Capstone Project

A Practical Approach on Implementing DDMRP on a Retail Company.

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Abstract

Several studies have approached the issues implicated in the retail supply chain management, including the key decisions related to inventories and product flows throughout the network. Despite this, as far as the authors know, none of the models presented until now have considered discarding demand forecasts and replacing them with real demand driven philosophies.
An adaptation of the DDMRP methodology will allow the comparison of both, the current situation and the behavior of the methodology on a Colombian home and construction goods retailer. This comparison will result on a verdict on whether the application of this philosophy is or not suitable for retail inventory management.

An adaptation of the DDMRP methodology was designed through a VBA application which allows testing the model while measuring the principal indicators determined on this study, which are the level of service and average stock levels. The final results were satisfactory, allowing improvements between 8% and 100% in the level of service, and 1% to 52% in the average stock level.

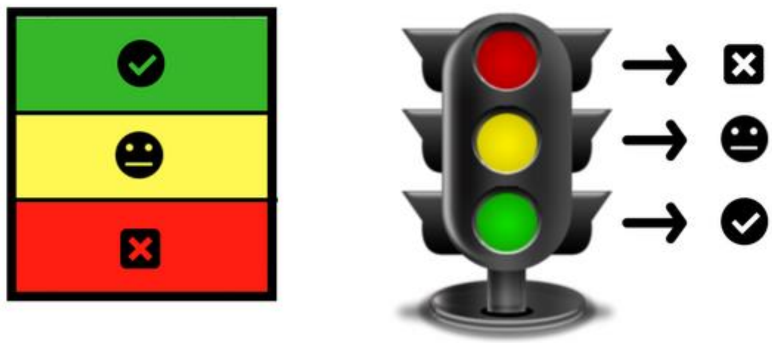
Keywords: Retail, inventories, DDMRP, methodology.

1. Justification and approach to the problem

Nowadays, inventories are fundamental pieces in retailer's daily activities. Increased competition has made retail inventory management a key strategic weapon for large retailers (Agrawal & Smith, 1996).

In recent years, most inventory management methods do not explicitly account for lost sales in updating demand forecasts. This can lead to systematic understocking of items that are in high demand (Agrawal & Smith, 1996). A new philosophy proposed by Ptak & Smith (2016), called DDMRP (Demand-Driven Manufacturing Resource Planning), allows an agile and flexible inventory management. The authors claim that DDMRP can be the answer to uncertainty due to demand. The DDMRP is a recent method focusing on manufacturing and distribution flows that is supposed to manage uncertainties better than traditional Manufacturing Resources Planning (Miclo, Milian, Fontanili, Lauras & Lamothe, 2016). DDMRP's implementation consists in 5 steps. In DDMRP, demand is not defined by the statement "what we can and will build" but the statement "what we can and will sell" (Ptak & Smith, 2013). The core of this philosophy is the introduction of dynamic buffers that helps with the replenishment process. These buffers have 3 different levels, like a traffic light as seen in Figure 1. When the available stock enters the red zone, the buffer is supposed to send an alert signal, meaning that the stock is in jeopardy and should be prioritized immediately. When entering the yellow zone, a replenishment order is supposed to be released in order to achieve the top of the green level, without a critical timing needed for the replenishment, in which the stock is “safe” and no action must be carried out.

Figure 1 Association between a traffic light and the buffer's levels



DDMRP is often compared to MRP since it is considered a better version of the classical method. Its authors “have developed a concept that embraces the strength and validity of MRP while taking care of its weaknesses in today’s environment” (Ihme & Stratton, 2015). Some applications of DDMRP have provided positive results regarding indicators such as Work in Process (WIP), Working Capital (WC) and On Time Deliveries (OTD). According to Miclo et al. (2016), DDMRP appears to dominate MRPII in all the scenarios as it enables to reach the same level of On Time Deliveries with less working capital (10% less in general).

Until now, DDMRP has only been applied on environments involving manufacturing processes, leaving the possibility of working in other scenarios such as retail and wholesalers. This project is be focused on the development of a methodology for applying DDMRP in retail companies given the fact that no one has researched on this topic deeply. Also, retails have several problems involving its inventories that may be intervened through the application of DDMRP. In this particular case study, an approach for implementing DDMRP on a Colombian retailer’s supply chain is presented. The main focus is on maintaining or improving the company’s level of service while decreasing its average inventory levels.

In the following section, more information on DDMRP is presented, as well as the challenges imposed by retail companies that make the application of DDMRP an interesting project.

2. Background/State of the art

DDMRP

DDMRP is designed to be a framework for production planning and control that incorporates MRP functionalities while explicitly addressing its known weaknesses (Ptak & Smith, 2011). Ihme & Stratton (2015) have evaluated DDMRP in the performance of a manufacturing company facing poor due-date performance, stock levels not corresponding to the actual market needs and overall system instability, while using MRP systems. The simulation results across 28 sample products showed how the aggregation and formalized signaling system (implemented through dynamic buffers) reduced high and low inventory alerts by 45% and stock outs by 95%.

On the other hand, a research was carried out in order to evaluate and compare the performance of DDMRP and MRP in terms of level of effective inventory in the system in an automobile company in Indonesia (Shofa & Widyarto, 2017). The authors designed a simulation model using data from the company. Based on the simulation, for the observed critical parts, DDMRP gave better results than MRP in terms of lead time and inventory level. DDMRP compressed the lead time part from 52 to 3 days (94% reduced).

Last, a Discrete-Event Simulation (DES) approach was used by Miclo et al. (2016) to evaluate the impacts on system behaviors, regarding both management methods: MRP and DDMRP. Results show insights on the interests of DDMRP. Such results show that DDMRP develops properties that are recognized to pull flow management policies [...] Regarding WIP, it is reduced in DDMRP scenarios compared to MRP (respectively 26% and 21% less than MRP).

Inventories in Retail

Effective inventory management is critical to retailing success (Dubelaar, Chow & Larson, 2001). Nowadays, one of the important issues in supply chain management is location-inventory decisions. In the conventional approach, the design of such a system is primarily related to the strategic issues by considering the number and location of facilities, (…) without addressing the operational problems such as inventory control and service levels. Typically, operational decisions in such a framework are usually adopted after the location is set. (…) Hence, the problem of joint inventory facility location has been introduced dissolving strategic and operational issues in an integrated framework. Vahdani, Soltani, Yazdani, & Meysam Mousavi (2017) present a three-level location-inventory problem in the supply chain network, taking inventory shortages and the associated demand into account in a policy of periodic review. Their proposed model takes three decisions: 1 location of plants and warehouses; 2 location of retailers; 3 inventory control decisions on the warehouses.

The single most vital decision that every retailer needs to make is how to maximize service level while keeping minimum inventory level. (…) Although inventory service levels have been widely discussed, the relationship between inventory levels and service levels in a retail supply chain context is still under represented as well as the underlying challenges in addressing this trade-off. In a typical retail supply chain inventory management is considered to be an operational decision, while customer service tends to be considered a marketing decision. Salam, Panahifar & Byrne (2016), examined this issue utilizing a simulation model based on company data in Thailand. The results suggested that the achievement of a responsive service level is dependent on managing an efficient supply chain in addition to logistic cost reductions. Furthermore, demand variability and service level have been found to have the most significant influence on the inventory level.

A great deal of the work in the area of stock management is devoted to identifying optimum values for parameters such as order size, order frequency, safety, stock, etc.(…) As we move towards the retailing sector, however, there may be several points at which inventories can be held. The problem then becomes one of moving available stock around the various alternative locations to maximize sales or minimize the likelihood of stock-out. The emphasis has changed from a static situation of ordering to a dynamic one of stock movement. Westwood (1999) proposed a simple model of forecasting and allocation in fashion markets, in a company with difficulties to determine priorities and avoid stock outs of the system; and an inability to cope with geographical variation in sales. The proposed model reduced the number of transfers handled per week and, which are completed up to a maximum of three days earlier than before.

In addition, an examination of the key factors within the control of store managers for optimizing inventory and store results was developed by Ayad (2008). This research integrated principles of action research and traditional research in a big box retail environment. Some of the statements that motivated this examination regarded the role of inventories on return on investment, and the high costs related to out of stocks in retail. While the study confirmed theories that link inventory to sales, merchandise selection, and technology, it emphasizes the role of people. Furthermore, it proves that different stores within same companies and different departments within same stores deliver different results due, mainly, to human factors – specifically, critical thinking, functional knowledge, and leadership.

Since the DDMRP methodology is generic, and, as far as the authors know, there is no studies on implementing DDMRP on the retail sector, then the following research question arises, *How can the DDMRP methodology be implemented in the retail sector*?

3. Objectives

To develop a methodology for implementing DDMRP in the retail environment and evaluate its impact compared to a current scenario.

- *Identify the logistic network of a retailer on which the DDMRP can be implemented.*
- *Propose a methodology for implementing DDMRP.*
- *Develop an application to evaluate the proposed DDMRP implementation.*

- *Measure the economic impact of implementing the DDMRP methodology in a retail environment based on a current scenario.*

4. Methodology

This project aims to analyze the DDMRP philosophy to design a methodology that allows adapting it to a retail environment, particularly in a Colombian retailer's supply chain. At first, it is important to understand the DDMRP philosophy.

4.1 DDMRP

"Demand Driven Material Requirements Planning (DDMRP) is a promising recent method that is designed to promote the flow by reducing variability and detecting demand variations" (Miclo, 2016). The implementation of DDMRP implies the location of dynamic buffers throughout the supply chain. The key of this method lies not only in the location of buffer, but also in how they deal with the policies problems: when and how much to order.

"In planning context, a buffer inventory is composed of 3 zones: red (the safety stock), yellow (the mean in-process replenishment quantity) and green (the replenishment size). These zones will visually help to decide on buffer replenishments: anytime the inventory enters the yellow zone a replenishment order is put to reach the green zone upper level." ((Miclo, Milian, Fontanili, Lauras & Lamothe, 2016)

Since the buffers are the main elements of the DDMRP philosofy, Ptak & Smith have established formulas to calculate the size of each of the buffer's zones, including all the initial parameters that will be studied in this project; as seen on Table 1:

Table 1 Formulas to calculate the size of each of the Buffer's zones

	Zone	Formula
	Green	$DLT^1 * ADU^2 * LTF^3$ (1)
		MOQ^4 (2)
		$DOC^5 * ADU$ (3)
	Yellow	$DLT * ADU$ (4)
	Red	Base Red + Security Red (5)
	Base Red	DLT * ADU * $LTFR^6$ (6)
	Security Red	Base Red * VF^7 (7)

1 *DLT: Decoupled lead time
2 *ADU: Average daily usage
3 *LTF : Lead time factor
4 *MOQ: Minimum order quantity
5 *DOC: Desired order cycle
6*LTFR: Lead time factor red
7*VF: Variability factor

Depending on the nature of the product, the factors (LTF, LTFR, VF) are going to be established to absorb the lead time and demand variabilities. The impact of each one will be considered to evaluate if it is necessary to use all of them or if some can be omitted on the retail environment.

The DDMRP is founded on the adaptability with an agile response and not on the precision of the forecasting, for this reason, and to have a fair comparison base without noise generation to attain the same retailer's condition only using the real data, without incorporating any demand forecasting methods, and just taking into account the DDMRP's effect.

Given the fact that this project aims to adapt and evaluate DDMRP's performance on retail, classical inventory policies will not be considered and no emphasis will be given on this field.

4.2 Capstone project methodology

Figure 2 Capstone project methodology

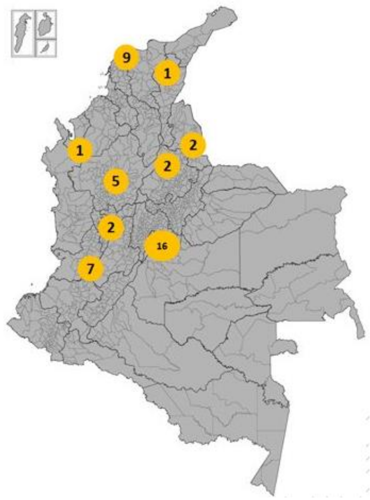
This section describes the steps followed through this capstone project to achieve the adaptation of the DDMRP methodology to a retail environment, which will be presented on the results section. Figure 2 illustrates the 5 general steps. At first, after analyzing the data a pareto was designed to establish the nodes and references that would be chosen. The location of the buffer kept the same idea suggested by the authors, locating them based on the knowledge of the supply chain. The definition of the buffer profiles maintained the classification proposed by the authors, but a significant change was made in the profile assignment process. The alerts found in the literature were studied and the buffer status alert was selected as the best for the adaptation. Two indicators were defined to evaluate the model's performance: The amount of days with zero stock and the average stock level.

To verify the functionality of the DDMRP's adaptation, a VBA tool was designed as a simulator of how the supply chain would have behaved if the retailer had implemented DDMRP. The simulated period was 273 days. 5 scenarios were built in order to compare the results and set up the same conditions of the retailer.

The following sections go into detail about on each one of the previous steps.

4.2.1 Identification of the logistic network and location of dynamic buffers To adapt the DDMRP philosophy to a retail environment, it was necessary to establish a section of the retailer's current logistic network. After receiving all the information and data related to the operation of the supply chain, it was found that the entire network consisted of 45 stores with 1092 references, as seen on Figure 3, which had a different behavior for each node. 22 nodes were selected based on a Pareto of the amount of sales registered, given the fact that the model feeds on daily sales records to build a reliable ADU. It is important to note that the criteria to select a store is the amount of days with sales records and not the amount of sales in units, given the fact that DDMRP adjusts its buffers based on the average daily usage regardless of the amounts sold.

Figure 3 Retailer's stores and DCs in Colombia



Once the 22 nodes were selected, the three references with higher sales registered on each one were chosen. It is important to note that 19 stores of the first 22 that qualified, had its own storage and sent orders directly to suppliers, with a lead time of 10 days. The remaining 3 "stores" were identified as Distribution Centers that attended the requirements of stores without any storage of their own. The lead time from the suppliers to Distribution Centers was also 10 days. Annex 1 shows the selected nodes. 36% of the selected stores were located in Bogota, while 26% were located in Cali; the remaining 38% is distributed throughout the rest of the country.

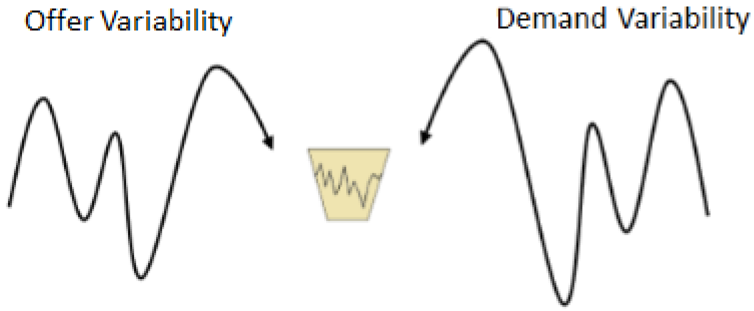
For each one of the 19 stores selected to test the model, the three references with the most days with sales records were chosen. In the case of distribution centers, their selection came as a consequence of three of the initial Pareto Stores not having their own storage, and therefore not having any historical stock data to compare to the retailer. When one of these stores showed up on the Pareto analysis, the distribution center assigned to it was chosen as a node where the model would be tested, for the first reference in amount of days with sales registered. For example, store IN034 was part of the Pareto Stores, but did not have storage of its own, therefore distribution center IN085 was chosen to test the model with reference 190320279 (the one in the top sales of store IN034).

In order to give the model a realistic approach, storage capacities were determined as the maximum amount stored on each store, for each reference according to the retailer's historical stock data. To have greater credibility of the data, the retailer asked to work with the information of 2017 (273 days from January 1st to September 30th).

It is important to note that no new nodes were set within the retailer's current logistic network due to the fact that the company is not considering an expansion of its supply chain at this moment.

As seen on Figure 4, buffers must deal with two kinds of variability: the offer's variability (which depends on the lead times) and the demand variability. Depending on the position of the supply chain where it is located, these variabilities will be mitigated or not. Taking this into account and considering the configuration of the retailer's current logistic network, it was decided to locate a buffer on every previously chosen node and for each reference in which the DDMRP would be tested.

Figure 4 Variabilities absorbed by a buffer



Transfers of product between stores are allowed nowadays in the retailer's replenishment policies. Nevertheless, the proposed adaptation of DDMRP does not allow these exchanges, because DDMRP buffers are supposed to be capable of maintaining its inventory without compromising the inventory of another store.

4.2.2 Definition of buffer profiles and levels

To simplify the choice of which parameters should be introduced in the equations mentioned on Table 2, the authors have defined a series of buffer profiles as shown on Table 2 These profiles are labels which guide the determination of the lead time factor (LTF), lead time factor red (LTFR) and variability factor (VF). 3 different categories are described by the authors, according to the nature of the product (M: Make, B: Buy, D: Distributed). The demand variability is classified into High = 3, Medium = 2, Low = 1; and the lead time magnitude can be classified as (short = 0, medium = 1, long = 2). The choice of the profiles should be made based on the perception of the product's nature, given the fact that there is not a defined scale for classifying variabilities and lead times.

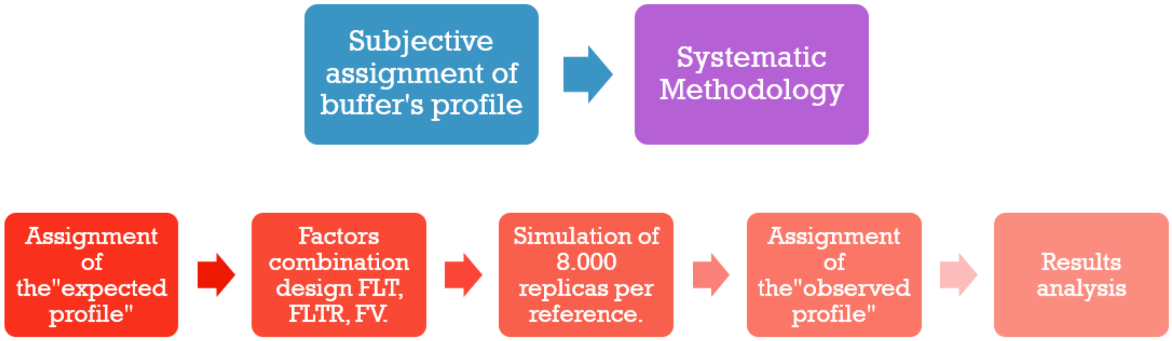
Table 2 Buffer Profiles

<table>
<tr><td></td><td></td><td>Make = M</td><td>Buy = B</td><td>Distributed = D</td><td></td><td></td></tr>
<tr><td rowspan="9">Variability`s categories</td><td rowspan="3">Low = 1</td><td>M10</td><td>B10</td><td>D10</td><td>Low = 0</td><td rowspan="9">Lead Time`s categories</td></tr>
<tr><td>M11</td><td>B11</td><td>D11</td><td>Medium = 1</td></tr>
<tr><td>M12</td><td>B12</td><td>D12</td><td>High = 2</td></tr>
<tr><td rowspan="3">Medium= 2</td><td>M20</td><td>B20</td><td>D20</td><td>Low = 0</td></tr>
<tr><td>M21</td><td>B21</td><td>D21</td><td>Medium = 1</td></tr>
<tr><td>M22</td><td>B22</td><td>D22</td><td>High = 2</td></tr>
<tr><td rowspan="3">High = 3</td><td>M30</td><td>B30</td><td>D30</td><td>Low = 0</td></tr>
<tr><td>M31</td><td>B31</td><td>D31</td><td>Medium = 1</td></tr>
<tr><td>M32</td><td>B32</td><td>D32</td><td>High = 2</td></tr>
<tr><td colspan="2" rowspan="9">MOQ APPLICATION</td><td>M10MOQ</td><td>B10MOQ</td><td>D10MOQ</td><td colspan="2" rowspan="9">MOQ APPLICATION</td></tr>
<tr><td>M11MOQ</td><td>B11MOQ</td><td>D11MOQ</td></tr>
<tr><td>M12MOQ</td><td>B12MOQ</td><td>D12MOQ</td></tr>
<tr><td>M20MOQ</td><td>B20MOQ</td><td>D20MOQ</td></tr>
<tr><td>M21MOQ</td><td>B21MOQ</td><td>D21MOQ</td></tr>
<tr><td>M22MOQ</td><td>B22MOQ</td><td>D22MOQ</td></tr>
<tr><td>M30MOQ</td><td>B30MOQ</td><td>D30MOQ</td></tr>
<tr><td>M31MOQ</td><td>B31MOQ</td><td>D31MOQ</td></tr>
<tr><td>M32MOQ</td><td>B32MOQ</td><td>D32MOQ</td></tr>
</table>

For this case study the only category that was taken into account was “Distributed”, given the nature of the products that were used. The MOQ (Minimum order quantity) application was not taken into account because the retailer did not provide this information. A first classification for each reference was obtained based on the known data provided by the retailer. The references were classified as D30 (D=Distributed;3=High demand variability;0=Low lead time variability). This was the “expected profile”.

Given the subjectivity of the choice of profiles, all the profiles on the “D” category were taken into account in the adaptation of the DDMRP for the retail environment. The main idea was to prove if one reference could have more than one profile. For that reason, all the chosen references were tested under 8.000 different combinations of the factors (LTF, LTFR and VF). To be able to validate the previous hypothesis, an “observed profile” was given to each reference taking into account the author’s classification. The expected and observed profiles were contrasted in order to confirm if the model’s best performance was obtained with the expected profile.

Figure 5 Systematic methodology for the assignment of buffer profiles



Due to a methodological gap found on the DDMRP methodology, a systematic methodology was designed to establish a better selection of the factors (LTF, LTFR, VF) related to the buffer's profile. The authors proposed a subjective procedure for the assignment of a reference to a profile, which depends on the perceived magnitude based on the demand's variability and the size of the lead time.

Figure 5 proposes the steps that should be followed that would fill the methodological void. The expected profile assignment was developed as proposed by the authors based on the variability coefficient and the proportion of the chosen lead lime (10 days) with the longest lead time in the retailer's sector. 8000 combinations of the profile's factors were designed and simulated in order to obtain the observed profile taking into account the best result of the two indicators.

The results of the analysis between the expected and observed profiles will be presented on the results section *6.4.1 "Interpretation of the results of the buffer profiles."*

4.2.3. Definition of alerts and indicators of the model

All the alerts presented by the DDMRP authors, as shown on Table 3, were studied and taken in consideration in order to analyze which ones could match with the retail environment. The conclusion of this analysis was that the only alert that was chosen was the buffer's status, basically the main alert that DDMRP uses, considering the inventory position and the sizes of the green, yellow and red zone.

Table 3 DDMRP Alerts

Alerts presented by the authors	Description	Observations
Available physic Stock	The moment the inventory level is under the top of the yellow zone, the alert makes the quantity requirement to fill the buffer to the top of the green zone	This is the most important alert of the replenishment policy. This policy was implemented in the adaptation of the DDMRP methodology
Projected buffer status alert	It is based on the projection of the consumption according to the ADU and it alerts how many days of available stock remains	This alert was not considered because the main purpose is to simplify the decision making on when to order
Synchronization alerts	This alert takes into account all the elements of the BOM (Bill of materials) of the parent piece and warns if a piece is about to run out in order to prevent that the operation	This alert is focused on a production environment, reason why it was not considered

	stops	
Lead time`s alerts	This alert shows how many days are left until the purchase order arrives and if the buffer will be left empty, and the requires the interaction between the planner and the supplier	This alert is focused on a production environment, reason why it was not considered

The average inventory and days with 0 inventory were the principal indicators of the adaptation of the DDMRP. The indicator of 0 days of inventory was chosen due to the lack of information on the real demand, this indicator is a close approach to a service level: every time the inventory reaches a level of zero (or very close to zero), the model assumes that there are shortfalls. The level of service can be calculated as the amount of shortfalls on the total sale.

4.2.4. Simulation

A simulator of the adaptation of the DDMRP for the retail environment was designed in order to validate the operation of the methodology and facilitate the comparison of its performance vs the retailer's current model. The simulator was built through a visual basic program, and its principal purpose is to provide the indicators defined for the model: Average inventory level and amount of days with zero stock. It can be classified as a discrete event simulation.

Table 4 Inputs and Outputs of the simulation

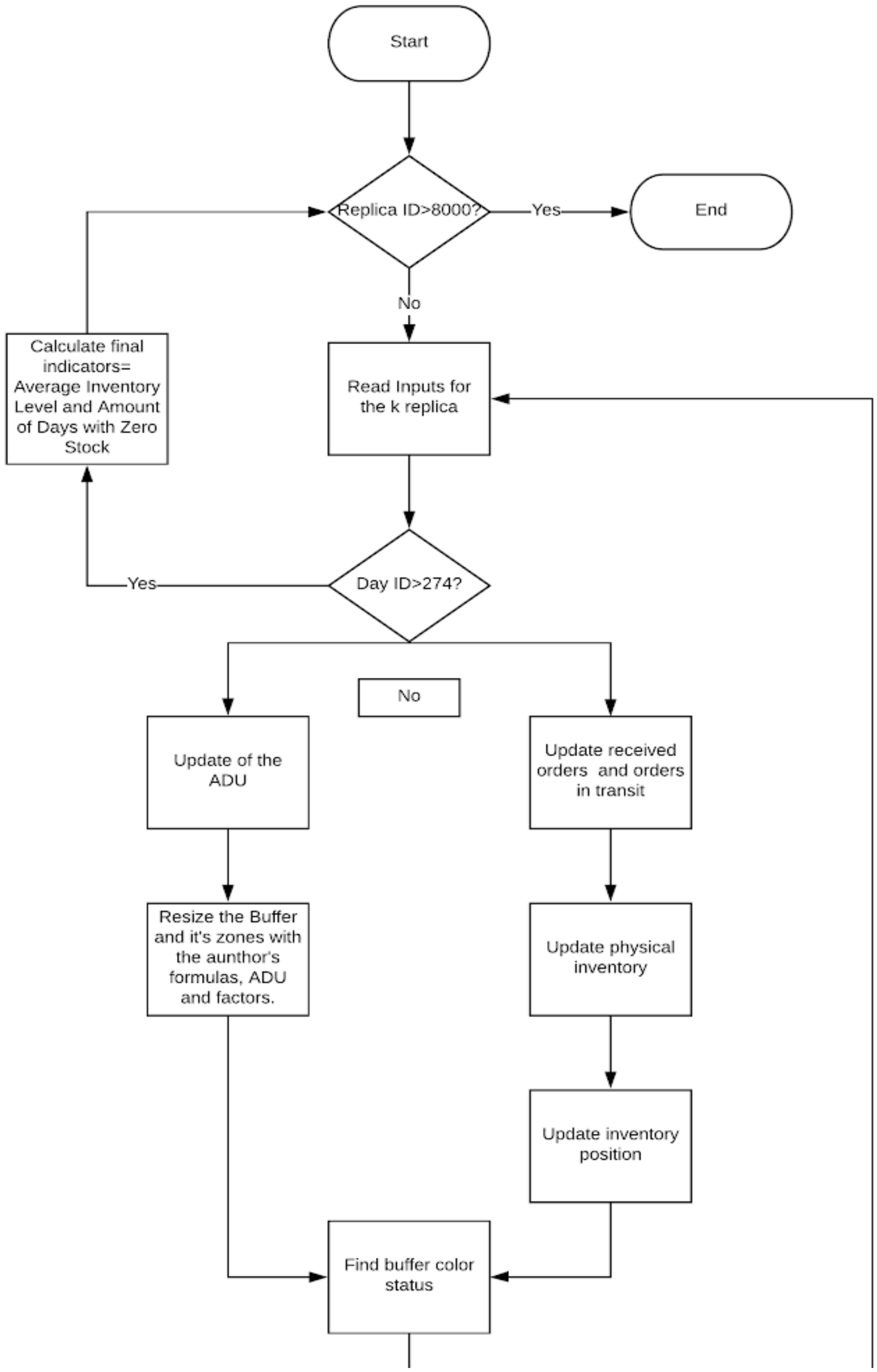
Inputs	Outputs
1.Lead Time	1.Average stock level per replica
2.Daily sales	2.Amount of days with zero stock per replica
3.n=Amount of days for the estimation of the ADU.	3.Combinations of factors related to outputs 1 and 2 (FLT,FLTR,VF)
4.Combinations of factors for each replica (FLT,FLTR,VF)	
5.Amount of replicas	
6.Initial stock	
7.Maximum storage capacity	
8.Amount of periods	

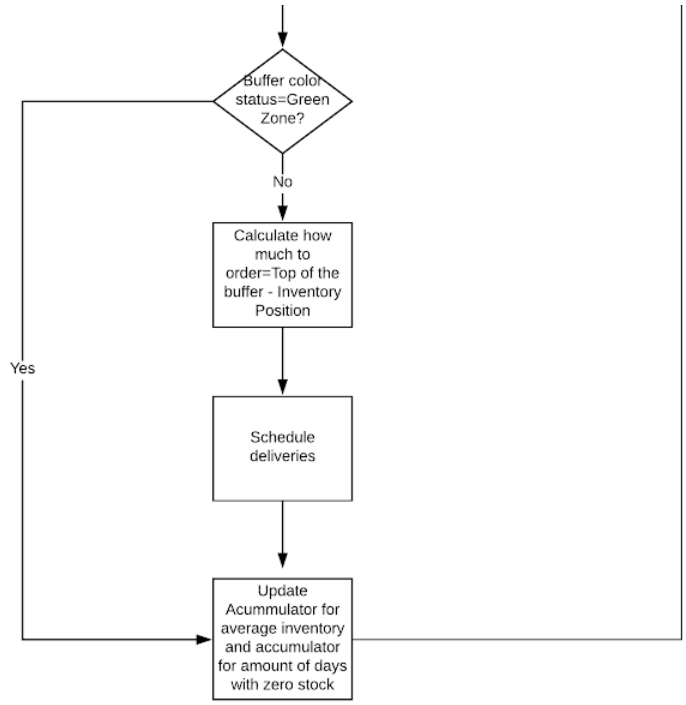
Table 4 displays the inputs and outputs of the simulation, and Figure 6 explains the flows and processes of the simulator. The first decision taken by the program is whether the cycle that counts the replicas was still active. If the counter was greater than 8.000, the simulation should end. The amount of 8.000 replicas was defined after determining the different combinations of factors that would be tested: There are three factors (lead time factor, lead time factor red and variability factors) and each one started on 0.05 and increased its value by 0.05 on each new replica. Each factor had 20 possible values, that combined with the others.

If the replica's counter is lower of equal to 8.000, the program proceeded to read the initial parameters (inputs) that depend on the current replica. The next step was to simulate the behavior of the model for 273 days (from January 1st, 2017, to September 30th 2017), which were defined by the retailer as the amount of periods that were suitable for testing the model. If the cycle that counts the amount of days per replica was still active, the simulation updated the average daily usage, based on a running rate with an n of 70 days. Then, it resized the buffer and its zones according to the author's formulas, the ADU and the previously defined factors. The received orders and orders in transit were updated in parallel to the previous calculations. Then, the physical inventory and the inventory position were updated.

Once all these calculations were carried out the program calculated the color status that corresponds to the current inventory position. If the color status was "Green", the simulation proceeded to updating the accumulators for the average inventory and the amount of days with zero stock; if it was "Yellow" or "Red", it calculated the amount of product that would be ordered, by subtracting the inventory position to the top of the green zone. Then, the new orders are scheduled, taking into account the lead time. At last, the program can update the accumulators for the indicators as previously explained. The cycle is then ready to go to the next replica.

Figure 6 Flow Chart of the simulation



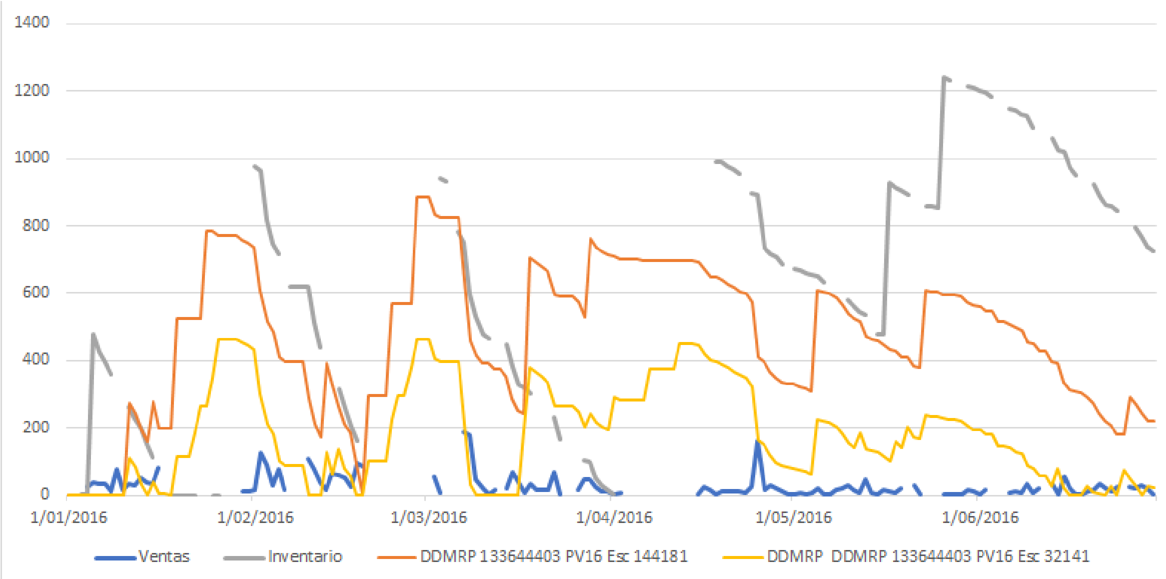


4.2.5. Reference scenario to compare/determine performance indicators

Having considered the description of the simulator, it is also reasonable to remember the two indicators defined to make the comparison between DDMRP's and the retailer's scenarios: the average inventory and days with 0 inventory.

Analyzing the data provided by the retailer, certain gaps were found on sales and inventory records complicating the comparison process with the adaptation of DDMRP to a retail environment. Figure 7 shows an example of a reference with several gaps on both, its inventory (grey line) and its sales (blue line). To make it possible to compare both scenarios, certain adjustments had to be done.

Figure 7 Sales Vs Inventory



Whenever the sales records showed a date without information, a value of 0 was assumed. On the other hand, an inventory record without information was adjusted based on the inventory of the previous day and the sales of the current day.

4.2.6. Compare the two scenarios based on the indicators and measure the economic impact

Given the lack of information provided by the retailer, it was not possible to calculate the total cost of storage for their model and the designed adaptation of the DDMRP. Nevertheless, for a better understanding of the impact of the implementation of the DDMRP methodology in a retail environment, the two indicators mentioned before (amount of days with zero stock and average stock level) were calculated in every instance of the simulation in order to compare them to the retailer's results in the same scenarios.

Once all the chosen stores and references were tested on the simulations, the results of the indicators for the DDMRP and the retailer were used to calculate their percentage of variation. This value was estimated as follows:

% Variation=(Retailer's result-DDMRP's result)/Retailer's result

In order to arrive at an estimate of the total improvement on each indicator, the accumulated average stock and amount of days with zero inventory were estimated for each model, and then the percentage of variation between the two cases was estimated as previously described. These percentages of variation allow the evaluation of the economic impact that the DDMRP will have over the retailer's cost of storage.

Table 5 Methodology of the Project

Objective	Activities	Industrial Engineering Tools	Presentation
1. Define the logistic network of a retailer on which the	1. Define the elements that will belong to the network.	Supply Chain Management	Retail Supply Chain Detailed

DDMRP can be implemented.	2. For each node set: quantity, location, capacity and functionality (store,hypercenter)		Diagram
	3. Determine the flows, constraints and general dynamics of the network (routing, lead times).		
	4. Locate dynamic buffer strategically		
2. Propose a methodology for the implementation of DDMRP.	1. Determine the buffer profiles to work with and their basic operating levels.	Forecast and demand analysis and control indicators design	Excel
	2. Establish replenishment and update policies for dynamic buffers		
	3. Definition of control tools, alerts and / or indicators for the system.		
3. Develop an application to evaluate the proposed implementation of DDMRP.	1. Simulate the behavior of the network with all the previously established conditions and the insertion of daily demand data.	Discrete Event Simulation	VBA App
4. Measure the economic impact of implementing the DDMRP methodology in a retail environment based on a current scenario.	1. Define reference scenario to make the comparison with the proposed methodology.	Performance indicators design and Discrete Event Simulation	VBA App
	2. Establish performance indicators for the scenarios.		
	3. Compare the two scenarios based on the defined indicators.		

5. Engineering Design Component

A methodology for implementing the DDMRP philosophy on a retail environment was the main design developed throughout this project. This design was developed by considering all the pillars and principles in which DDMRP is based and the generic steps proposed by its authors for its implementation.

A simulation of the behavior of a Colombian retailer's supply chain was developed, to evaluate the performance of the implementation of DDMRP on this environment, and its comparison with the performance of the retailer's current inventory management model. This simulation will ultimately allow the measurement of the new methodology's suitability in this type of environment. This suitability will be measured using the previously defined indicators: Level of service and amount of days with zero stock.

The designed process for the proposed methodology began with the careful study of the DDMRP philosophy, and the understanding of its principles. The general steps proposed by the authors were followed as presented and the different parameters, decisions and policies proposed were modified to match the retail environment. For example, the logistic network had to be simplified in order to make it suitable for being tested through a VBA program.

After having defined the logistic network for the implementation of DDMRP, the policies, initial parameters, buffer profiles and indicators that would be used, a simulation was designed in order to evaluate the performance of the model. Once this simulation was complete, several tests were carried out on it to continue the understanding of the methodology's impact and a comparison scenario was designed so that it was possible to compare the obtained results to a Colombian retailer's model performance.

The Definitive Expected Design Requirements for the design of the methodology for the implementation of DDMRP are:

● The presentation of the methodology will feature as a series of simplified steps that must be followed according to a predetermined order: These steps should be followed as presented on chapter 4. Methodology.

● The results or indicators on the VBA Applications must be presented following the same format to ease the comparison of scenarios: The results of the VBA applications used to evaluate the model's performance follow the same format and allow an easy query of the results.

Certain design constraints were considered given the limitations that these represented during the design and testing of the implementation of the DDMRP methodology in the retail environment:

● The size of the supply chain: Retail companies generally have several stores and outlets throughout a territory, it exports its products to diverse markets all over the world and might operate thousands or few of thousands SKU's. The magnitude of this network involves complexity that must be simplified by focusing the application on a specific product line moving through a small amount of nodes. Throughout the development of this project, the magnitude of the supply chain was a constant concern, which was solved by choosing the Pareto nodes on the network and the 3 references with the greater amount of sales registers on each node.

● Variability on Lead Times: Factors such as the weather, or road congestion at certain times during the day generate variability in the real lead times within the network. This leads to the need to make assumptions that allow the determination of average values for these data. At the beginning of the project this issue was tackled by eliminating the atypical values from the historical registered lead times, so that the values obtained when building an average were close to reality. Later, the retailer confirmed that the previously estimated lead time was the same used on its current inventory management model.

- Lack of data: Considering the different variables that interfere in the determination of the buffer levels in DDMRP, it is possible that some of these variables are not measured or recorded by the company. This situation may be solved with the simulation of data that maintains consistency with the usual behavior of the network. Given the nature of the references in which the methodology was tested, and the gaps found on the historical data provided by the retailer, it was determined that the best way to obtain the missing data was not by simulating it but adjusting the existing ones with the available information. For example, the missing information for inventory was updated using the inventory from the days before the gap, and the sale of the day with missing information.

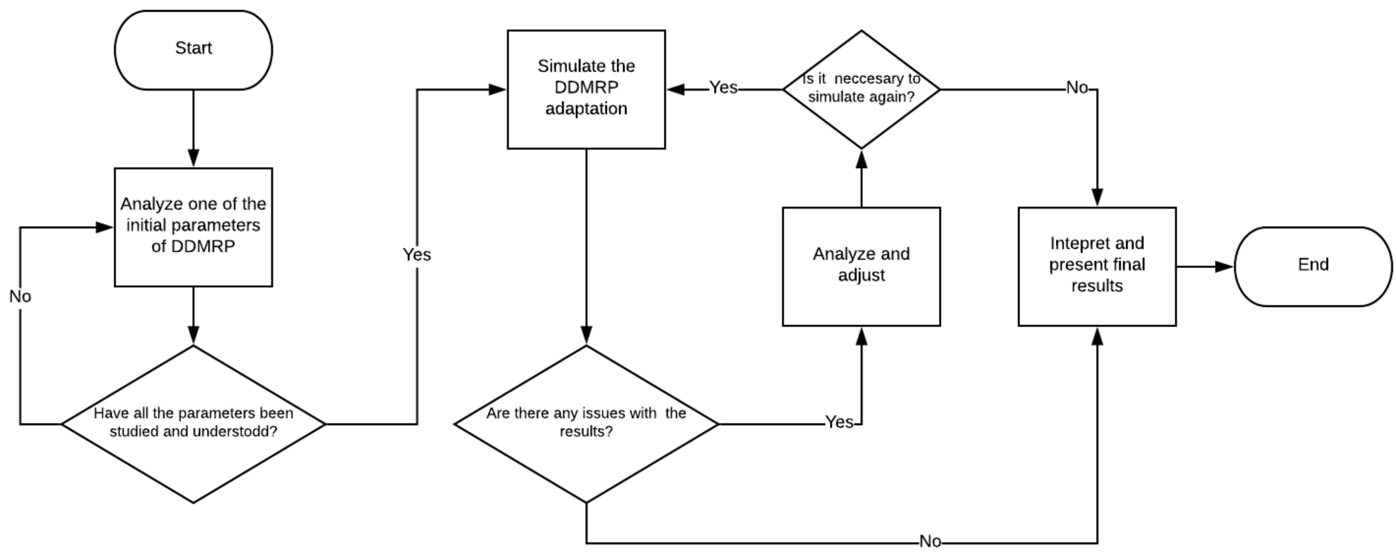
6. Results

The presentation of the results of the methodology to adapt the DDMRP philosophy on a retail environment through three stages that are explained on Figure 8 At first, several iterations were developed in order to understand the behavior and impact of the initial parameters of the DDMRP on the model's performance. The studied parameters are: Buffer size and zone distribution, average daily usage, lead time factor and variability factor.

The second phase implied testing the designed adaptation through a simulation, whose results were studied carefully. In case of having any issues on the results or on their comprehension, certain adjustments were made, and the simulation could be tested again in order to evaluate the new results.

At last, the interpretation of the final results is presented along with its comparison to the performance of the retailer's current scenario.

Figure 8 Flow Chart of the results presentation



6.1 Understanding the behavior and impact of the initial parameters

In this section, several tests are carried out, where all the different initial parameters of the classic DDMRP philosophy were studied independently in order to gain a better understanding of their functionality and impact over the model's final results.

6.1.1 Size of the Buffer Zones

In this test, all the parameters were summarized into two basic variables, the total size of the buffer and the percentage of that size assigned to each zone. It is important to emphasize that the ADU was not used since its main function is to determine the sizes of the buffer and the zones that are already being established.

Both the percentages and the total size, were constant values for each replica where the average inventory and days with zero inventory were the principal outputs. For the percentage of each zone, a few scenarios were proposed as seen in Table 6.

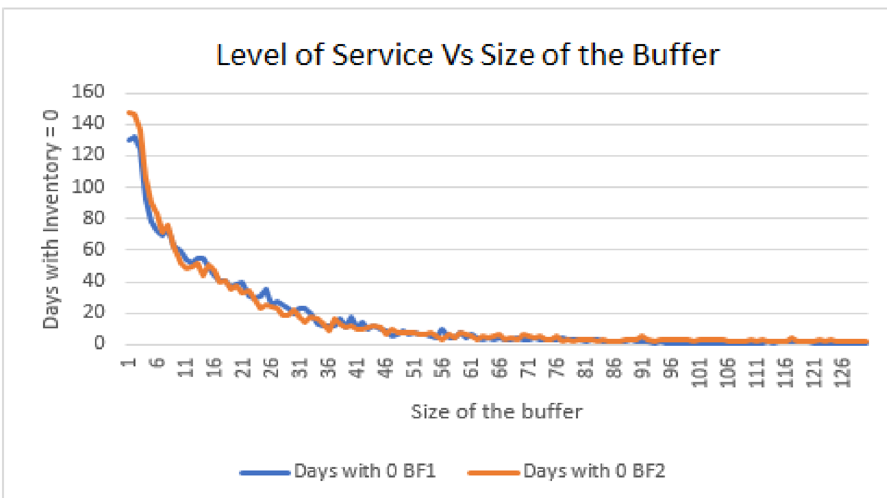
Table 6 Scenarios for the Buffer Zones

Scenario	Green	Yellow	Red Base	Security Red
1	25%	25%	25%	25%
2	70%	10%	10%	10%
3	60%	20%	10%	10%
4	50%	30%	10%	10%
5	50%	20%	20%	10%

6	40%	40%	10%	10%
7	40%	30%	20%	10%
8	40%	20%	20%	20%
9	30%	30%	30%	10%
10	30%	30%	20%	20%

The results of one of the scenarios (Scenario 9) are shown on Figure 9, where the size of the buffer is noticeably inversely proportional to the amount of days with zero stock. This consistent behavior among the different tested scenarios allowed to conclude that, the bigger the size of a buffer, the less days with shortfalls will appear at the end of the simulation, given the fact that a bigger buffer implies a greater amount of units on stock.

Figure 9 Level of service vs Size of the buffer



It is also important to note that some of the 10 different tested scenarios presented the exact same results, having in common the same percentage assigned to the green zone, even if the other zones had different distributions. This led to the conclusion that the green zone is certainly the one that defines the DDMRP's replenishment policy. Despite the previous affirmation, it is important as well to emphasize the importance of the total size of the buffer in order to accomplish the service level, and that introduces the necessity to understand which factor calculates and resizes the buffer, which is the ADU.

6.1.2. ADU

In order to continue finding the real impact of each initial parameter over the model's behavior, the simulation was modified to include the ADU to determine the size of the buffer. The scenarios used to build the percentage of buffer intended for each zone were kept. The ADU was estimated as a running rate with an n of 70 days. The amount of references used to test the model increased to a total of 9, each one on two stores. Three references had a high amount of sales registered, another three had a moderate amount of sales, and the last ones had a few sales registered. The references used in each of the new scenarios are classified as "National", and they are provided by a plant located in Colombia.

The initial amount of stock was also changed on each replica, but no significant impact was found for this variable due to the fast adaptability of the DDMRP buffers and the influence of the ADU that provides a dynamic update. Therefore, it was decided to work with an initial stock of zero until any relevance was found for this parameter. The Lead Times used were taken from the average value of the data provided by the company, where the "peak values/atypical data" were not removed.

In an attempt to make the scenarios used on the simulations more similar to the actual scenario of the retailer's operation, the model was changed in order to study its behavior in only one store and not two at a time as it was done before. The result for the average stock level would now show the reality for the store without any bias from the other store's stock value.

It is important to note that the parameters that were not studied on this version of the simulation (Lead Time Factor and Variability Factor) were "included" in the model through a security stock that was equivalent to 30% of the buffer size.

6.1.3 Lead Time Factor (LTF), Lead Time Factor Red (LTFR) and Variability Factor (VF)

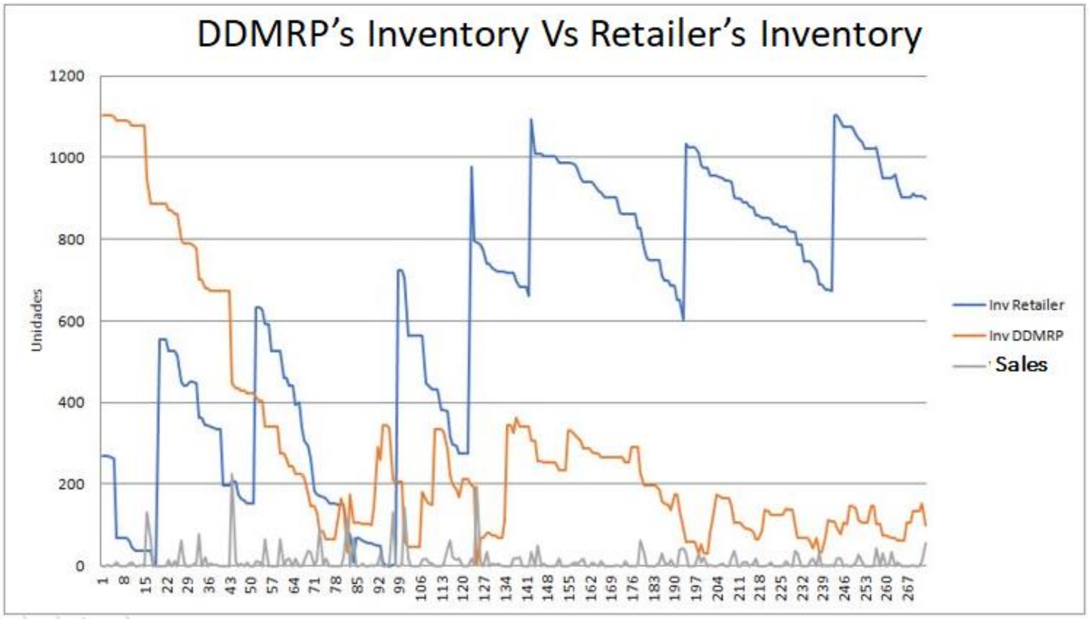
The last part of the process of analyzing the initial parameters of DDMRP involved finding the impact of the Variability (VF) and Lead Time Factors, this last one was divided into Lead Time Factor (LTF) and Lead Time Factor Red (LTFR). The simulation was modified so that the sizes of the color zones were no longer controlled by constant percentages throughout the whole simulation, but by the usual equations provided by the DDMRP authors. 8000 replicas were designed with different combinations of these factors for each one of the stores.

It should be noted that the values used as Lead Times for each reference were established based on the graphs of the retailer's stock levels as well as the average value for the registered lead times provided by the retailer, without the atypical data found on the records. For 8 of the 9 scenarios the resulting LT was 10 days while for scenario #2 it was 12. The value of 10 days was later confirmed by the company as the real value used on their model.

The main conclusion found on this exercise was the convenience of applying the model to references with a high or medium level of rotation; the ones with lower levels of rotation did not adapt to the model as expected due to the lack of data to build a reliable ADU. The lead time and variability factors were dynamic on their behavior, not showing any pattern in relation to the other variables involved in the model.

The information for the retailer's inventory level was graphed along with the stock levels of the resulting replicas provided by the DDMRP, and the sales values related to the simulated period. As seen on Figure 10, which shows two of the resulting replicas, the DDMRP allows lower stock levels in comparison with the ones found in the company's historical data, while maintaining availability of product on periods where the retailer had records of zero stock on hand (orange line). Some of the possible resulting scenarios offer even lower stock levels in a more aggressive situation resulting on an increase on the amount of days with zero stock, but always keeping it on the same level provided by the company (71 days, yellow line).

Figure 10 Sales Vs Inventory



6.2 Testing the designed adaptation through a simulation

After having understood the dynamics involved on DDMRP and the impact of the parameters used on the model, the simulation was tested in order to evaluate the performance of DDMRP on the retailer's supply chain. The global results of the simulation are displayed on Table 7. 88,33% of the tested references performed better than the retailer with the new policy, while 8,33% had a performance to highlight (green) and only 3,33% had a discrete performance (red).

Table 7 Global results of DDMRP.

Test	DDMRP with initial stock=Retailer's initial stock
%References with better performance than Corona	88,33%
%References with a performance to highlight	8,33%
%References with a worse performance than Corona	3,33%

6.2.1 DDMRP with initial stock = retailer's initial stock

The scenario in which the DDMRP adaptation was tested had the same characteristics of the retailer's supply chain. A lead time of 10 days and the same initial stock for each reference were assumed on each store.

Table 8 shows the results of the simulation for two different references. Reference 59, is presented as a case to highlight because one of its indicators had a slight decrease (-15,96%) while significantly improving the amount of days with zero stock (100%) .

On the other hand, reference 47 was classified as a red result, because both indicators had a discrete performance when compared to the retailer's results on the same scenario: The amount of days with zero stock decreased by 14% and the average stock decreased by 46%.

Annex 1 shows the complete chart with the results for the 19 stores and 3 Distribution Centers tested on the simulations.

Table 8 DDMRP results

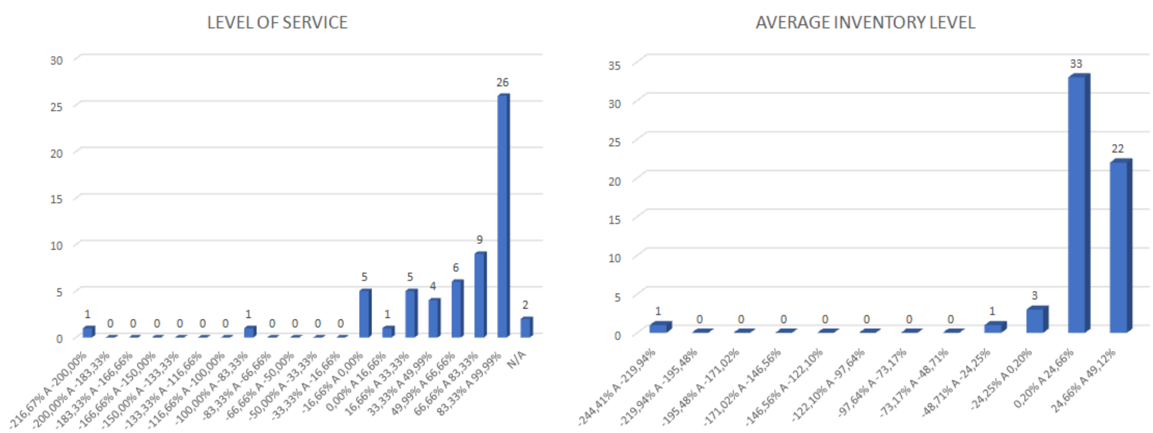
ID	Reference	Store	%IMPROVEMENT #Days Zero Stock	%IMPROVEMENT Average Stock Level
59	133504476	IN089	100,00%	-15,96%
47	145830206	IN035	-14,29%	-46,29%

6.3 Final Results

The final results of the simulations carried out to measure the performance of DDMRP on the retailer's supply chain showed that DDMRP was better than the retailer's current model on 88,33% of the studied cases. On average, the adaptation of the methodology allowed the reduction of inventories by 15,29% while improving the level of service by 56,11%

Figure 11 shows the percentages of improvement with their frequencies for each indicator. Certain references move away from the overall result given the poor quality of the data provided by the retailer, which presented gaps on the information of sales and inventories and had a negative impact on the calculation of the ADU.

Figure 11 Improvements of the DDMRP compared to the retailer's current model



6.4 Buffer Profiles

After having tested the methodology through simulations, a new classification of buffer profiles was given to each of the tested references on each of its nodes. The resulting classification of buffer profiles corresponds to the profiles previously explained on Table 2. All the scenarios tested through the simulation were previously classified into an "Expected Profile". Ultimately, new Buffer Profiles were assigned according to the resulting Lead Time and Variability Factors found after testing 8000 replicas with different combinations (as explained in the methodology section). The resulting Classification is shown on Annex 1.

It is important to note that only 12 out of 57 stores and 2 out of 3 Distribution Centers had the same Buffer Profile assigned at the beginning of the study. This behavior is justified given the high variability of the sales data: Some days had no information registered, and in certain cases atypical values showed up, this happens when a customer wants a certain volume of a reference and there is no availability of it on the store. The retailer tells the customer the exact day when it will be available again and the customer comes back on that date. The consequence of this situation is the high variability coefficients obtained for each reference, which oscillate between 60% and 295%.

6.4.1 Interpretation of the results of the buffer profiles

It was previously mentioned that there were 8.000 combinations of the factors (LTF, TLFR and VF) per each reference, and the best one would provide as output the best combination considering the indicators compared on the different scenarios, therefore where the reference should be classified. As a result, Table 9 shows the amount of references classified on each new DDMRP profile. The results of the observed profiles are shown on Annex 2.

Table 9 Buffer Profiles Classification

PROFILE	Number of References
D10	3
D11	2
D12	3
D20	2
D21	3
D22	6
D30	14
D31	7
D32	20

Although it is important to highlight that there were results with other combinations as good as the ones chosen in Table 9, in consequence there is more than one profile that could be used to have a good performance, as opposed to the assignment proposed by the authors. It is important to note that the removal of the atypical values from the sales was not considered viable given the fact that the comparison scenario would not be like the one used to test DDMRP. To go deep on the classifications, all the atypical data should be removed.

6.5 Measure the economic impact of the implementation of the DDMRP methodology in a retail environment

Table 10 shows the results of the percentual variations obtained when comparing the retailer's model to the DDMRP methodology. The final test shows a reduction of 77% on the amount of Days with Zero Stock and a reduction of 27% in Average Stock Level.

It is important to note that this percentual variation equals the monetary reduction that the Company would perceive with the implementation of the model if a price is given to the two main indicators measured throughout these simulations.

Table 10 DDMRP Global improvements

	% Variation vs Retailer

	Accumulated Days Zero Stock	Accumulated Average Stock Level	#Days Zero Stock	Average Stock Level
Retailer´s Results	1653	11847,09		
DDMRP Final Results	375	8.626.37	-77%	-27%

6.6 Findings

6.6.1. Intuitive explanation of the behavior of the DDRMP

It was possible to summarize the DDMRP policy in a retail environment, as a simple policy where two dynamic parameters exist: a reorder point and a quantity to order. Both parameters depend on the fluctuation of the ADU as a result of how they are calculated. First, the reorder point is the limit between the yellow and the green zones as seen on Figure 12 and second, the quantity depends on the new sizes of the complete buffers according to the level of the inventory position. DDMRP behaves similarly to a P(Q,R) policy shown on Figure 13.

Figure 12Buffer sizing

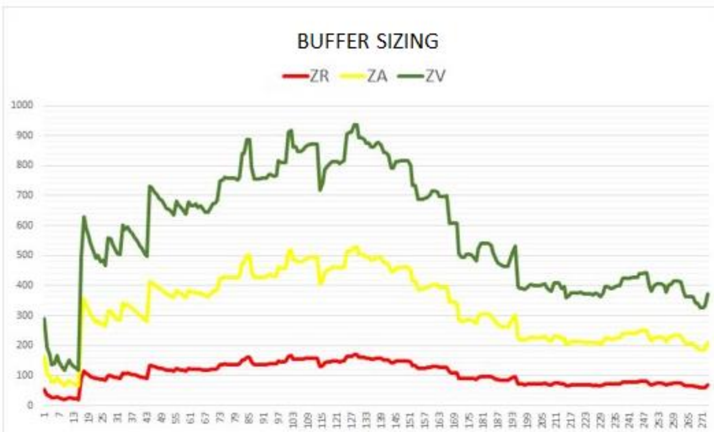
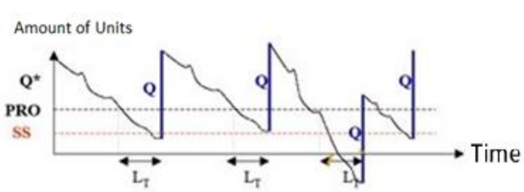


Figure 13 Classic Inventory Management Policy

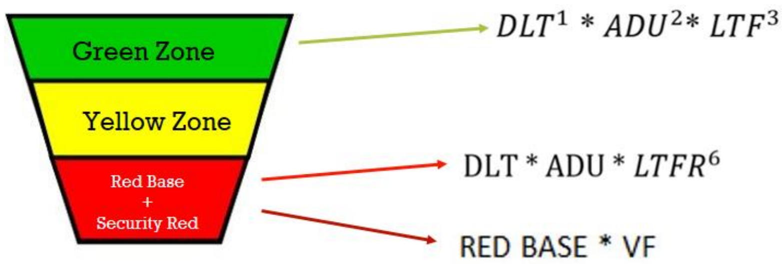


6.6.2. Limitation on the calculation of the buffer's zones

The second finding was a limitation on the formulas to estimate the sizes of the zones presented by the authors. Due to the link between the formulas of the red zones, as shown of Figure 14, there is an unnecessary growth of the buffer's total size, which results in an increase in inventories. The formula for the security red can be modified in order to omit the red base and only include factors that absorb the demand's variability.

On the other hand, another limitation occurs when the demand's variability is too high and neither the base red nor the security red can not absorb it. As a consequence, the lead time factor in the green zone increases its value, and its main ´function is affected since it does not have the freedom to define the best supply policy.

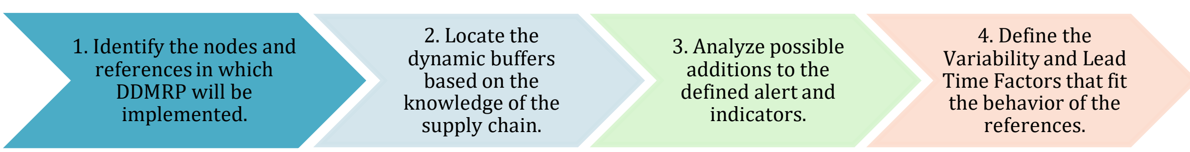
Figure 14 DDMRP buffer and formulas



6.7 Methodology for the implementation of DDMRP on a retail environment

Based on the process developed to carry out this project, the following generic steps (Figure 15) have been defined as a guide for the implementation of DDMRP on retail. These steps are subject to the changes that each supply chain requires for its successful implementation. In the case of step four, it is suggested to use a simulator that allows trying different combinations of factors and choosing the one that yields the best results.

Figure 15 Steps for the implementation of DDMRP on retail



7. Conclusion and Recommendations.

After having designed, tested and analyzed an adaptation of the DDMRP for the retail environment it is possible to conclude that the DDMRP methodology is certainly flexible and dynamic and it was possible to design an adaptation of it for the retailer's supply chain that had a significantly better performance than the company's current model for managing inventories. The testing of the adaptation also proved that references with higher amounts of days with sales registered allow better results than the ones with lower amounts of historical data registered. This happens because the ADU, which is calculated as a running rate, is fed on the daily sales data, and the lack of information makes the peaks on sales have a greater impact on the ADU's size.

DDMRP can be explained as a classic inventory management model with dynamic parameters: A dynamic point of re order; order quantity and top of buffer. These are considered dynamic because they are updated daily based on the real sales information, and they never take forecasting into account while taking decisions. This prevents over stocking.

Having a limit on the storage capacity was not an influential factor on the results. For every reference tested with and without constraints on the storage capacity the results were the same or very similar. Nevertheless, if the model is going to be implemented, it is necessary to include this constraint given the fact that no storage is infinite.

On the other hand, the initial amount of product in stock does have a great impact on the model's results. A higher amount can absorb atypical values on sales and reduces the amount of days with stock equal to zero, improving the level of service. But having too much initial stock may affect the average stock level, especially if the sales rate is low and does not consume the stock as fast as expected.

In this case study the Lead Time and Variability Factors became an output of the simulations, instead of being an input as usually suggested by the authors. The most important finding regarding this aspect is that there may be several combinations of factors that work for the same reference, unlike what is proposed by the authors, who usually classify references within a single profile. This happens because of the great variability among the sales for most of the references in which DDMRP was tested.

The adaptation of the DDMRP methodology a retail environment allowed improvements between 8% and 100% in the level of service, and 1% to 52% in the average stock level, which reduce the company's storage costs wherever a DDMRP buffer is located. Despite the great variability found on the sales registered for each reference on each store, which had a variability coefficient greater than 60% for all the cases, the DDMRP was able to perform better than the retailer's current model in every case, absorbing the variability and adapting itself to the unexpected peaks that constantly showed up.

Some recommendations for upcoming adaptations or implementations of DDMRP on a retail environment include highlighting the importance of having a good source of information that collects the historical data of the daily sales since this feed the model and guarantees a better performance. The DDMRP model works better if it has truthful and reliable information.

It is possible to deepen the study of the behavior of the Lead Time and Variability Factors, due to the significant impact they have over the model's results. This can be done especially if the studied demands or sales have reliable historical data and a less volatile behavior. Studying the demands and removing atypical values that may have a negative impact on the determination of the factors would allow refuting or confirming with better arguments the classification proposed by the authors.

8. Annex Table

Table 11 Annex List

No. Annex	Name	Development	Type of File	Short Link	Relevance for the Document (1(+) - 5(-))
1	Final Results DDMRP Simulations	Own	Excel	https://goo.gl/YXQcdi	1
2	Classification of Buffer Profiles	Own	Excel	https://goo.gl/KXTjFc	2
3	Simulator Evidence	Own	Excel	https://goo.gl/s8nQWj	1

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