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# Simulation-based optimization of buffer sizing in demand-driven distribution requirements planning

**Yassine Erraoui**
Industrial Engineering Department, Mohammadia School of Engineers, University Mohammed V, Zip Code 765, 10090, Rabat, Morocco, y.erraoui@emi.ac.ma (corresponding author)
**Abdelkabir Charkaoui**
The Laboratory of Engineering, Industrial Management and Innovation, Faculty of Science and Techniques, University Hassan 1st, Zip Code 577, 26000, Settat, Morocco, abdelkabir.charkaoui@uhp.ac.ma
**Zineb Aman**
SMARTiLAB Laboratory, Moroccan school of Engineering Sciences, Angles Rues Zerhoun, Ejoukak and, Rue Ait Brahim, Rabat 10000, Morocco, z.aman@emsi.ma

***Keywords:*** demand-driven DRP, buffer sizing, bullwhip effect, working capital, on-time service.
***Abstract:*** Demand-Driven Distribution Requirements Planning (DDDRP) has emerged as an effective alternative to traditional forecast-driven planning systems by relying on strategically positioned buffers to protect logistics flows against demand and lead-time variability. However, buffer sizing in DDDRP is still largely based on fixed parameters, which may limit its effectiveness in complex multi-echelon distribution networks. This paper proposes a simulation–optimization framework for the tactical calibration of buffer sizes in a demand-driven distribution context. The approach integrates discrete-event simulation, developed using Arena software, with a metaheuristic optimization engine (OptQuest) to dynamically adjust buffer sizing parameters under realistic material and information flow conditions. The model is applied to a multi-echelon distribution network characterized by heterogeneous demand and lead-time profiles. The results demonstrate that the proposed framework significantly improves the trade-off between working capital and service level, which are two primordial indicators for an optimal distribution, while enhancing the stability of downstream and upstream logistics flows. By bridging the gap between theoretical DDDRP sizing rules and their practical implementation, this study contributes to the literature on demand-driven logistics planning and provides decision support for distribution managers. Future research perspectives include the integration of capacity constraints, multi-product flows, and stochastic supply delays.

## 1 Introduction

In today's volatile and increasingly demand-driven markets, the ability to plan and execute supply chain operations in a responsive manner has become a critical competitive advantage. Traditional planning systems, such as Material Requirements Planning (MRP) and Distribution Requirements Planning (DRP), are primarily structured around forecast-driven logic. Although effective in relatively stable environments, these systems are well known for amplifying variability as demand information propagates upstream along the supply chain—a phenomenon widely referred to as the bullwhip effect (Lee et al., 1997) [1]. To mitigate these limitations, the Demand-Driven MRP (DDMRP) methodology has emerged as a hybrid planning approach that integrates real-time consumption signals, strategically positioned buffers, and decoupling strategies to stabilize material flows and protect service levels (Ptak and Smith, 2016) [2].

At the core of DDMRP lies the concept of strategically positioned inventory buffers, which are dimensioned using predefined, rule-based formulas. These buffers are designed to absorb demand variability and form the foundation of demand-driven planning. However, despite the conceptual clarity of this approach, real-world DDMRP implementations often rely on fixed or heuristically selected sizing parameters. This raises legitimate questions regarding the optimality of buffer configurations under realistic and dynamic operating conditions.

In response to these challenges, recent research has increasingly explored the use of simulation and optimization techniques to enhance the performance of DDMRP-based systems. For instance, Wang et al. (2015) [3] proposed a dynamic drum–buffer–rope model for hospital inventory management, employing Powell search methods to adjust buffer levels based on system feedback. Achergui et al. (2021) [4] addressed the joint problem of buffer positioning and sizing in multi-level environments using constraint programming, while other studies have optimized key sizing parameters—such as the Lead Time Factor (LTF), Variability Factor (VF), and Decoupling Order Cycle (DOC)—through simulation-based Taguchi methods. In parallel, doctoral research and recent studies have demonstrated the potential of hybrid metaheuristics, including genetic algorithms, for fine-tuning buffer configurations across multi-echelon distribution networks (Miclo, 2016) [5].

Foundational contributions by Erraoui et al. (2019) [6] introduced the first formal model dedicated to buffer sizing within a Demand-Driven Distribution Requirements Planning (DDDRP) context. This work was later extended by Erraoui et al. (2022) [7], who embedded the sizing logic within a simulation architecture and demonstrated the performance benefits of adaptive buffer calibration. Together, these studies emphasized the need for integrated simulation–optimization frameworks capable of dynamically adjusting buffer parameters in response to real-world demand and lead-time variability.

Building on this body of literature, the present paper proposes a simulation–optimization framework for tactical buffer sizing in a multi-echelon distribution network. The framework is implemented using discrete-event simulation in Arena software, with optimization performed through OptQuest metaheuristics. The objective is to identify suitable lead-time and variability parameter configurations that minimize inventory-related costs while maintaining a targeted service level. By combining flow-based simulation with performance-driven optimization, the proposed approach provides a practical decision-support tool for improving the effectiveness of DDDRP-based distribution planning.

The remainder of the paper is structured as follows. Section II reviews the theoretical foundations of Demand-Driven Distribution Requirements Planning (DDDRP), with emphasis on its core principles, buffer sizing logic, and identified research gaps. Section III presents the proposed simulation–optimization framework, including the distribution network description, model parameters, simulation logic implemented in Arena, and the OptQuest-based optimization strategy, along with the associated results and discussions. Finally, Section IV concludes the study and outlines directions for future research.

# 2 Theoretical background

## *2.1 From push systems to demand-driven distribution*

Traditional planning systems in manufacturing and distribution, notably Material Requirements Planning (MRP) and its extension MRP II, have historically operated according to a push-based logic, in which production and replenishment decisions are driven by forecasted demand rather than actual consumption. Initially formalized by Orlicky (1975) [8] and later expanded by Wight (1984) [9], MRP systems provided structured, time-phased planning mechanisms but remained highly dependent on forecast accuracy. This dependency often led to the amplification of demand variability as information propagated upstream along the supply chain—a phenomenon widely known as the bullwhip effect (Lee et al., 1997) [1]. The bullwhip effect is associated with excessive inventory levels, degraded service performance, and operational instability in upstream processes (Figure 1). Subsequent studies, including those by Disney and Towill (2003) [10], further demonstrated the inherent sensitivity of MRP- and DRP-based systems to even minor demand fluctuations.

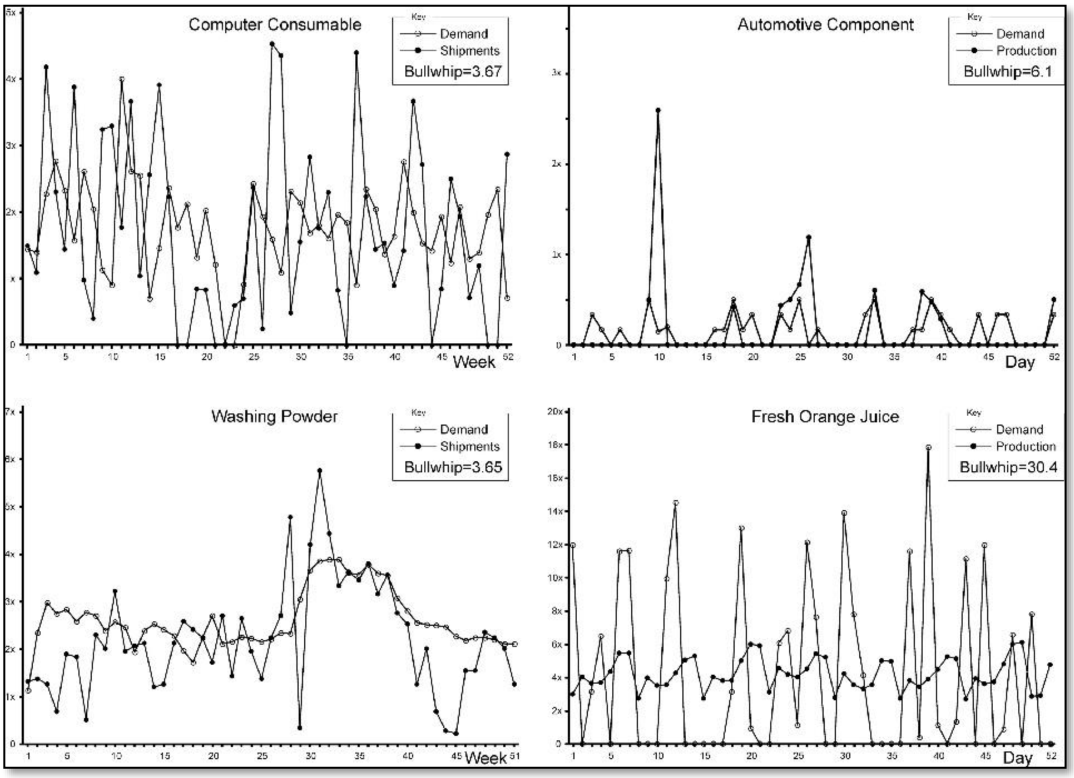


*Figure 1 Bullwhip effect in different sectors*

In response to these limitations, supply chain planning has progressively shifted toward pull-based and demand-driven strategies that prioritize real-time consumption signals over forecast-driven estimates. Holweg (2005) [11] characterized this transition as a move toward greater responsiveness, in which organizations seek to shorten lead times and reduce their reliance on demand projections. Within this context, Demand-Driven MRP (DDMRP) emerged as a hybrid planning approach that combines the structural discipline of MRP with the adaptability of pull systems. Developed by Ptak and Smith (2016) [2], DDMRP introduces strategically positioned inventory buffers and decoupling points to isolate variability and stabilize material flows. More recently, Uzun et al. (2024) [12] demonstrated the relevance of simulation tools for modeling and evaluating the performance of demand-driven systems under conditions of uncertainty (Figure 2).

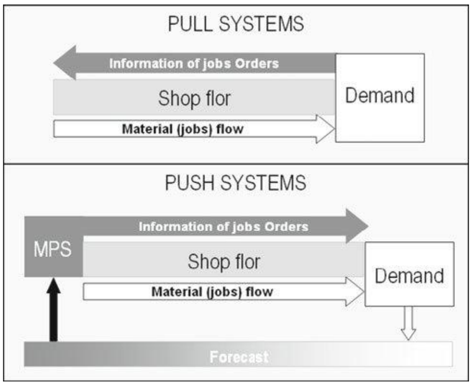


*Figure 2 Difference between Push and Pull systems*

## 2.2 Principles of Demand-Driven Distribution Requirements Planning (DDDRP)

Demand-Driven Distribution Requirements Planning (DDDRP) represents a modern evolution of conventional planning approaches, specifically designed to address the limitations of forecast-driven systems such as MRP and DRP. Originating from the work of Ptak and Smith (2016) [2] and further developed by Erraoui et al. (2019) [6], DDDRP adopts a flow-based, decoupling-centered strategy that integrates actual demand signals into the planning and execution processes. Its architecture is structured around five core components, each contributing to improved responsiveness and stability across the supply chain.

*a. Strategic Inventory Positioning* – T his component focuses on identifying optimal decoupling points within the distribution network. Rather than buffering inventory at every node, DDDRP strategically places buffers where they provide the greatest protection against demand and lead-time variability.

*b. Buffer Profiles and Levels* – At each decoupling point, DDDRP deploys a three-zone buffer structure composed of a red zone (safety stock), a yellow zone (average consumption over the decoupled lead time), and a green zone (replenishment quantity or order cycle). These zones are calculated using parameters such as Average Daily Usage (ADU), Decoupled Lead Time (DLT), and a variability factor. Erraoui et al. (2019) [6] were among the first to formally model this buffer structure within an analytical framework.

*c. Dynamic Buffer Adjustments* – Unlike traditional static inventory policies, DDDRP enables dynamic buffer adjustments in response to evolving demand patterns and operational conditions, allowing the system to adapt continuously to changes in variability.

d. *Demand-Driven Planning* – Planning decisions are governed by the Net Flow Position (NFP) (Figure 3), which compares on-hand inventory, open supply orders, and qualified demand. The effectiveness of this mechanism was explored and validated by Erraoui et al. (2022) [7].

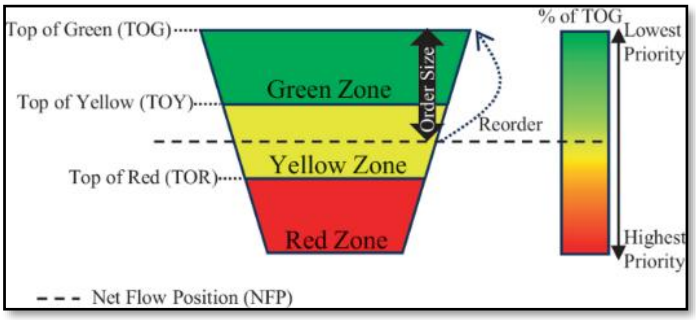


*Figure 3 Net Flow Position in a buffer*



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*e. Visible and Collaborative Execution* – This component emphasizes operational transparency and coordinated execution across the supply chain, enabling faster decision-making and improved alignment among stakeholders.

## 2.3 Buffer sizing in DDDRP

Buffer sizing represents one of the most critical tactical decisions in the implementation of DDDRP. Once strategic inventory positions have been defined, each buffered point must be assigned an appropriate buffer profile composed of three zones: the red zone, which provides protection against variability; the yellow zone, which covers average expected consumption over the decoupled lead time; and the green zone, which determines the replenishment quantity or order cycle.

The theoretical foundation of buffer sizing in DDDRP, as described by Ptak and Smith (2016) [2], relies on deterministic relationships based on the Average Daily Usage (ADU) and the Decoupled Lead Time (DLT), combined with two calibration coefficients—the Lead Time Factor and the Variability Factor. These parameters define the buffer zones and ultimately determine replenishment behaviour within the demand-driven planning framework. The corresponding sizing relationships are expressed as follows (1), (2), (3):

$$YZ = ADU * DLT \tag{1}$$

$$GZ = YZ * LT\_Fac\_green \tag{2}$$

$$RZ = YZ * LT_{Fac_{red}} + YZ * LT\_Fac\_red * Var\_Fac \tag{3}$$

Despite their practical appeal, DDDRP buffer sizing rules are often implemented using fixed parameter values, which limit their flexibility and responsiveness. Such static configurations constrain buffer performance, particularly in multi-echelon distribution networks exposed to high demand variability and complex dependency structures.

Recognizing these limitations, Erraoui et al. (2019) [6] were among the first to propose a formal modeling framework for DDDRP buffer sizing, integrating buffer dimensions into a structured analytical formulation. Their work introduced explicit decision variables and mathematical relationships governing buffer behavior, highlighting the role of sizing in stabilizing the Net Flow Position and improving service performance. Building on this foundation, Erraoui et al. (2022) [7] extended the framework by embedding the sizing logic within a simulation-based architecture, enabling dynamic evaluation of buffer behavior under stochastic demand conditions. Their results demonstrated the sensitivity of both service level and working capital to buffer calibration, thereby motivating the use of optimization techniques for parameter tuning.

More recent studies have further explored simulation–optimization approaches to overcome the limitations of traditional DDDRP sizing rules. Wang et al. (2015) [3] developed a dynamic drum–buffer–rope (DDBR) model for hospital inventory management, in which buffer sizes are adapted in response to demand fluctuations using a system dynamics framework combined with a Powell search algorithm. Their approach proved effective in synchronizing inventory decisions across a multi-echelon internal supply chain while reducing stockouts and inventory costs. Similarly, Achergui et al. (2021) [4] addressed the joint optimization of buffer positioning and sizing in complex bill-of-material environments under DDDRP logic. Their enhanced linear model, solved using CP Optimizer, achieved improved computational efficiency and service-level performance, particularly in hybrid make-to-order/make-to-stock contexts. Another notable contribution is provided by Miclo (2016) [5], who proposed a three-phase simulation-based methodology to optimize buffer parameters such as the Lead Time Factor, Variability Factor, and Decoupled Order Cycle. By combining Taguchi experimental design with historical data analytics, their approach significantly outperformed default parameter settings derived from the original DDMRP formulation. Finally, Younespour et al. (2024) [13] presented a comprehensive investigation of DDDRP buffer sizing using simulation-based optimization and heuristic methods, including hybrid genetic algorithms, emphasizing the importance of multi-echelon coherence in buffer calibration and proposing a hybrid DDMRP–hedging strategy that improves service levels while reducing inventory costs.

Building on these contributions, the present study integrates DDDRP buffer sizing logic into a discrete-event simulation model and couples it with OptQuest metaheuristics to identify parameter configurations that minimize inventory-related costs while maintaining target service levels.

## 2.4 Research gaps and motivation

Although DDDRP provides a powerful conceptual framework for improving supply chain responsiveness, its practical implementation—particularly with respect to buffer sizing—remains largely heuristic and manually driven. In many industrial applications, buffer parameters are still defined using default or experience-based values, relying on fixed lead-time and variability factors as originally proposed by Ptak and Smith (2016) [2]. Such practices lack the adaptability required to address the dynamic and stochastic nature of real-world distribution networks.

Previous work by Erraoui et al. (2019) [6] represented an important step toward formalizing buffer sizing as a quantitative decision problem rather than a static managerial choice. This perspective was further reinforced by Erraoui et al. (2022) [7], who demonstrated the value of integrating simulation-based methods with DDDRP logic to evaluate buffer behavior under uncertainty and network interactions. Nevertheless, despite these advances, there remains a noticeable lack of scalable frameworks that combine discrete-event simulation, optimization techniques, and DDDRP principles in a unified and operationally applicable manner.

This paper addresses this gap by proposing a simulation–optimization framework that leverages Arena software and OptQuest metaheuristics to calibrate DDDRP buffer sizing parameters in a multi-echelon distribution network. By integrating flow-based simulation with performance-oriented objective functions, the proposed approach enables dynamic buffer tuning, leading to improved service levels and reduced working capital requirements under realistic operating conditions.

## 3 Buffer sizing optimization

The study focuses on a three-echelon distribution network operated by a Moroccan food manufacturing company. Finished products are produced at a central factory and delivered to hypermarkets through one of seven distribution centers (DCs), as illustrated in Figure 4. The empirical data used in this study include:

- historical sales data covering the last five years,
- distribution lead times,
- distribution and inventory-related costs.

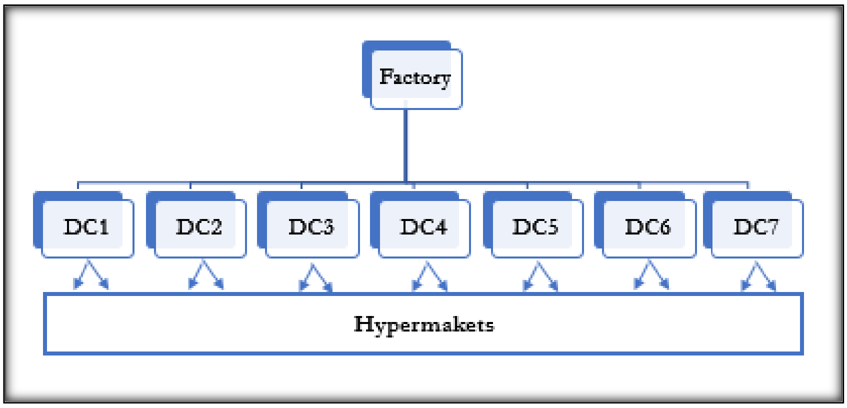


*Figure 4 Distribution network of the case study*

### *3.1 Distribution network modeling*

Table 1 and figure 5 present the essential parameters for each implementation of the model, as well as the flowchart of DDDRP process.

*Table 1 Modeling parameters*

| Parameter | Description |
|---|---|
| **i** | Day of the year |
| **ADU(i)** | Average daily usage on day i |
| **Initial_Stock** | Initial stock at the distribution point (day 0) |
| **Stock(i)** | Stock at the distribution point on day i |
| **FS(i)** | Future Spike relative to day i |
| **Qualified_demand(i)** | Qualified demand calculated on day i |
| **Open_Supply(i)** | Open supply orders on day i |
| **Arrived_Supply(i)** | Supply orders that arrived on day i |
| **Demand(i)** | Customer demand received on day i |
| **Threshold(i)** | Threshold for future Spike calculation on day i |
| **RZ(i), YZ(i), GZ(i)** | Buffer dimensions for red, yellow, and green zones respectively on day i |
| **TOR(i), TOY(i), TOG(i)** | Top levels of the red, yellow, and green buffer zones on day i |
| **LT_Factor_Red(i)** | Lead time factor for the red zone on day i |
| **LT_Factor_Green(i)** | Lead time factor for the green zone on day i |
| **Var_Factor(i)** | Variability factor of demand on day i |

| | |
|---|---|
| **DLT** | Decoupling lead time: the longest unbuffered delay between two buffered points |
| **Q(i)** | Order quantity set on day i |
| **NFP(i)** | Net Flow Position in the buffer on day i |
| **Priority(i)** | Planning priority on day i |
| **ABI(i)** | Average Buffer Inventory on day i |

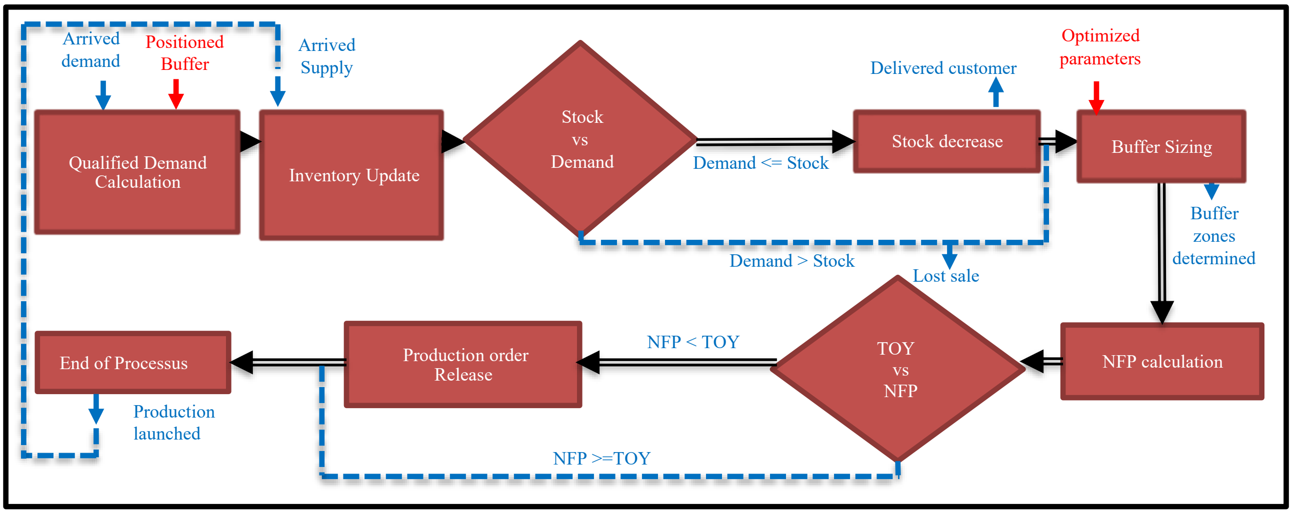

*Figure 5 Modeling flowchart*

The following algorithm details the blocks of the flowchart, which are numbered from 1 to 8. They describe the execution steps of a demand-based distribution spread over a 365-day horizon. The algorithm is structured as follows:

```
// Bloc 1 :  Qualified Demand Assignment
For (i=DLT; i<=365; i++)
{
      Threshold(i) = RZ(i)/2 ;
      for (k=i+1 ; k<=i + DLT ; k++)
      {
            if Demand (k) >= Threshold(i)
            FS(i)=FS(i)+Demand (k) ;
      }
Qualified_Demand(i)=Demand(i)+FS(i) ;

// Bloc 2 : Stock increasing
Stock(i)=Stock(i)+Arrived_Supply(i) ;

// Bloc 3 and 4 : Comparison between Demand and Stock
If (Demand (i) <= Stock(i))
{
Stock(i) = Stock(i) - Demand(i) ; // the client is delivered
}

// Bloc 5 : Buffer zones Calculation
YZ(i)=ADU(i)*DLT(i) ;
GZ(i)=YZ(i) ∗ LT_Factor_Green(i);
RZ(i)= YZ(i) ∗ LT_Factor_Red(i)+ YZ(i) ∗ LT_Factor_Red(i) ∗FacVar(i);
TOR(i)=RZ(i) ;
TOY(i)= TOR(i)+YZ(i) ;
TOG (i)= TOY (i)+GZ(i) ;
ABI(i)=RZ(i)+GZ(i) ;
```

```
// Bloc 6 : Calculation of Net Flow Position taking in consideration open supplies
for (k=i-1 ; k>=i-DLT ; k--)
{
Open_Supply(i)=Open_Supply(i)+Q(k) ;
}
NFP(i)=Stock(i)+Open_Supply(i)-Qualified_Demand(i) ;
If TOG(i) ≠ 0
{
Priority(i)=NFP(i)/TOG(i) ;
}

// Bloc 7 and 8 : Comparison between net flow position and top of yellow in Buffer
If (NFP(i)<=TOY(i))
{
Q(i)=TOG(i)-NFP(i) ; // A supply is open
}
Open_Supply (i + DLT) = Q (i);
}
```

### *3.2 Flow simulation logic in Arena software*

The simulation model was developed using Arena software and represents the operational dynamics of a demand-driven distribution network (Figure 6). The modeled system consists of one factory, seven distribution centers (DC1 to DC7), and customer demand streams (Figure 7). The simulation implements the core decision logic of the Demand-Driven Distribution Requirements Planning (DDDRP) methodology.

The model is structured into modular blocks that sequentially manage demand processing, buffer sizing, inventory updates, order fulfillment, and factory replenishment decisions. This modular design facilitates the detailed representation of material and information flows across the distribution network and enables the systematic evaluation of buffer-related decision rules.

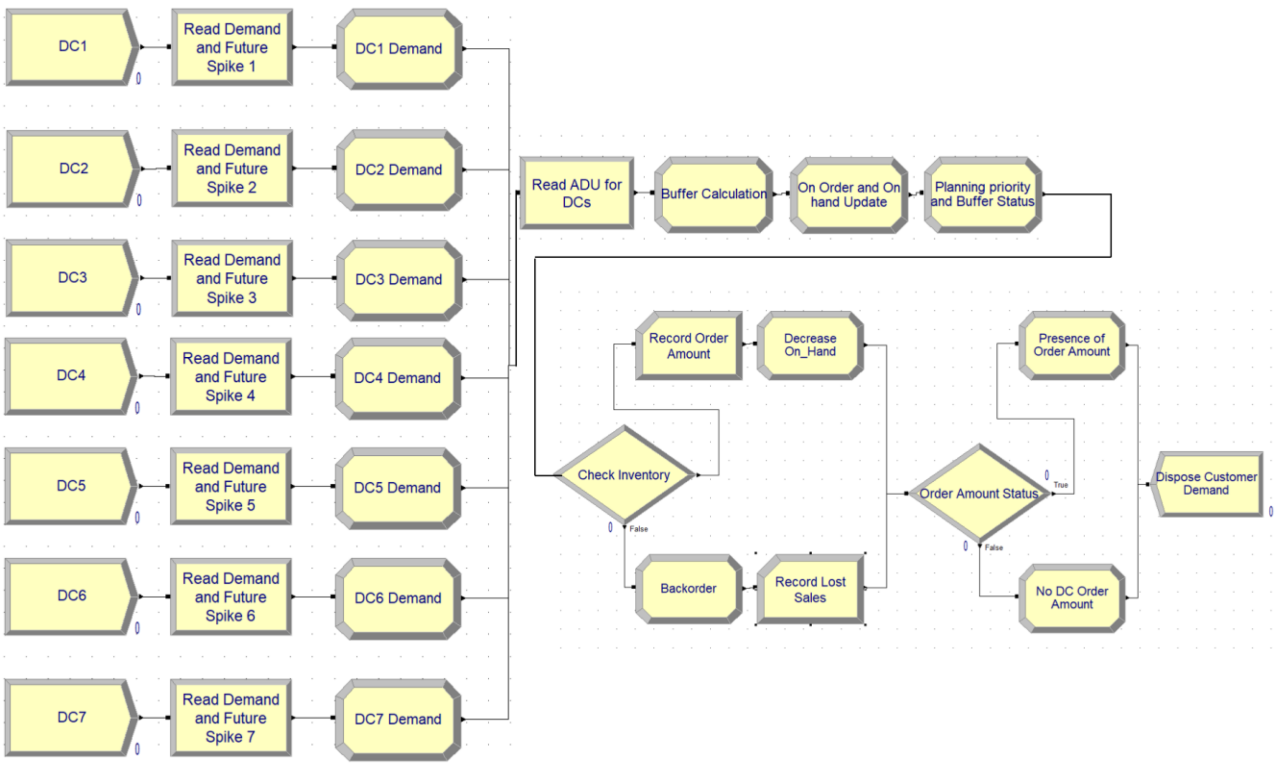


*Figure 6 Modeling of process inside the distribution centers*

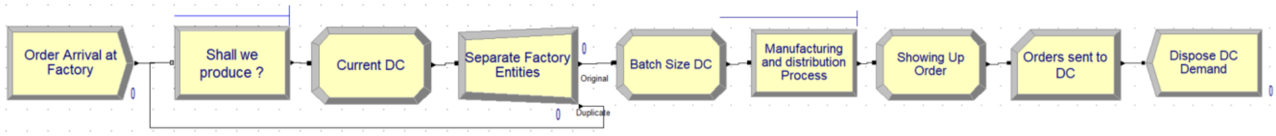


*Figure 7 Modeling of process inside the factory*

The Arena simulation captures the operational flow of a demand-driven distribution system based on DDDRP principles. The process begins with the collection of daily customer demand and anticipated demand spikes for each distribution center (DC1 to DC7). These inputs are used to compute the qualified demand, which reflects expected requirements by combining actual consumption with short-term variability considerations.

Buffer sizing is then performed using the Average Daily Usage (ADU), lead time factors, variability factors, and the Decoupled Lead Time (DLT). These parameters dynamically determine the dimensions of the red, yellow, and green buffer zones for each distribution center. Following buffer calculation, inventory levels are updated by tracking on-hand stock and open supply orders, which are required to compute the Net Flow Position (NFP), a central control variable in DDDRP logic. Based on the NFP, planning priorities are established and inventory availability is assessed to fulfill customer orders. When sufficient stock is available, orders are delivered and inventory is reduced; accordingly, otherwise, backorders are generated and lost sales are recorded. This logic enables an accurate assessment of service performance at the distribution level.

In parallel, the simulation incorporates a representation of the factory, which responds to replenishment signals generated by buffer consumption at the distribution centers. When NFP values and planning priorities indicate the need for supply, the model evaluates whether production orders should be launched. Replenishment orders are grouped by destination distribution center and processed through manufacturing and distribution stages. Once production is completed, finished goods are dispatched and delivered to the corresponding DCs. This factory-level logic reflects a pull-based supply mechanism aligned with DDDRP principles, where production is initiated based on actual buffer status rather than forecasted demand.

The complete simulation flow enables the evaluation of key performance indicators, including On-Time Service (OTS), Working Capital (WC), Net Flow Position, and Lost Sales. These indicators provide a robust basis for analyzing and comparing alternative buffer sizing strategies under realistic operating conditions.

## *3.3 Optimization logic and parameters*

### 3.3.1 Objective function

Within the DDDRP approach, buffer size represents the quantity of inventory allocated to protect material flow against demand variability and can therefore be interpreted as protection stock. As illustrated in the DDDRP framework, this quantity must be maintained at an optimal level to avoid shortage situations that negatively affect service performance, as well as excess inventory situations that unnecessarily increase holding costs. Consequently, effective buffer sizing requires a balance between maintaining sufficient inventory levels and achieving a satisfactory service level.

To capture this trade-off, the objective function $f$ incorporates two key performance indicators: On-Time Service (OTS) and Working Capital (WC), which reflects the financial impact of inventory and work-in-process. The formulation of f considers a target service level, denoted as the Desired On-Time Service (DOTS), which represents the company’s service expectations. When the achieved OTS falls below DOTS, penalties are incurred due to insufficient service performance.

It is assumed that each percentage point decrease in OTS below DOTS generates a penalty valued at PEN. Accordingly, the total penalty is expressed as (4):

$$Penalty = PEN * (DOTS - OTS) * 100 \tag{4}$$

This formulation applies only when OTS < DOTS; otherwise, no penalty is incurred. The resulting objective function is therefore defined as (5):

$$f = Min\,\{WC + MAX(0\,;\,PEN * (DOTS - OTS) * 100)\} \tag{5}$$

The On-Time Service rate is computed as the ratio of achieved sales to total demand, including lost sales (6):

$$OTS = \frac{ACHIEVED\ SALES}{TOTAL\ SALES} \tag{6}$$

In the DDDRP framework, optimal buffer sizes correspond to optimal values of the parameters appearing in Equations (1)-(3), namely the Lead Time Factor, the Variability Factor, and the Decoupled Lead Time (DLT). To identify suitable parameter values, an iterative improvement process was adopted, based on the minimization of the proposed objective function (Figure 8).

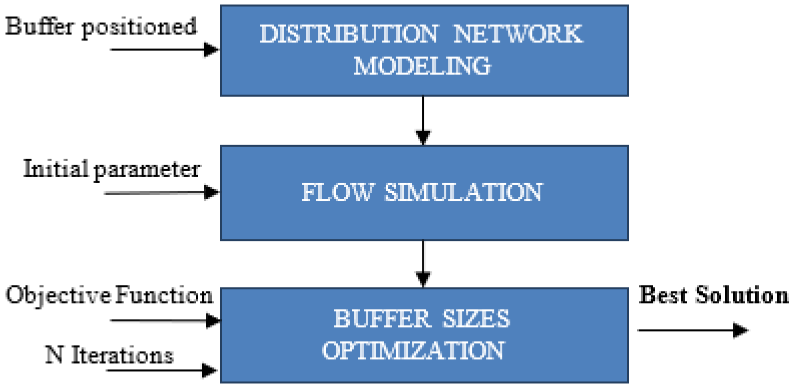


*Figure 8 Optimization approach*

Once the buffer positioning configuration is established, an initial set of sizing parameters is defined to initiate the optimization process. The discrete-event simulation model developed in Arena software records key performance indicators over the planning horizon, which are subsequently evaluated through the objective function. The optimization is performed iteratively using OptQuest, Arena's built-in optimization engine.

OptQuest integrates several metaheuristic strategies, including tabu search, scatter search, and neural network-based prediction models, to efficiently guide the search for optimal parameter values (Adenso-Díaz and Laguna, 2006; Bartz-Beielstein, 2006; Hong and Nelson, 2006) [14-16]. During the optimization process, parameter values are progressively adjusted across simulation runs until a predefined stopping criterion is reached, such as a maximum number of iterations. The procedure terminates by selecting the parameter configuration that yields the minimum objective function value. Table 2 presents the initial parameter values, their variation ranges, and the corresponding optimization steps.

*Table 2 Values of initial, margins and steps of optimized parameters*

| DC | Lead Time Factor | | | | Variability Factor | | | | DLT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Initial | Min | Max | Step | Initial | Min | Max | Step | Initial | Min | Max | Step |
| DC1 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC2 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC3 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC4 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC5 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC6 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |
| DC7 | **0.5** | **0.1** | **0.9** | **0.01** | **0.5** | **0.1** | **0.9** | **0.01** | **3** | **1** | **4** | **1** |

### 3.3.2 Optimization execution and termination

The optimization process begins with the evaluation of the objective function for an initial parameter configuration. OptQuest then iteratively updates the parameters, computing the corresponding objective function value at each iteration and systematically recording both the results and their associated configurations. In the present study, the optimization was conducted over 500 iterations, a limit chosen to balance solution quality and computational effort. Figure 9 illustrates the objective function formulation, the minimum value obtained during the optimization process, and the evolution of objective function values across iterations.

The optimization procedure produced the best combination of four decision variables for each buffered distribution center, resulting in a total of 28 calibrated parameters across the network. Each optimization iteration corresponds to a full-year simulation of distribution flows, from which performance indicators are extracted. In this study, the complete optimization process of 500 iterations required approximately 30 minutes of computation time. The results reveal significant heterogeneity in optimal buffer parameters across distribution centers. In particular, the optimal Lead Time Factors for DC1 and DC5 differ, reflecting differences in replenishment lead times. Consistent with DDDRP principles, longer lead times require lower lead time factors, which result in smaller green zones and promote smaller, more frequent replenishment orders—an advantageous behavior for items with extended replenishment cycles.

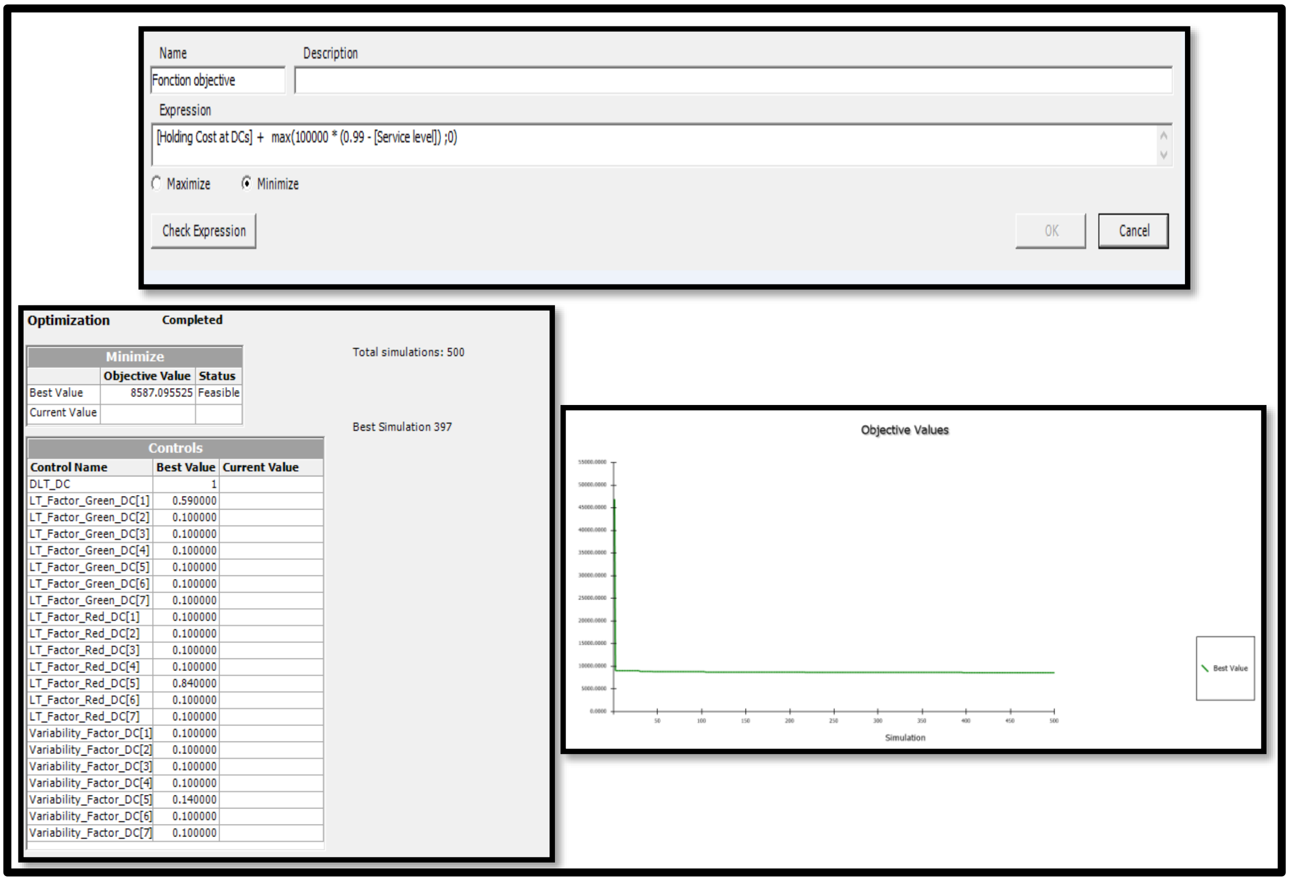


*Figure 9 Optimization results with OptQuest*

With respect to Variability Factors, deviations were observed primarily at DC5, indicating that products supplied through this distribution center are subject to higher demand or supply variability. This finding suggests the need for increased protection at DC5 and highlights the importance of locally calibrated buffer parameters rather than uniform settings across the network.

## *3.4 Discussion and future directions*

This study evaluated the Demand-Driven Distribution Requirements Planning (DDDRP) approach by first establishing its theoretical foundations through alignment with well-known paradigms such as lean distribution and the theory of constraints. In this context, key DDDRP principles—including demand-driven logic, variability isolation, and protection buffering—were shown to provide a coherent framework for improving flow stability in multi-echelon distribution networks. Building on this conceptual grounding, a tactical buffer sizing model was developed and embedded within a simulation–optimization framework.

The proposed model relies on the Average Daily Usage (ADU) as a central input for buffer sizing, reflecting the consumption rate of an item at a given location. To enhance responsiveness to demand fluctuations, ADU was computed over a short-term horizon, which proved more effective in capturing local variability. In addition, the Decoupled Lead Time (DLT), defined as the cumulative distribution lead time across the network—including parent nodes—was incorporated to reflect structural dependencies within the distribution system. Buffer positioning decisions were evaluated through total storage cost minimization while considering broader return-on-investment (ROI) perspectives, recognizing that effective buffer placement aims not only at cost reduction but also at improving flow protection and responsiveness.

With buffer positions fixed, buffer sizing optimization was conducted using a dual-objective perspective that balances working capital (WC) and on-time service (OTS). The optimization results confirmed the relevance of this approach, as optimal parameter values varied significantly across distribution centers, reflecting heterogeneity in local demand patterns and lead-time characteristics. In particular, lower lead time factors were found to be more appropriate for nodes with longer replenishment cycles, as they generate smaller green zones and encourage more frequent, lower-volume replenishment orders. Conversely, higher variability factors were required in specific locations—such as DC5—where demand or supply uncertainty was more pronounced. These findings clearly indicate that uniform parameter settings are suboptimal in distributed networks and that buffer sizing should be locally adapted based on operational conditions.

Furthermore, the integration of discrete-event simulation with metaheuristic optimization provided a robust evaluation environment that simultaneously considers cost-related and service-level indicators over a full planning horizon. Compared with static, rule-based DDDRP sizing approaches, the proposed framework enables more informed and data-driven decision-making, supporting the alignment of tactical buffer management with strategic supply chain objectives.

Despite these contributions, several directions for future research remain. First, the current model assumes infinite storage capacity at distribution centers, which simplifies the analysis but limits realism. Future extensions could incorporate finite capacity constraints to better represent space limitations and the associated trade-offs between buffer size and available storage. Second, real-world distribution networks typically manage multiple product families with distinct flow characteristics. Extending the model to handle multiple products would improve its applicability and allow the investigation of shared resources, prioritization rules, and flow interference effects. Third, while this study primarily focused on demand variability, additional sources of uncertainty—such as supply variability and managerial variability—should be considered. Incorporating unreliable suppliers, transportation delays, and human resource constraints would further enhance the realism of the model. Finally, scalability issues associated with large networks may require linearized formulations and alternative solution techniques. Although OptQuest proved effective in this study, future research could benchmark it against other metaheuristic approaches, such as genetic algorithms, simulated annealing, or particle swarm optimization, to compare solution quality, convergence speed, and computational efficiency.

## 4 Conclusion

This paper proposed a simulation–optimization framework for the tactical sizing of inventory buffers within a Demand-Driven Distribution Requirements Planning (DDDRP) environment. Grounded in established supply chain principles—such as lean distribution, the theory of constraints, and flow protection—the study developed a buffer sizing model based on Average Daily Usage (ADU) and Decoupled Lead Time (DLT) as core inputs. The framework was implemented using discrete-event simulation in Arena software and optimized through OptQuest metaheuristics, with the objective of balancing working capital (WC) and on-time service (OTS).

The results demonstrate that optimal buffer parameters vary significantly across distribution nodes, reflecting local lead-time structures and variability profiles. In particular, the findings confirm that static, uniform sizing rules are inadequate for heterogeneous distribution networks. By contrast, the proposed dynamic sizing approach improves service performance without generating excess inventory, highlighting the benefits of locally adapted buffer calibration. The use of simulation enabled a realistic representation of logistics flows over a full planning horizon, while OptQuest effectively guided the search toward high-performing parameter combinations.

From a practical logistics perspective, this study provides decision-makers with a structured methodology to calibrate DDDRP buffers based on operational data rather than fixed heuristics. The framework supports more responsive and resilient distribution planning by aligning tactical buffer decisions with strategic objectives related to inventory efficiency and service reliability.

Despite these contributions, several avenues for further research remain. Future work could incorporate finite storage capacity constraints to better reflect physical limitations in distribution centers. Extending the framework to multi-product or product-family environments would enhance its applicability in real-world networks. In addition, future studies should consider broader sources of variability, including supply disruptions and managerial or organizational factors affecting flow execution. Finally, although OptQuest proved effective in this study, comparative analyses with alternative metaheuristic optimization methods—such as genetic algorithms or simulated annealing—could provide further insights into solution quality and computational performance under increasing network complexity.

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