocation decision is then triggered when a ConWIP ticket comes back (*i.e.* when a shampoo is manufactured), for the buffer (FP or GFP, depending on the policy) with the highest priority. The priority of a buffer is the ratio of its current stock position and its ToY (Ptak and Smith 2016). If there is no

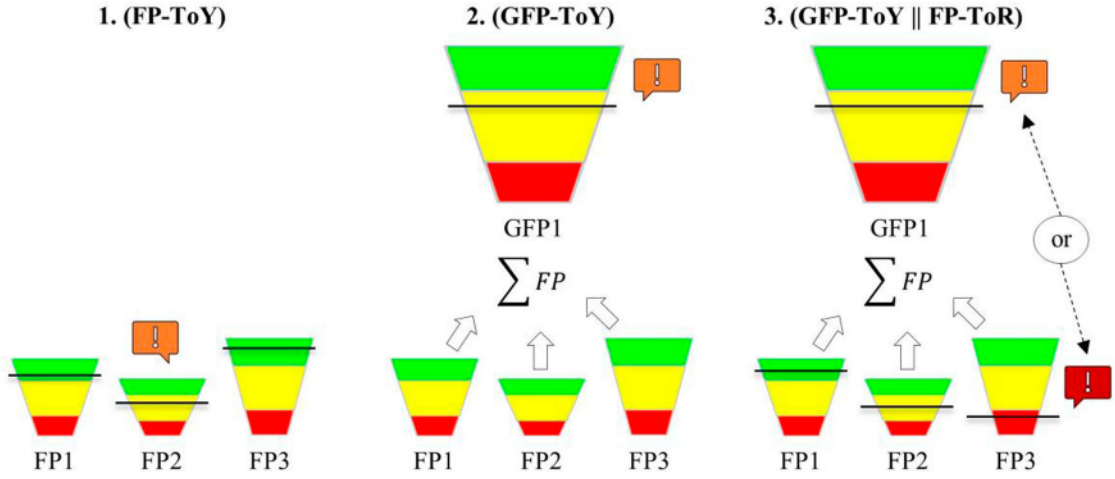

Figure 6. The first three policies: (FP-ToY), (GFP-ToY), and (GFP-ToY || FP-ToR).

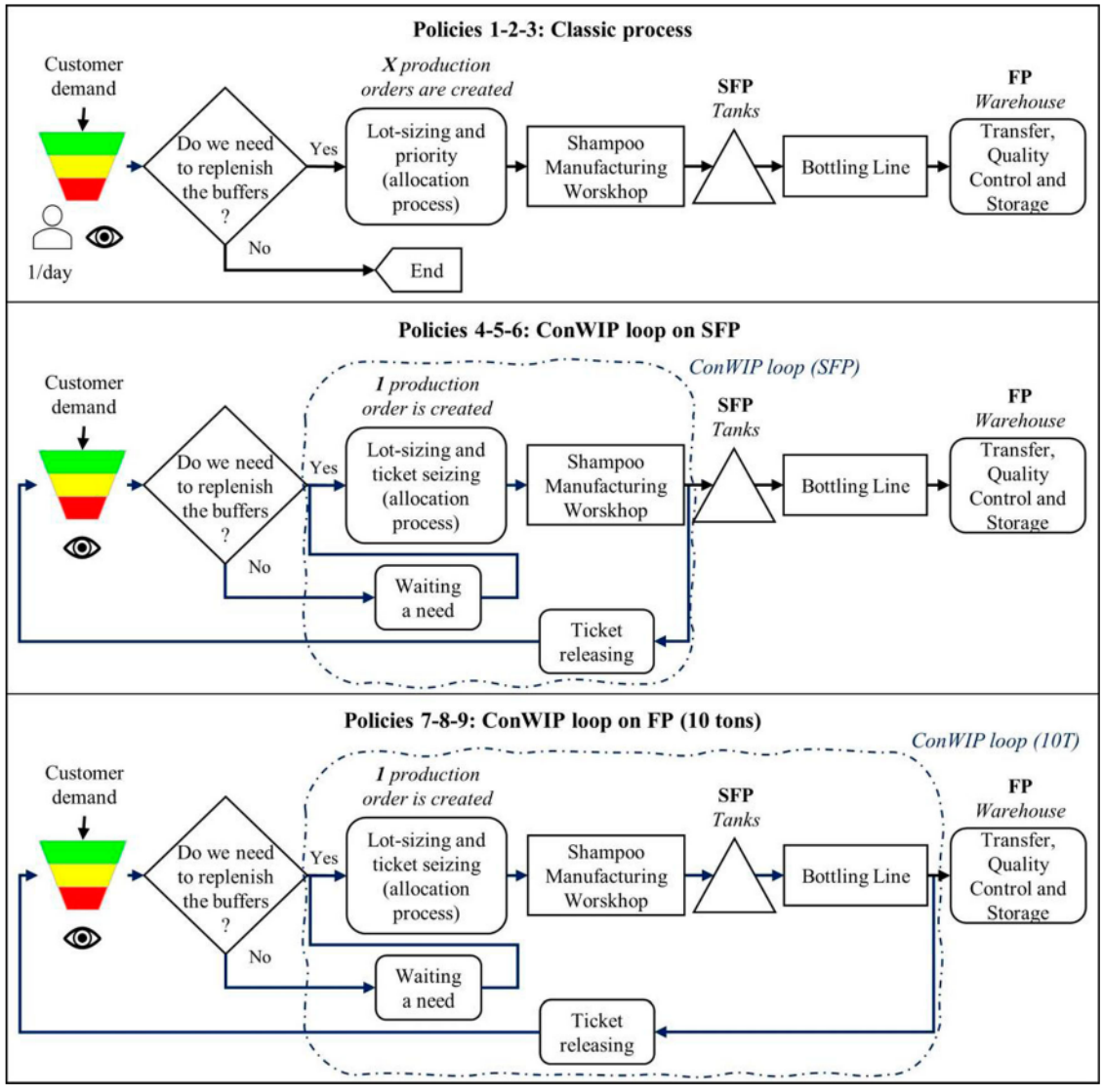

Figure 7. Triggering of the allocation decision for the nine policies.

production need (no buffer has reached a threshold), the ConWIP ticket waits until a need arises.

This choice of the loop is logical from a process point of view: the allocation decision generates two to four bottling orders but only one production order for the SFP, then when the SFP is manufactured, a ticket comes back to create another production order for another SFP (and two to four bottling orders). We assume this ConWIP loop allows to wait until the last moment before deciding on the allocation between FPs of the same GFP, making it more precise. It should also reduce the waiting times in the loop but surely increase the time between recognising a need and creating the production order.

Finally, policies 7, 8, and 9, respectively named (FP-ToY)-ConWIP(10 T), (GFP-ToY)-ConWIP(10 T), and (GFP-ToY || FP-ToR)-ConWIP(10 T), combine the three first policies with a ConWIP loop surrounding the entire production process (manufacture of SFP and bottling of FPs). In this case, ConWIP tickets represent a tonnage of shampoo (either in the manufacture of shampoo, in the SFP stocks, in the bottling line, or in the pool of ConWIP tickets). This choice of the loop is logical from a bottleneck point of view: the bottling line is the bottleneck station, and the only way to relate the manufacture of an SFP and the bottling of a FP is the shampoo volume. As the batch size for a manufacture order of SFP is either six or ten tons, we decided that whenever 10 tons of shampoo are available in the ConWIP tickets pool, the allocation decision is triggered for the buffer with the highest priority. It will then seize six or tens tons, depending on the recipe of the SFP. At the end of the bottling line, just before the warehouse transfer, each bottling order releases its own tonnage into the pool (for example, 10 000 bottles of 400 mL release about 3.4 Tons).

For policies 4–9, it is necessary to determine the number of ConWIP tickets in the loop. We simulated a different number of tickets and found that the optimal number is three tickets for policies 4–6 and thirteen tickets (*i.e.* 130 tons) for policies 7–9. We discuss the impact of sizing the number of tickets in the results.

During the validation of the initial model (section 4.1), the DLT parameter was set to five weeks and the number of shifts to 2.5. The choice of parameters results mainly from discussion with the industrial partner, since it is impossible for a model of this size and complexity to find the optimum set of parameters: there are more than 500 stock buffers in the model, all of which have their own parameters in a rolling horizon. It is therefore preferable to compare the nine methods presented above under conditions close to reality. Thus, the choice of the initial parameters is analyzed in the two other dimensions of the DoE.

4.2.2. The parameter DLT

As shown in Dessevre et al. (2019), the DLT parameter for the FP buffers impacts the tradeoff between services rates and inventory levels. A large DLT offers a better customer service level but high inventory levels, while a low DLT reduces inventory but also lowers the customer service level. We assume that the best policies are able to maintain a high customer service rate, even if we reduce the stock levels (by reducing the DLT). Three realistic values of DLT in the use case are assessed: six weeks, five weeks, and four weeks.

4.2.3. The bottling line capacity

In real life, the bottling line can work with two or three shifts a day per week. To analyze the impact of capacity decisions on flow times (and by extension on service rate), we propose to evaluate three capacity possibilities: two shifts, three shifts, and 2.5 shifts (modelled as two shifts one week followed by three shifts one week, on a loop).

4.2.4. Performance measures

Based on industrial partner objectives and the classic indicators of the literature, we choose to analyze results regarding seven performance measures:

- The customer service rates. There are three in the model: the direct customer service rate (for direct customers from the distribution centre), the international distributor's customer service rate (related to the distributors supplied by the distribution centre), and the retailer customers service rate (which are the customers of the distributors);
- The workshop service rate is defined as the probability that an order has its flow time less than or equal to the allotted time (Hopp and Spearman 1996), which is the DLT in our case. Thus, the workshop service rate can be expressed by Equation 4.

$$Workshop\ Service\ Rate = P(Flow\ Time \leq DLT) \quad (4)$$

- The flow times of production orders and their decomposition. We define the flow time as the time between recognising the need for an order (when the stock position reaches the ToY on a buffer) and the receipt of goods (storage in the warehouse). In our case, flow time is decomposed into the allocation time (which is the time between recognition of a need and the allocation decision), the queuing time before manufacturing SFP, the manufacturing time of SFP, the queue time in front of the bottling line, the bottling time of FP, and the transfer time to the distribution centre;
- The loading rate of the bottling line: this rate can be highly affected by the line capacity;

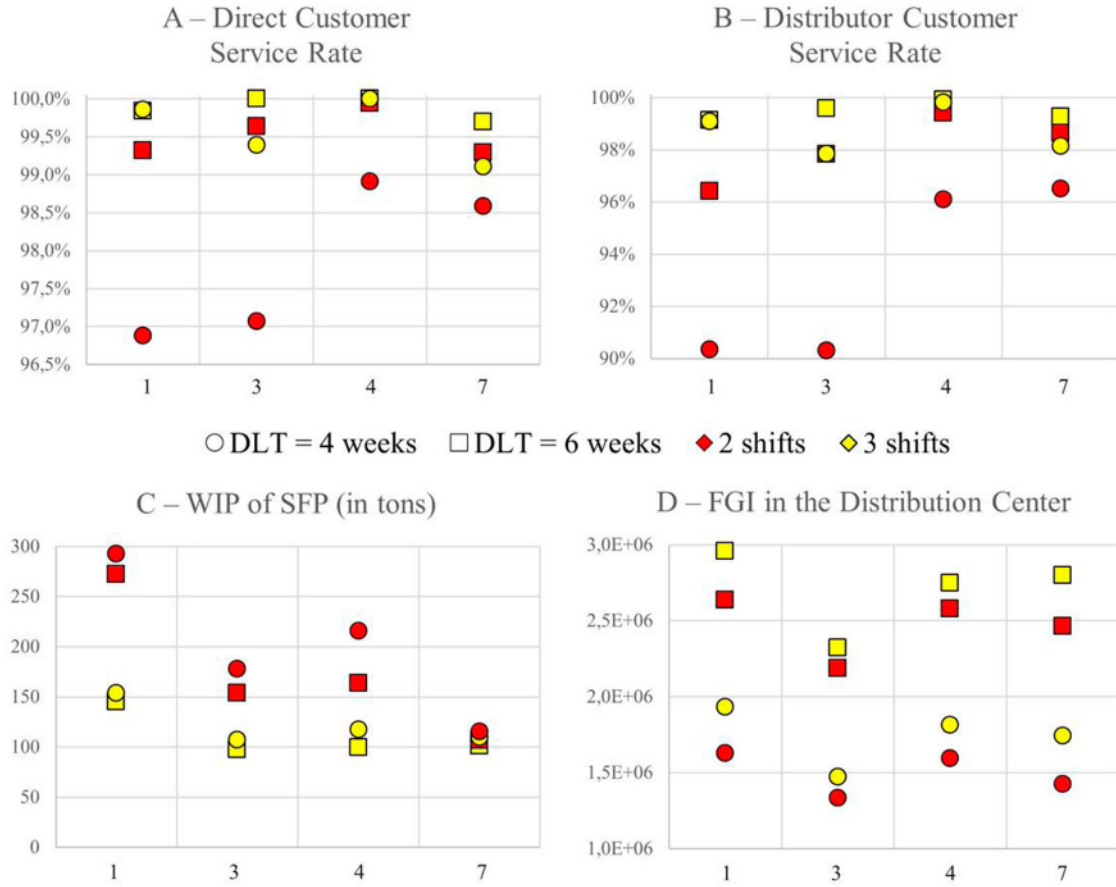

Figure 8. Performance measures depending on the policy (abscissa), DLT (shape), nd capacity (colour) – Part 1.

- The average WIP in the manufacturing process or in tanks (refers to SFP) and in the bottling line (refers to FP);
- The average FGI in the distribution centre; and
- The throughput of the bottling line.

5. Results

To simplify, we choose to present only the results of the best four policies, for scenarios with a DLT of four or six weeks and two or three shifts. Therefore, only the policies 1, 3, 4, and 7, respectively named (FP-ToY) which is the classic DDMRP rule, (GFP-ToY || FP-ToR) with the virtual buffer of GFP, and (FP-ToY)-ConWIP(SFP) and (FP-ToY)-ConWIP(10 T) with ConWIP loops are represented. Figure 8 exhibits the different performance measures of the four policies (on the abscissa), with the two values of DLT (the shape of points) and the two capacities (the colour of points). Figure 9 is complementary and presents the rest of the performance criteria. Finally, Figure 10 illustrates different parts of the flow times (the allocation time and the queue times).

5.1. *Impact of the policy choice*

For the first policy, where the allocation decision is triggered whenever a FP buffer reaches its ToY, the direct customer service rate is one of the best (A, Figure 8), but the distributor customer service rate is lower than those of policies 3, 4, and 7. Moreover, it increases the WIP of SFPs in the plant as well as the FGI of FPs in the distribution centre (C and D, Figure 8). The flow times with this policy are quite low, and this is explained by the fact that the allocation time is null (B, Figure 10). The largest part of the flow times comes from waiting times in the system (queues in front of the shampoo manufacturing workshop and the bottling line, C and D Figure 10) and the two weeks of transfer and quality control to the warehouse.

Policy 4 and 7, a combination of policy 1 and a ConWIP loop triggering the allocation decision, have the best customer service rates. By delaying the allocation decision with a ConWIP loop, we wait until the last moment to determine the quantities to be bottled, making the production more precise. In fact, the waiting times in policy 1 are moved to the allocation times.

Policy 2 (not represented in the figures) reduces both the WIP and the FGI compared to the first policy, but

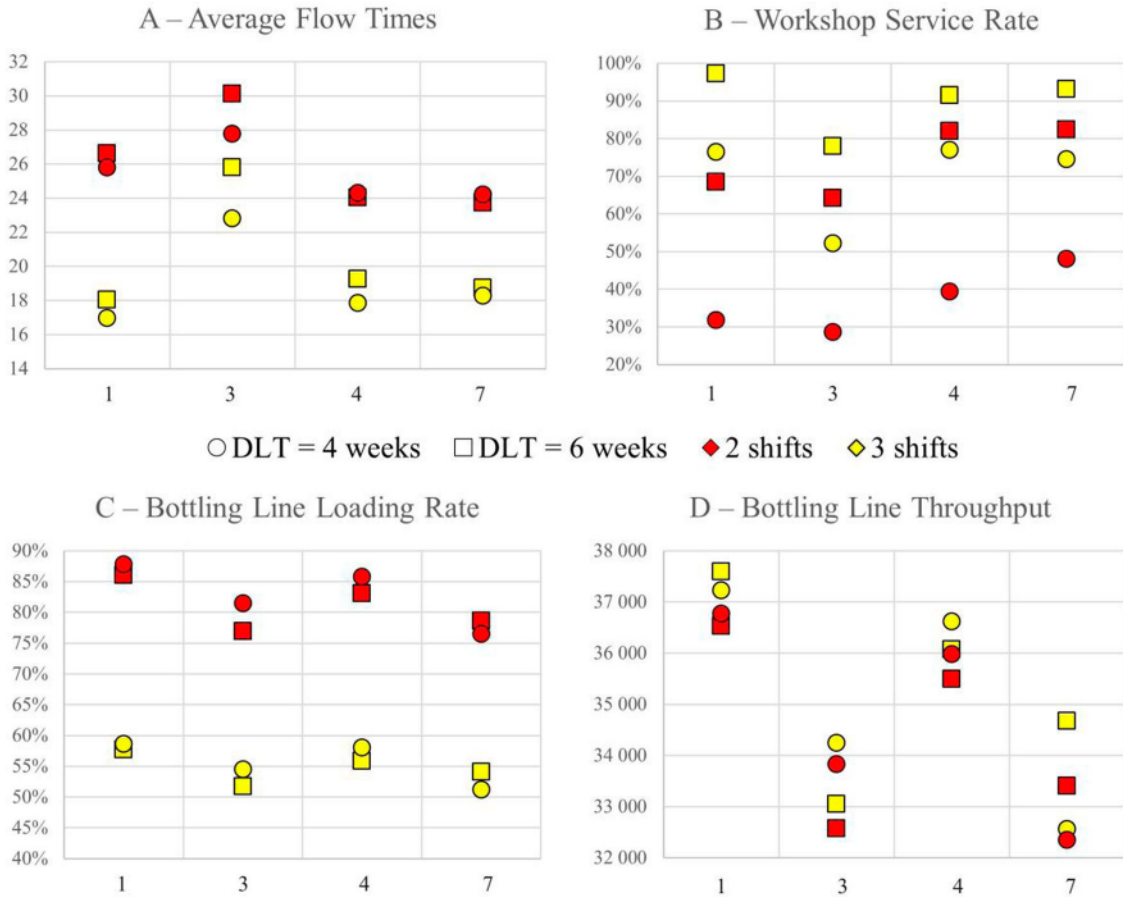

Figure 9. Performance measures depending on the policy (abscissa), DLT (shape), and capacity (colour) – Part 2.

the customer service rates are low due to the long allocation time. That is why the third policy was created to trigger the allocation decision if a FP buffer reaches its ToR while the GFP buffers are above it. This policy is better than the first one in terms of customer services rates, WIP, and FGI, because the times in queues are reduced to the detriment of the allocation time. With this policy, the allocation decision is triggered by a FP buffer reaching its ToR around 20% of the time, hence the higher service rates than the second policy. However, policies 6 and 9 are not as efficient as expected: with these policies, even if a FP buffer reaches its ToR, it must wait for a ConWIP ticket to come back. Consequently, the allocation time is longer, degrading the service rates.

5.2. Decomposition of flow times

Figure 10 presents the decomposition of flow times into allocation and queue times (in front of the shampoo manufacturing workshop and the bottling line). The other parts of flow times are similar (manufacturing time of shampoo and transfer time to the warehouse), and the differences in bottling times are of the order of a few hours.

For the first policy, for example, the allocation time is null (B, Figure 10), but the average queue times are longer than with other policies (around two days for the shampoo manufacturing workshop (C, Figure 10) and three to twelve days for the bottling line (D, Figure 10)). On the contrary, the queue times for policy 7 are very low (less than a day), but the allocation times are longer (around five to nine days). Consequently, even if the flow times are equivalent for policies 1 and 7 (A, Figure 10, in yellow and orange), unnecessary waiting times in queues for policy 1 are moved and transformed into waiting time for a ticket for policy 7, delaying the allocation decision, and therefore the quantities to be bottled are more precise.

Thereby, policy number 4, for which a ConWIP loop is added to the classic DDMRP generating batches of SFPs, is the best policy: it offers a higher customer service rate than the others (close to 100%) while limiting the WIP of SFPs (−34% compared to the classic DDMRP) and the FGI in the distribution centre, and allows better control on flow times.

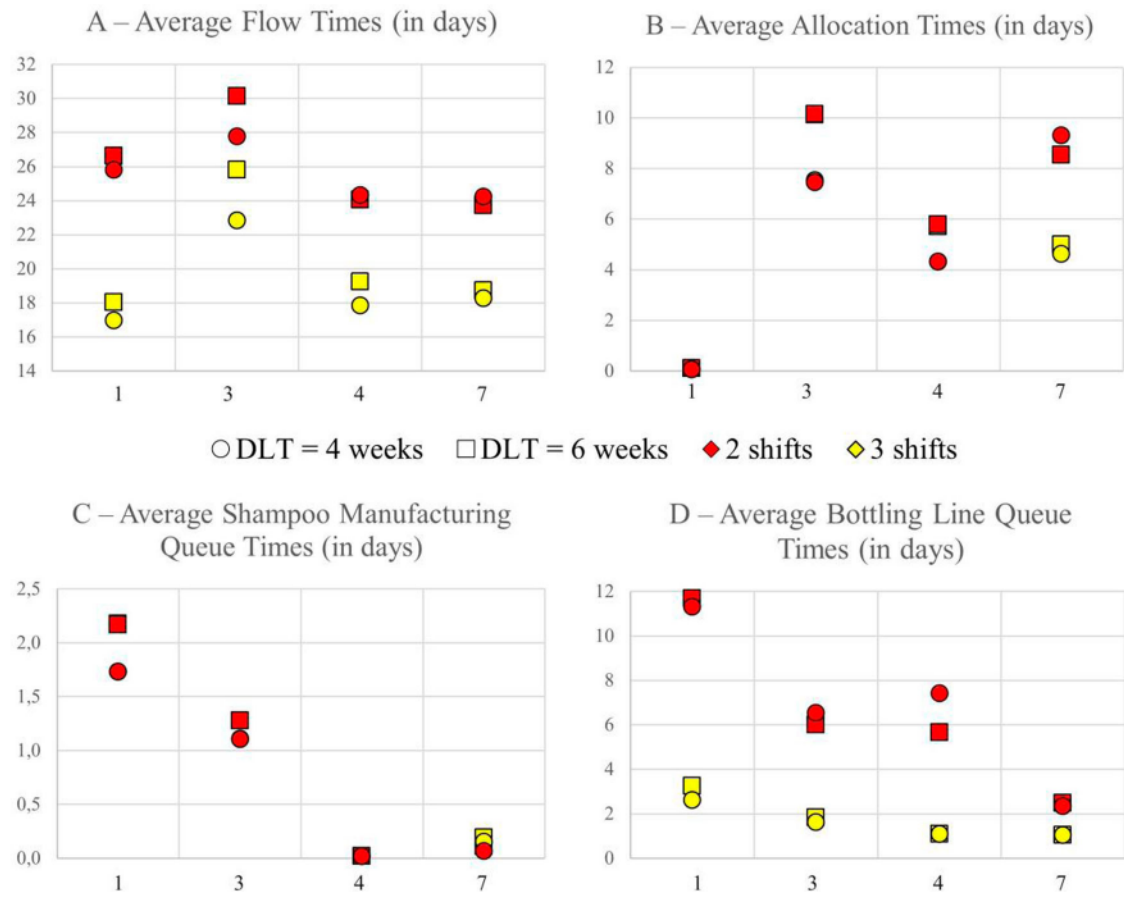

Figure 10. Average flow times, allocation times, and queue times.

5.3. Impact of the sizing of the DLT parameter

The impact of DLT sizing can be seen on the Figures 8–10 by comparing the different shapes: circles for four weeks and squares for six weeks. The consequences of the different values for the DLT parameters are:

- The larger the DLT, the higher the service rates (Figure 8), and the longer the flow times (Figure 9);
- The larger the DLT, the lower the bottling line loading rate (except for policy 7) and the lower its throughput (Figure 9). This is surely caused by the initial stocks, which are slightly higher with a larger DLT, and therefore there is less to produce; and
- The larger the DLT, the lower the WIP (because flow times are reduced), but the higher the FGI (Figure 8) because the buffers' zones are bigger.

We can conclude that the greater the time allocated, the more stocks we have, and thus the better the service rate. This conclusion is true for the nine policies. But increasing stocks is never a good solution, it is more interesting to control the flow times, so they are less than the allocated time.

An ANalysis Of VAriance (ANOVA) is a statistical test used to analyze the difference between the means of different factors. A two-way ANOVA is used to estimate how the mean of a quantitative variable changes according to the levels of two categorical variables. In our case, the statistical test is used to measure the effect of DLT and the choice of policy on the performances. For space reasons, only the ANOVA related to the scenarios with 2.5 shifts and the calculations for flow times is presented. Calculations of means, variances, and F-values are summarised in Table 2.

Since the F-value for the "DLT" variable is lower than F_6^2 (for alpha = 0.01), we cannot conclude it is statistically significant. However, the F-value for the "Policy" variable is greater than F_6^3: thereby, the choice of policy has a statistically significant effect on the flow times and performance measures.

5.4. Impact of capacity and loading rate

The impact of capacity is represented in Figures 8–10 by the different colours: three shifts in yellow and two shifts in red. The choice of capacity directly impacts the

Table 2. Calculations of means, variances, and F-values for the best policies in the scenarios with 2.5 shifts.

		Policy				
Flow times (in hours) (2.5 shifts)		1	3	4	7	Mean
DLT (in weeks)	4	19.2	24.3	19.0	20.3	20.71
	5	20.0	25.7	19.6	20.1	21.37
	6	20.7	27.1	20.4	20.5	22.16
	Mean	19.97	25.72	19.66	20.30	21.41
Variables	Sum of Squares (SS)	SS / SS(Total)	Degrees of freedom	Mean SS	F-value	F_6^x(99%)
DLT	4.20	5%	2	2.10	6.88	10.93
Policy	74.96	93%	3	24.99	81.89	9.78
Residual	1.83	2%	6	0.31		
Total	80.99					

bottling loading rate (Figure 9): the fewer shifts there are, the more the loading rate increases. This causes a chain of events with disastrous consequences on performance.

First, increasing the loading rate generally increases the flow times (Figure 9). In detail, this increases the queue times in front of the bottling line for policies 1, 3, and 4; the queue times in front of the shampoo manufacturing workshop for policies 1 and 3, and the allocation times for policy 7 (where the queue time is moved from the bottling line to the allocation decision, Figure 10).

Consequently, the number of bottling orders above the DLT increases, and the workshop service rate decreases (Figure 9). And since orders take longer, they are late, and the number of shortages increases, decreasing the customer service rates (Figure 8).

Finally, the increase in queue times in front of the bottling line causes the shampoo to wait in the tanks (before being bottled), increasing the WIP of SFP (Figure 8). At the same time, the FGI is reduced, but not for the right reasons. Policies 4 and 7 appear to be less affected by the increase in the loading rate: flow times remain under control, and WIP and service rates are also under control.

The loading rate of the bottling line (which is the bottleneck of the plant) is one of the most important indicators to consider, and the choice of capacity affects all company performance criteria. Thereby, an ANOVA is used to measure the effect of the number of shift and the choice of policy on the performances. For space reasons, only the ANOVA related to the scenarios where DLT is set to 5 weeks and the calculations for flow times is presented. Calculations of means, variances, and F-values are summarised in Table 3.

Since the F-values are greater than F_6^x (for alpha = 0.01) for both the "Shifts" and the "Policy" variables, they are both statistically significant. It is therefore important to choose the right policy but also to monitor the loading rate of the bottling line.

5.5. Impact of the number of ConWIP tickets

The number of ConWIP tickets is a key parameter for a ConWIP loop. Bad settings can lead to a drop in performance: too few tickets will reduce the throughput, while too many tickets will be useless. With a single ticket, for example, the WIP will be reduced, but the throughput will also be since a production order elsewhere than on the bottleneck machine will prevent maximising its use. The cycle time in the loop will be reduced, but the waiting times for a ticket will increase drastically, and therefore flow times. Conversely, if there is an infinite number of tickets in the loop, they become useless since they are free even before a need occurs.

We illustrate these phenomena with policy 7 in Figure 11 (the DLT is set to five weeks and the capacity to 2.5 shifts), where the number of tickets varies from 5 to 18 (*i.e.* 50 tons to 180 tons of shampoo in the loop).

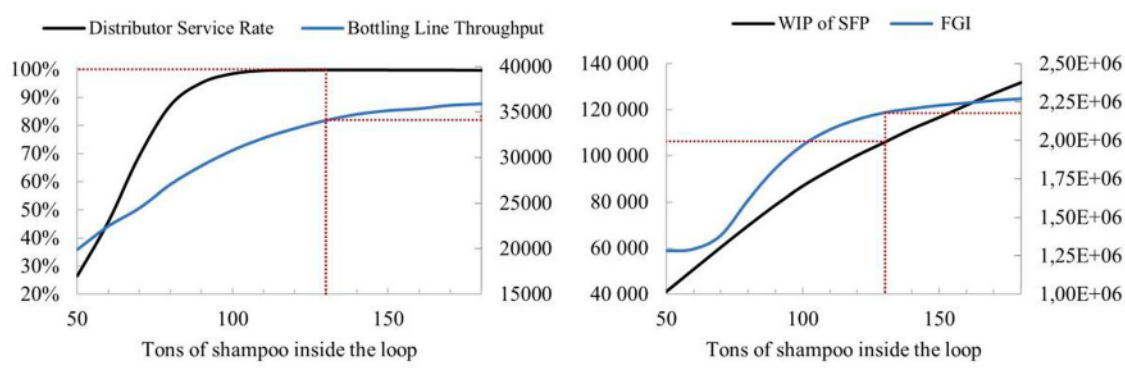

Figure 11. Performance indicators depending on the number of ConWIP tickets (policy 7, DLT = 5 weeks, 2.5 shifts).

Table 3. Calculations of means, variances, and F-values for the best policies in the scenarios with DLT = 5 weeks.

		Policy				
Flow times (in hours) (DLT = 5 weeks)		1	3	4	7	Mean
Shifts	2	26.1	28.8	23.6	23.7	25.56
	2.5	20.0	25.7	19.6	20.1	21.37
	3	17.5	24.4	18.5	18.3	19.69
	Mean	21.18	26.35	20.59	20.70	22.20
Variables	Sum of Squares (SS)	SS / SS(Total)	Degrees of freedom	Mean SS	F-value	$F_6^x(99\%)$
Shifts	73.09	49%	2	36.54	39.33	10.93
Policy	69.18	47%	3	23.06	24.82	9.78
Residual	5.57	4%	6	0.93		
Total	147.84					

Under 100 tons of shampoo, the distributor service rate is lower than 100%, and beyond 150 tons, the throughput begins to reach an asymptote. On the other side, the WIP of SFP is steadily rising, and the FGI reaches an asymptote too. The dotted red line represents our choice of the number of tickets, 13, which seems to be a good compromise.

6. Conclusion, recommendations and openings

In the paper, we compared and analyzed nine different policies to manage a divergent process with DDMRP stock buffers, where the fixed batch size of the components affects the finished products bottled with the same component. The first policy was an application of the DDMRP rule to manage a stock buffer. In contrast, the others were new policies, including a virtual buffer for the generic finished product and ConWIP loops to delay the allocation decision that fixes the production quantities.

6.1. Managerial insights

As managerial insights, we highly recommend using a policy delaying the allocation decision. According to the customer service rates, the average flow times, the WIP, and the FGI, three policies (namely 3, 4, and 7) delaying the allocation decision were better than the classic DDMRP rule. Policy 4, which combines the classic DDMRP rule and a ConWIP loop surrounding a part of the process, outperforms the others: the WIP is reduced by 34% while customer service rates remain high. The ConWIP loop, in addition to limiting the WIP, moves the unnecessary waiting times in queues and transforms them into waiting time for a ticket, delaying the allocation decision. Therefore, the quantities to be bottled are more relevant. With a ConWIP loop, we reduce the number of material misallocations. However, it is important to determine the correct number of tickets to avoid loss in performance.

We also challenged the nine policies in scenarios with different values for the DLT parameter and the bottling line capacity. In conclusion: the greater the DLT, the better the service rate, but also the more stocks we have. For the capacity of the bottling line (the bottleneck of the process), we showed how important it is to control the loading rate to avoid a disastrous chain of events leading to an increase in WIP and a decrease in service rates. Therefore, we recommend monitoring the loading rate regardless of the policy adopted. The two ANOVAs presented show that the choice of policy and capacity management (i.e. the number of shifts) significantly impact the results.

6.2. Openings

To go further, we could discuss the allocation decision, especially the way of calculating the quantities to bottle. In this article, we sought to logically replenish the FP buffers at the same filling percentage. Another method of calculation might be more suitable. Moreover, we compared nine policies to determine when the allocation decision should be triggered, but other policies may be optimal. Furthermore, the divergent process could be avoided by positioning SFP buffers before the bottling line. Thus, the bottling orders would become independent of each other. This solution has not been mentioned in this paper because it is not yet feasible by the industrial partner (conservation difficulty in keeping the shampoo for a long time, space required to store the tanks, etc.). Still, convincing results obtained by simulation could help to change the production process.

Note that other research questions are still unsolved in addition to the three questions addressed in this paper. For example, further research can investigate the impact of changing the minimum lot size on the bottling line, the rule to decide on a production campaign, and the way to propagate end-customer demand all along the supply chain. Furthermore, the dermo-cosmetic plan is a multi-input-multi-output large-scale system, so the coupling relationship between variables could be the next angle of attack to study this complex system.

Finally, in our model, we have set the parameters lead time factor and variability factor to 50% for all

buffers (the 95 in the warehouse and the 477 in the subsidiaries). More research can be conducted to optimise these parameters or to dynamically adjust them like Martin et al. (2019), especially because the demand and the production process data frequently change in the dermocosmetic industry, and it would therefore be interesting to determine the sampling frequency of the parameters of the simulation model to meet the real-time performance of the actual production.

Disclosure statement

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

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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.

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Appendices

The direct Customer Service Rate (CSR), distributor CSR, WIP of SFP (in tons), FGI in the Distribution Center (DC), Flow Times (FT, in days), and Bottling Line Loading Rate (BLLR).

	Policy							
N°	DLT	Shifts	Direct CSR	Distributor CSR	WIP of SFP	FGI in the DC	FT (in hours)	BLLR
1	30	3	99,8%	99,1%	145	2,96E+06	18,0	58%
		2.5	99,7%	98,6%	183	2,86E+06	20,7	69%
		2	99,3%	96,4%	272	2,64E+06	26,6	86%
	25	3	99,9%	99,1%	146	2,43E+06	17,5	58%
		2.5	99,8%	98,4%	183	2,33E+06	20,0	70%
		2	99,0%	95,2%	275	2,11E+06	26,1	87%
	20	3	99,9%	99,1%	154	1,93E+06	17,0	59%
		2.5	99,6%	98,0%	189	1,85E+06	19,2	70%
		2	96,9%	90,3%	293	1,63E+06	25,8	88%
2	30	3	98,0%	86,4%	100	2,21E+06	26,7	51%
		2.5	97,9%	85,5%	119	2,17E+06	28,2	61%
		2	97,5%	83,8%	160	2,08E+06	31,2	75%
	25	3	96,7%	81,7%	102	1,78E+06	25,2	52%
		2.5	96,5%	80,8%	123	1,74E+06	26,6	62%
		2	95,8%	78,4%	165	1,65E+06	29,7	76%
	20	3	94,5%	76,3%	109	1,35E+06	23,8	53%
		2.5	94,1%	75,0%	128	1,31E+06	25,2	64%
		2	92,3%	71,0%	175	1,22E+06	28,4	79%
3	30	3	100,0%	99,6%	98	2,32E+06	25,8	52%
		2.5	100,0%	99,2%	114	2,28E+06	27,1	62%
		2	99,6%	97,8%	154	2,19E+06	30,1	77%
	25	3	99,9%	99,3%	100	1,89E+06	24,4	53%
		2.5	99,8%	98,6%	116	1,85E+06	25,7	64%
		2	99,3%	96,4%	160	1,76E+06	28,8	79%
	20	3	99,4%	97,9%	107	1,47E+06	22,8	55%
		2.5	99,2%	96,6%	127	1,43E+06	24,3	65%
		2	97,1%	90,3%	178	1,33E+06	27,8	82%
4	30	3	100,0%	99,9%	99	2,75E+06	19,2	56%
		2.5	100,0%	99,9%	113	2,71E+06	20,4	67%
		2	99,9%	99,4%	164	2,58E+06	24,0	83%
	25	3	100,0%	99,9%	106	2,26E+06	18,5	57%
		2.5	100,0%	99,8%	120	2,22E+06	19,6	68%
		2	99,9%	99,1%	178	2,08E+06	23,6	84%
	20	3	100,0%	99,8%	118	1,82E+06	17,9	58%
		2.5	100,0%	99,6%	135	1,77E+06	19,0	69%
		2	98,9%	96,1%	216	1,60E+06	24,3	86%
5	30	3	85,3%	57,5%	92	1,89E+06	29,5	48%
		2.5	85,4%	57,0%	101	1,87E+06	30,3	57%
		2	84,9%	55,8%	126	1,81E+06	32,3	70%
	25	3	81,4%	50,4%	103	1,51E+06	28,2	50%
		2.5	81,1%	50,1%	111	1,49E+06	28,8	60%
		2	79,5%	48,0%	141	1,42E+06	31,4	74%
	20	3	74,8%	43,0%	108	1,15E+06	26,8	52%
		2.5	74,3%	42,4%	117	1,13E+06	27,5	63%
		2	72,0%	39,8%	156	1,07E+06	30,3	78%
6	30	3	99,9%	99,4%	106	2,18E+06	30,7	49%
		2.5	99,7%	99,0%	116	2,15E+06	31,6	59%
		2	99,0%	96,5%	151	2,06E+06	34,4	74%
	25	3	99,6%	98,4%	112	1,77E+06	28,5	51%
		2.5	99,3%	97,6%	123	1,73E+06	29,5	61%
		2	97,2%	91,3%	169	1,64E+06	33,2	77%
	20	3	97,2%	93,8%	124	1,38E+06	26,4	53%
		2.5	96,4%	91,8%	139	1,36E+06	27,5	64%
		2	90,8%	75,8%	210	1,24E+06	32,4	81%
7	30	3	99,7%	99,3%	101	2,80E+06	18,7	54%
		2.5	100,0%	99,8%	102	2,70E+06	20,5	65%
		2	99,3%	98,7%	107	2,47E+06	23,7	79%
	25	3	100,0%	99,9%	104	2,26E+06	18,3	54%
		2.5	100,0%	99,8%	106	2,18E+06	20,1	65%
		2	99,9%	99,4%	111	1,99E+06	23,7	80%
	20	3	99,1%	98,1%	110	1,75E+06	18,3	51%
		2.5	99,3%	98,3%	112	1,66E+06	20,3	62%
		2	98,6%	96,5%	115	1,43E+06	24,2	77%

(*continued*).

Table A1. Continued.

	Policy							
N°	DLT	Shifts	Direct CSR	Distributor CSR	WIP of SFP	FGI in the DC	FT (in hours)	BLLR
8	30	3	81,7%	50,4%	92	1,82E+06	29,1	43%
		2.5	82,3%	51,2%	94	1,82E+06	29,6	52%
		2	83,5%	53,3%	99	1,79E+06	31,0	66%
	25	3	77,4%	44,4%	97	1,46E+06	27,9	44%
		2.5	77,7%	45,0%	99	1,43E+06	28,8	52%
		2	79,3%	46,8%	105	1,41E+06	30,2	68%
	20	3	69,4%	36,5%	100	1,07E+06	27,0	45%
		2.5	70,2%	37,3%	103	1,07E+06	27,5	54%
		2	72,3%	39,6%	110	1,04E+06	29,5	70%
9	30	3	99,1%	97,7%	93	2,04E+06	31,6	47%
		2.5	99,4%	98,1%	97	2,03E+06	31,9	56%
		2	99,2%	97,5%	106	2,00E+06	33,0	70%
	25	3	97,9%	95,4%	99	1,62E+06	29,6	48%
		2.5	97,2%	93,7%	103	1,61E+06	30,0	57%
		2	96,7%	92,4%	111	1,57E+06	31,0	71%
	20	3	92,8%	85,3%	104	1,24E+06	27,0	49%
		2.5	91,2%	81,7%	108	1,23E+06	27,5	58%
		2	90,8%	81,3%	114	1,19E+06	28,9	75%