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An Intelligent Dynamic Clustering Framework with Neural Network-Based Product-to-Facility Assignment for Supply Chain Network Design Under Uncertainty

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Abstract

Growing Supply Chain (SC) complexity, demand volatility, and environmental pressures have increasingly limited the effectiveness of traditional static and non-intelligent network design approaches. These limitations are particularly evident in multi-period settings characterized by uncertainty, where adaptive, data-driven decision mechanisms are required. This study develops an integrated framework for designing a multi-period stochastic bi-level SC network to improve operational efficiency, enhance resource-allocation flexibility, and minimize total network costs. First, an enhanced Constrained K-Means algorithm is developed to dynamically reconfigure service zones over time while accounting for capacity restrictions and cluster-balance requirements. Subsequently, an Artificial Neural Network (ANN) classifies products according to their physical and functional characteristics and determines whether they should be routed through the central warehouse or cross-docking centers. The outputs of these two data-driven modules are incorporated as structured inputs into a bi-level stochastic optimization model that jointly addresses location, allocation, and routing decisions under uncertainty. In addition, a dynamic cluster-improvement algorithm iteratively adjusts cluster configurations based on shortage rates, thereby strengthening network responsiveness and resilience. The proposed framework is evaluated through a real-world case study. The numerical results indicate cost reductions of up to approximately 32% in specific periods, together with more stable resource utilization and improved overall SC performance.

Keywords: Supply chain network design, Dynamic clustering, Neural networks, Uncertainty, Machine learning, Constrained K-means.

1 | Introduction

The increasing complexity of modern Supply Chains (SCs) driven by globalization, market volatility, environmental regulations, and rapidly shifting customer expectations presents significant challenges for

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network design and management. To maintain a competitive edge, organizations must develop responsive, adaptive systems capable of operating efficiently under deep uncertainty. Consequently, advanced analytical approaches, intelligent decision-support systems, and data-driven optimization have become indispensable components of contemporary SC management. Among the various logistics strategies employed to improve network performance, cross-docking has received considerable attention. By facilitating the direct transfer of goods from inbound to outbound transportation vehicles with minimal to no intermediate storage, cross-docking drastically reduces inventory holding costs, accelerates product flows, and enhances distribution flexibility across the network [1].

Despite the extensive literature on SC network design, many existing models rely on static assumptions regarding facility allocation, network configuration, and operational decision-making. Such approaches fail to capture the dynamic reality of modern markets, where demand patterns, customer preferences, and operational conditions continuously evolve. Recently, Artificial Intelligence (AI) and Machine Learning (ML) techniques have emerged as powerful tools to bridge this gap [2]. Through their ability to process massive datasets, uncover hidden patterns, forecast demand, and automate complex decisions, AI-based approaches offer substantial opportunities to enhance inventory management, resource allocation, customer service levels, and overall network resilience [3].

Motivated by these developments, this study proposes an integrated, data-driven framework for the design of a stochastic multi-period SC network that incorporates both dynamic spatial structuring and intelligent product-routing decisions. The proposed framework uniquely fuses ML with mathematical programming via two complementary methodologies:

I. Dynamic spatial partitioning: A Constrained K-Means clustering algorithm is employed to partition demand points into balanced service zones while strictly respecting operational capacity limits. Unlike conventional static clustering, this mechanism dynamically updates cluster structures across the planning horizon to reflect evolving demand distributions.

II. Intelligent product classification: An Artificial Neural Network (ANN) is developed to classify products according to their operational characteristics, including time sensitivity, physical attributes, and distribution requirements. Based on these features, the ANN intelligently predicts whether products should be routed through a central warehouse or channeled via cross-docking facilities.

A core theoretical contribution of this research lies in the integration of both dynamic clustering and intelligent product classification into a unified, bi-level stochastic optimization framework. Rather than treating demand allocation and routing rules as static, predefined parameters, our approach embeds the ML outputs directly into the mathematical optimization model. This mathematical coupling allows the network's physical structure to adapt continuously to fluid operational environments, ensuring tighter alignment between strategic network design and real-world market behavior. Managerially, the proposed framework is designed to yield quantifiable benefits, including minimized total SC resilience against demand uncertainty. By bridging data-driven predictive modeling with prescriptive optimization, this research provides a practical, intelligent decision-support tool for organizations navigating highly volatile environments, ultimately contributing a novel methodology to both the SC optimization literature and the growing field of AI-driven logistics management.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and identifies the main research gaps. Section 3 presents the proposed framework, including the clustering method, product-classification approach, mathematical model, and improvement algorithm. Section 4 reports and discusses the numerical results, and Section 5 concludes the study and outlines directions for future research.

2 | Literature Review

SC networks are increasingly challenged by demand uncertainty, environmental concerns, and operational disruptions, making efficient network design and cross-docking strategies important research topics. Several studies have developed mathematical models to improve SC performance through cross-docking and transportation optimization. Rezaei et al. [4] proposed a sustainable Closed-Loop Supply Chain (CLSC) model considering economic, environmental, and social objectives. Mousavi and Tavakkoli-Moghaddam [5] developed a model for cross-docking location and transportation scheduling, and Mogale et al. [6] designed a sustainable freight transportation network with capacitated cross-docking facilities aimed at reducing transportation costs and carbon emissions. Abbasi-Tavallali et al. [7] utilized a system dynamics approach to investigate the impact of cross-dock-to-destination distances in reverse logistics networks. Similarly, Tabatabaei et al. [8] introduced a bi-objective model for transportation scheduling and routing in a green reverse SC network, achieving improvements in both cost efficiency and fuel consumption. Kazemi et al. [9] proposed a multi-objective model for cross-docking location selection and demand splitting in perishable product SC, demonstrating significant improvements in freshness preservation and cost reduction. Furthermore, Kangi et al. [10] examined an integrated forward and reverse logistics network incorporating capacity allocation and routing decisions under soft time-window constraints. Lozano-Diez et al. [11] developed a resilient pharmaceutical SC network under epidemic conditions and showed that cross-docking facilities can substantially improve service levels while reducing operational costs.

Recent studies have further expanded the role of cross-docking and advanced analytics in SC network design. Wang et al. [12] proposed a Multi-Criteria Decision Making (MCDM) framework for cross-dock terminal location selection and demonstrated the importance of strategic cross-docking decisions in improving overall SC efficiency. Potoczki et al. [13] developed an integrated model for cross-dock location and supply mode planning in retail distribution networks, highlighting the benefits of jointly optimizing facility location and transportation decisions. Moreover, Shi [14] combined K-Means clustering and priority-based classification techniques to optimize cold-chain logistics networks, demonstrating the effectiveness of data-driven clustering approaches in improving resource utilization and reducing distribution costs.

In parallel with advances in optimization modeling, ML and AI techniques have increasingly been applied to SC management. Recent research has shown that AI-based approaches can enhance demand forecasting, disruption detection, inventory management, and network planning by extracting knowledge from large-scale operational data. For example, Ashraf et al. [15] proposed a hybrid deep-learning framework for disruption detection in digital SC twins, enabling proactive responses to SC risks. These developments indicate a growing shift from static optimization approaches toward intelligent and adaptive decision-support systems capable of operating in uncertain and rapidly changing environments.

Despite these advances, two important gaps remain in the literature. First, most existing models assume that demand-point allocations are fixed and do not dynamically adapt to changing demand patterns over time. Second, product routing decisions are generally based on distance and cost considerations, with limited attention given to intelligent product classification based on operational characteristics such as perishability, time sensitivity, and handling requirements.

To address these gaps, this study proposes an integrated framework that combines Constrained K-Means clustering and ANN within a bi-level stochastic SC network design model. Demand points are dynamically clustered into balanced service zones, while products are intelligently classified to determine their most appropriate routing through either central warehouses or cross-docking centers. The outputs of both mechanisms are incorporated into the optimization model, enabling more adaptive, realistic, and efficient SC decisions under uncertainty.

3 | Proposed Intelligent Supply Chain Network Design Framework

This section presents the proposed framework in four subsections. Section 3.1 addresses the clustering of demand points; Section 3.2 examines product diversity and the role of the ANN in product type classification; Section 3.3 develops the mathematical model for the SC network, and Section 3.4 presents the improvement algorithm. The overall problem approach is also illustrated in *Fig. 1*.

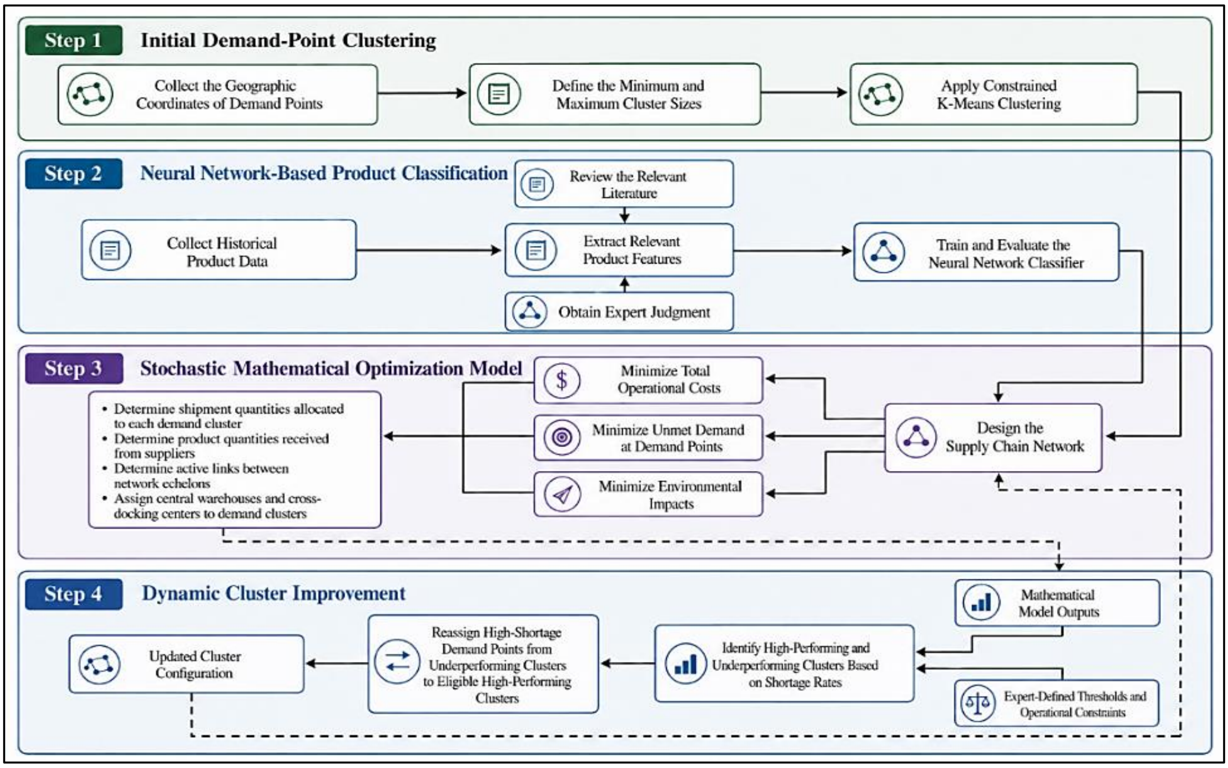

Fig. 1. Proposed framework of the present study.

3.1 | Clustering Demand Points

In a realistic SC network design, how demand points are allocated to service zones plays a foundational role in determining the spatial structure of the system. In practice, this allocation faces various constraints: Resource capacity limitations, workload balance requirements, and the need for dynamic adaptation to demand fluctuations. To address these challenges, a Constrained K-Means algorithm is employed to create balanced clusters aligned with operational constraints.

Unlike the classical K-Means algorithm, which solely minimizes the distance between members and cluster centers, the constrained version generates more operationally realistic clusters by incorporating capacity constraints, minimum and maximum cluster sizes, and other problem-specific requirements. Suppose a set of demand points is given as $X = \{x_1, x_2, \dots, x_n\} \subset \mathbb{R}^d$, and the objective is to partition them into K clusters with centers $\{c_1, c_2, \dots, c_K\}$ subject to specific clustering constraints. The objective function, which minimizes the total squared distance between points and their assigned cluster centers, is defined by *Eqs. (1)-(4)*, where $z_{ik} \in \{0,1\}$ is a binary variable equal to 1 if the point x_i is assigned to cluster k, and 0 otherwise; L_k and U_k denote the minimum and maximum number of members in each cluster, respectively.

$$\min_{Z,C} \sum_{i=1}^{n} \sum_{k=1}^{K} z_{ik} \|x_i - c_k\|^2. \tag{1}$$

Subject to.

$$\sum_{k=1}^{K} z_{ik} = 1. \tag{2}$$

$$L_k \leq \sum_{i=1}^{n} z_{ik} \leq U_k. \tag{3}$$

$$z_{ik} \in \{0,1\}. \tag{4}$$

Constraint (2) ensures that each demand point is assigned to exactly one cluster. *Constraint (3)* enforces cluster capacity, requiring each cluster k to contain between L^k and U^k members. Additionally, cluster centers are defined as the weighted average of assigned points, as expressed in *Eq. (5)*:

$$c_k = \frac{\sum_{i=1}^{n} z_{ik} x_i}{\sum_{i=1}^{n} z_{ik}}, \qquad \forall k \in K. \tag{5}$$

Since the choice of K (number of clusters) directly affects clustering quality and consequently the overall SC structure, this value is determined in a data-driven manner using the Silhouette Score. This criterion evaluates clustering quality by simultaneously measuring intra-cluster cohesion and inter-cluster separation [16]. In this study, clustering is performed across multiple candidate values of k, and the value yielding the highest Silhouette Score is selected as the optimal number of clusters. Importantly, the constrained clustering process is executed only after the optimal k has been identified.

This constrained clustering model preserves the classical K-Means objective of minimizing intra-cluster dispersion while enabling structural control over cluster size and composition. In the proposed framework, constrained clustering is not only used initially to define the base structure of service zones but is also revised throughout each planning period. As demand patterns or resource constraints change, the clustering adapts accordingly, increasing the spatial flexibility of the SC and preventing resource allocation imbalances as discussed further in Section 3.4. The output of the constrained clustering is fed as a structural input into the bi-level stochastic mathematical model.

3.2 | Neural Network-Based Product Classification

In this section, ANNs are employed for intelligent product-type decision-making. In a realistic SC network design, products are generally classified into two categories: those sent directly to the central warehouse, and those that must first be routed to cross-docking centers. The distinguishing factor between these two groups lies in their physical and economic characteristics. Products sent directly to the central warehouse tend to be high-volume or high-tonnage items for which direct delivery to the final destination is justified in terms of cost and efficiency. In contrast, products with low weight, high variety, or highly dispersed geographic demand are more economically suited to cross-docking, where they can be consolidated with other goods before final delivery.

Determining product type based solely on fixed rules or human judgment can lead to inaccurate or inefficient decisions due to product diversity, demand variability, and dynamic SC conditions. Therefore, in this study, an ANN is used to classify products for routing. This network is trained on historical data and real product features, enabling it to automatically determine whether each product should be routed to the central warehouse or to a cross-docking center.

For each product i, a feature vector $x_i \in \mathbb{R}^d$ is defined as input to the neural network. The model output $y_i \in [0,1]$represents the probability that the product belongs to the class "send to cross-docking center". The computational structure is expressed in *Eq. (6)*:

$$y_i = \sigma\left(\sum_{j=1}^{H} w_j^{(2)} \cdot \sigma\left(\sum_{k=1}^{d} w_{jk}^{(1)} x_{ik} + b_j^{(1)}\right) + b_j^{(2)}\right). \tag{6}$$

After full model training, for each new product, a decision is made by computing y_i. If $y_i \geq \tau$, the product is assigned to the "send to cross-dock" class; otherwise, it is sent to the central warehouse, as expressed in *Eq. (7)*. The decision threshold τ can be determined empirically or via sensitivity analysis:

$$\text{Class}_i = \begin{cases} \text{if } y_i \geq \tau \;\; \text{send to cross} - \text{dock}, \\ \text{if } y_i < \tau \;\; \text{send to regular warehouse}. \end{cases} \tag{7}$$

3.3 | Bi-Level Stochastic Supply Chain Network Design

In this section, the mathematical model for a three-layer SC network design is presented within a bi-level stochastic multi-period framework. The model captures the complete network structure by accounting for product flows across the various layers of the SC and incorporating uncertainty scenarios, as illustrated in *Fig. 2*. The notation and indexing are provided in *Table 1*.

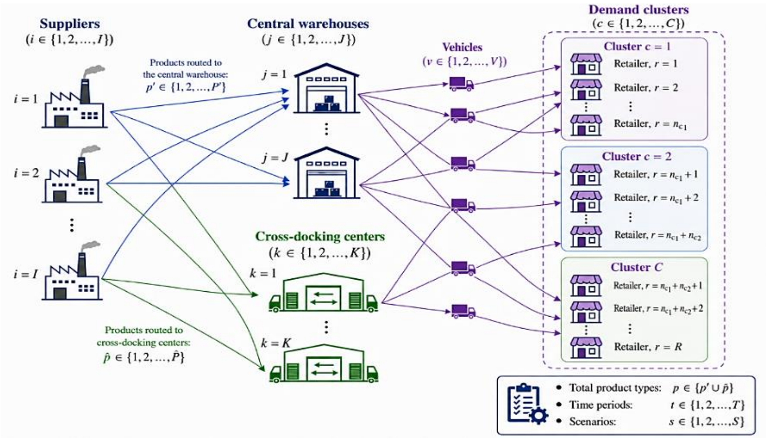

Fig. 2. Supply chain network structure.

Table 1. Notation and Indexing.

Symbol	Description
Sets	
$\hat{p} \in \{1,2,\dots,\hat{P}\}$	Types of products routed to cross-docking centers
$p' \in \{1,2,\dots,P'\}$	Types of products routed to the central warehouse
$p \in \{p' \cup \hat{p}\}$	Total product types in the network
$i \in \{1,2,\dots,I\}$	Suppliers
$j \in \{1,2,\dots,J\}$	Central warehouses
$k \in \{1,2,\dots,K\}$	Cross-docking centers
$r \in \{1,2,\dots,R\}$	Retailers (stores)
$t \in \{1,2,\dots,T\}$	Time periods
$s \in \{1,2,\dots,S\}$	Scenarios
$c \in \{1,2,\dots,C\}$	Demand clusters
$v \in \{1,2,\dots,V\}$	Vehicles
Parameters	
$EC^{s}_{e\in\{ij,ik,jr,kr\}t}$	Environmental cost of shipping between two layers e in period t under scenario s
$TC^{s}_{e\in\{ij,ik,jr,kr\}t}$	Transportation cost between two layers e in period t under scenario s
$VC^{s}_{e\in\{jc,kc\}t}$	Vehicle routing cost between two layers e in period t under scenario s
lc^{s}_{rpt}	Shortage cost of product p for retailer r in period t under scenario s
$lc^{s}_{k\hat{p}t}$	Shortage cost of product p for cross-docking center k in period t under scenario s
$lc^{s}_{jp't}$	Shortage cost of product p' for central warehouse j in period t under scenario s
hc^{s}_{rpt}	Holding cost of product p for retailer r in period t under scenario s
$hc^{s}_{k\hat{p}t}$	Holding cost of product p for cross-docking center k in period t under scenario s
$hc^{s}_{jp't}$	Holding cost of product p' for central warehouse j in period t under scenario s
$D^{s}_{rp't}$	Demand for product p' at retailer r in period t under scenario s
$D^{s}_{r\hat{p}t}$	Demand for product p at retailer r in period t under scenario s
$dis^{s}_{e\in\{jc,kc\}t}$	Distance between two layers e in period t under scenario s
$Cap_{o\in\{j,k,r,v\}}$	Maximum capacity of the facility o
M	Big-M constant
PS_{s}	Probability of scenario s occurring

Table 1. Continued.

Symbol	Description
Decision Variables	
$y_{e\in\{ij,ik,jc,kc\}t}$	1 if a link between two layers e is active in period t; 0 otherwise
$x^{s}_{ik\hat{p}t}$	Quantity of product p shipped from supplier i to cross-dock k in period t under scenario s
$x^{s}_{ijp't}$	Quantity of product p' shipped from supplier i to central warehouse j in period t under scenario s
$x^{sv}_{jrp't}$	Quantity of product p' shipped from warehouse j to retailer r in period t under scenario s via vehicle v
$x^{sv}_{kr\hat{p}t}$	Quantity of product p shipped from cross-dock k to retailer r in period t under scenario s via vehicle v
I^{s}_{rpt}	Inventory of product p at retailer r in period t under scenario s
$I^{s}_{jp't}$	Inventory of product p' at central warehouse j in period t under scenario s
$I^{s}_{k\hat{p}t}$	Inventory of product p at cross-docking center k in period t under scenario s
l^{s}_{rpt}	Shortage of product p at retailer r in period t under scenario s
$l^{s}_{jp't}$	Shortage of product p' at central warehouse j in period t under scenario s
$l^{s}_{k\hat{p}t}$	Shortage of product p at cross-docking center k in period t under scenario s

$$\begin{aligned}\text{Min } z = \sum\nolimits_{S} PS_s \Big(&\sum\nolimits_{I,J,P',T} x^{s}_{ijp't}\cdot\left(TC^{s}_{ijt}+EC^{s}_{ijt}\right)+\sum\nolimits_{I,K,\hat{P},T} x^{s}_{ik\hat{p}t}\cdot\left(TC^{s}_{ikt}+EC^{s}_{ikt}\right)\\ &+\sum\nolimits_{K,R,\hat{P},T,V} x^{sv}_{kr\hat{p}t}\cdot\left(TC^{s}_{krt}+EC^{s}_{krt}\right)+\sum\nolimits_{J,R,P',T,V} x^{sv}_{jrp't}\cdot\left(TC^{s}_{jrt}+EC^{s}_{jrt}\right)\\ &+\sum\nolimits_{K,\hat{P},T} I^{s}_{k\hat{p}t}\cdot hc^{s}_{k\hat{p}t}+\sum\nolimits_{J,P',T} I^{s}_{jp't}\cdot hc^{s}_{jp't}+\sum\nolimits_{R,P,T} I^{s}_{rpt}\cdot hc^{s}_{rpt}\\ &+\sum\nolimits_{K,\hat{P},T} l^{s}_{k\hat{p}t}\cdot lc^{s}_{k\hat{p}t}+\sum\nolimits_{J,P',T} l^{s}_{jp't}\cdot lc^{s}_{jp't}+\sum\nolimits_{R,P,T} l^{s}_{rpt}\cdot lc^{s}_{rpt}\\ &+\sum\nolimits_{J,C,T,S} dis^{s}_{jct}\cdot VC^{s}_{jct}\cdot y_{jct}+\sum\nolimits_{K,C,T,S} dis^{s}_{kct}\cdot VC^{s}_{kct}\cdot y_{kct}\Big).\end{aligned} \tag{8}$$

$$I^{s}_{k\hat{p}t}-l^{s}_{k\hat{p}t}=\sum\nolimits_{I} x^{s}_{ik\hat{p}t}-\sum\nolimits_{R,V} x^{sv}_{kr\hat{p}t} \quad \forall K,\hat{P},t=1,S. \tag{9}$$

$$I^{s}_{k\hat{p}t}-l^{s}_{k\hat{p}t}=\sum\nolimits_{I} x^{s}_{ik\hat{p}t}+I^{s}_{k\hat{p}(t-1)}-\sum\nolimits_{R,V} x^{sv}_{kr\hat{p}t}-l^{s}_{k\hat{p}(t-1)}, \quad \forall K,\hat{P},t\geq 2,S. \tag{10}$$

$$I^{s}_{jp't}-l^{s}_{jp't}=\sum\nolimits_{I} x^{s}_{ijp't}-\sum\nolimits_{V,R} x^{sv}_{jrp't}, \quad \forall J,P',t=1,S. \tag{11}$$

$$I^{s}_{jp't}-l^{s}_{jp't}=\sum\nolimits_{I} x^{s}_{ijp't}+I^{s}_{jp'(t-1)}-\sum\nolimits_{R,V} x^{sv}_{jrp't}-l^{s}_{jp'(t-1)}, \quad \forall J,P',t\geq 2,S. \tag{12}$$

$$I^{s}_{rpt}-l^{s}_{rpt}=\sum\nolimits_{J,V} x^{sv}_{jrp't}+\sum\nolimits_{K,V} x^{sv}_{kr\hat{p}t}-D^{s}_{r\hat{p}t}-D^{s}_{rp't}, \quad \forall R,P,t=1,S. \tag{13}$$

$$\begin{aligned}I^{s}_{rpt}-l^{s}_{rpt}=\sum\nolimits_{J,V} x^{sv}_{jrp't}+\sum\nolimits_{R,V} x^{sv}_{kr\hat{p}t}+I^{s}_{rp(t-1)}-l^{s}_{rp(t-1)}-D^{s}_{r\hat{p}t}-D^{s}_{rp't},\\ \forall R,P,t\geq 2,S.\end{aligned} \tag{14}$$

$$\sum\nolimits_{I}\sum\nolimits_{P'} x^{s}_{ijp't}\leq\left(Cap_j-\sum\nolimits_{P'} I^{s}_{jp'(t-1)}\right), \quad \forall J,T,S. \tag{15}$$

$$\sum\nolimits_{I}\sum\nolimits_{\hat{P}} x^{s}_{ik\hat{p}t}\leq\left(Cap_k-\sum\nolimits_{\hat{P}} I^{s}_{k\hat{p}(t-1)}\right), \quad \forall K,T,S. \tag{16}$$

$$\sum\nolimits_{P'} x^{s}_{ijp't}\leq M\times y_{ijt}, \quad \forall I,J,T,S. \tag{17}$$

$$\sum\nolimits_{\hat{P}} x^{s}_{ik\hat{p}t}\leq M\times y_{ikt}, \quad \forall I,K,T,S. \tag{18}$$

$$\sum\nolimits_{K,\hat{P},V} x^{sv}_{kr\hat{p}t}+\sum_{J,P',V} x^{sv}_{jrp't}\leq Cap_r-\sum\nolimits_{P} I^{s}_{rp(t-1)}, \quad \forall R,T,S. \tag{19}$$

$$\sum\nolimits_{V} x^{sv}_{kr\hat{p}t}\leq D^{s}_{r\hat{p}t}\times y_{kct}, \quad \forall K,R,\hat{P},T,S. \tag{20}$$

$$\sum\nolimits_{V} x^{sv}_{jrp't} \leq D^{s}_{rp't} \times y_{jct}, \qquad \forall J, R, P', T, S. \tag{21}$$

$$\sum\nolimits_{K} y_{kct} + \sum\nolimits_{J} y_{jct} \leq 2, \qquad \forall R, C, T, S. \tag{22}$$

$$\sum\nolimits_{R,P'} x^{sv}_{jrp't} \leq Cap_{v}, \qquad \forall J, V, T, S. \tag{23}$$

$$\sum\nolimits_{R,\hat{P}} x^{sv}_{kr\hat{p}t} \leq Cap_{v}, \qquad \forall K, V, T, S. \tag{24}$$

$$y_{e\in\{ij,ik,jc,kc\}t} \in \{0,1\}. \tag{25}$$

$$x^{s}_{ik\hat{p}t}, x^{s}_{ijp't}, x^{sv}_{jrp't}, x^{sv}_{kr\hat{p}t}, I^{s}_{rpt}, I^{s}_{k\hat{p}t}, I^{s}_{jp't}, l^{s}_{rpt}, l^{s}_{jp't}, l^{s}_{k\hat{p}t} \geq 0, \text{int}. \tag{26}$$

The objective function *Eq. (8)* minimizes total SC costs, comprising transportation and environmental costs between network layers, inventory holding costs, and shortage costs at warehouses and retailers. *Eqs. (9)* and *(10)* govern inventory levels at cross-docking centers. *Eqs. (11)* and *(12)* control inventory at the central warehouse. *Eqs. (13)* and *(14)* handle retailer inventory levels. *Eq. (15)* controls product flow from suppliers to the central warehouse based on warehouse capacity. *Eq. (16)* enforces the same restriction for suppliers to cross-docking centers. *Eqs. (17)* and *(18)* permit product transfers only when active links between suppliers and warehouses exist. Equation (19) enforces retailer capacity limits. *Eqs. (20)* and *(21)* regulate active connections between warehouses and retailers based on cluster demand. *Eq. (22)* ensures the number of active warehouse-to-cluster links is controlled. *Eqs. (23)* and *(24)* enforce vehicle capacity constraints. *Eqs. (25)* and *(26)* specify the domains of decision variables, ensuring they are properly defined as integer, binary, or non-negative.

3.4 | Dynamic Cluster Improvement Algorithm

After performing the initial clustering with the Constrained K-Means algorithm and determining product types via the ANN, both outputs are fed into the SC network mathematical model, which is solved for each period. In this stage, decision variables are determined, including store-to-cross-dock or store-to-central-warehouse assignments, shipment quantities, and demand fulfillment levels at retail stores.

For each cluster, the shortage rate, defined as the ratio of unmet demand to total cluster demand, is then computed to identify how much demand each cluster has failed to satisfy. This indicator is used to evaluate cluster performance in demand fulfillment and to identify network weak points, helping decision-makers assess clusters in terms of stability and resilience against demand variability.

Based on this assessment, a Lower Threshold (LR) and an Upper Threshold (UR) are defined by the decision-maker. Clusters with shortage rates below LR are classified as super-optimal clusters, indicating either low demand pressure or high demand coverage. This classification helps management identify surplus network capacity for high-demand periods. Conversely, clusters with shortage rates above UR are classified as sub-optimal, either because of high demand load or complexity-driven fulfillment failure. Identifying these enables targeted improvement of potential bottlenecks and critical network points.

When both super-optimal and sub-optimal clusters are identified, stores within sub-optimal clusters that carry the highest share of unmet demand are selected for potential transfer to the nearest super-optimal cluster. This decision follows the principle of "maximum impact with minimum relocation," transferring the fewest high-shortage stores to clusters with available response capacity, thereby reducing network shortage rates and rebalancing clusters.

However, any transfer is subject to operational conditions. First, the transfer must not cause the super-optimal cluster to exceed its maximum size, as doing so would increase operational load and degrade service quality. Second, after a transfer, the sub-optimal cluster must not fall below the minimum cluster size, as this would increase fixed service costs and lead to economic inefficiency. Additionally, the distance from the new cluster center to the transferred store must not exceed a maximum acceptable radius (r), in order to preserve cost and time efficiency and prevent increased transportation costs and service delays.

If all conditions are satisfied, the transfer is executed, and the clustering is updated. This process continues iteratively until either the number of transfers reaches the decision-maker's specified limit or no further transfers are feasible. If the general transfer conditions are not met, the process moves to the final clustering stage, where the cluster structure is finalized for the current planning period and returned to the mathematical model for subsequent periods. In this way, a dynamic, data-driven cluster improvement algorithm is formed that optimizes the SC network structure against environmental changes and uncertainties by improving demand responsiveness, balancing clusters, and reducing shortage rates. The algorithm is illustrated in *Fig. 3*.

Algorithm 1. Dynamic cluster improvement algorithm.

Input: Demand-point coordinates, trained neural network classifier, scenario-dependent demand data, scenario occurrence probabilities, supply chain parameters, planning horizon (T), shortage-rate thresholds (LR) and (UR), minimum and maximum cluster sizes, maximum service radius (Rmax), and maximum number of accepted transfers per planning period (Nmax).
Output: Product-routing classes, period-specific final cluster configurations, and optimized allocation, shipment, inventory, shortage, vehicle-based shipment, and active-link decisions.
1. Classify each product as either central-warehouse routed or cross-dock routed using the trained neural network.
2. Determine the appropriate number of demand clusters using the Silhouette Score.
3. Generate the initial demand clusters using constrained K-means subject to the prescribed minimum and maximum cluster sizes.
4. Set CurrentClusters ← InitialClusters and t ← 1.
5. WHILE t ≤ T DO.
6. Set AcceptedTransfers ← 0.
7. Solve the stochastic supply chain cost-minimization model using CurrentClusters, the product-routing classes, and the scenario-dependent network data.
8. Obtain the optimized allocation, shipment, inventory, shortage, vehicle-based shipment, and active-link decisions.
9. For each cluster c, calculate the probability-weighted expected shortage rate:
  SR(c,t) ← ExpectedUnmetDemand(c,t) / ExpectedDemand(c,t)
  If ExpectedDemand(c,t) = 0, set SR(c,t) ← 0.
10. Classify each cluster as:
  I. High-performing, if SR(c,t) < LR.
  II. Acceptable, if LR ≤ SR(c,t) ≤ UR.
  III. Underperforming, if SR(c,t) > UR.
11. WHILE at least one high-performing cluster and one underperforming cluster exist
  AND AcceptedTransfers < Nmax DO.
12. Rank all stores assigned to underperforming clusters in descending order of their probability-weighted expected unmet demand.
13. For each candidate store, rank the high-performing clusters in ascending order of distance from that store.
14. Search the ranked store-destination pairs and select the first pair satisfying all of the following conditions:
  I. The destination cluster does not exceed its maximum size after the transfer.
  II. The origin cluster does not fall below its minimum size after the transfer.
  III. The transfer distance does not exceed Rmax.
  IV. Facility-capacity and network-feasibility constraints remain satisfied.
15. IF a feasible store-destination pair exists THEN.
16. Transfer the selected store from the origin cluster to the destination cluster.
17. Update the memberships and centers of the affected clusters.
18. Set AcceptedTransfers ← AcceptedTransfers + 1.
19. Re-solve the stochastic supply chain model using the updated cluster configuration.
20. Recalculate the expected shortage rates and update the cluster classifications.
21. ELSE.
22. Terminate the cluster-improvement procedure for period t.
23. END IF.
24. END WHILE.
25. Set FinalClusters(t) ← CurrentClusters.
26. Store the optimized decisions associated with FinalClusters(t).
27. IF t < T THEN.
28. Set CurrentClusters ← FinalClusters(t).
29. Set t ← t + 1.
30. ELSE.
31. Terminate the procedure.
32. END IF.
33. END WHILE.
34. RETURN the product-routing classes, period-specific final cluster configurations, and optimized supply chain network decisions.
End Algorithm

4 | Numerical Results

In this study, the proposed modeling approach with dynamic clustering was implemented to analyze cost trends over a 12-month horizon, involving 3 scenarios, 150 retail stores, 10 central warehouses, and 5 cross-docking centers. The model was implemented in Python using the PYOMO optimization library and solved with the IBM ILOG CPLEX Optimizer. Computational experiments were conducted on a system with an Intel® Core™ i7-12700H processor at 2.30 GHz, 16 GB RAM, and a 64-bit Windows 11 operating system.

As illustrated in *Fig. 3*, total costs without the proposed approach began at 6,678,791,511 Tomans in Month 1 and reached their minimum of 3,637,424,258 Tomans in Month 8. With the proposed approach, costs were consistently lower on average, reaching 3,262,627,081 Tomans in the same month, representing reductions of approximately 10% to 30% in most months. Notably, in Month 3, the proposed algorithm reduced costs from 5,538,913,182 Tomans to 3,751,781,287 Tomans, a saving of 32%. In Month 10, despite cost increases in both cases, the proposed approach better controlled cost escalation and maintained greater stability. In the final months, as demand naturally increases, costs rise in both cases, but the gap between the two approaches demonstrates that the proposed model yields more controlled fluctuations and greater operational stability.

Overall, this analysis clearly shows that the use of the dynamic clustering algorithm and ANN-based decision support leads to significant improvements in cost management, reduction of uncertainty-related risks, and more efficient resource allocation.

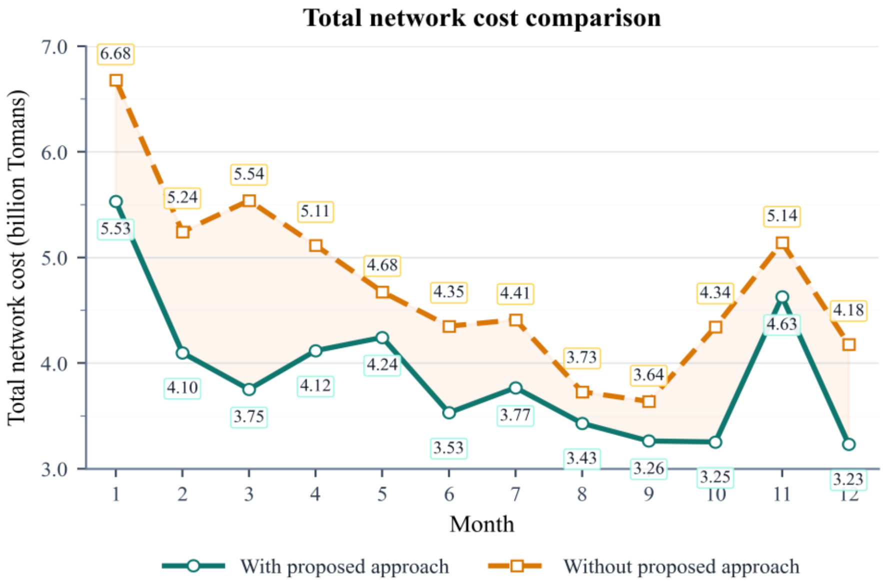

Fig. 3. Comparison of total network cost changes with and without the proposed model under the worst-case scenario.

5 | Conclusion

This study proposed an integrated, data-driven framework for designing a multi-period, bi-level stochastic SC network that combines mathematical modeling with ML techniques to enable more realistic, flexible, and intelligent operational decision-making. In the first component, an improved Constrained K-Means clustering algorithm was developed and implemented, enabling the allocation of demand points to balanced and controllable service zones. This algorithm not only determines the initial spatial structure of the network but is also updated and reconfigured throughout the planning horizon to reflect changes in demand patterns. Subsequently, ANNs were used for intelligent product classification to accurately determine optimal routing. These two structural inputs are directly incorporated into a multi-level stochastic mathematical model under uncertainty.

The proposed model, by accounting for the dynamic and complex nature of SC, achieved significant improvements in total network costs and resource allocation efficiency, and substantially enhanced the system's capacity to respond to demand fluctuations and environmental changes. Furthermore, the proposed framework, by introducing cluster stability indicators and a store reallocation mechanism based on shortage rates, lays the groundwork for the gradual improvement of the network structure. For future development, several research directions can be considered: extending the model to perishable products or those with seasonal demand; employing reinforcement learning algorithms for adaptive decision-making in environments with demand shocks; and designing real-time frameworks based on online data that can automatically update the network structure in response to sudden changes.

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Data Availability

The data used in this study are available from the corresponding author upon reasonable request.

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