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POLYTECHNIQUE MONTRÉAL

affiliée à l'Université de Montréal

Evaluation and Configuration of a Demand-Driven Distribution Resource Planning (DDDRP)

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Ménoire présenté en vue de l'obtention du diplôme de *maîtrise ès sciences appliquées*

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Ce mémoire intitulé :

Evaluation and Configuration of a Demand-Driven Distribution Resource Planning (DDDRP)

présenté par : **Fatemeh HAJI MOHAMMAD**

en vue de l'obtention du diplôme de *Maîtrise ès sciences appliquées*

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RÉSUMÉ

L'optimisation de la chaîne d'approvisionnement est la clé du succès pour les industries, en particulier les systèmes de fabrication, afin de rester compétitifs. Parmi les travaux connexes, ceux qui ont porté une attention particulière aux techniques des réseaux de distribution en réseau d'approvisionnement sont l'intense intérêt de ce projet. Quelques techniques existantes et approches existantes telles que la planification des ressources de distribution (DRP) régulent leur objectif d'optimisation du niveau de stock (stock de sécurité) et du coût total de possession de la chaîne d'approvisionnement. Pour atteindre l'objectif mentionné, ce projet se concentre sur l'examen d'une nouvelle technique appelée Demand-Driven Distribution Resource Planning (DDDRP) qui s'inspire de la Demand-Driven Material Requirement Planning (DDMRP). Nous démontrons que la nouvelle technique est capable de combler certaines des lacunes liées aux approches précédentes pour optimiser le réseau de distribution. Dans l'approche DRP, qui est établie sur la prévision de la demande, des tableaux DRP sont appliqués pour calculer le niveau l'inventaire contient le stock de sécurité dans la chaîne d'approvisionnement. Alors que l'approche DDDRP dans laquelle les demandes réelles ou l'utilisation quotidienne moyenne (ADU) jouent un rôle clé, essaie de positionner des tampons dans les nœuds, ce qui conduit à la minimisation du coût total de détention de la chaîne d'approvisionnement. Pour ce faire, nous formulons le modèle d'optimisation et le résolvons. Ensuite, les résultats de deux indicateurs de performance sont comparés avec les deux approches DRP et DDDRP dans le cas d'un réseau de distribution de vingt-deux nœuds. Les résultats indiquent que le volume total du niveau tampon, qui est mis dans la réseau de distribution par la technique DDDRP par rapport au volume total de l'inventaire qui est placé dans la réseau par la technique DRP est réduit de 66%.Il est également démontré que le coût total de stockage au niveau de la réseau d'approvisionnement avec la technique DDDRP diminue de 74%.

ABSTRACT

Optimizing supply network is crucial importance to industries, especially to manufacturing systems, in order to remain competitive. Among the related literature, those that have paid close attention to techniques for distribution networks in the supply chain are the particular interest of this project. Some existing techniques and approaches such as Distribution Resource Planning (DRP), set their goal on optimizing the level of inventory and the total holding cost of the supply network. To achieve the mentioned goal, this project focuses on examining a novel technique named Demand-Driven Distribution Resource Planning (DDDRP), which is inspired by Demand-Driven Material Requirement Planning (DDMRP). We claim that the new technique is able to address some of the deficiencies of the previous approaches to optimize the distribution network. In the DRP approach, which is established on demand forecasting, DRP tables are applied to calculate the level inventory contains the safety stock in the supply network. The DDDRP approach, in which the actual demands or Average Daily Usage (ADU) play a key role, attempts to position buffers in the nodes, which leads to the minimization of the total holding cost of the supply network. To do so, we formulate the optimization model, and solve it. Then, the results of two performance measures are compared with two approaches DRP and DDDRP using a twenty-two node distribution network as a case study. The results indicate that the total amount of the buffer, which is put into the distribution network by the DDDRP technique compared to the total amount of the inventory that is placed in the supply network by the DRP technique, is reduced by 66%. It is also shown that the total holding cost of the inventory in the supply network with the DDDRP technique decreases by 74%.

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LIST OF SYMBOLS AND ABBREVIATIONS

ADU	Average Daily Usage
DC	Distribution Center
DDDRP	Demand Driven Distribution Resource Planning
DDMRP	Demand Driven Material Requirement Planning
DLT	Decoupled Lead-Time
DN	Distribution Node
DRP	Distribution Resource Planning
EDI	Electronic Data Interchange
IOBPCS	Inventory and Order-Based Production Control System
ISL	Inventory Stocking Location
JIT	Just In Time
MPS	Master Production Schedule
MRP	Material Requirement Planning
PCT	Production Cycle Time
POH	Projected On-Hand
RDC	Regional Distribution Center

RFID	Radio Frequency Identification
RRP	Retail Resource Planning
SKU	Stock Keeping Unit
TOC	Theory Of Constraints
WIP	Work In Process

CHEPTER 1 INTRODUCTION

1.1 Context and general objective

With the growing trend today's world toward the field of logistics as a major part of supply network activity, inventory control is a core factor in attaining an efficient supply network. Dealing with inventory control is a common issue in different industries, which indicates how modern logistics depend on the large network supplying materials, products and commodities. The variables associated with the supply network, namely demand lead-time, transportation cost, and production time, are prone to change due to the nature of transferring material through the supply network. An effective inventory control system is able to act as a hedge against fluctuations. There are numerous studies conducted in the field of inventory control, which take different techniques, safety stock placement, and the amount of safety stock needed in supply network to manage demand uncertainties, and maintain customer service level.

The aim of this project is to evaluate the application of a more effective inventory control technique to the multi-echelon supply network. The supply network is characterized by flowing the products through a distribution network consisting of one source location and a number of distribution centers (DC). Firstly, the classic inventory control system, namely distribution resource planning (DRP), is investigated in related literature. DRP was chosen as the basis of comparison in this project, owing to its significant role in inventory control practices. Second, the state-of-the-art approach in the mentioned field, named Demand-Driven Distribution Resource Planning (DDDRP), inspired by Demand-Driven Material Requirement Planning (DDMRP) is developed. Third, the strategic buffer positioning throughout the supply network is extended based on the new inventory control approach.

1.2 Statement of the Problem and Description

The fact that the industrial world is growing rapidly hardly needs to be emphasized. In order to survive and remain competitive among other companies and satisfying diversified demands in every industry, retaining the high level of customer satisfaction toward the products is the foremost goal of every company. Satisfying demands should be considered a mission and efforts should be made by providing the customers with the products and the time they desire. Along with this fact, companies ought to pay heed to their profit as well. Every company needs to pay special attention to distribution and inventory management. To this end, numerous methods and approaches have been developed to enhance supply network performance. Among these approaches, Distribution Resource Planning approach (DRP), which is defined as a systematic approach to drive a distribution process in a more effective manner by specifying which product, in what amount of quantity, and in which place should be delivered to meet the demand (Rizkya et al., 2018). DRP has been evidenced to work well where there is an integrated supply network (E Suwanruji, 2000). DRP is able to calculate the lot size, ordering frequency, and the amount of safety stock in each distribution node in supply network (Rizkya et al., 2018).Certainly, applying the DRP technique has benefits in reducing the total cost of the supply network and upgrading the level of customer satisfaction. However, the DRP system is assumed to be a proactive approach, since the level of inventories is determined based on forecasting methods which, in turn, results in some issues such as the bullwhip effect (E Suwanruji, 2000).

The bullwhip effect is considered a phenomenon in which the supply network becomes prone to fluctuation, and instability and as a result, increasingly rising supply network costs. In this regard, companies are confronted with shorter customer tolerance time, higher complexity, and numerous competitors that apply traditional inventory management techniques such as DRP, and face complications such as shortage in some network sites and surplus in others. Cross-shipping is then needed, which imposes considerable additional costs (related to transportation expenditures, loss of potential sales, long lead-times, and the lack of agility associated with resources) and bring about more diversion from actual demand signals and bullwhip effects (Ptak and Smith, 2019). According to Ptak and Smith (2019), “demand forecasts can be based on extrinsic (external) or intrinsic (internal) factors”. The definition implies that as demands move from customers to suppliers, variability increases significantly. As a result, inventory can move quickly from being backordered to being surplus. Then, distribution systems have to deal with unreal batches, signifying any batch that does not come from actual demands. Ptak and Smith (2019) have noted that nowadays forecast is associated with a high level of inaccuracy and, it is even more reliable in complex environments when the forecasts is more detailed and discrete, and can be done at a farther time. The other issue with the inventory management in supply network is that the amount of inventory positioned in each distribution network, which may cause the supply network to run into problems such as high holding costs.

According to Y. Erraoui et al. (2019), difficulties, concerning the distribution system and centers such as; occupying more space for storing the excess inventory, passing the products with delay through the distribution network on account of shortage in supplies, lead to customer dissatisfaction. All the costs related to the supply network including holding costs, and transportation costs make the distribution system inefficient and create chaos in the system. Even, if a system often has enough inventories, it will be just located at the wrong places. In other words, using the basic distribution network models in today's complex distribution environment is too simplistic. As a result, all efforts should be devoted to eliminating or lowering resource inefficiency.

As a conclusion of abovementioned, an efficient and well-designed distribution network plays a prominent role in enterprise performance and customer satisfaction. Recently, a new approach inspired by the Demand Driven Material Requirement Planning approach (DDMRP) concepts was proposed by Y. Erraoui, Charkaoui, A., & Echchatbi, A, (2019), to optimize the distribution flow in Distribution Resource Planning (DRP). In accordance with the definition given by "The Demand Driven Institute-World Leader in Demand Driven Education" 2020), DDMRP is "a planning method relayed to multi-echelon networks with the primary objective of improving the flow of any information through the network by virtue of strategic management of positioning stock buffers in nodes. This objective supports taking advantage of combining various aspects of Material Requirement Planning (MRP), DRP-distribution resource planning, Lean concepts, the theory of constraints, and variability control of Six Sigma. Demand-Driven Distribution Resource Planning (DDDRP) focuses on the distribution part of the supply network and aims to make the DRP more sensitive to actual demand (Ptak and Smith, 2019).

1.3 Objectives and research hypothesis

This project aims to:

- Develop a DDDRP model that seeks to improve the performance of the supply network, and achieves a higher efficiency than basic DRP in terms of reduction in total costs, the bullwhip effect and delivery-time in the supply network.
- Optimize buffer positions in a distribution network with the objective of minimizing supply network holding costs

In this project, we consider that:

1- A multi-echelon distribution network is composed of different nodes (customers, warehouses, depots and production plants) ;

2- Data about network nodes are known;

3- Each node (except nodes of the first echelon) is served by one supplier, and that the capacity of each node is infinite.

1.4 Report structure

The remainder of the report is structured as follows.

Chapter 1 presents a literature review of previous studies on the traditional inventory management techniques in the supply network namely Distribution Resource Planning (DRP), giving an explanation of the bullwhip effect and the efforts made to reduce this effect in the existing literature. Afterward, a review of new approaches to inventory management in the supply network, available studies in safety stock placement in supply network, and calculating safety stock levels through traditional techniques, and new approaches to positioning buffers in the supply network will be presented. At the end of the chapter, the contribution of the project, to the existing literature will be elaborated.

In Chapter 2, a non-linear model is presented with the objective of minimizing the total holding cost of the supply network. Thereupon, the mathematical model is explained in detail in this chapter.

In Chapter 3, the model is validated and a case study is investigated thereafter, the analysis of the results is represented, and the efficiency of the traditional approach will be compared with that of the new approach.

Lastly, Chapter 4 presents the conclusion of the project, and offers recommendations for future studies.

CHAPTER 1 LITERATURE REVIEW

1.1 Introduction

Supply network and distribution network issues have recently attracted the attention of researchers. Among researches in this field, those who have focused on inventory management in the supply network, provide important insights into controlling fluctuations and variations caused by the bullwhip effect in the supply network. Researches have proven that the costs associated with the supply network are impacted deeply by the bullwhip effect phenomenon. In order to reduce costs and make the product flow faster, many researchers have attempted to detect and examine techniques for and approaches to alleviating the demand and supply variations that result in higher costs. In this chapter, we review the state-of-the-art research related to the DRP process, weaknesses, the bullwhip effect, and revision the causes for it, as well as the techniques adopted to reduce this effect. In the rest of the chapter, safety stock positioning in the supply network in previous research as well as a review of new approaches to address deficiencies, are discussed.

1.2 DRP roles and process

Wahyuningsih (2018) provides two different meaning of DRP concerning distribution requirement planning, and distribution resource planning. The first one stands for a technique for replenishing inventories in distribution centers, while the second one has a more extensive meaning, which integrates planning and control from interconnected resources to ameliorate system implementation. As of 1970, DRP was considered an effective method for controlling inventory levels in each distribution center of the supply network. According to the literature, many companies have taken advantage of implementing DRP since it was developed (Martin, 1992). According to Hou, Chaudhry, Chen, and Hu (2015), during the 1980s-1990s, DRP along with Material Requirement Planning (MRP) and Just In Time (JIT) were taken into account as advanced management strategies for obtaining competitive advantage in the physical distribution sector in the United States. DRP is defined as an effective time-phased approach to controlling the flow of the products efficiently, between distribution centers in multi-echelon supply networks during the decade. Martin (1992), expounded on the ability of DRP in determining the exact inventory level and demand that each node needs. Hence, it brings down all costs, incurred to the supply network (including storing places), giving rise to a noticeable integration in different parts of the supply network.

There are many cases in the existing literature confirming the benefits of DRP implementation in supply network systems, such as decreasing the inventory investment and costs associated with the supply network. These positive effects have occurred on account of applying the integration of production scheduling and forecasting demand. This integration results in a proper cooperation among different parties involved in the supply network. As a time-phased approach, it is obvious that there are differences between the DRP approach and the order-point replenishment (probabilistic) approach. The goal is to optimize the system by proving local optimum at each stock point, and it is regarded as one of its crucial differences with DRP. DRP maintains a global perspective to the distribution network, whereas the order-point replenishment approach focuses on concentrates on minimizing the costs of the network for each stock point. In other words, the order-point replenishment approach does not support a comprehensive view to the supply network. Watson and Polito (2010) examine and simulate the traditional DRP-based solution and the Theory Of Constraints(TOC)-based solution for a multi-echelon multi-product distribution network. Considering the costs, including inventory transportation costs, and retail-level replenishment, they admit that the TOC-based solution outperforms the DRP-based solution from a financial perspective. A comparative study is conducted by E Suwanruji (2000) on two inventory management and control strategies, which are the DRP approach the and order-point replenishment system, with the common objective of minimizing the level of inventory through a supply network while satisfying demands. They assume that the supply network consists of manufacturing, distribution, and retail facilities with multi-product. As a result of the simulation test, which they designed to examine the performance of two strategies, DRP proved to outperform the other approach, under the condition in which demand and replenishment times are uncertain. Sinulingga (2016) have investigated the chain of distribution in an Indonesian company, activate in the mill industry. According to their study, the distribution strategy of the company is restricted by applying the trial and error for demand forecasting in each DC. This approach results in stock-out and delays in the chain, which leads to customer dissatisfaction. In order to address the problem, the DRP technique was implemented through the distribution network by starting from the first step, which is demand forecasting, then calculating order quantity, and safety stock. It can be deduced that the most prominent effect of using DRP in the distribution system of the company is a reduction in costs among DCs.

D. T. Nguyen, Adulyasak, and Landry (2021) have discussed the implementation of the supply network wide integrated DRP(SC-wide integrated DRP -based on the flowcasting concept in which retailers play an important role in the network) by a retailer based in Canada, in order to gain an understanding of the potential advantages and effects of the approach. Comparing the results of the simulation of SC-wide integrated DRP through a three-level chain, with that of the combination of reorder point planning (ROP) and DRP reveals the better performance in regard to SC-wide integrated DRP in terms of the requirement of the calculation logic. The results also emphasize the positive role of information sharing on reducing the bullwhip effect (BWE). R. Magdalena, & Suli, T, (2019) has acknowledged the implementation of the DRP method as a one that is based upon time series regarding each distribution center (DC). R. Magdalena, & Suli, T (2019) also confirm that through the DRP technique the shortfall of products, which results in delays in delivery to customers, can be avoided. As reported by Martin (1992), DRP has been established based on some data such as sales forecasts, customer orders, accessible inventory, purchasing or manufacturing orders, and safety stock policies. With the integration of the mentioned data, DRP will simulate the requirements for developing supply network strategies, and specify the amount of required products. It will also determine when and where the stock should be refilled (D. T. Nguyen et al., 2021). Rizkya et al. (2018), discuss DRP as an inventory policy, which optimize the level of inventory through the supply network through a number of steps. The DRP process initially, starts with demand forecasting based on historical data from the sales department. The next steps follow by determining lot sizing and safety stock levels, making master schedule and lastly the final step is running DRP. The achievement of implementing DRP in this work is the reduction in order frequency, and subsequently, order and distribution costs.

According to Martin (1992) : "DRP is a management process by which the needs of inventory stocking locations(ISLs) are determined and, it ensures that supply sources will be able to meet the demand". He provides insights for the DRP process by proposing some phases to be implemented.

The first phase consists of sales forecasting, current and future customer orders, the amount of available inventory for sale, the designation of purchase or manufacturing orders, associated lead-times, the methods of transport, safety stock policies, and minimum products that are required to be purchased or manufactured. In the second phase, time-phased logistic strategy will be designed based upon the inputs in phase one. The most prominent questions arising in this phase are as follows: which products in what amount, where and when is required to be supplied, how much is the capacity of the transportation system, required resources and inventory investments, and the level of production or purchased products. Eventually, in the third phase, DRP compares the available required resources, and the resources needed in the future. This phase focuses on creating an integration and feedback into the system (Martin, 1992).

As depicted in Figure 2-1, the bill of distribution, order entity, forecasting inventory control, and open PO’s/MO’s are functioned as inputs for the DRP management process. The processed inputs in the next step conducted to transportation and resource requirement planning and scheduling. In the following, it should be determined whether the planning is realistic or not. If it is created in accordance with the existing realities, the next step, which is building the master production schedule (MPS), will be carried out.

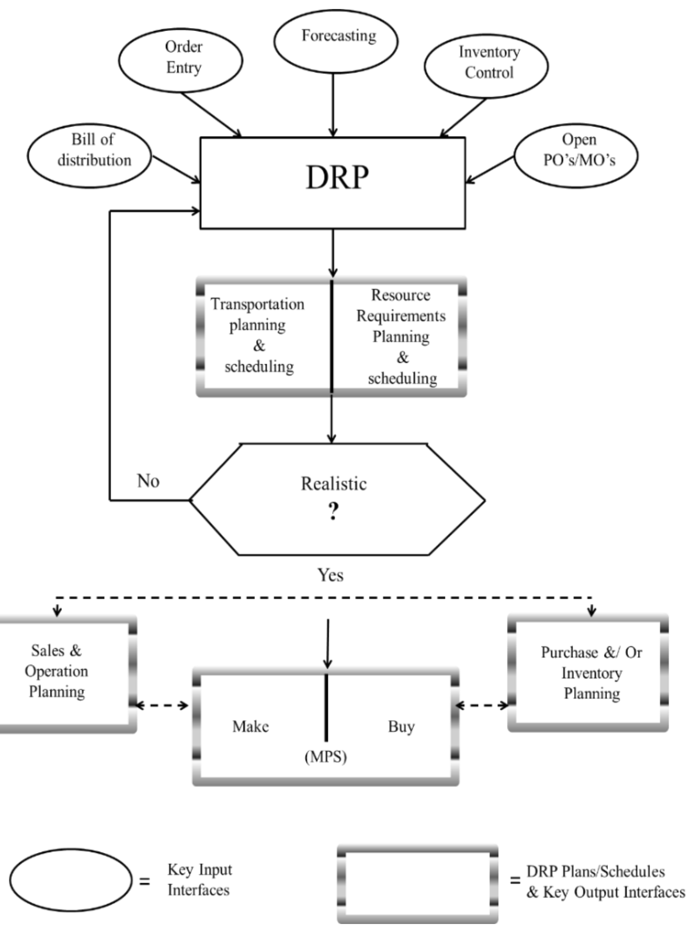

Figure 1-1The DRP management process (Martin, 1992)

1.3 Multi-echelon distribution network and DRP display

Wahyuningsih (2018) identified DRP as a technique for managing inventory distribution by creating a framework to perform integrated push systems. He proposed some steps for data processing as prerequisites to the DRP process:

1. Making forecasts for demand

2. Lead-time estimation

3. Calculation of the amount of Lot Size

4. Computing Safety Stock (Includes backup and warehouse goods)

5. Generating a DRP (Wahyuningsih, 2018)

In Figure 2-2, a simple two-echelon distribution network is presented by Martin (1992). The Figure 2-2 includes the DRP display for each distribution center (DC), the lead-time (LT), the amount of safety stock, and the order quantity.

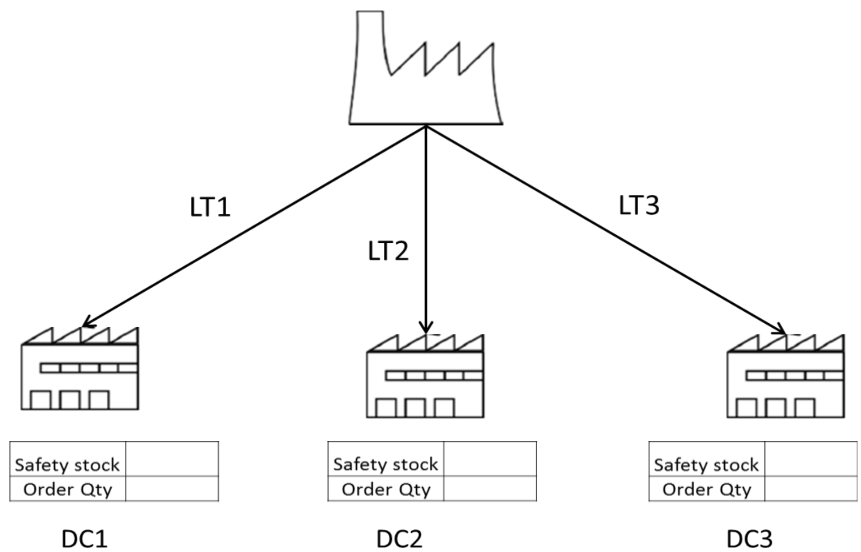

Figure 1-2 A two-echelon distribution network (Martin, 1992)

According to Martin (1992), The first step of the DRP process, after gathering the required data, is creating and completing tables like Table 1-1. In this table, the amount of available items, the amount of safety stock, the lead-time, and the order quantity (lot size) should be determined in the data processing step. The first row of the table is the forecast extracted from the sales department, which is considered as the demand for each item. The items in transit are planned to be delivered. There is the possibility of the physical situation of these items. They could be either on the road or in the process; they might be in the process of being packed or picked up in the supply source location as well. The amount of inventory stock available from the last specified period, which is called Projected On-Hand (POH), is shown in the third row of Table 1-1. The forth row in Table 1-1 is associated with the items that are delivered, which is named Plnd.Shpmts.-Rcpt.Date. The last row in Table 1-1, indicates the items that are Plnd.Shpmts.-Ship.Date, which is related to the items that are unreleased, and still in the planning stage.

Table 1-1 DRP display for each distribution center (Martin, 1992)

On hand Balance - Safety stock - Lead-time - wks Order quantity -	Past Due	Week							
		1	2	3	4	5	6	7	8
Forecast									
In transit									
Projected On Hand									
Plnd.Shpmts.-Rcpt.Date									
Plnd.Shpmts.-Ship.Date									

Considering t as the time period, the following equations for each distribution center is calculated for DRP display:

$$POH_{t+1} = POH_t - Forcast_{t+1} + Rcpt.Date_{t+1} \quad 1\text{-}1$$

$$POH_{t+1}: Projected\ on - hand\ in\ period\ t+1 \quad 1\text{-}2$$

$$POH_t : Projected\ on - hand\ in\ period\ t \quad 1\text{-}3$$

$$Forcast_{t+1} : Demand\ forecast\ in\ period\ t+1 \quad 1\text{-}4$$

$$Rcpt.Date_{t+1} : Planed\ shipment\ reciept\ date\ in\ period\ t+1 \quad 1\text{-}5$$

When Plnd.Shpmts.-Ship.Date is specified for all distribution centers according to Table 1-1, they appear in the row related to each distribution center in Table 1-2.In fact, the table is created in order to indicate a summary of the planned shipments to the stores from the supply source. The total amount of items that should be shipped from the supply source will be determined in the last row of Table 1-2.

Table 1-2 Summary of planned shipment to the stores (Martin, 1992)

	Past Due	Week							
		1	2	3	4	5	6	7	8
DC1									
DC2									
DC3									
Totals									

Martin (1992) demonstrates some of the benefits of regional distribution centers (RDC). He considers RDCs for multi-echelon distribution networks. The advantages associated with creating RDCs are generally categorized into two groups: one group concerns economic matters, and the other has to do with customer service issues. For the economic category, the benefits can be noted as improving the freight rate, and cutting down warehouse costs, as well as the safety level of inventory. While the system is facing a high volume of products moving toward distribution centers, enhancing the freight rate can overcome product delivery issues. The second issue is associated with the distance existing in transporting the demands between suppliers and centers; the shorter the distance is, the lower the cost of transportation would be. As discussed, the amount of safety stock is directly linked to the forecast practices. Holding cost of the DCs decreases while the amount of safety stock which is kept in distribution centers, are minimum. In this case, the summation of safety stock level in RDCs will be less than that in DCs. There is also the possibility of forecasting deviation for each center in a situation where one center might sell less products, and the other sell more. For the second category, which is termed customer service matters, RDCs that are closer to customers could be served much faster, and this results in cutting costs, including transportation costs, whereas establishing RDCs will not always result in reduction cutting down the amount of inventory, improving freight rate or warehouse costs. Improved economic situation, as well as high level of customer service, will definitely originate from well-executed DRP processes and well-managed RDCs .A three-level distribution network is presented in Figure 1-3 (Martin, 1992).

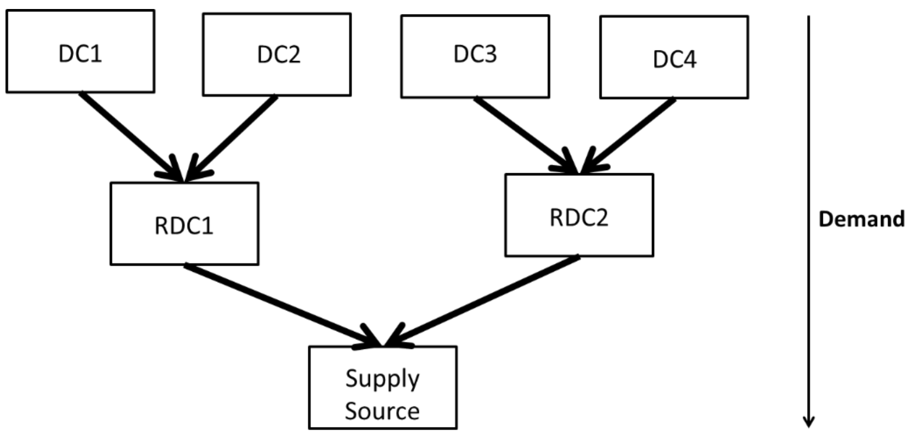

Figure 1-3 A Three-echelon distribution network using regional distribution centers

(Martin, 1992)

Calculating DRP display for the distribution network in Figure 1-3 is very similar to the previous network calculation as Figure 2-2. The difference between the Table 1-3 and the Table 1-1 is that the first table represents the standard DRP display. The most important differences are pertaining the names assigned to the components of the two tables; for instance, Gross requirements for items in store or a distribution center in the Table 1-3 is equivalent to forecast in the Table 1-1. The term scheduled receipt in Table 1-3 is also equivalent to transit in the Table 1-1. Scheduled receipts is defined as the quantity of items that are scheduled to come into stock. For the items in store or a distribution, planned order items in Table 1-3, are still in planning stage and unreleased are equivalent to Plnd.Shpmts.-Ship.Date in the Table 1-1 . For the items in store or a distribution, the scheduled receipts in Table 1-3 are equivalent to Plnd.Shpmts.-Rcpt.Date in Table 1-1, and they are scheduled for future shipment from the supply source.

$$POH_{t+1} = POH_t - Grossrequirement_{t+1} + Planned\ order_{t+1} \quad 1\text{-}6$$

Table 1-3 Standard DRP display for a distribution center (Martin, 1992)

On hand Balance - Safety stock - Lead-time - wks Order quantity -	Past Due	Week							
		1	2	3	4	5	6	7	8
Gross Requirement									
Scheduled Receipts									
Projected On Hand									
Planned Orders									

The planned orders in Table 1-3 for all distribution centers, appear as gross requirement in Table 1-4 related to the regional distribution center.

Table 1-4 Standard DRP display for a regional distribution center (Martin, 1992)

On hand Balance - Safety stock - Lead-time - wks Order quantity -	Past Due	Week							
		1	2	3	4	5	6	7	8
Gross Requirement									
Scheduled Receipts									
Projected On Hand									
Planned Orders									

Eventually, the planned order items in Table 1-4 show up as distribution demands in the master production schedule (MPS) table related to the supply source in Table 1-5.

Table 1-5 Supply source-master production schedule display (Martin, 1992)

On hand Balance - Safety stock - Lead-time - wks Order quantity -	Past Due	Week							
		1	2	3	4	5	6	7	8
Distribution Demands									
Scheduled Receipts									
Projected On Hand									
Master Scheduled-Rcpt.									
Master Scheduled-Start									

In addition to gross requirement, sometimes the RDCs have a forecast of product per week to serve the customers in their own area. Generally, it is better to utilize the bills of distribution especially in the case of facing several levels for distribution network. Therefore, we should let each level to be planned and the DRP is run before moving to the next level. By doing this, any potential problems with running the DRP in each step can be addressed beforehand (Martin, 1992).

1.4 The bullwhip effect and, approaches to its reduction

Over the1970s, DRP was introduced to tackle the defects related to order point approach to inventory management which was based on dependent demand logic of material requirement planning (MRP) (Watson & Polito, 2010). According to Ptak and Smith (2019), the nervousness inherent in MRP is defined by APICS as small changes in upstream levels that cause significant changes in downstream levels. This can also be generalized for DRP since it is established based on MRP logic concepts. The most important and influential disadvantage of DRP is that, it is focused on sales forecasts. MRP and DRP have a tendency to be dependent in everything; therefore, the supplying cycle will be too long to respond to the actual demands, which, in turn, this leads to signal distortion and frequent changes in forecasts (Ptak and Smith, 2019). All these causes give rise to a phenomenon called the bullwhip effect. The first research on the bullwhip effect has been conducted by Battersby and Forrester (1963). They stated that the small fluctuations in demands in downstream (customer level) will increase dramatically through the supply network when it moves toward the upstream (Battersby & Forrester, 1963). H. L. Lee, Padmanabhan, V., & Whang, S, (1997) identified four main causes of the bullwhip effect as following: 1. Update of demand forecasts: which happens when every party in the supply network handles the early demand as their own view and updates the demand forecasts based upon their own historical data, then they modify and respond to the fluctuation in turn; therefore, intensive fluctuations will occur through the supply network. 2. Price fluctuation: customers buy products based upon the winning offers rather than their real needs; therefore, the buying patterns deviate from consumption patterns 3.Order batching stands for the reinforcement of order variability while having high costs of frequent order processing, and 4. Shortage gaming: arises when customers overstate their real needs for the fear of shortage, and it leads to excessive demand for supply.

Lin, Naim, Purvis, and Gosling (2017) investigate the application and role of Inventory and Order Based Production Control System (IOBPCS) in about 113 selected papers from 1982 to 2015 in supply network dynamics and the reduction of the bullwhip effect. Among the papers reviewed, some emphasized that all forecasting methods have a direct impact on the bullwhip effect. The authors also consented that information sharing in the supply network, and generally supply network collaboration has a positive impact on bullwhip reduction. F. Chen, Drezner, Z., Ryan, J. K., & Simchi-Levi, D, (2000.) assume that the retailers in supply network apply a standard forecasting technique to approximate certain parameters of the demand process. Moreover, the purpose of the research is also to quantify the variability in each echelon of supply network. They considered a simple two-stage supply network for their study, which contained a single retailer and a single manufacturer, then they extended the study to a multi-echelon supply network and concluded that the bullwhip effect can be decreased by centralizing demand information. For example, if we consider that, customer demand information is accessible for all stages in the supply network.

Fransoo (2000) Regarding the work of H. L. Lee, Padmanabhan, V., and Whang, S (1997) attempts to measure the bullwhip effect in the supply network. He concludes that there are some criteria under which measuring the bullwhip effect can be carried out correctly. For instance, the sequence of aggregation data is prominent in the measuring process, such as inbound demand and outbound demand in different echelons. Since each echelon may contribute to the creation of a different level of bullwhip effect, bullwhip effect measurement should occur dependently for each echelon. Finally, each individual result from every cause in the measurement process should be determined. Dejonckheere, Disney, Lambrecht, and Towill (2003) have demonstrated that the main cause of the bullwhip effect phenomenon is applying different forecasting methods for replenishment policies in the supply network due to the variance amplification. They, therefore, develop new replenishment rules to reduce variance amplification although they assert that bullwhip effect is unavoidable when there is cascade forecasting.

Dejonckheere, Disney, Lambrecht, and Towill (2004) have tested the effective impact of information sharing in multi-echelon supply networks with the help of two types of replenishment rules which are order-up-to (OUT) policies, and smoothing policies. They demonstrate that for the OUT policies, information sharing was quite beneficial in reducing the bullwhip effect. However, it cannot be fully eliminated. For the other policies, they show that the role of information sharing in the upstream levels of supply network where the order variance related to superior levels occurs is crucial. P. Nguyen (2007) assert that the optimal supply network performance will not happen. They also pointed out the pivotal role of cooperation and demand information sharing in reducing the causes of the bullwhip effect. They also propose some reasons for the bullwhip effect, such as order synchronization, which occurs when the demand orders in the supply network levels do not match. When retailers order their required demand in batch and not daily, but weekly, in order to economize their orders, order batching happens. Consequently, the amount of their orders do not match that of the customer's and it is usually greater than that. Xie (2012) applies Automatic Pipeline feedback compensated Inventory and Order-Based Production Control System (APIOBPCS), and Order-Up-To (OUT) policy while the fuzzy estimate for uncertain demand in a single-echelon supply network. They measured the bullwhip effect as the variance amplification and used possibility variances. They also pointed out that the bullwhip effect will be notably reduced by applying fuzzy approaches compared to probability theories. They concluded that when the lead-time is shorter, the bullwhip effect will be less in the supply network. However, it cannot be fully eliminated even if there is no lead-time.

Jeong and Hong (2017) examine the impact of information sharing bullwhip effect in a four-echelon supply network. They tested four levels of demand forecast shared at each level called information sharing rate (ISR). They concluded that: 1. the higher ISR decrease the BWE more than the lower ISR. 2. The impact of ISR reduced when one moves towards downstream. 3. Balance of ISR across echelon has an impact on BWE. 4. A very inconsistent ISR may have the opposite effect on BWE. In brief, the results of their study prove the crucial role of cooperation and collaboration in the supply network. Cao, Xiao, and Sun (2016) discuss the other type of the supply network which namely supply and demand-driven supply network. This chain operates with supply-driven and customer demand-driven simultaneously. As such, the bullwhip effect is this chain is different from the demand-driven supply network. In this chain, which includes one retailer and one supplier, the demand function, the supply function and the price adjustment function are considered in the model at the same time. Cao et al. (2016) have pointed out the crucial role of suppliers in reducing the Bullwhip effect (BWE) by using the previous historical data information. Moreover, they emphasize the collaboration of suppliers rather than retailers. They conclude that it is highly beneficial for suppliers to have a production plan and apply a suitable sales strategy for retailers to repel the BWE according to sensitivity analysis.

Campuzano-Bolarín, Mula, and Peidro (2013) have applied fuzzy estimation rather than exponential smoothing for demand forecasts into a three-echelon supply network, and concluded that some forecasting approaches are able to lower some dynamics in the supply network such as bullwhip effect (which occurred because of forecast errors in each stage of supply network), under special circumstances. Enns & Suwanruji (2000) have also suggested some drawbacks associated with DRP, like requirement accessibility of data throughout the supply network, high costs and system tensions, which result in environment uncertainty.

As the discussion ensued in previous section, different, more accurate demand forecasting methods developed in the literature so as to confine or reduce the bullwhip effect. There are various methods offered to reduce demand variation in the supply network, among which some laid emphasis on the cooperation and integration of participants in the chain. Zhao, Xie, and Leung (2002) analyze the demand forecast patterns chosen by retailers and capacity tightness faced under the decision adopted by suppliers associated with the production plans, notably reveal the value of information sharing. They conclude that information sharing leads to a fundamental saving in costs and provokes members of the chain to share information to enhance supply network performance. With the help of simulation tests, Barlas and Gunduz (2017) examine some of the sources of the bullwhip effect and benefits of information sharing in the reduction of the bullwhip effect, as well as on parameters such as demand and lead-time. Lastly, they conclude that the single forecasting process at each echelon is the principal cause of the bullwhip effect. Moreover, information sharing includes sharing the both demand and forecast, which has a considerable impact on reducing the bullwhip effect.

Wright and Yuan (2008) argue that double exponential smoothing forecasting method alongside an appropriate ordering policy is more efficient than simple exponential smoothing in the reduction of the bullwhip effect. Cannella, López-Campos, Dominguez, Ashayeri, and Miranda (2015) illustrate that when all information includes the order, the level of inventory and the demand are available for upstream parties in chain, information distortion as well as the bullwhip effect can be reduced dramatically. Wilck (2018b) has summarized techniques for managing the bullwhip effect in his article and discussed the effective role of information sharing in reducing it. Likewise, he has introduced some tools such as RFID (Radio frequency identification) , and Electronic Data Interchange (EDI) that facilitate the coordination in supply network which, in turn, has information sharing in its heart; such as Coordination in forecasts and ordering policies. He has also suggested that information sharing is only effective when coordination occurs fast enough. In other words, the supply network lead-time should not be that long. Wilck (2018a) summarized the cause of the bullwhip effect, the factors contributing to them, and some techniques as presented in the Table 1-6.

Table 1-6Summary of the causes and management techniques for the Bullwhip effect (Wilck, 2018b)

Bullwhip Causes	**Contributing Factors**	**Techniques to Manage**
Demand Forecast Updating	No concept of true demand	Sharing sales information
	Multiple forecasts	Centralized control
	Long lead-time	Reducing lead-time
Order Batching	High fixed order costs	Synchronized ordering
	Random ordering	Reducing lot sizes
	Correlated ordering	
Price Fluctuation	Fluctuation in prices	EDLP
	Promotions	Volume-based quantity discounts
	Lot-size quantity discounts	
Shortage Gaming	Inflated orders	Allocate based on past sales
	Free returns policies	Capacity reservation

With all these taken into account, the BWE is an inevitable issue in supply networks, and as such efforts have been made in numerous works to reduce. Since much research has already been conducted on this issue, in this project we try to address the issue with the help of novel approaches such as Demand-Driven Material Requirement Planning (DDMRP).

1.5 CPFR: an efficient approach to supply network

There is an approach named Collaborative Planning Forecasting and Replenishment (CPFR) to optimize the supply network. It is defined as a business practice that combines the intelligence of multiple trading partners in the planning and fulfillment of customer demand. It links sales and marketing best practices to supply chain planning and execution processes. The objective of this approach is to increase availability to the customer while reducing inventory, transportation and logistics costs. Chuchoque-Urbina, Caro-Gutiérrez, and Montoya-Casas (2021) applied CPFR approach and compared the performance of a collaborative three-level chain with the traditional one in terms of cost of the chain. The objective of their distribution strategy was the minimization of the cost. The results of their study showed that total monthly cost reduced and the customer satisfaction increased compare to the traditional approach. This approach also can be an efficient approach to reduce the bullwhip effect. Actually, the collaboration among different parties in supply network assists to prevent the nervousness of bullwhip effect, despite using of demand forecasting in each level of supply network.

1.6 A review of the DDMRP approach and its role in distribution systems

As mentioned by Ptak and Smith (2019), Demand-Driven Material Requirement Planning (DDMRP) has been inspired by a manufacturing strategy focusing on meeting the demand. The objective is to meet any demand from different sources, making it agile and fast. The main goal of DDMRP is to protect the inventory flow of goods or materials from oscillations and to keep them in the optimal range. DDMRP concepts proceed from Material Requirement Planning (MRP), DRP, Lean Six-Sigma, Theory of Constraints (TOC) and innovation. DDMRP consists of three steps with five components, which are strategic inventory positioning, buffer profiles and levels, dynamic adjustment, demand-driven planning, and visible collaboration execution as depicted in the Figure 1-4.

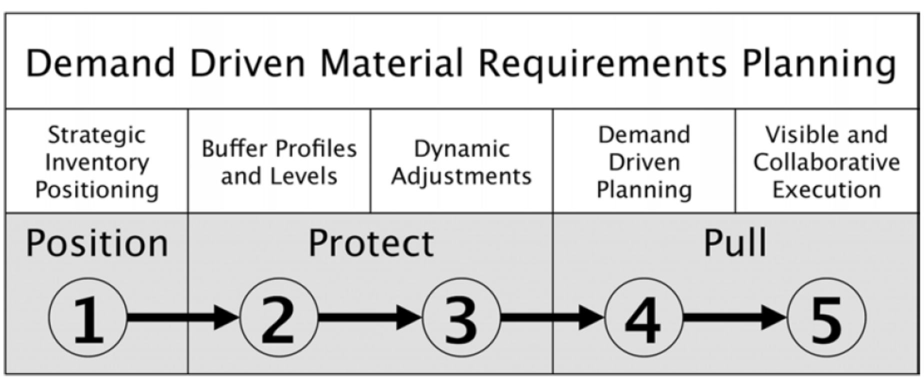

Figure 1-4 The five components of DDMRP (Ptak and Smith, 2019)

Decoupling is defined by APICS as:" creating independence between supply and use of material. Commonly denotes providing inventory between operations so that fluctuations in the production rate of the supplying operation do not constrain production or use rates of the next operation." Decoupling disjoints the events happening on one side from ones happening in the other side (Ptak and Smith, 2019).

One of the most important questions that is arose in DDMRP process is where the buffer should be positioned. The first step of the process is to place the buffer through which the variability in the supply network is prevented in order to reduce the planning horizon and lead-times. The second step is to determine the buffer profile and levels in decoupling points. The buffers include three zones that are calculated with a special formula proposed by Ptak and Smith (2019) . The buffer profile is defined as a group of parts that have the same characteristics. Their connections are specified as three factors. The first factor is item type, which is classified into three categories of manufactured, purchased or distributed. The second factor, which is the lead-time factor, is categorized in three groups: short, medium, and long. These may differ based on the enterprise's environment and the part type. The lead-time factor is a percentage of the Average Daily Usage (ADU) within the decoupled lead-time of the part. The longer the lead-time of the part is, the smaller the lead-time factor should be (Ptak and Smith, 2019). The third factor is the variability, which can have two dimensions of supply and demand and be categorized into low, medium, and high for each dimension. The distributed part, or Stock Keeping Unit (SKU), which is located in downstream locations, is affected by demand variability; Nevertheless, at the central buffers, it can be protected from large demand variability if the downstream positions.

The most significant step in DDMRP is determining where the decoupling points, and the related buffer should be placed. To this end, some factors should be described: 1- Customer tolerance time, which is defined as the time the customer would wait for being served or receiving products before referring to an alternative. 2- Market potential lead-time defined as a lead-time permitting the price to increase or to take additional business by other customers. 3- Sales order visibility horizon, which is the time in which the awareness of sales orders or actual relevant demand occur. 4- External variability related to demand and supply. 5- Inventory level, and flexibility, which is defined as the locations in the bills of material or distribution network in which the best options and lead-time compression exist to meet system needs, and 6- Critical operation protection, which can be interpreted as crucial resources that affect the flow and ought to be protected.

The third step is dynamic buffer adjustment, which is responsible for updating buffer levels based on average daily usage. The fourth step is demand planning based on net flow position, not on sales forecasts. The final step stands for visible and collaborative execution. It interprets signals on open supply priorities against the on-hand buffer status. The priority is specified by the buffer status rather than the due date (Ptak and Smith, 2019). Y. Erraoui, Charkaoui, A., & Echchatbi, A, (2019) have suggested Demand-Driven Distribution Resource Planning (DDDRP) as an optimization method for distribution networks. The process steps are akin to DDMRP steps. To be specific, Y. Erraoui, Charkaoui, A., & Echchatbi, A, (2019) have been inspired by DDMRP process. In the first step, buffers should be placed in distribution nodes, then buffer profile level has to be specified, dynamic adjustment should be done, demand-driven planning comes next, and finally, the open supply orders is executed. The first step, which is positioning the buffer in distribution centers (DCs), carries out financial point of view. The goal of the second step is the absorption of variability by decoupling points. Calculating buffer levels requires some parameters such as distribution lead-times, which include launch and preparation time, the loading, transiting, unloading and, stocking delays. Ptak and Smith (2019) have included this as a Decoupled Lead-Time (DLT) between two consecutive centers. Average Daily Usage (ADU) is considered the initial inventory level represented in Figure 1-5. Y. Erraoui et al. (2019) have used the following expressions to calculate DDDRP buffer levels:

$$Red\ Base = ADU * DLT * Lead - time\ factor \tag{1-7}$$

$$Red\ Safety = Red\ Base * Variability\ factor \tag{1-8}$$

$$Total\ Red\ Zone = Red\ Base + Red\ Safety \tag{1-9}$$

$$Yellow\ Zone = ADU * DLT \tag{1-10}$$

$$Green\ Zone = ADU * DLT * Lead - time\ factor \tag{1-11}$$

The Top Of Green (TOG) is introduced by Ptak and Smith (2019) as expressions 2-12 and 1-13.

$$TOG = (Red\ Base + \ Red\ Safety) + Yellow\ zone + Green\ zone \qquad 1\text{-}12$$

$$\begin{aligned} TOG = {} & (RADU * DLT * Lead - time\ factor) \\ & + (ADU * DLT * Lead - time\ factor) * Varaibility\ factor \\ & + ADU * DLT + ADU * DLT * Lead - time\ factor \end{aligned} \qquad 1\text{-}13$$

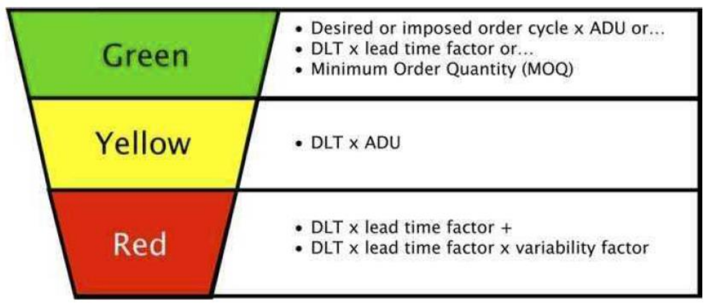

Figure 1-5 The buffer equation summary (Ptak and Smith, 2019)

Similar to DDMRP, dynamic adjustment in DDDRP keeps the buffer level and profile updated daily based on ADU. Demand driven planning generates supply orders by applying the following equation:

$$OH + OS - QS = Net\ flow\ position \qquad 1\text{-}14$$

Where:

$OH: On - hand\ quantity$

$OS: Open\ supply\ quantity$

$QS: Qualified\ sales\ order\ demand$

In net flow position equation 1-14, OH is the quantity of stock physically available; OS is open supply order or on-order, which is defined as the quantity of stock that has been ordered, but not yet received; QS is qualified sales order demand, which is equal to the sum of sales orders past due, sales orders due today, and qualified spikes (Ptak and Smith, 2019).
The final step of DDDRP is the execution uses on-hand buffer as a signal to open supply order. The lower the on-hand level, the higher the priority of order to be supplied (Y. Erraoui, Charkaoui, A., & Echchatbi, A,, 2019).

The demand-driven operating model is illustrated in Figure 2-6. As the figure illustrates, all components of the model from the first step, which is sales and operations planning, to the final step, which is the execution, are demand-driven, which means based on actual demands.

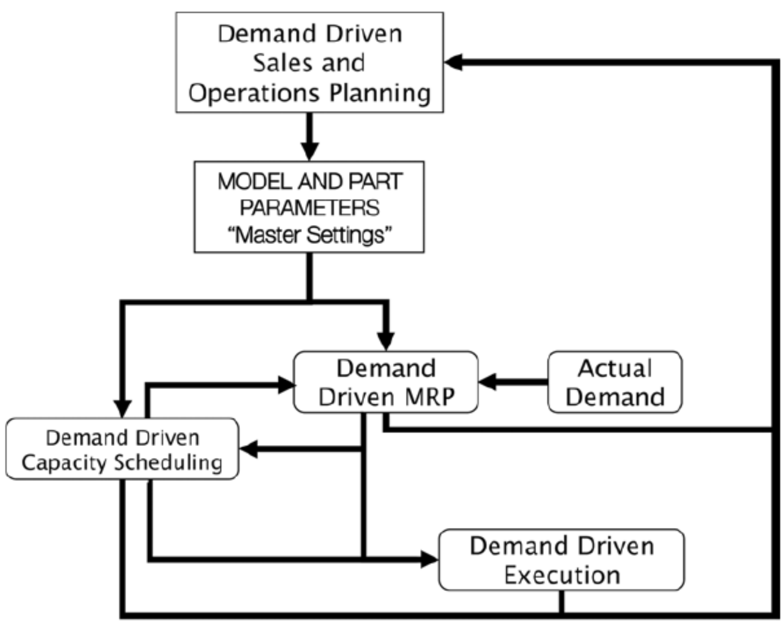

Figure 1-6 Demand Driven Operating Modal Schema

(Ptak and Smith, 2019)

1.5 A comparative view of demand-driven and traditional concepts in distribution networks

According to Section 1.2, The DRP process is based on sales forecast; On the other hand, the DDMRP approach deals with actual demands. Accordingly, this section presents a comparative view of these two approaches in terms of internal and external circumstances that are influential in inventory management concepts, and can be connected to distribution planning, during the 20th century and today. In the past, the structure of supply network s was not as complex as today; In particular, it was integrated and localized. In other words, it served only domestic customers. Nowadays, however, the structure is more extensive and disintegrated. It can spread all over the world, and serve customers in different countries. Product life cycle has been turned into short-term from long-term. With the advancement of technology, customers' preferences are more customized as well. Customer tolerance times have been reduced dramatically from months or weeks to days, or even twenty-four hours. As a consequence, lead-time parts have become shorter now. Since the customer tolerance times were longer and the supply network was more domestic than today in the past, customers had to wait to get what they needed. Whereas today, because of supply network dispersion and its distribution all over the world, many products can be delivered to customers in a very short time. Therefore, product complexity and customization, as well as product diversity have increased dramatically. Moreover, concerning variety, life cycle, and customer tolerance time, forecast accuracy is a less reliable approach to planning for the supply network. Considering the less variety and longer product life cycle in the past, any amount of inventories held in stores was not a matter of importance. Today, however, stakeholders would prefer to reduce the working capital, which refers to the total amount of stock in the supply network. With the assistance of technology and accessibility of information, today's customers, manufacturers, and suppliers are accessible in seconds. Thus, transactional friction has been significantly reduced compared to the past (Ptak and Smith, 2019). Using DRP for planning distribution practices is less profitable, and can also be frustrating. For instance, the DRP programming horizon is static, and it utilizes the safety stock in the distribution network to protect against stock-out in the supply network, whereas DDDRP takes advantage of buffer positioning based on a dynamic point of view (Y. Erraoui, Charkaoui, A., & Echchatbi, A,, 2019). Calculating buffer levels brings up to date in accordance with the average daily usage of the products consumed by customers. This policy can respond to every change associated with the supply network and, consequently, meets the customers' needs as soon as possible. Another key concept in DDDRP approach is the concept of decoupled lead-time, defined as the longest cumulative coupled lead-time chain in a distribution item's product structure (Y. Erraoui, Charkaoui, A., & Echchatbi, A,, 2019). In fact this is a response to shorten customer tolerance time. This subject can motivate us to probe into the literature to discover different approaches. In the next section, we investigate one of the most effectual factors in the decoupling approach in the supply network.

1.5.1 Safety stock (buffer) positioning in the supply network (distribution networks)

In an ordinary situation, customers' demand and supply service time are both uncontrollable variables with constant fluctuation. The combination of the two variables may lead to a stock-out status. A stock-out situation occurs when the level of stock in the system is lower than the customers' demand or hardly covers them. Stock-out causes the loss of revenue, customer satisfaction, and profit. On the other hand, holding too much inventory incurs extra costs. Demand uncertainty requires the safety stock to be kept in the supply network. Safety stock is considered an extra inventory further than the expected demand, held with the purpose of avoiding stock-out. Safety stock has two impacts on company costs: it reduces the cost of stock-out and increases the holding cost (Tersine, 1994) . In fact, it is considered a trade-off between holding costs and the cost of stock-out.

According to Li and Jiang (2012), the problem of specifying the place and the level of safety stock to be held in the supply network is considered an inventory positioning or a safety stock placement problem. There have been many approaches to safety stock placement or safety stock positioning in the supply network. The main intention of this part is to review some of these approaches in the 21th century. Li and Jiang (2012) consider that supply network players collaborate completely, so that the decision for the safety stock problem can be made according to a centralized decision-making paradigm. They address the safety stock problem in an acyclic network in which there is no directed cycle and each node is supplied by nodes in the previous level. They define the problem as a scheduling one and employ Constraint Programming (CP) to find solutions. They then test the combination of CP and Genetic Algorithm (GA), which improve CP solutions. The CP algorithm reached optimal solutions for small problems and near-optimal solutions for medium size problems. Finally, the hybrid CP-GA improves the quality of the solutions compare to either the CP or the GA.

Ghadimi, Aouam, and Vanhoucke (2020) try to solve an integrated production capacity and safety stock placement problem under the Guaranteed Service Approach (GSA). The problem is determined as a mixed integer non-linear problem (MINLP) for a general acyclic supply network and spanning tree network. For the first network structure, the Lagrangian decomposition method was applied to solve the problem, and for the other structure, the Lagrangian relaxation heuristic used with the budget constraint as a dual. The tests show that the Lagrangian relaxation heuristic reaches the optimal or near-optimal with a better running time compared to the Lagrangian decomposition method. Simchi-Levi and Zhao (2005) evaluate the continuous review base-stock policy in a tree structure supply network where demands follow Poisson distribution and the lead-times are assumed to be stochastic, sequential and exogenous. They pursue the stochastic-service model approach and propose an algorithm to fit base-stock levels in a single-product multi-echelon supply network and minimized inventory cost considering the meeting service level for external customers. They establish a vision into the effect of safety stock placement in a different supply network topology, according to recursive equations and represent the dependencies of backordered delays across the stages.

Funaki (2012) minimizes the total cost of the supply network (a combination of processing, transit, and holding costs). He developed a model for the combination of strategic safety stock placement and supply network design for assembly-type products according to” modified guaranteed service model with due-date based demand (stationary or non-stationary)”. Finally, the efficacy of the optimization procedure is confirmed, and it is possible to be applied to the real world. Boulaksil (2016) proposes an approach to determine the amount of optimal safety stock to be placed in each level of a supply network system with the aim of maintaining a specific customer service level, while assuming that the customer demands follow the Martingale Model of Forecast Evolution

(MMFE). They conclude that when faced with high demand uncertainty, safety stocks are positioned in downstream levels, while, safety stocks move to up-stream levels under the condition that the lead-times are shorter and demands are less uncertain. Klosterhalfen and Minner (2010) make a comparison between two approaches, namely the Guaranteed-service approach and, stochastic service approach for safety stock optimization in two-stage distribution system. Afterward, they present that the cost difference between the two approaches is four percent. Moreover, they came to conclusion that, there is better efficiency for processing time in large warehouses, and better service level for retailers.

Moncayo-Martínez and Zhang (2013) define a problem to place the optimal amount of inventory in each level in a supply network including a supplier, a manufacturing plant, or a transport mode in a supplying, manufacturing, or delivering stage according to the resource option in the stage. The target is meeting the customer service level with a minimum total cost. They then propose an ant colony-based optimization approach to minimize the total cost and lead-time of the network at the same time. Besides calculating the efficiency of their optimization, the approach was the innovation of their work. Grahl, Minner, and Dittmar (2014) suggest considering differentiated service times for safety stock positioning. The results indicate that applying differentiated service times in a guaranteed-service approach leads to reduction in the total cost of the network. H. Chen and Li (2015) attempt to optimize (R,Q) policy under the guaranteed-service approach and consider demands follow Poisson distribution for each stock location and also, assumed that, the order cost is fixed and operating costs are flexible. They apply a mathematical programming model by which the total cost of the system is optimized considering a special cycle service level. The sub-problems were solved by dynamic programming algorithm, and, the authors admit the efficiency of the algorithm and procedure. Kumar and Aouam (2018b) regard the Production Cycle Time (PCT) as a parameter in placing safety stock on the level of the network. They argue that the lot-sizing policy is influential in PCT, and set up time. They integrate strategic safety stock positioning and tactical lot-sizing. They also minimized inventory cost besides system-wide production under the constraint of meeting the service level. Ultimately, their results yield a smaller lot size, shorter lead-times, and the desired safety stock. In another study, they discuss batch sizing as an important factor in manufacturing lead-time and they argue that lead-time can be reduced by investment in set up time reduction. They minimize holding costs, WIP (work in process), and set-up reduction investment. Numerical studies on three-level network, put emphasis on effectiveness of using set up reduction while promoting the integration of tactical lot-sizing, and safety stock positioning. (Kumar & Aouam, 2018a).

In another study, Kumar and Aouam (2019) propose a model for position safety stock under guaranteed service with the objective of optimizing production capacity, and smoothing service time between levels. They evaluate the model and conclude that holding safety stock is crucial for production smoothing. They demonstrate that integrating guaranteed service level and production smoothing is substantial in cost saving.

1.5.2 Calculating safety stock levels with DRP approach

With DRP approach, the demand during lead-time is assumed to follow normal distribution (Brander (2006) and Silver (1998)) . Thus the safety stock level (SS) for a determined product is calculated via equation 1-15 :

$$SS = \sigma * \Phi^{-1}(\pi) \qquad 1\text{-}15$$

σ is the standard deviation of the total demand during lead-time for the specific product, and Φ^{-1} (π) is the standard normal inverse cumulative density function at a π service level. According to Lee and Rim (2019), if lead-time and demand are considered independent random variables, σ can be calculated via equation 1-16. Thus, equation 1-15 can be expressed as equation 1-17.

$$\sigma = \sqrt{L\,\sigma_D^2 + \mu_D^2\,\sigma_L^2} \qquad 1\text{-}16$$

$$SS = \sqrt{L\,\sigma_D^2 + \mu_D^2\,\sigma_L^2} * \Phi^{-1}(\pi) \qquad 1\text{-}17$$

Where L is the average replenishment lead-time (in this project we assume it as delivery time), σ_D is defined as the standard deviation of daily demand, μ_D is the average daily demand, and σ_L is standard deviation of replenishment lead-time(delivery time).

Subject to the following assumptions:

- a service level is π =0.99 and a demand following a normal distribution, the $\Phi^{-1}(\pi)$ is equal to 2.325;
- we assume that L is the mean delivery-time between a specific node and its parent;
- if we assume that the delivery-time is deterministic, σ_L can be considered as zero;
- we consider the average daily demand (ADU) instead of μ_D;
- according to Mirzaee (2017), we can use standard deviation of the ADU (σ_{ADU}) instead of σ_D.

The safety stock level (SS), previously expressed by equation 1-17, can be finally calculated using equation 1-18.

$$SS = 2.325\sqrt{L\,\sigma_{ADU}^2} \tag{1-18}$$

1.5.3 Inventory level

According to Courtois (2003), the mean inventory level is equal to the half of the economic order quantity (EOQ) plus the safety stock level (SS). According to Courtois (2003) economic order quantity is calculated as equation 1-19. In this equation, E is the order cost of the inventory per day. H is the holding cost of one unit of inventory per day.

$$EOQ = \sqrt{\frac{2\,ADU * E}{H}} \tag{1-19}$$

The inventory level is calculated by equation 1-20.

$$I = \frac{EOQ}{2} + SS \qquad \text{1-20}$$

We insert equation 1-18 in equation 1-20. Finally, equation 1-21is obtained.

$$I = \frac{EOQ}{2} + 2.325\sqrt{L\,\sigma_{ADU}^2} \qquad \text{1-21}$$

1.6 A new approach to buffer positioning in distribution networks

Conventional MRP and DRP for distribution systems are less capable of protecting the flow of material or information in a proper way. The crucial step to protect the flow is to be agile to prevent the signal distortions that give rise to bullwhip effect which caused by the dependent nature of DRP. Ptak and Smith (2019) have regarded decoupling as the only way to stop system nervousness and the bullwhip effect through the chain. To understand decoupling point positioning in a distribution network, the concept of demand variability is of paramount importance. Demand variability is known as a principal form of variability related to distribution networks (Ptak and Smith, 2019). Figure 1-7 demonstrates a simple, ordinary two-echelon distribution networks. There is a source unit, which supplies the warehouses in different regions, and there are the regional warehouses, which are supplied by the source unit. As depicted in Figure 1-8, regional warehouses have more demand variability compared to the source unit for an assumed period of time. The natural smoothing effect at the source unit is also visible. It is obvious that this kind of variability should be mitigated, otherwise, the network will be impacted deeply by shortages (Ptak and Smith, 2019).

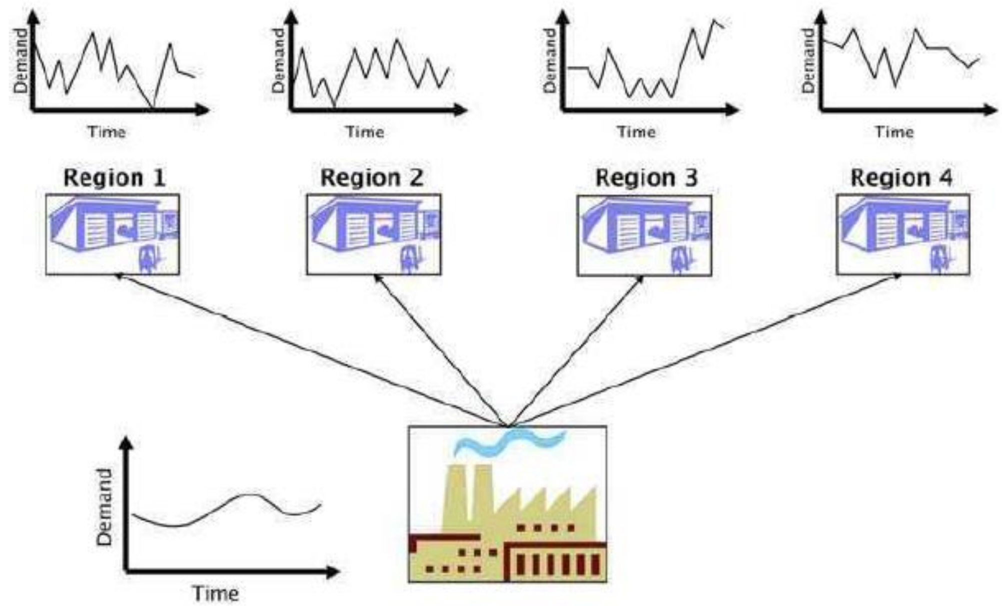

Figure 1-7 A typical distribution network (Ptak and Smith, 2019)

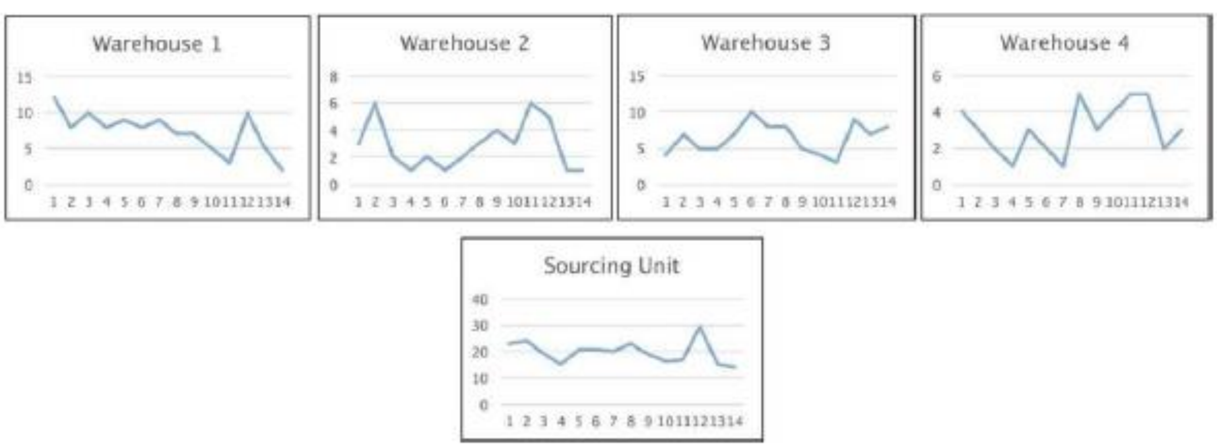

Figure 1-8 Daily demand charted for all locations (Ptak and Smith, 2019)

According to Ptak and Smith (2019), there is a tendency to push out the majority of the inventory closest to consumption locations. While some conclusions indicate that in these structures it will be essential to decouple source unit. It is confirmed that it should be considered more variable and longer lead-time for the regional centers whose demands are much more variable. However, the majority of systems have enough inventory, but they are not located in the right places. If the inventory is positioned in the right place, demands are better met, cross-shipping is eliminated, and the lead-time of the source unit and that of the regional centers become independent.

Ptak and Smith (2019) propose some configurations to address the problems of typical distribution networks, all of which emphasize decoupling. One of the basic models of distribution networks is presented in Figure 2-9. In this model, a decoupling hub located near the sourcing unit, is considered a central buffer hub. This configuration results in the elimination of cross-shipping through sending goods directly from the hub to regional centers. Thanks to this hub, lead-times will be shortened and the bullwhip effect will be minimized.

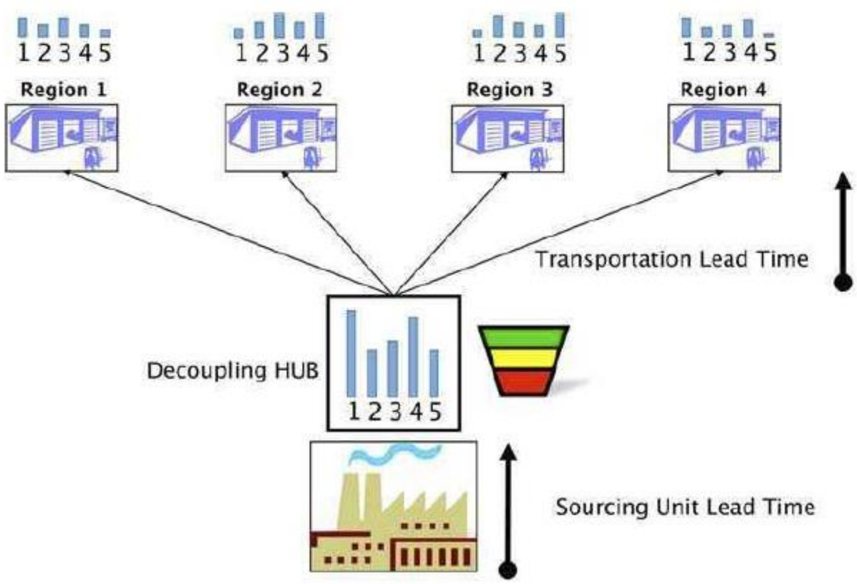

Figure 1-9 Decoupled distribution network (Ptak and Smith, 2019)

The second configuration, proposed by Ptak and Smith (2019) , is a multi-hub configuration shown in Figure 2-10. In this configuration, every warehouse can be a hub and a spoke at the same time. The role of the hub is to serve the regions that are relative geographically, and spokes are available for other regional warehouses. Taking advantages of the hub and spoke configuration, can reduce transportation costs using bidirectional transportation lanes (Ptak and Smith, 2019).

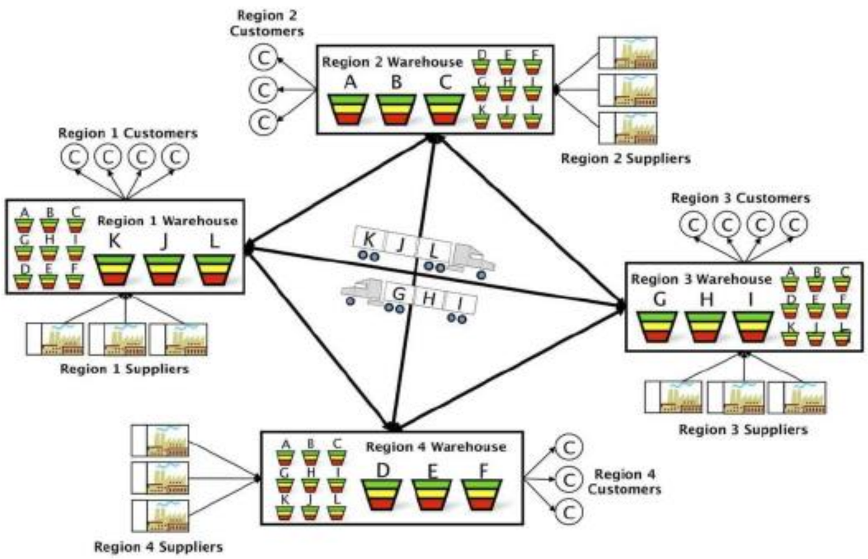

Figure 1-10 Multi-hub configuration (Ptak and Smith, 2019)

The third configuration, proposed by Ptak and Smith (2019) and depicted Figure 2-11, in is a hybrid configuration that considers a partial hub and a spoke. This model is useful in sourcing units that have limited space. Slow-moving items can be kept in the decoupling hub and fast-moving items are sent to regional centers directly from spoke (sourcing unit). Attention must be paid to slow-moving items, since they often create an imbalance in the network. Trucks can be loaded with both slow-moving and fast-moving items (Ptak and Smith, 2019).

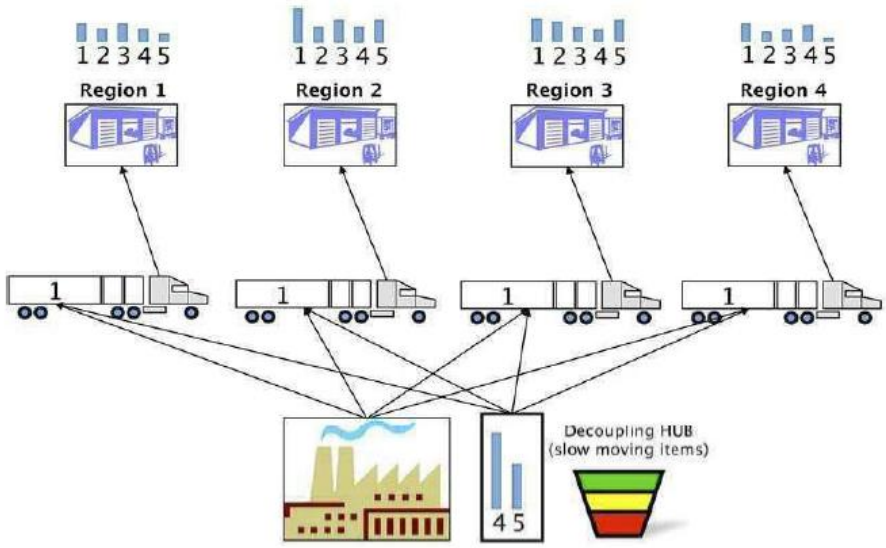

Figure 1-11 The hybrid configuration (Ptak and Smith, 2019)

Almost all the above-mentioned configurations that have been taken into consideration in the previous section, intended to optimize safety stock in the supply network under different assumptions and various parameters. In DDDRP approach, the first step is “strategic inventory positioning”, which consists of positioning the buffer in distribution centers in the supply network.(Figure 2-12) They also represent decoupling point buffer which is the amount of inventory that is created to decouple supply and demand. The definition offered by APICS is:” An amount of inventory kept between entities in a manufacturing or distribution network to create independence between processes or entities”(Ptak and Smith, 2019).

According to a comparative research on MRPII and DDMRP by Miclo, Fontanili, Lauras, Lamothe, and Milian (2016), it is concluded that buffers positioned through the supply network through the DDMRP approach can effectively adjust the fluctuation in the network.

Buffers have three functions in DDMRP, which includes: shock absorption, lead-time compression, and supply order generation (Ptak and Smith, 2019). The objective of decoupling inventory is to disconnect the rate of use from the rate of supply of the item. (p. 43). Buffers will be placed based on protecting variability (results in the bullwhip effect) through distribution flow as well as respecting customer tolerance time. Positioning buffer regarding to the objective of minimizing the cost of supply network, leads to calculating decoupled lead-time which will automatically shorten delivery lead-time. Moreover, this approach takes advantage of actual demand in the network instead of forecasting that has identified as a source of bullwhip effect in literature. It is important to point out the role of information sharing regarding actual demand in distribution network. From a planning perspective, the right materials will not be available without the right information (Ptak and Smith, 2019). The literature, stressed information sharing as one of the key elements of reducing the bullwhip effect, and it is here that its importance becoming even more clear. The literature also highlights the importance of reducing the lead-time to diminish the bullwhip effect, which is achievable through decoupling lead-time.

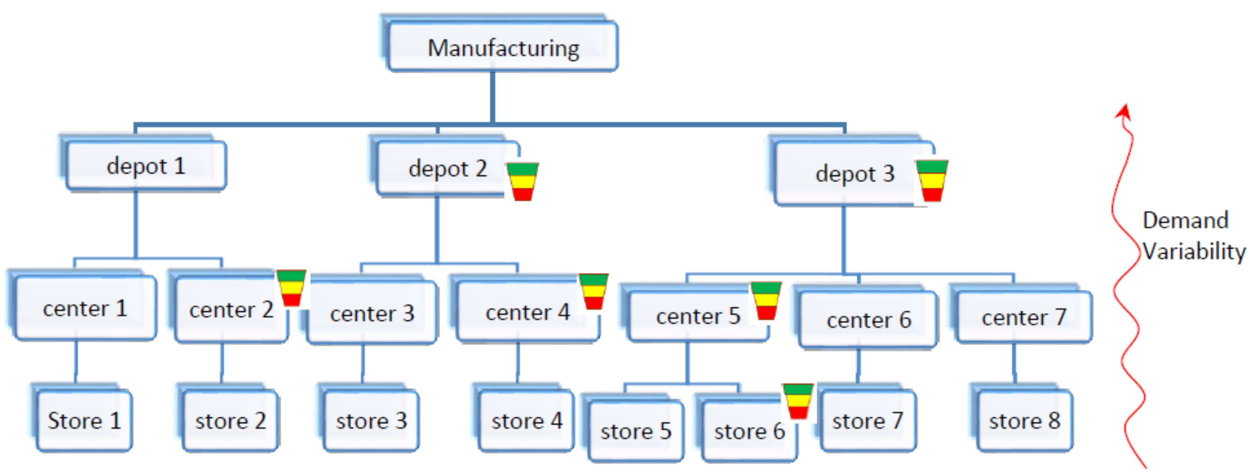

Figure 1-12 Buffer positioning in distribution network

(Y. Erraoui, Charkaoui, & Echchatbi, 2019)

1.7 Research contribution

The first and foremost, function of DRP is planning and controlling the product flow through the supply network. To perform well, the DRP process uses some steps mentioned in the previous sections. The first step is demand forecasting, which is based on historical sales data. According to the literature, cascade use of forecasting results in instability in the supply network, which, in turn, causes the bullwhip effect. As a result, any kind of cascade use of forecasting is unreliable to apply to inventory management in the supply network. Therefore, it is the time for a major change in the approaches and perspectives that depend on forecasts. DDDRP is an approach inspired by DDMRP concepts, in which actual demands play a crucial role. DDDRP is supposed to take the actual demands instead of the demand forecasts into account to manage the level of inventory in distribution networks. Some issues related to the novel approach are raised; for example, in which nodes, and based on which factors the buffers should be positioned through the network, and what is the effect of buffer positioning on lead-time (delivery time).

This project differs from the traditional approach to the positioning problem in some respects. In this project, we address the issues related to determining the location of the buffers in distribution networks, and also the possible changes in total holding cost of the network. To achieve the objectives of this project, the novel DDDRP approach is examined and evaluated through new methods and tools.

1.8 Conclusion

In this chapter, we presented a summary of the literature on the DRP process, the bullwhip effect phenomenon, its effect on the supply network, and different techniques to reduce it. Then we make a reviewed of DDMRP concepts as a different approach to inventory management, and its inspiring role in distribution networks. We also discussed the approaches to safety stock positioning in the supply network, and the traditional approach to calculating the amount of safety stock in a specified period in the supply network. Finally, the new approach named DDDRP, which is inspired by DDMRP, proposed a new technique for buffer positioning in the supply network.

In Chapter 2, the objective of the project is explained, the methodology to implement the mathematical model is proposed. In Chapter 3 , analysis and results are represented.

CHAPTER 2 OBJECTIVES AND METHODOLOGY

2.1 Introduction

The objective of this project is firstly to develop a DDDRP model for a multi-echelon distribution network, and to propose an approach to set buffers at nodes in a multi-echelon supply network in a perspective of minimizing the holding cost of buffers through the supply network.

This chapter presents the case study and hypothesis, the mathematical model and a discussion. Finally, the conclusion of the chapter is explained.

According to Li and Jiang (2012), there are different supply network structures some of which are illustrated in Figure 3-1. The figure presented four configurations a, b, c and d. In configuration a which is named serial network, each node is served by the previous node. There is also just one supplier for each client. In configuration b which is named spanning tree network, each client might be served by different suppliers, not only one. Configuration c is named general acyclic network in which every client can be served by only one supplier, while each supplier can have several client. The important point in this configuration is that each node can only be supplied by the previous node. The last configuration which is named general acyclic network with arbitrary arcs is somehow similar to general acyclic network, but the difference between these two configuration is that in configuration d, nodes can be served not only by their previous node, but they can be served by the upper level nodes than their previous node.

For this project the structure of the supply network is assumed to be a general acyclic network.

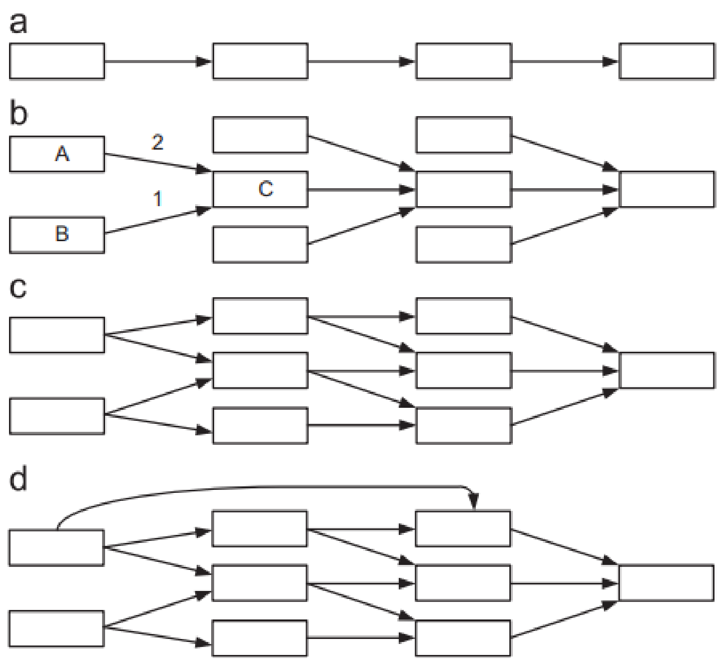

Figure 2-1 different supply network network structures : (a) serial network, (b) spanning tree network, (c) general acyclic network, (d) general acyclic network with arbitrary arcs (Li & Jiang, 2012)

2.2 Problem definition

In this project, the problem is formulated as a multi-echelon inventory optimization. According to Figure 3-2, and as presented in Chapter 1, we consider a multi-echelon distribution network with *i* stages and *j* nodes including a manufacturing plant, and (*j-1*) distribution nodes (DN). We assume that each DN, which refers to a warehouse or a depot, is served by a single supplier. Nevertheless, each DN can have more than one child (the node that is supplied by the previous node which is considered as a parent). The manufacturing plant is considered an infinite capacity supply source. Products are then sent either to warehouses to be stored and maintained temporarily, or to depots to be inspected, segregated and dispatched after orders are received from customers. We assume that the holding cost depends on the location of the distribution node in the network, and those distribution nodes have infinite capacity. Products are then sent either to warehouses to be stored and maintained temporarily, or to depots to be inspected, segregated and dispatched after orders are received from customers (Y. Erraoui, Charkaoui, A., & Echchatbi, A,, 2019). We assumed that each customer has a normally distributed daily demand with the mean Average Daily Usage (ADU), and standard deviation (s.d.). ADU of different customers are considered to be independent, while ADU for the distribution nodes are calculated based on customers' ADU. We set a customer tolerance time, which refers to the time by which customers expect to receive their demand. According to APICS, customer tolerance time is "the amount of time potential customers are willing to wait for the delivery of a good or a service" (Ptak and Smith, 2019). The lead-time (delivery time) between the nodes is known and include transportation delays. Next, we propose a model that determines the optimal position of buffers and identifies buffer levels in each DN based on its ADU and decoupled lead-time (delivery time).

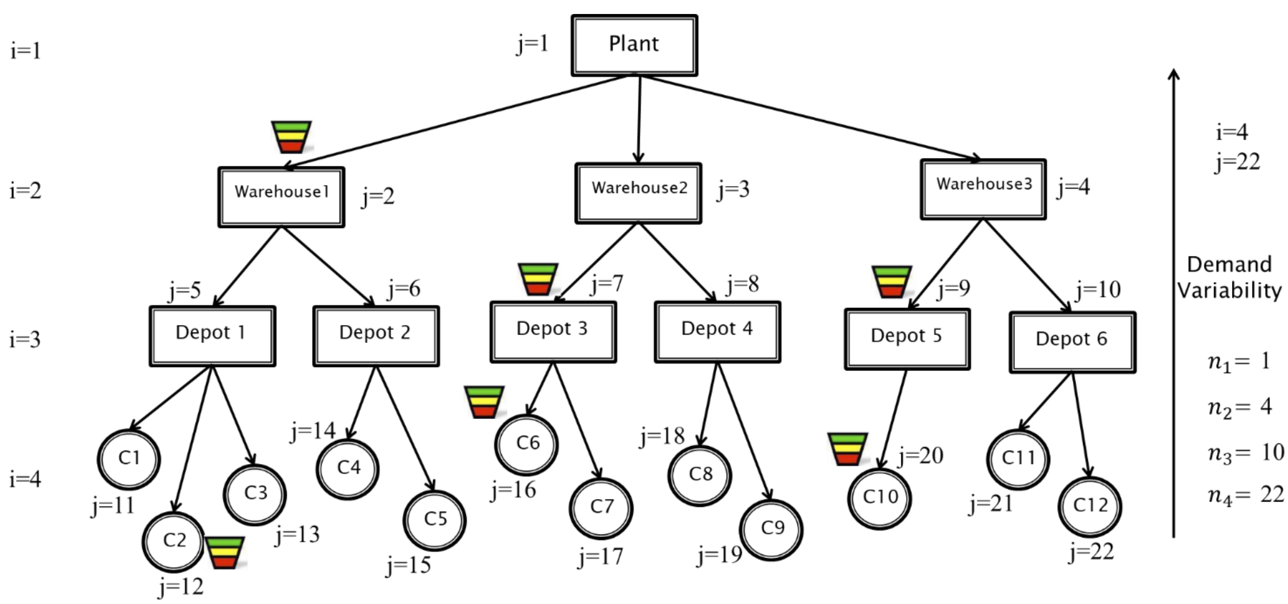

Figure 2-2 A multi-echelon distribution network and buffer positioning

(inspired by (Y. Erraoui et al., 2019)

2.3 Mathematical model

The mathematical model is formulated as a mixed-integer non-linear problem (MINLP). The objective of the model is to minimize the holding cost of the distribution network, which refers to the holding cost of the buffers in the distribution nodes. We use the following indices/sets, parameters, and decision variables.

Indices/Sets:

Table 2-1Indices/Sets

i	$Index\ of\ the\ distribution\ network\ stages$	$i = 1,2, \ldots I$
j	$Index\ of\ nodes\ including\ manufacturing\ plant, warehouses\ and\ depots$	$j = 1,2, \ldots J$

According to Table 2-1, the plant is considered as$j = 1$. The plant is also located in the first stage, and distribution nodes are located in the second, third and fourth stage.

<u>Parameters:</u>

Table 2-2 Parameters

n_i	$Number\ of\ the\ nodes\ in\ stage\ i\ plus\ the\ nodes\ in\ upper\ levels\ of\ the\ stage\ i$
$a_{jj'}$	$= 1\ if\ j'is\ a\ child\ of node\ j, 0\ otherwise.$
LT_j	$Lead - time\ betwenn\ node\ j\ and\ its\ supplier\ including\ launch\ and\ preparation\ time\ of\ the\ orders, the\ loading, transiting, unloading\ and\ stocking$
h_j	$Holding\ cost\ at\ node\ j$
CTT_j	$Customer\ tolerance\ time\ for\ customer\ node\ j$
ADU_j	$Demand\ at\ node\ j$
v_j	$Variability\ for\ node\ j$

n_i is defined as the number of nodes in stage i plus the nodes in upper levels of the stage i. For instance in Figure 3-2 , n_3 is equal to 10. n_2 is equal to 4.

The first node is the supply source does not have any predecessor, which means that:

$$a_{j1} = 0 \qquad \forall\, j \qquad \text{2-1}$$

In general:

$$a_{jj'} = 0 \qquad \forall\, j \ > j'$$

Each node but node 1, has a unique parent (one predecessor), which means that:

$$\sum_{j=1}^{j'-1} a_{jj'} = 1 \qquad \forall\ j' > 1 \tag{2-2}$$

We assume that the actual demand of final customers ($\forall\, j\ > n_{i'-1}\ \ where\ \ i' = max\{i\}$) are known. For each node other than final customers, ADU is calculated as the summation of all ADUs of the child nodes as presented by equation 2-3.

$$ADU_j = \sum_{j'=j+1}^{J} a_{jj'} *\ ADU_{j'} \qquad \forall\, j \le n_{i'-1}\ \ where\ \ i' = max\{i\}\ ) \tag{2-3}$$

The variability factor v_j reflects the demand variability and can be calculated by equation 2-4 based on the standard deviation for each particular part (Ptak and Smith, 2019). For each parent node, the variability factor is the summation of multiplication of ADU and variability factor over all related child nodes divided by ADU of the parent node. We assume that the variability factor for customers' nodes ($\forall\, j\ > n_{i'-1}\ \ where\ \ i' = max\{i\}$) known.

$$v_j = \frac{1}{ADU_j}\left(\sum_{j'=J+1}^{J} ADU_{j'} *\ a_{jj'} *\ v_{j'}\right) \qquad \forall\, j \le n_{i'-1}\ \ where\ \ i' = max\{i\}\ ) \tag{2-4}$$

Decision variables:

Table 2-3 Decision variables

δ_j	$A\ binary\ variable\ that\ takes\ 1\ if\ a\ buffer\ is\ located\ in\ node\ j, otherwise\ 0$
DLT_j	$Decoupled\ lead - time\ for\ node\ j$
k	$Equal\ to\ maximum\ of\ \ DLT_j$
α_j	$lead - time\ factor\ for\ node\ j$
B_j	$Mean\ inventory\ level\ at\ node\ j$
TOG_j	$Summation\ of\ three\ buffer\ zones(green, yellow, red)$

The purpose of the definition of δ_j is to specify the nodes to which the buffers are to be assigned. It actually specifies the nodes containing buffers, and helps calculate the buffer level in the specified nodes more easily. It takes 1 if the buffer is assigned to a node, otherwise it takes 0.

DLT_j is a positive variable defined as decoupled lead-time(delivery time), which can be defined as the longest cumulative coupled lead-time chain in a manufactured time's product structure (Ptak and Smith, 2019) . According to Ptak and Smith (2019) DLT is calculated by summing all the manufacturing and purchasing lead-times in that chain. The decoupled lead-time always includes the manufacturing lead-time of the parent. We consider decoupled delivery time for distribution network configuration. It is a cumulative lead-time that depends on the position of buffers in the network that we want to optimize. For the first node, we consider $DLT_1 \ = 0$.

α_j is a variable that depends on DLT_j and takes a number between zero and one.

B_j is also a function of DLT_j, k, δ_j ,and α_j . B_j is specified to the buffer level that is actually the mean inventory level that is positioned in each qualified node in the network.

The objective of the model is to optimize the buffer positions in the network under the condition of minimizing the holding cost of the network. The objective function presented by equation 2-5 is subject to the constraints 2-6 to 2-10 .

Objective Function:

$$Minimize\ Z = \sum_{j=1}^{J} B_j \times\ h_j \qquad 2\text{-}5$$

Contraints :

$$\begin{cases} DLT_{j'} = LT_{j'} + \sum_{j=1}^{j'-1}(a_{j,j'} * \left(1-\delta_j\right)DLT_j\ ) & \forall j' > 1 \\ DLT_1\ = 0 & \end{cases} \qquad 2\text{-}6$$

$$DLT_j \leq CTT_j \qquad \forall j \qquad 2\text{-}7$$

$$\alpha_j = \frac{DLT_j}{K} \qquad \forall j \qquad 2\text{-}8$$

$$TOG_j = DLT_j * ADU_j * [v_j * \alpha_j + \alpha_j + 1 + \alpha_j] \qquad 2\text{-}9$$

$$= DLT_j * ADU_j + DLT_j * ADU_j * \alpha_j [v_j + 2]$$

$$B_j = \frac{1}{2} * \delta_j * \ TOG_j = \ \frac{1}{2} * \delta_j * DLT_j * ADU_j * [v_j * \alpha_j + 2\alpha_j + 1] \qquad 2\text{-}10$$

The constraint related to equation 2-6 enables us to compute the *DLT* of node j dependently weather there is a buffer or not. When a buffer is positioned in a node (δ_j =1) DLT_j is simply equal to the delivery time for node j(contains the parents nodes). When no buffer is positioned in a node (δ_j = 0) DLT_j is the summation of *DLT* for its parent nodes plus the delivery time of node j. For the first node, we consider $DLT_1 = 0$, since DLT_j is less than the amount of customer tolerance time.

Constraint 2-7 guarantees to respect the customer tolerance time; since, DLT_j is less than the amount of customer tolerance time.

Constraint 2-8 expresses lead-time factors as a function of *DLT*. Since α_j varies between 0 and 1. Therefore, k logically must take the value as maximum of *DLT*.

Constraint 2-9 calculates the Top of Green (TOG) in buffer level, which is required to calculate the buffer. In the literature, the TOG as displayed in Figure 3-3, is a variable consists of the summation of all the levels in buffer that are red, yellow, and green. Ptak and Smith (2019) propose the expression 2-9 to calculate the TOG. In our model we show the lead-time factor as α_j , and variability factor as v_j ; After substitution the parameters and the variables in expression2-9, expression 2-10 will be obtained.

In equation 2-10 which is an hypothesis for the problem, the mean inventory level (buffer level Bj) is considered a half of TOG in each node containing a buffer.

If we substitute B_j by the expression presented in equation 2-10, the objective function 2-5 becomes equal to the equation 2-11.

$$Minimize\ Z = \sum_{j=1}^{J} \frac{1}{2} \delta_j * DLT_j * ADU_j * [\alpha_j(v_j + 2) + 1)] * h_j \qquad \text{2-11}$$

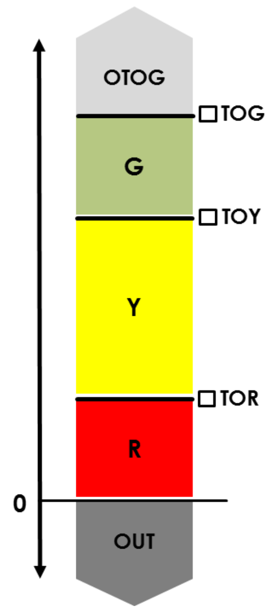

Figure 2-3 Top of Green(TOG) display

(Ptak and Smith, 2019)

The complete model with objective function and constraints is as follows:

<u>Objective Function:</u>

$$Z = Min \sum_{j=1}^{I} B_j * h_j \qquad \text{2-12}$$

<u>Computing B_j</u>

$$TOG_j = DLT_j * ADU_j * [v_j * \alpha_j + \alpha_j + 1 + \alpha_j] = DLT_j * ADU_j + DLT_j * ADU_j * \alpha_j[v_j + 2] \quad \text{2-13}$$

$$B_j = \frac{1}{2} * \delta_j * TOG_j = \frac{1}{2} * \delta_j * DLT_j * ADU_j * [\alpha_j(v_j + 2) + 1)] \quad \text{2-10}$$

$$Z = Min \sum_{j=1}^{J} \frac{1}{2} * \delta_j * DLT_j * ADU_j * [\alpha_j(v_j + 2) + 1)] * h_j \quad \text{2-12}$$

As we have in equation 2-8 ,we have $\alpha_j = \frac{DLT_j}{K}$:

$$B_j = \frac{1}{k} * \delta_j * DLT_j^2 * ADU_j * \left[\left(\frac{v_j}{2} + 1\right)\right] + \frac{1}{2} * \delta_j * DLT_j * ADU_j \quad \text{2-14}$$

$$Z = Min \sum_{j=1}^{I} (\frac{1}{k} * \delta_j * DLT_j^2 * ADU_j * \left[\left(\frac{v_j}{2} + 1\right)\right] + \frac{1}{2} * \delta_j * DLT_j * ADU_j) * h_j \quad \text{2-15}$$

<u>Contraints :</u>

$$DLT_{j'} = LT_{j'} + \sum_{j=1}^{j'-1} a_{j,j'} * (1 - \delta_j) DLT_j \qquad \forall j' > 1 \qquad \text{2-6}$$

$$DLT_j \leq CTT_j \qquad \forall j \qquad \text{2-7}$$

$$K \geq DLT_j \qquad \forall j \qquad \text{2-16}$$

2.4 Resolution method

The purpose of this project is proposing a model to optimize the buffer in the supply network. We applied a mathematical modeling approach to reach this goal. We modeled the mathematical model, which is formulated in the previous section, as a Mixed Integer Nonlinear Problem (MINLP) where decision variables are assumed to be binary or continuous. In order to address this problem, the convexity status of the problem should be determined in the first step. The structure of the objective function in this model is convex. In most mixed integer non-linear problems, solvers handled by branch and bound procedure, whereas solving relaxed sub problems. There are many algorithms for solving smooth (continuously differentiable) convex MINLP problems, in the literature. Some of the related methods used in solvers include branch and bound, decomposition method, and cutting plane method. Many smooth convex algorithms are in commercial use in different solution packages such as GAMS studio (https://www.gams.com/), AIMMS (https://aimms.com/), AMPL (https://ampl.com/) and LINDO (https://www.lindo.com/) (Westerlund, Eronen, & Mäkelä, 2018). For the model of this project, GAMS solution package with taking advantage of BARON solver was utilized to solve this problem.

Firstly, a small scale problem is solved with GAMS in order to validate the model and then, a larger scale problem is solved with GAMS to test the efficiency of the model. The larger scale problem solved with both methods of conventional DRP technique and DDDRP technique. The both techniques are compared in terms of total holding cost of the supply network and the level of inventory which is located in the nodes of the supply network.

2.5 Conclusion

In this chapter, we first described a multi-echelon distribution network as a case study, and investigated the nodes, relationships, level and different elements needed to define the model. Then, we defined the sets, parameters and decision variables for the mathematical model related to the network according to DDMRP concepts by Ptak and Smith (2019). In the subsequent section, the structure of the problem will be developed with defining the objective function and the specified constraints. In Chapter 3, we will describe the resolution method, the DDDRP model, and the results of comparing it with the traditional DRP approach.

CHAPTER 3 RESULTS AND DISCUSSION

3.1 Introduction

This chapter is organized and explained as follows: first, we validate the DDDRP model presented in chapter 3 using a small scale of a nine-node distribution network. The problem is solved, and then results are compared to those obtained with GAMS for the nine-node distribution network with the same data. Next, we solve a twenty-two-node distribution network with GAMS, and we compare the results using the DRP approach and the DDDRP approach.

3.2 Model validation

First, the DDDRP model is solved using a small scale with a nine-node distribution network as presented in Figure 4-1. The figure presents a plant as a resource node, two warehouses, which are fed by the resource, three depots, which are supplied by warehouses, and lastly, three customers in the last level, which are satisfied by the depots. The results of solving the model are then compared to those obtained with the optimisation model solved with GAMS.

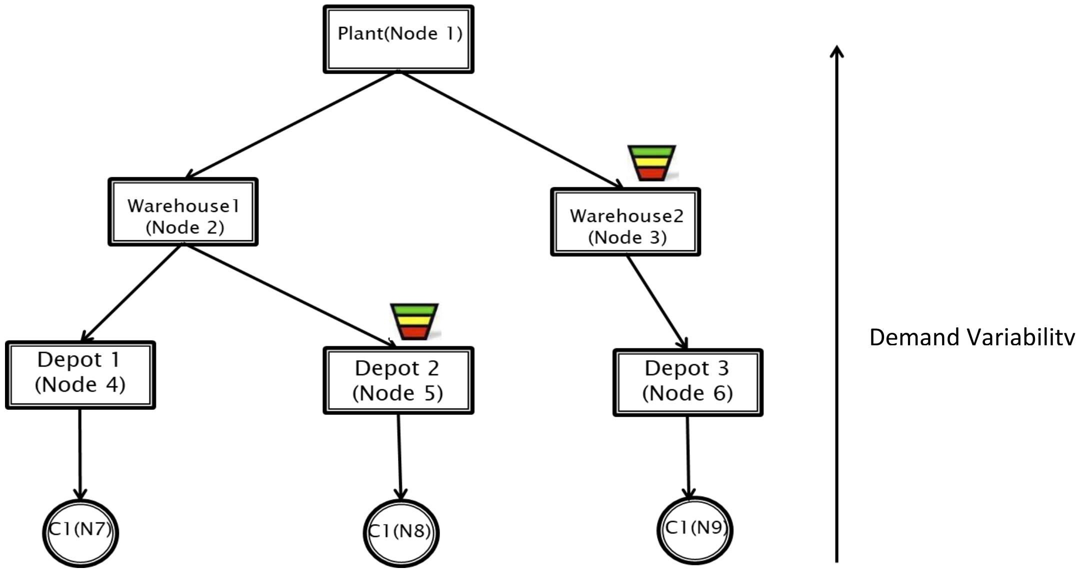

Figure 3-1 A nine-node distribution network

3.2.1 Results of solving a small scale of the model

The results of solving (it will be described later in the report) a small scale of the model is visible in the Table 3-1.

Symbols in the table are as follows:

- N : Number of the node
- S : Node status level in network
- CTT: Customer tolerance time
- ADU: Average daily usage (mean demand that follows normal distribution)
- S.D. : Standard deviation of mean demand that follows normal distribution

- H: Holding cost of the node
- LT: Lead-time (delivery time)
- V: Variability factor
- α: Lead-time factor
- DLT: Decoupled lead-time(delivery time)
- B: Buffer amount
- Z : Value of the objective function

Table 3-1Results of solving a nine-node distribution network problem

Set			Parameters					Decision variables			
S	N	CTT	ADU	S.D.	V	H	LT	δ	DLT	B	Z
1	1	-	2183	-	0.5	50	0	0	0	0	0
2	2	-	1471	-	0.5	60	7	0	7	0	0
2	3	-	712	-	0.8	5	4	1	4	1,955	9,778
3	4	-	829	-	0.3	75	11	0	18	0	0
3	5	-	642	-	0.8	3	5	1	12	8,166	24,498
3	6	-	712	-	0.8	50	10	0	10	0	0
4	7	32	829	80	0.3	64	12	0	30	0	0
4	8	19	642	230	0.8	80	9	0	9	0	0
4	9	13	712	210	0.8	64	3	0	13	0	0
											Z total: 34,276

In Table 3-1, we consider an average daily usage (*ADU*) for each customer in the last stage (nodes 7, 8, and 9), which follows a normal distribution with variable mean and standard deviation for each. Then for the nodes other than the customers', the *ADU* is calculated with equation 2-3. The variability factor for customer's nodes is determined with the standard deviation of the demand normal distribution. The variability factor for the other nodes is calculated based on equation 2-4.

We intentionally considered the holding costs for the nodes 3 and 5 lower than the holding costs for the other nodes of the network. Obviously, δ for the mentioned nodes should take one. The other variables are calculated by related formulas. Finally, we obtain the result according to Table 3-1.

3.2.2 Results of solving the model with GAMS

In this section, the results of solving a small scale of the model are compared to those obtained by GAMS. (See Table 3-2).

Table 3-2 Results of solving a nine-node distribution network problem with GAMS

Set		Parameters						Variable			
S	N	CTT	ADU	S.D.	V	H	LT	δ	DLT	B	Z
1	1	-	2183	-	0.5	50	0	0	0	0	0
2	2	-	1471	-	0.5	60	7	0	7	0	0
2	3	-	712	-	0.8	5	4	1	4	1955	9778
3	4	-	829	-	0.3	75	11	0	18	0	0
3	5	-	642	-	0.8	3	5	1	12	8166	24498
3	6	-	712	-	0.8	50	10	0	10	0	0
4	7	32	829	80	0.3	64	12	0	30	0	0
4	8	19	642	230	0.8	80	9	0	9	0	0
4	9	13	712	210	0.8	64	3	0	13	0	0
											Z total: 34,276

In Table 3-2, the explanation of the set, parameters, and variables in the model of the network is as following:

CTT is the customer tolerance time, and the values are only assigned to the nodes in the last level.

S.D. is the standard deviation of the mean demand (*ADU*).

We assign the values to holding cost of keeping buffers in each node in the network and we denote it as *H*.

LT is the delivery time for a specific node to be supplied by its parent in the network.

We have three variables in the model, which are defined as following. δ is a binary variable which take the value one, when the buffer is put in the node, and it takes zero when no buffer is put in a specific node. When the buffer is put in a specific node, the amount of the delivery time that is assigned to its parents nodes takes zero. Since, there are buffers, which are positioned in this node, and it should be shorter than the cumulative lead-time in which no components are available in the path. (Definition of *DLT*).

B is the buffer level, which is calculated by equation 2-10. The buffers are put in the nodes whose δ takes 1.

We solved a nine-node distribution network problem with GAMS. After solving the problem, buffers are put to the nodes 3 and 5 with the same results as obtained before in Table 3-1. Obviously, the value of δ for the nodes 3 and 5 is equal to one. The results of the *DLT* values which obtained by GAMS are the same as those of obtained before in Table 3-1. In this way, the validation of the model has been verified.

In the output of running the problem, we obtained 30 for *K*, which is a parameter equal to the maximum of *DLT* according to equation 2-8. Therefore, this equation in model is also validated. The solver obtained 34,276 for the objective function which is exactly the same value that is obtained by solving the model in Table 3-1. The execution time for solving the problem was 0.207 seconds.

3.3 Application to a large scale problem

In the section, we apply the DDDRP model to a twenty-two node distribution network (See Figure 3-2), and solved with GAMS. Then, we compare the network performance with the DRP approach and with DDDRP approach.

3.3.1 Results of the DDDRP model

The optimization results obtained with the DDDRP model applied to the twenty-two-node distribution network are presented in Table 3-3.

Table 3-3 Results of solving a twenty-two-node distribution network with GAMS

Set		Parameters						Variable		
S	N	CTT	ADU	S.D.	V	H	LT	δ	DLT	B
1	1	-	9045	-	0.5	0.0019	2	0	0	0
2	2	-	4028	-	0.5	0.003	3	1	3	17,370
2	3	-	2608	-	0.5	0.0049	3	1	3	11,247
2	4	-	2409	-	0.5	0.0045	3	1	3	10,388
3	5	-	2359	-	0.5	0.0057	3	1	3	10,173
3	6	-	1669	-	0.8	0.0079	2	1	2	4,005
3	7	-	1271	-	0.3	0.008	2	1	2	2,732
3	8	-	1337	-	0.5	0.0072	2	1	2	3,008
3	9	-	765	-	0.5	0.014	3	1	3	3,299
3	10	-	1644	-	0.5	0.0065	2	0	2	0
4	11	3	829	80	0.3	0.01	3	0	3	0
4	12	4	642	230	0.8	0.015	3	0	3	0
4	13	3	888	210	0.5	0.0099	2	0	2	0
4	14	4	712	150	0.5	0.015	3	0	3	0
4	15	4	957	270	0.8	0.012	3	0	3	0
4	16	4	652	180	0.5	0.016	3	0	3	0
4	17	4	619	110	0.3	0.017	2	0	2	0
4	18	3	820	140	0.3	0.012	3	0	3	0
4	19	4	517	280	0.8	0.019	2	0	2	0
4	20	3	765	150	0.5	0.013	2	0	2	0
4	21	4	863	150	0.5	0.013	2	0	4	0
4	22	4	781	270	0.8	0.014	2	0	4	0

When the model is validated with the smaller scale presented in the section 3.2, after, the model is solved with a larger scale; in this problem, there are twenty-two nodes in the distribution network, contains twelve nodes in the last level. According to Table 3-3, which presents the results of solving the model with GAMS, *H* is the holding cost of one unit of the product in the nodes of the supply network, and its value is different in terms of each node. The binary variable (δ) for the nodes 2,3,4,5,6,7,8 and 9 takes the value one; as a result, the buffers are put in those nodes. It is obvious that there is no buffer assigned to the rest of the nodes. The decoupled lead-time (delivery time) (*DLT*) is another variable of the problem, which is calculated according to the buffer level that is placed in the nodes, considering equation 2-6. Finally, the value of the objective function is obtained as $ 333, which is the total optimized holding cost of the supply network per day. (The execution time of running the model with GAMS is acceptable (1.310 seconds)).

3.3.2 Assessment of the performance of the DDRP approach compared to the DRP approach

In this section, we compare the inventory levels and the holding costs over the twenty-two nodes of the distribution network with the DRP approach vs. the DDDRP approach.

With DRP approach, we can compute the inventory level *I* for a specific product at each node using equation 1-21, as presented in section 1.5.3.

$$I = \frac{EOQ}{2} + 2.325\sqrt{L\,\sigma_{ADU}^2} \qquad \text{2-21}$$

In the Table 3-4, the total holding cost (*THCI*) generated with DRP approach is obtained by the summation of the multiplying the holding cost of one unit of the product in-to the amount of inventory (*I*) that is assigned to each node.

With DDDRP approach, we can obtain the buffer level (*B)* for a specific product at each node by solving the DDRP model using GAMS and the equation 2-10, which is presented in section 2.3.

$$B_j = \frac{1}{2} * \delta_j * TOG_j = \frac{1}{2} * \delta_j * DLT_j * ADU_j * \left[v_j * \alpha_j + 2\alpha_j + 1\right] \qquad \text{3-10}$$

The total holding cost (*THCB*) generated with the DDDRP approach is obtained by multiplying the holding cost of one unit of the product in-to the amount of buffer (*B)* that is assigned to each node.

Table 3-4 A comparison between level of inventory, and total holding cost in DDDRP and DRP

		Holding cost/unit/day	DRP		DDDRP	
S	N	H	I	THCI	B	THCB
1	1	0.0019	39,808	75	0	0
2	2	0.003	20,993	62	17,370	52
2	3	0.0049	13,194	64	11,247	55
2	4	0.0045	13,454	60	10,388	47
3	5	0.0057	13,070	74	10,173	58
3	6	0.0079	9,407	74	4,005	32
3	7	0.008	6,869	54	2,732	22
3	8	0.0072	7,242	52	3,008	22
3	9	0.014	4,373	61	3,299	46
3	10	0.0065	9,068	58	0	0
4	11	0.01	4,394	43	0	0
4	12	0.015	3,852	57	0	0
4	13	0.0099	4,926	48	0	0
4	14	0.015	4,265	63	0	0
4	15	0.012	5,647	67	0	0
4	16	0.016	3,852	61	0	0
4	17	0.017	3,318	56	0	0
4	18	0.012	4,613	55	0	0
4	19	0.019	2,884	54	0	0
4	20	0.013	4,329	56	0	0
4	21	0.013	4,648	60	0	0
4	22	0.014	4,630	64	0	0
Total			188,835	1,331	62,222	333

In Table 3-4, *H* is the holding cost of one unit of the product in the nodes of the supply network, and its value is different in terms of each node, while it is the same for both approaches. As we can see, in DRP approach, inventories are placed for every node in the network; while in DDDRP approach, buffers are put in the nodes that are necessary according to the optimization model solved by GAMS. In the last row of the table, the total amount of inventory *I*, which is placed in DRP technique, is equal to 188,835 units of product. While the amount of buffer *B* that is put in the network in DDDDRP technique experiences a 66% of reduction compared to the amount of inventory in DRP technique. The total holding cost of keeping the buffer in network in DDDRP technique (*THCB*) is \$ 333, which corresponds to the total holding cost of the optimized network per day, which is 74% reduced compared to the total holding cost of keeping the inventory in DRP technique(*THCI*) whose cost is equal to \$ 1,331 per day. We can conclude that DDDRP technique outperforms the DRP technique in terms of saving the amount of inventory which should be located in nodes, and consequently cutting down the total holding cost of the supply network. This is summarized by Table 3-5. Thus, we can conclude that the DDDRP approach can considerably modify the flaws and shortcomings of the DRP approach such as the high cost of the inventory that is imposed on the supply network.

Table 3-5 Comparing the efficiency of DRP and DDDRP approaches

	DRP	DDDRP	Percentage of reduction (%)
Total holding cost/day (\$)	1,331	333	74%
Total Inventory/day	188,835	62,222	66%

Figure 3-2 presents a visual comparison, for each node, between the amount of inventory *I* obtained with the DRP approach, and the optimal buffer level B generated with the DDDRP model. As is shown in Figure 3-2, keeping inventories is not required in all nodes in DDDRP approach: buffers are required only in nodes 2,3,4,5,6,7,8 and 9. However, with DRP approach, holding inventories is mandatory, which is obvious in the figure, where inventories are put in all nodes of the network. Besides, even node by node (for nodes 2,3,4,5,6,7,8 and 9), *I* is higher than *B*. It is important to underline that in both approaches the amount of inventory/buffer is higher in upstream levels than those in downstream of the supply network. But in upstream level, the level of inventory in DRP is still higher that the level of buffer in DDDRP technique. From the node 10 onwards, the level of buffer in DDDRP is equal to zero, while in DRP we have amount of inventory in every node.

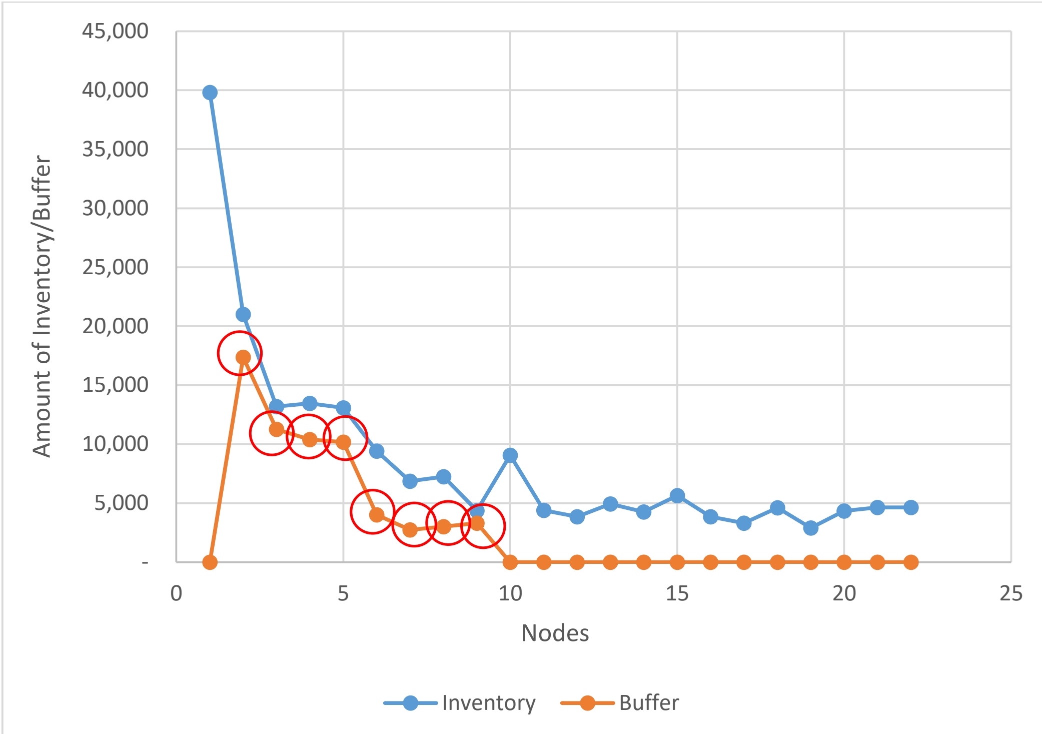

Figure 3-2Amount of inventory for each node in DRP and buffer in DDDRP

According to Figure 3-3, in DDDRP approach, buffers are put in 9 the nodes, while the inventory is put in all nodes of the network in DRP approach. As a result, the total holding cost of the network in DDDRP approach is lower than that of the DRP approach. Besides, we can see in Figure 3-3 that the level of inventory in DRP by node is higher than the level of buffer in DDDRP.

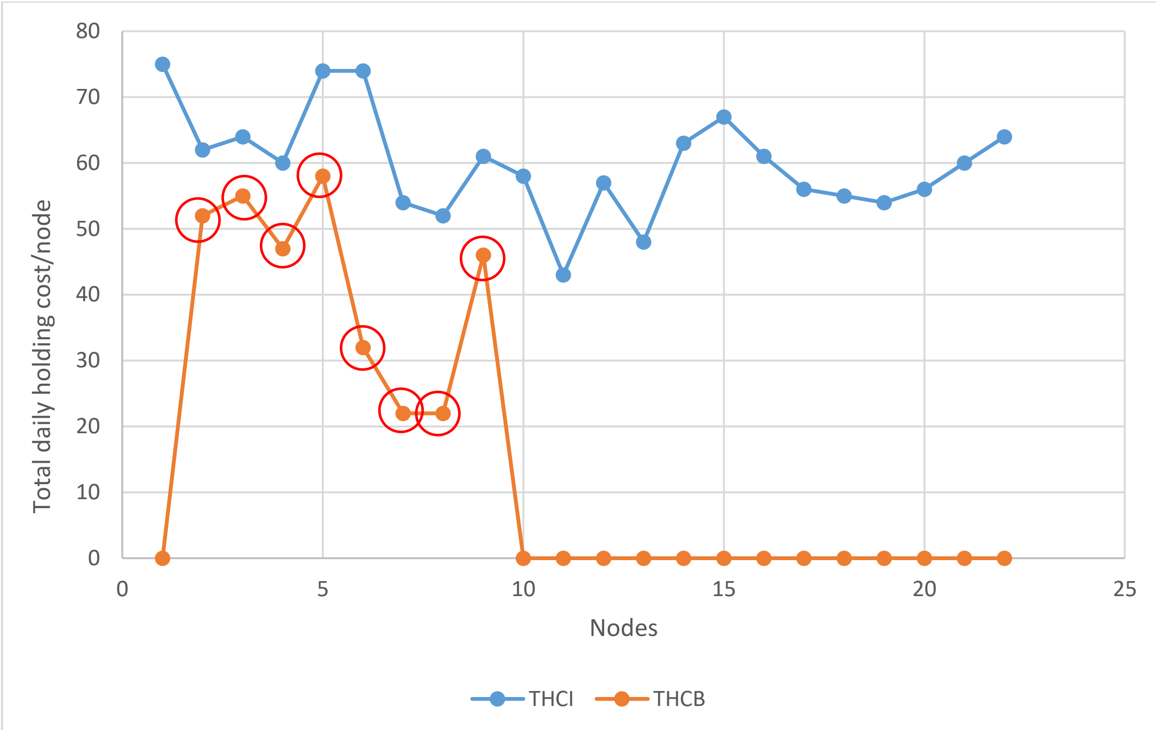

Figure 3-3Total holding cost of inventory/buffer for each node in distribution network in DRP and DDDRPP approaches

3.4 Conclusion

In this chapter, we start by validating the model. Then, we apply and solve the DDDRP model for a case study including a twenty-two-node distribution network. Through this case study, we compare the inventory levels in the different nodes using DRP and DDDRP approaches. The results show that the DDDRP outperforms the traditional DRP approach in terms of the total amount of the inventory in distribution network, and the total holding cost of the inventory. Based on statement of the problem expressed in 0, applying DDDRP technique in supply network, is able to reduce the high total cost of holding inventory in the network by decoupling. By utilizing this technique, it is unnecessary for network to hold inventory in every node of the network.

CHAPTER 4 CONCLUSION AND RECOMENDATIONS

5.1 Summary

The key steps of this project can be summarized as follows: Firstly, we started with the review of the traditional inventory management technique through the distribution network of the supply network is called DRP. Then, we investigated the consequences of cascade use of forecasting which result in serious problems for the efficiency of the distribution network system. We proposed a novel technique for optimizing the distribution network by calculating the buffer levels, which are positioned through the network with the objective of minimizing the total holding cost. The traditional approach applies the DRP tables to calculate the level of inventory contains the safety stock for the network. To calculate the safety stock, the DRP approach assumes that the demand during lead-time is determined based on demand forecasts, while in DDDRP approach the demand is assumed to be actual. Then, the problem is defined, and formulated in the form of a mathematical model, and solved with operation research tools. Firstly, a smaller size of the model was defined in order to validate the model. Then, a larger size model was created, and both traditional and new techniques were examined in terms of validating the model and efficiency in managing the inventory level through the supply network. Two factors are considered to evaluate the performance rate, which are two variables, related to the DDDRP model: buffer/inventory levels, and total holding cost of the supply network. As a result, DDDRP appears to dominate DRP in all the factors examined; the results showed that the total amount of the inventory, through the whole supply network, is reduced by 66 %. It is also demonstrated that, the total holding cost of the supply network is reduced by 74%.

5.2 Recommendations based on results

As it is obtained in the previous section, taking advantage of DDDRP technique definitely leads to cutting down the total cost of the supply. Besides, the lead-time (delivery time) compression can in turn decrease transportation costs as well. A factor that results in better customer service (due to the less backordered items) and preventing excess inventory is to obtain the right-size inventory that is possible with DDDRP technique. The total holding cost of the supply network is another factor which is improved through DDDRP technique. DDDRP technique is demand-driven, and as discussed in Chapter 1, the basis role of the information sharing is strongly emphasized in the process. Therefore, it is highly recommended that all members of the supply network focus on cooperation to achieve the goal of the supply network. Information sharing, and also establishing a close relationship with customers are the first and foremost issue in this field without which the project is not possible. One of the crucial ways to build this strong relationship and cooperation is improving the customer service level, which is obtained by on-time delivery and reducing the delivery time. It is concluded that this system is like a positive reinforcing loop which fortifies better customer service level, lower costs, and taking advantage of the techniques that can help them.

5.3 Perspectives

Some of the future research directions in the context of this project could be the consideration of transportation costs. In this project, the holding cost of the buffers in the distribution network is assumed to be the total cost of the supply network. Taking transportation costs into account increases the complexity of the problem, but it will be more realistic.

Another direction for future research studies is designing an optimal supply network applying DDDRP technique and transportation design. It would be an interesting extension, if this aspect is included.

Finally another research worth conducting is calculating and comparing the amount of the bullwhip effect for the two approaches in question.

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