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Vendor Managed Inventory in Practice: Efficient Scheduling and Delivery Optimization

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ABSTRACT

Vendor Managed Inventory (VMI) is a widely adopted strategy in supply chain management, where the vendor assumes responsibility for maintaining inventory levels at the customer's location. This paper presents a model to solve the VMI problem, focusing on optimizing inventory replenishment and reducing overall supply chain costs. The study employs a heuristic approach, breaking down the VMI problem into manageable phases, including clustering customers, determining service sequence lists, and optimizing delivery routes. The model is applied to a practical case study, demonstrating its effectiveness in minimizing stockouts while maintaining efficient inventory levels. This paper also examines key factors like delivery quantity optimization, route scheduling, and cost minimization. The model's effectiveness is demonstrated by specific performance criteria, such as reduced stockouts, improved service levels, and minimized transportation costs. The findings indicate that the suggested model can significantly enhance supply chain efficiency, providing organizations with a solid framework for enhancing their Vendor Managed Inventory procedures. These enhancements are accomplished while preserving simplicity and usefulness, without the need for overly complex technological systems.

1. Introduction

In today's global marketplace, organizations are continually exploring ways to improve supply chain processes and reduce operational costs [1]. With customers becoming more demanding, product life cycles shortening, and competition intensifying, supply chain management (SCM) has emerged as a key area for securing competitive advantages [2]. A significant development in SCM is the adoption of Vendor Managed Inventory (VMI), a collaborative model in which the supplier takes on the responsibility of managing inventory levels at the customer's location [3]. This approach

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enables better alignment of supply with demand, reduces inventory costs, and enhances service quality.

First introduced in 1985 through a partnership between Walmart and Procter & Gamble, VMI has since gained widespread adoption across numerous industries [4,5]. By shifting inventory management responsibilities to the supplier, VMI enhances efficiency in inventory replenishment, improves inventory visibility, and helps mitigate the bullwhip effect—a phenomenon in which demand variability intensifies as orders progress up the supply chain, often resulting in inventory inefficiencies [6,7]. Unlike the traditional inventory model, where each link in the supply chain manages its stock independently frequently leading to poorly aligned decision, VMI fosters collaboration, enabling vendors to maintain optimal stock levels for their customers.

The adoption of VMI has been largely driven by rapid advancements in information and communication technologies (ICT). With the rise of internet of things (IoT) and artificial intelligence (AI), VMI systems can now leverage real-time data to make more informed decisions [8,9]. For example, IoT-enabled devices provide vendors with real-time sales and consumption data, enabling precise, timely restocking to align with changing demand. Furthermore, AI algorithms enable accurate forecasting by analyzing historical trends, consumer behavior, and market dynamics, making VMI systems more efficient, reducing stock outs and excess inventory, and optimizing operations overall.

Traditionally, each supply chain member managed inventory independently, often resulting in overstocking, stock outs, and inefficiency. The introduction of VMI transformed this approach by allowing suppliers to handle inventory levels, which improved efficiency and quickly gained traction across industries like automotive, electronics, and consumer goods. Today, VMI is widely used in manufacturing, healthcare, and food and beverage sectors [10], especially for managing short-life products such as fresh produce and blood supplies, where precise inventory control minimizes waste and financial losses while maintaining high service levels.

The rapid advancements in ICT have significantly improved VMI systems. Technologies like IoT, AI, and Big Data analytics facilitate real-time data sharing and decision-making along the supply chain [8]. For example, IoT devices in inventory and transportation networks continuously gather data from smart sensors, allowing suppliers to monitor stock levels and demand fluctuations. These systems can automatically place replenishment orders when inventory drops to a certain threshold, preventing stock outs. AI enhances VMI by providing predictive analytics, enabling suppliers to forecast future inventory needs based on historical sales data and market trends [9]. This capability allows for proactive restocking, reducing shortages during peak demand and minimizing excess inventory in quieter periods. The smart replenishment system illustrates this integration by utilizing IoT-enabled household devices that transmit consumption data directly to suppliers. This allows for efficient inventory management at the consumer level and has proven especially effective in the markets for consumer electronics and household goods.

Despite the notable advantages of VMI, several challenges limit its broader adoption, particularly in complex and diverse supply chains. A major challenge is supplier diversity; suppliers often have varying capabilities and inventory management strategies, which can lead to inconsistent performance across the supply chain. This issue is even more pronounced in multi-tier supply chains, where some suppliers may focus on their own priorities rather than aligning with the overall supply chain goals. Consequently, inventory management can lack uniformity, causing inefficiencies. Additionally, accurate demand forecasting remains a critical challenge. Although VMI relies on real-time data for inventory control, inaccurate forecasts can still result in stock outs or overstocking, particularly in supply chains with high demand variability or extended lead times [7,11].

VMI relies on strong trust and collaboration between suppliers and buyers, as both need to share sensitive information, such as sales forecasts and inventory levels, to make the system effective. However, this transparency can be challenging due to limited trust or inadequate inventory management practices, which can hinder VMI success [12]. Furthermore, the high setup costs associated with implementing VMI systems, especially when incorporating advanced technologies like IoT and AI can be a significant barrier for smaller organizations.

In recent decades, environmental sustainability has become an important consideration within VMI systems. Literature increasingly discusses how VMI models address carbon cap-and-trade policies and manage carbon footprints, particularly in industries with significant emissions [13,14]. Beyond optimizing inventory levels, these systems aim to reduce the environmental impact of supply chain operations. For example, VMI systems can plan transportation routes to reduce fuel consumption and emissions, ensuring timely delivery with a lower carbon footprint. By minimizing overstock, VMI also helps reduce waste, promoting a more sustainable supply chain. In sectors dealing with perishable goods, VMI effectively manages inventory to prevent spoilage, thereby lowering the environmental impact associated with disposal of unused products. As awareness of climate change grows, the adoption of sustainability-focused VMI systems is likely to expand further [15,16].

This research aims to develop an optimized VMI model that addresses key challenges in delivery scheduling, inventory replenishment, and cost efficiency across a supply chain network. It emphasizes practical strategies in customer grouping, service sequence optimization, and route planning to create a comprehensive framework that enhances overall supply chain performance. In essence, this study seeks to prevent stock outs, reduce transportation costs, and ensure timely deliveries.

2. Methodology

The research employs a structured approach in solving the VMI problem and breaks down the entire process into three key phases: customer grouping, optimization of service sequence, and delivery scheduling. First, hierarchical clustering is used to group customers according to their close location, a process that reduces handling individual customers as sub-populations and considers them for route planning in finding suitable delivery routes. A standardized Euclidean distance metric is used to calculate the distance between customers. It clusters on pre-defined thresholds. A cluster of customers is done whereby each cluster, after segmentation, will be associated with one Service Sequence List (SSL). SSL includes all the customers in a sequence of serving, minimizing stockouts by serving higher-priority customers first.

Next, it does the delivery scheduling by allocating day-to-day delivery routes, using a route planning algorithm in accordance with the service sequence and geographical distribution of customers. It will implement the K-Nearest Neighbors algorithm, where customers will be assigned to the closest distribution center, and the travel routes will also be optimized to reduce the total distance covered by the delivery vehicles. Key performance indicators regarding the total distance traveled, quantities delivered, and inventory levels will be used to assess model performance. Based on that, the pseudo-code describing the algorithm used in the delivery scheduling process adopted in this research could look something like this:

Algorithm Route_Scheduling:
Input: Customer_Coordinates, Distribution_Center_Coordinates, Service_Sequence_List (SSL), Distance_Matrix
Output: Optimal_Route, Total_Travel_Distance
Step 1: For each cluster, get customer and DC coordinates.
Step 2: Apply K-NN to assign customers to nearest DC.
Step 3: For each day:
a. Start from DC.
b. Select customers from SSL.
c. Compute distance between DC and first customer.
d. Traverse all customers using Minkowski distance.
e. Return to DC, ensuring no cycling.
Step 4: Calculate total travel distance for each cluster.
Step 5: Calculate total routing cost using travel distances and operational costs.
Return: Optimal routes and routing costs.

3. Case study

3.1. Introduction to the Problem

This case study will analyze the inventory management process for optimization using a combined IRP-VRP approach. The aim is to find the best routes and time of delivery in order to prevent stock outs in the stores while minimizing operational costs in the suggested scenario. It structures a two-phase approach. The first phase focuses on the SSL generation, which determines the service order of customers based on their usage rates and inventory capacities. The second phase focuses on optimizing the scheduling routes between distribution centers and customers so that vehicles travel the least distance while delivering the required inventory quantities.
The total dataset consisted of 244 customers in this study and was divided into clusters using Hierarchical Clustering. Each of the clusters would be served by one distribution center, and each distribution center would perform deliveries using one assigned vehicle.

3.2. Clustering and Customer Grouping

It has been inefficient to treat every customer uniquely because of such a huge number of customers, considering routing and inventory management. Hierarchical Clustering was used in order to handle this and group them based on their closeness to each other geographically. This technique allows the construction of a tree-like structure, known as a dendrogram, by joining customers concerning their similarity in location.
The algorithm works by first computing the distances between each pair of customers using the Euclidean distance metric. The formula for calculating the Euclidean distance is as follows:

$$d_{st}^2 = (x_s - x_t)(x_s - x_t)' \tag{1}$$

Here, x_s and x_t are the coordinates of two customers. For standardization, we also use Standardized Euclidean Distance, which scales the difference between customer coordinates by the corresponding element of the standard deviation. After computation of distances, the algorithm first combines customers into binary clusters, then groups them into larger clusters until the resulting hierarchical tree is obtained. We chose a cut-off point that divided the 244 customers into eight clusters, each serviced by a single distribution center. The method has the advantage that we can easily adjust the level of clustering based on the size and geographic dispersion of the customers.

Figure 1 shows how the method groups customers from individual pairs into larger clusters. The vertical axis represents the distance between customers, while the horizontal axis corresponds to the original customer data.

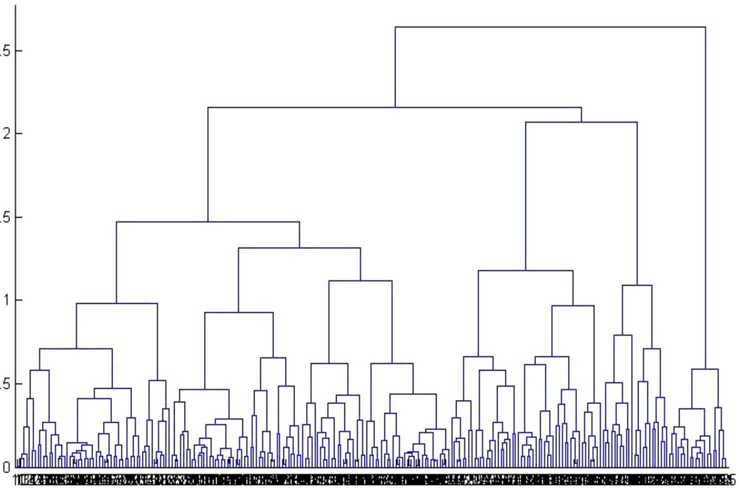

Fig.1. Hierarchical clustering

3.3. Service Sequences List (SSL)

Once the customers were grouped into clusters (Figure 2), determining the Service Sequences List (SSL) for each cluster was the next step. SSL represents the list that dictates the order in which customers will be visited each day, based on their inventory usage rates. This is important because each customer has a different stock depletion rate, and a delay in supply could lead to stockouts and disrupt the production line.

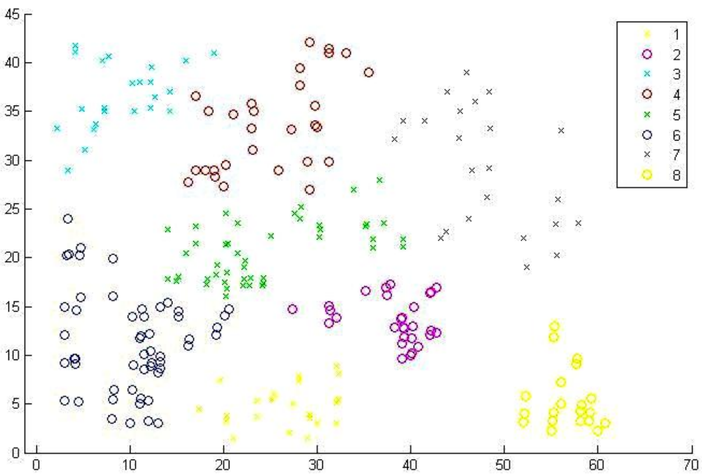

Fig.2. Clustering the customers

The SSL is calculated based on the customer's inventory capacity (IC) and usage rate (UR). This ensures that the stock level at the customer's site never falls below a safety threshold, referred to as the Stockout Time (ST). Stockout time can be calculated as follows:

ST = IC - (UR*8)

Where:

IC is the inventory capacity,

UR is the usage rate per hour,

The factor of 8 corresponds to an 8-hour workday.

Then, customers are sorted according to their stockout times, and the SSL is adjusted to prioritize those whose inventory levels are most at risk. For example, if a customer has a high usage rate and is nearing their inventory capacity, they are placed earlier in the service sequence. The resulting SSL is presented in Figure 3, where customers are ordered according to their service priority. For instance, the SSL for Cluster 1 shows that the customer with the highest risk of stockout is visited first, followed by others based on their depletion rates. A figure illustrating the SSL for Cluster 1 can be included to better visualize the prioritization of customers.

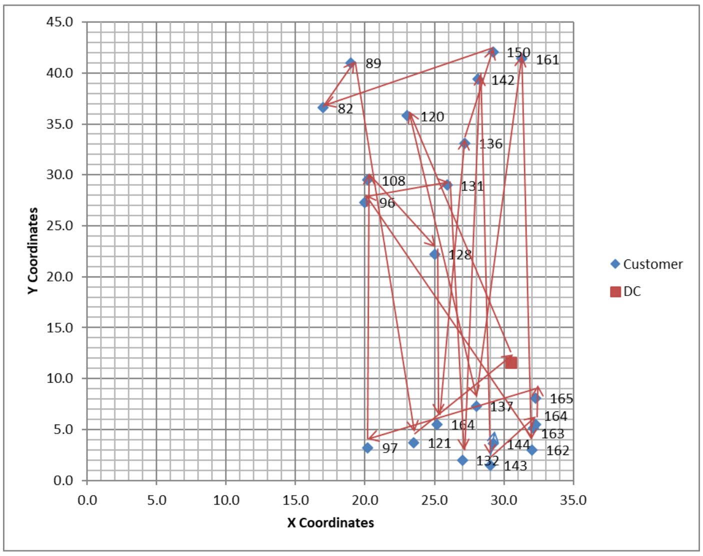

Fig. 3. Route Service Sequences List Day 1 in Cluster 1

3.4. Delivery Quantity Calculation

The next step is to calculate the quantity of inventory to be delivered to each customer. The objective is to avoid exceeding the inventory capacity of the customer while ensuring that sufficient inventory is delivered to prevent stockouts. The delivery quantity is constrained by both the lower bound (LL) and upper bound (UL):

$$\mathrm{LL_i} \leq \textstyle\sum_{\mathrm{i}} \mathrm{dlv_i} \leq \mathrm{UL_i} \tag{2}$$

$$\mathrm{LL} = (\mathrm{tU_i} - \mathrm{UR} + \mathrm{lU_i}) \tag{3}$$

$$\mathrm{UL} = (\mathrm{tU_i} + \mathrm{IC} - \mathrm{Ii_0} - \mathrm{lU_i}) \tag{4}$$

Where:

tUi is the usage rate of the customer by the end of the day,

lUi is the usage rate during the day,

IC is the customer's inventory capacity,

Ii0 is the initial inventory level.

The algorithm used compares the upper and lower bounds to prevent the delivery quantity from exceeding the customer's capacity, while still delivering enough amount to avoid stockouts. These calculations make an outputs in tabular forms depicting delivery quantities per each customer in a definite cluster.

For illustration, Customer 5 who has been grouped under cluster 1 has 15 calculated delivery quantity on the third day from the 5 delivered amounting to 75 in a week. The delivery quantities for all the customers are also summarized according to each of the days so that at no one point in time would the customer be out of stock. Figure 4 shows the delivery quantity to customers 1-20.

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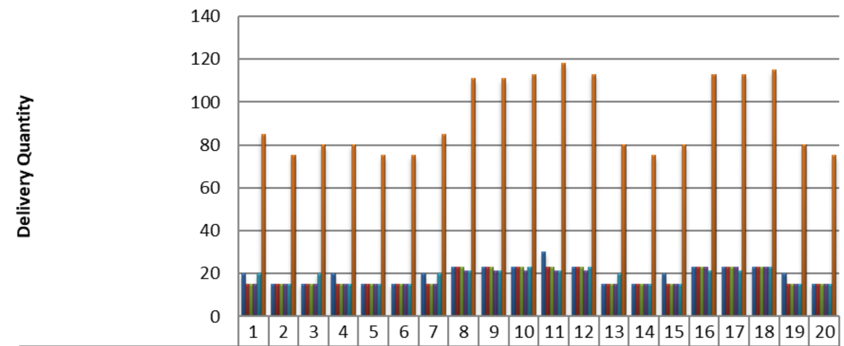

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
day 1	20	15	15	20	15	15	20	23	23	23	30	23	15	15	20	23	23	23	20	15
day 2	15	15	15	15	15	15	15	23	23	23	23	23	15	15	15	23	23	23	15	15
day 3	15	15	15	15	15	15	15	23	23	23	23	23	15	15	15	23	23	23	15	15
day 4	15	15	15	15	15	15	15	21	21	21	21	21	15	15	15	23	23	23	15	15
day 5	20	15	20	15	15	15	20	21	21	23	21	23	20	15	15	21	21	23	15	15
total delivery quantities	85	75	80	80	75	75	85	111	111	113	118	113	80	75	80	113	113	115	80	75

Fig. 4. Delivery Quantity to Customers 1-20

3.5. Route Scheduling and Travel Distance

Upon establishing the delivery quantities, we advance to Phase II, wherein the route schedule is optimized according to the Service Sequences List. To do this, we employed the K-Nearest Neighbors (K-NN) algorithm, which allocates each consumer to the closest distribution center according to their geographical coordinates. This guarantees that each distribution center caters to the nearest consumers, hence reducing travel distances.

The K-NN algorithm assigns customers to distribution centers by computing the distance between customer coordinates and distribution center coordinates. The Minkowski distance metric, which encompasses both Euclidean and Manhattan distances, is employed to calculate distances. The algorithm operates in the following manner: The algorithm designates a distribution center as the initial point of reference. It allocates customers according to the SSL for each day. The vehicle departs from the distribution center, services each customer in the sequence dictated by the SSL, and returns to the distribution center, guaranteeing that no customer is serviced more than once. The cumulative trip distance is computed for each day.

Figure 5 depicts the trip distances for each cluster over a five-day period demonstrates the optimization attained by this approach. The total trip distance for Cluster 1 on Day 1 is 577.96 km, with cumulative distances recorded for each cluster across all days.

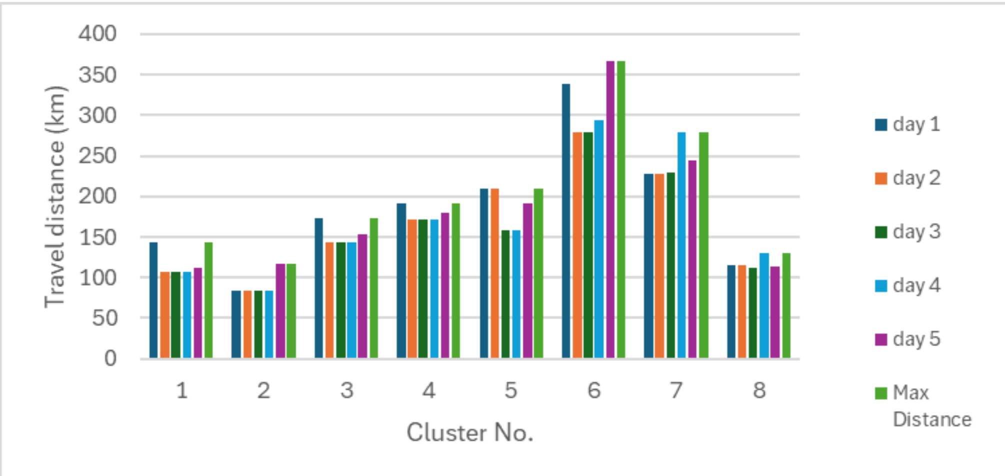

Fig. 5. Trip distances

3.6. Cost Calculation

The cost computation is essential to the case study, as the aim is to reduce the operating expenses related to inventory delivery. The overall Routing Cost (RC) is determined by multiplying the trip distance (TD) by the operational cost (OC) for each vehicle. The formula for routing expenses is:

$$\text{RC} = \sum_{i}^{n}(\text{TDi} * \text{OCi}) \quad (5)$$

Where:

TDi is the travel distance for each cluster i,

OCi is the operational cost, which includes fuel, maintenance, and other related costs.

Maintenance costs, such as oil changes and tire replacements, are added to the fuel cost to determine the total operational cost for Cluster 1. The same procedure is followed for all clusters, and the total routing cost is computed as the sum of the costs for each cluster. The final routing cost is approximately €6551 per year for all eight clusters.

4. Conclusions

This paper demonstrates how, by integrating over the Inventory Routing Problem (IRP) & Vehicle Routing Problem (VRP) into the Vendor Managed Inventory (VMI) system, the suppliers of inventories can minimize costs. Through Hierarchical Clustering, Service Sequence Lists and K-NN, the customers were classified, the priority of delivery was established and the most efficient routes for delivering the packages to the various customers was achieved. These endeavours yielded significant reductions in costs and in general optimization of the supply chain operations.

Future research can thus extend from the current study by including factors like handling multiple products, other delivery vehicles types, and real factors like traffic conditions and specific delivery time zones. Through these extensions further, the model could be posited to have even greater application value and flexibility to supply chain management.

Conflicts of Interest

The authors declare no conflicts of interest.

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