Advances in Consumer Research
https://acr-journal.com/
Volume-3 | Issue-3 | March 2026

Original Researcher Article

A Data-Driven Multi-Echelon Supply Chain Optimization Model and Cluster-Based Analysis in India's Public Paddy Distribution Network

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ABSTRACT
Effective management of public food distribution networks has assumed significance in maintaining the objectives of food security, and cost-effectiveness particularly in the agrarian economy of demand uncertainty and infrastructural bottlenecks. This paper proposes a multi-echelon linear programming approach, integrated with cluster analysis, to optimize the supply chain of paddy in the Food Corporation of India (FCI) in the Sambalpur area of the state of Odisha. The proposed method considers the process of flowing paddy from the millers to the depots, and from depots to the central pool, taking into consideration the associated handling charges of procurement, transportation, milling, and storage. Employing the official data of the FCI for the year 2024-2025, the problem has been identified to arrive at the optimum network of the proposed approach, resulting in the lowest total cost of the network considering the projected demand. A supporting cluster analysis finds a level of heterogeneity for the depots, enabling the grouping of the depots according to efficiency and thus facilitating specific operational intervention. Sensitivity and relative analysis show the performance to strongly vary with demands and to remain relatively insensitive to supplies and costs, with the optimal solution remaining more-or-less unchanged. The results and implications help to address the concerns for increased operational efficiencies, demands, and planning in the public food chains.
Keywords: Multi-echelon supply chain; Public food distribution; Linear programming; Sensitivity analysis; Cluster analysis; Agri-food logistics

INTRODUCTION:

Managing the supply chain is very important for ensuring the smooth flow of goods from the producer to the consumer in agrarian countries, where the supply of perishable products such as "paddy" on a day-to-day basis is of prime importance. Multi-echelon supply chains, which entail complex procurement, storage, and distribution processes in the supply network, are usually characterized by inherent uncertainty in the areas of demand and supply chains (Gupta, 2023; Sharma et al., 2023).

The prevailing supply-chain model of major cereal grains including paddy, in India includes a blended structure that balances between the state-procured warehouse and privately-owned self-storage system. The empirical analysis conducted at the sub-national system, specifically in the state of Odisha, shows that seasonal variations, insufficient warehousing, and logistical constraints sometimes affect the throughput efficiency of such networks (Odisha State Civil Supplies Corporation Limited, 2022). Within such limits, the depot-grouping strategy has come up as a relevant mechanism of consolidating and strategically maintaining storage resources in a geographical area, hence simplifying operations and reducing transportation costs. This method can be deployed in combination with traditional methods of supply-chain diagnostics to drive a holistic optimisation of inventory management, freight routing, and warehousing, which will eventually lead to higher productivity and performance (Gupta, 2023; Sharma et al., 2023).

The latest developments in artificial intelligence and machine learning have provided new opportunities to ensure the efficiency and sustainability of multi-echelon supply chains. Using AI/ML-based predictive analytics to make decisions about the demand, potential disruptions, routing and outliers in the conditions of the storage, it is possible to decrease the need of human intervention in the supply-chain decision making (Zhang et al., 2020). The application of this combined model to paddy distribution, especially by creating clusters of depots to plan a multi-echelon, can provide one of the most effective methods to achieve the goal of realising savings in wastage, better service standards, and the overall food-security network in the regional scale, in the case of Sambalpur, Odisha.

Literature Review

Complexities and costs of multi-echelon supply-chain management, as well as the demanding requirements of resilience and sustainability, make this an area of research area of prime importance. The literature outlines multi-, single-, and transshipment as key approaches to the inventory management methods as determinative instruments to control the stock and cost policies (Sun, 2020). The trade-off between the expenses associated with excess inventory and the consequences of backlogging is one of the essential aspects of decision-making (Farhangi, 2021). Flexible and robust stochastic programming models are used to strengthen resilience in the uncertainty of demand (Almeida et al., 2018). The best formulation of a supply-chain network based on redistribution, aggregation, and mixed-integer linear programming techniques can be used to reduce the overall costs and maximise the levels of service (Alsalem et al., 2019). The model analysis of performance by simulation makes it easy to compare cost versus service trade-offs in the context of different policy frameworks (Eddoug et al., 2018). In the case of perishable goods, having a well-planned storage and management system is very essential in reducing the uncertainties associated with the deterioration process in order to lower costs (M V & V, 2023). Decision-support systems that are based on simulations also aid in the discovery and validation of distribution-inventory management models (Sbai and Boukachour, 2023). Major innovations have been achieved in this field with AI-ML improvements: reinforcement learning strategies can be used to solve multi-objective optimisation problems in uncertain systems (Zhou et al., 2025), hybridisation like LNN-XGBoost can be used to increase order-strategy accuracy and eliminate bullwhip effects (Huang et al., 2025), and robust optimisation can be used to ensure that immunisation-chain networks are resilient to any uncertainty linked to demand variations or product inspection conditions (Alavifard et al., 20 The inventory-management strategy that is based on review even better optimises the performance when the state of demand uncertainty occurs (Guo et al., 2025), whereas the uncertainties in the lead time and the demand, during the lot-size allocation and backlog control, are tackled with the help of the robust scheduling methods (Farhangi, 2021).Besides inventory control applications, clustering has implications in purchasing and distribution networks, as K-means algorithms enhance route optimization and depot usage (Sharma et al., 2023). Models used in depot clustering also allow for green re-design in agri-food chains (Guastaroba & Speranza, 2013). In addition, multi-objective location-route frameworks illustrate hypotheses related to clustering and green outcomes (Calik et al., 2022). Moreover, metaheuristic clustering algorithms have been used for finding optimal solutions in multi-depot routing with applications in urban wastes (Beliën et al., 2014), and decomposition routes used in clustering simplify assignments to depots in multi-period inventory routes (Van Anholt et al., 2015). Fuzzy clustering analysis is helpful in evaluating suppliers and creating product categories in supply chains (Öztayşi & Işık, 2014), and probabilistic clustering analysis enables green assignments in capacity-constrained facilities (Ahmadi-Javid & Seddighi, 2013). Fuzzy demand functions using clustering analysis have been used to optimize timeliness in perishable food transportation (Tavakoli-Moghaddam & Raziei, 2016), and routing using clustering analysis enables green designs in reverse-logistics distribution (Ghezavati & Beigi, 2016).At last, the digital and AI-based innovations are also transforming the agri-food chains, where the use of predictive analytics helps to enhance the ability to respond to disruption (Zhang et al., 2020), artificial intelligence helps to strengthen the demand forecasting and routing (Patel & Desai, 2023), anomaly detection helps to enhance the safety monitoring (Sharma & Gupta, 2025), machine learning helps to enhance the predictive assessment for the food grain supply chain (Yadav et al., 2025), the integration of IoT with ML helps to facilitate the real-time monitoring and shelf-life prediction for the agri-food chains (Sinha et al., 2023), and digital technologies help to enhance the transparency, coordination, and efficiency (Kumar & Singh, 2025). These achievements, along with the contributions of the approached methodology, clearly illustrate that the combination of classical optimization, simulation, clustering, and more advanced AI-based techniques could achieve a remarkable improvement in the efficiency, robustness, and sustainability of multi-

2.1 Gaps Analysis

1. Most of the current literature on multi-echelon supply chains has been concentrated on industrial and business kinds of supply chains. Public food supply chains have not received much attention, in which the complexities and policy constraints are different from those in industrial supply chains and cannot be captured properly in the current literature.

2. There has been limited research work done to assess the applicability of the capacity, holding cost, and different demands toward the flexibility and resilience of optimal solutions for the supply chain problem. This has limited the knowledge associated with the efficiency of the scaled-up food models when operating under dynamic environments.

3. Although clustering algorithms are common in logistics-related tasks such as segmenting, routing, and allocation problems, their utilization in public food distribution networks is an area yet to be fully explored. Not much research work was done to explore where clustering can help to identify latent patterns or variability.

Table 1: Summery Table

Authors	Model	Economic	Social	Environmental	Product	Facility (Level)	Uncertainty	Solution Technique	AI/ ML-based	Clustering-based
Guastaroba & Speranza (2013)	Depot clustering	✓	✓	✓	Agri-food	Depots & farms	Sustainability concerns	Sustainable depot redesign		✓

Authors	Model	Economic	Social	Environmental	Product	Facility (Level)	Uncertainty	Solution Technique	AI/ ML-based	Clustering-based
Ahmadi-Javid &Seddighi (2013)	Probabilistic clustering	✓		✓	General SC	Facilities	Capacity uncertainty	Facility allocation optimization		✓
Beliën et al. (2014)	Meta-heuristics clustering	✓		✓	Urban waste collection	Depots & routes	Routing uncertainty	Clustering metaheuristics		✓
Öztayşi & Işık (2014)	Fuzzy clustering	✓			Supplier networks	Suppliers	Evaluation uncertainty	Supplier evaluation & category formation		✓
Van Anholt et al. (2015)	Decomposition route clustering	✓			General SC	Depots - demand nodes	Inventory-routing uncertainty	Decomposition-based clustering		✓
Tavakoli-Moghaddam & Raziei (2016)	Fuzzy demand clustering	✓		✓	Perishable goods	Warehouses & depots	Demand uncertainty	Fuzzy demand models		✓
Ghezavati & Beigi (2016)	Clustering-based routing	✓		✓	Reverse logistics	Distribution networks	Uncertainty in returns	Reverse logistics design		✓
Zhang et al. (2020)	Predictive analytics	✓		✓	Agri-food	Supply chains	Disruption uncertainty	Predictive resilience modeling	✓	
Calik et al. (2022)	Multi-objective location–routing	✓	✓	✓	General SC	Depots & routes	Sustainability trade-offs	Location-routing optimization		✓
Sharma et al. (2023)	K-means clustering	✓		✓	Procurement-distribution	Depots & routes	Routing uncertainty	Clustering for routing		✓
Patel & Desai (2023)	AI-enabled forecasting & routing	✓		✓	Agri-food	Distribution nodes	Demand uncertainty	AI for forecasting & routing	✓	
Sinha et al. (2023)	IoT–ML integration	✓		✓	Perishable goods	Distribution & storage	Shelf-life uncertainty	IoT–ML monitoring	✓	
Zhou et al. (2025)	Reinforcement learning	✓	✓	✓	General SC	Multi-echelon nodes	Uncertainty in demand	Multi-objective RL	✓	
Huang et al. (2025)	LNN–XGBoost hybrid	✓			General SC	Ordering nodes	Bullwhip effect	AI-hybrid forecasting	✓	
Sharma & Gupta	Anomaly	✓	✓	✓	Food safety	Supply chains	Inspection	AI anomaly	✓	

Authors	Model	Economic	Social	Environmental	Product	Facility (Level)	Uncertainty	Solution Technique	AI/ ML-based	Clustering-based
(2025)	detection						uncertainty	detection		
Yadav et al. (2025)	ML predictive quality	✓		✓	Food grains	Supply chains	Quality uncertainty	ML predictive assessment	✓	
Kumar & Singh (2025)	Digital technologies	✓	✓	✓	Agri-food	Supply chains	Coordination & disruption uncertainty	Digital SC transparency & efficiency	✓	
Present study	Multi-echelon linear programming with cluster analysis	✓	✓		Agri-food (paddy)	Millers, depots & central pool	Capacity, demand & cost uncertainty	Optimization with sensitivity and cluster analysis	✓	✓

2.2 Objectives

1. To propose and optimize a multi-echelon linear programming model of the structural and functional dynamics of the FCI supply chain in Sambalpur, for the levels of central pool, depot, and miller, the primary objective being the minimization of aggregate operational cost, explicitly considering the activities of procurement, transportation, milling, and storage within an integrated decision-making framework.

2. To perform a sensitivity analysis in the model optimized through controlled variations in storage capacity, inventory holding cost, and demand levels with the aim of assessing stability, robustness, and adaptability of the supply chain under alternative policy and operational scenarios, and also to identify the parameters that are most affecting system-wide efficiency and resource utilization.

3. To complement the analysis with cluster analysis that may define similarities and heterogeneities among depots and millers regarding demand patterns, capacity utilization, and cost behavior to drive data-based segmentation and allow for more focused policy intervention in the FCI supply chain.

3.Methodology

3.1 Dataset Information

The proposed research uses data from the Food Corporation of India, obtained through their Odisha Regional Office website at https://fci.gov.in/region/odisha-region/ for the operational year 2024-2025. The Sambalpur District Office, which includes Sambalpur, Bargarh, and Jharsuguda districts, is employed to conduct analysis because of its proximity to additional research themes. The work proposes the development of multi-echelon linear programming along with cluster analysis to ensure the efficiency of cost coordination between millers, depots, as well as the main food pool. The proposed idea specifically concentrates on an economic perspective with cost minimization for food procurements within the proposed model to ensure efficient food security with minimized waste for improved public network performance.

Table 2 : Data Set details

Sl. No.	Variable Name	Description	Category	Coding
1	Depot ID	Unique identification code for each depot	FSD Attabira, FSD Balijhori CWC Bargarh, SWC Attabira SWC Nagenpalli, SWC A. Katapalli, SWC Godbhoga SWC Kendupalli, OSWC Nagenpalli, CWC Kendupalli FSD Hirakud, CWC Kalamati	D1-D12
2	Capacity (MT)	Total storage capacity of each depot	-	-
3	Average Stock (MT)	Average stock level maintained at each depot	-	-
4	Handling Cost (₹/MT)	Handling cost per metric ton at depot	-	-
5	Central Pool ID	Identification number for central pool centers	FCD 1 (Jharkhand), HZD (Jharkhand), DMSJ (Bihar) FCD 2 (Jharkhand), NGRH 1(Jharkhand), JSME 1 (Jharkhand), NGRH 2 (Jharkhand), HZBN (Jharkhand), JSME 2 (Jharkhand), DUMK 1 (Jharkhand), DUMK 2(Jharkhand), FCMI (Bihar)	CP1-CP12
6	Distance (km)	Distance between central pool and depot	-	-
7	Cost per metric ton (₹)	Transportation cost per metric ton between pool and depot	-	-
8	Demand (metric ton)	Total demand in metric ton for the depot from central pool	-	-
9	Total Cost (₹)	Total transportation cost from central pool to depot	-	-
10	Miller ID	Unique identification code for each miller	Shree Rajeswari Rice mill, maa Laxmi rice mill Bargarh, bholeshankar rice ind Sambalpur, hanuman food products Bargarh, om ramchandi rice mill Bargarh, Annapurna rice mill Bargarh, lath industries bargah, kaleswar rice mill bargarh, sakhambari hi tech sambalpur, bhagabati rice mill bargarh ab ind sambalpur, srinivash rice mill bargarh	M1-M12
11	Distance (km)	Distance between miller and depot	-	-
12	Cost per MT (₹)	Transportation or milling cost per metric ton	-	-
13	Maximum Supply (metric ton)	Maximum quantity of supply handled by the miller	-	-

3.2 Cluster Analysis

Clustering methods are widely applied in supply chain and logistics research to identify patterns, segment entities, and support decision-making in complex networks. Among the most widely used methods, the K-means algorithm partitions data into clusters by minimizing the variance within clusters. Its computational efficiency and scalability make it suitable for large datasets, such as customer segmentation, depot allocation, and inventory grouping in multi-echelon supply chains. Nevertheless, K-means is also prone to local minimization with respect to the choice of initial centroids and can adversely influence the quality of the clustering output (Wu et al., 2024; Zhang et al., 2023).

Partitioning Around Medoids (PAM), or k-medoids, is used to overcome part of the weaknesses of K-means by using real data points, or medoids, as centres of the clusters. This method adds resistance to outliers and noisy data, and can be especially useful when interpretability and reliability of cluster representatives is important e.g. in supply chain applications, like cluster membership of a supplier, or when analysing the site of a depot. In addition to its strong points, PAM is more computationally expensive than K-means, which could restrict its use with large datasets (Liu et al., 2023; Mikrou and Sapidis, 2024).

Hierarchical Clustering (HC) forms clusters in a hierarchical (bottom-up and top-down) fashion to create a dendrogram that graphically displays the relationships between clusters. The HC algorithm does not assume a set number of clusters, as does K-means or PAM, allowing it to be used in an exploratory manner and be able to detect multi-level structures. This helps it to deal with tiered supplier networks or demand patterns or multi-echelon supply chain network complexity (Lu and Dong, 2023; Zhang et al., 2023). Combining K-means with PAM and HC complement each other, and combined with optimization or simulation frameworks, they optimize, improve resiliency, and sustainability of supply chain decision-making.

Table 3: Assumptions and Notations

Indices		i € I	:	Set of millers
		j € J	:	Set of depots
		k € K	:	Set of central pool
Parameters	Supply side	S_i	:	Supply capacity of miller I (MT)
		C_{ij}	:	Transport cost per MT from miller i to depot j
		D_{ij}	:	Distance between miller i and depot j
	Intermediate node (depot)	Cap_j	:	Maximum storage capacity of depot j (MT)
		H_j	:	Handling cost per MT at depot j

	Demand side	D_k	:	Demand recruitment at central pool k (MT)
		T_{jk}	:	Transport cost per MT from depot j to central pool k
		D_{jk}	:	Distance between depot j and central pool k
Decision Variable		$X_{ij} \geq 0$	:	Quantity shipped from miller i to depot j (MT)
		$Y_{jk} \geq 0$	:	Quantity shipped from depot j to central pool k (MT)

3.3 Mathematical Model

The model used in the research is a deterministic, single period, cost minimization multi-echelon linear programming that is based on the aim of maximizing the efficiency of the paddy supply chain of the Food Corporation of India. The mathematical formulation presented reflects the process-flow of commodities going down the commodity passing down the miller unit to depot unit to the central pool points.

3.4 Objective Function

The objective is to minimize the total system cost, comprising transportation costs across echelons and handling costs at depots:

$$Z = \sum_{i \in I} \sum_{j \in J} C_{ij} X_{ij} + \sum_{j \in J} \sum_{k \in K} T_{jk} Y_{jk} + \sum_{j \in J} H_j \left(\sum_{i \in I} X_{ij} \right)$$

Subject to:

Supply constraints

$$\sum_{j \in J} X_{ij} \leq S_i \forall i \in I$$

Depot capacity constraints

$$\sum_{i \in I} X_{ij} \leq Cap_j \forall j \in J$$

Flow conservation at depots

$$\sum_{i \in I} X_{ij} = \sum_{k \in K} Y_{jk} \ \forall j \in J$$

Demand satisfaction

$$\sum_{j \in J} Y_{jk} = D_k \forall k \in K$$

Non-negativity

$$X_{ij}, Y_{jk} \geq 0$$

The proposed formulation will aim at reducing the overall operation cost of the presented FCI supply chain and at the same time allowing viable and balanced material movements at all levels. By so doing, the structural interdependences of public food distribution networks are represented by a common objective of transportation and

handling decisions under constraints of supply, capacity, flow-balance, and demand. The resultant flow patterns and cost that have been optimized through this formulation give feeds to further sensitivity and cluster analysis that seek to establish performance heterogeneity and policy-relevant information

Table 4: Constraints

Supply Constraints (millers)	:	$\sum_{j \in J} X_{ij} \leq S_i \forall\ i \in I$
Depot capacity Constraints	:	$\sum_{i \in J} X_{ij} \leq Ca_j \forall\ j \in J$
Flow balance at depots (inflow=outflow)	:	$\sum_{i \in J} X_{ij} = \sum_{i \in J} Y_{jk} \ \forall\ j \in J$
Demand satisfaction at central pool	:	$\sum_{j \in J} Y_{jk} = D_k \forall\ k \in K$
Non negativity	:	$X_{ij}, Y_{jk} \geq 0$

3.5 Case Study on FCI

The Food Corporation of India (FCI), incorporated in 1965 by the Food Corporations Act, is the backbone of the food security system in India. Its prime activities involve procurement, storage, as well as the distribution of food grains to stabilize prices and maintain buffer stocks. Optimal depot management is required to achieve the aims of the Public Distribution System and other welfare programs. In the Odisha State, the FCI is assisting in managing procurement as well as distribution activities along with the Odisha State Civil Supplies Corporation Limited. Geographical diversity and changes in seasonal crop production in Odisha make the optimal management of depot activities significant to ensure on-time delivery and the avoidance of wastages. Sambalpur is a pivotal zone in Odisha that constitutes a significant part of the storage and subsequent distribution chain for FCI. There are several other depots in this region that act as intermediate points for the storage of food grains, thus helping in the smooth flow of grains from procurement points to respective sales points.Depot clustering is relevant in this regard because it enables depots that are geographically close to be clustered strategically. Depot clustering can thus ensure that FCI has an optimized ability to react to demand variability and maximize reduced spoilage by understanding demand variability across regions, as well as the capacity of infrastructure to support such demand, as suggested by Sharma et al. (2023; Guastaroba & Speranza, 2013).

The design of multi-echelon supply chain is therefore very essential when used by FCI in order to manage movement of food grains at all the levels of its hierarchical structure, which includes procurement centres, regional warehouses, and lastly the retail outlets. Multi-echelon strategies plan inventory, storage, and transportation decisions at each of the levels in a trade-off between cost effectiveness and service rate, and resilience to disruptions. These researches presuppose much value to FCI in Sambalpur because they offer a point of reference on addressing some of the generic issues that most supply chains encounter, including stockouts and overstocking, and delays in the distribution process. Multi-echelon planning enables sufficient supplies to the regions with high demands without necessarily reducing the efficiency of the networks. Beyond this, AI and machine learning methods with depot clustering and multi-echelon design can be used to predict the demand, optimize routes in real-time, and identify anomalies regarding storage conditions to have better performance outcomes in terms of operational and food security.

The use of the insight so obtained through the depot clustering and multi-echelon supply chain researches may help FCI in making sure to optimize storage utilization, minimize operational cost, maximize service reliability and resilience in the food grain delivery system of the Sambalpur area. Along with the purpose of increasing the efficiency of logistics, these methods are also of great importance in the scope of other food security goals in India and thus are among the most important areas of research and methods of implementation into the public distribution networks.

3.6 Supply Chain Management of FCI

The Food Corporation of India (FCI) has a multi-level system of supply chain which distributes the supply of paddy and rice among procurement units, millers and regional depots to the central pool. The supply chain is not always distant and seasonal and thus is a complex system that needs careful planning and coordination of the Food Corporation of India and the Odisha State Civil Supplies Corporation to guarantee smooth flow of the stock and the quality of the food supplied. The intricacy of the supply chain system therefore requires the necessity of the optimal distribution of resources, and making sound decisions.

Figure 1 In Figure 1 below (The integrated GIS-based three-echelon rice supply chain network) we have the spatial structure and directional movement of food grains in Odisha, Jharkhand and Bihar. The higher echelon is the upstream millers, which are found majorly in the Bargarh-Sambalpur district of Odisha, because of the regionalization of the rice milling plants. These millers distribute processed rice to a network of depots that are located in Odisha and they also serve as intermediate consolidation and storage sites. High-level of inbound flows convergence at the depot level underscores the vital buffering and aggregation of inbound flows in the supply chain.

The downstream echelon includes central pool sites that are located in Jharkhand and Bihar which are points of end aggregation and demand delivery points of the public distribution system. Directional arrows show the one directional movement of rice between millers and depots and then to central pools, which clearly shows the inter-state in the case of commodities. Some of the depots have more than one outbound connection indicating that they are critical consolidation centres in the optimal structure of the network. The GIS overlay of state boundaries gives a spatial background, putting emphasis on the inter-regional character of food grain allocation without contradicting the presumed multi-echelon linear programming framework

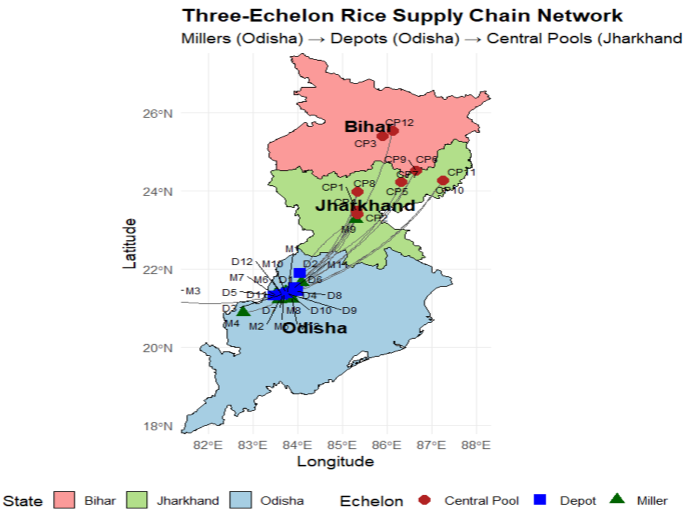

Figure 1: FCI Paddy Distribution Network

3.7 Dataset of FCI

The dataset utilized in this research is sourced from official operational records of the Food Corporation of India for the 2024–2025 procurement year. It encompasses miller-wise supply capacities, depot-level storage constraints, handling charges, inter-facility transportation distances, and central pool demand requirements for the Sambalpur region. The dataset reflects actual operational conditions and is structured to enable multi-echelon optimization and cluster-based analytical modelling.

Table 5:Miller Data

Miller ID	Depot_ID	Distancekm	CostperMT	MaxSupplyMT
M1	D5	68.8	445	6582
M2	D3	100.7	535	2756
M3	D6	34.6	337	2085
M4	D11	99	529	1873
M5	D3	28	300	1546
M6	D11	64.6	434	1536
M7	D7	17.9	247	1373
M8	D10	31.3	321	1192
M9	D2	19.1	258	1131
M10	D9	9.5	205	983
M11	D4	56.4	411	943
M12	D8	16.8	295	918

Table 6: Depot Data

Depot ID	Location	CapacityMT	Avg. Stock MT	HandlingCostMT
D4	FSD Attabira	156600	10440	24832.15
D5	FSD Balijhori	651430	50110	19049.46
D1	CWC Bargarh	151380	10092	24873.2
D9	SWC Attabira	60784	7598	12331.96
D12	SWC Nagenpalli	483575	19343	38705.75
D8	SWCA. Katapalli	361746	16443	32120.3
D10	SWC Godbhoga	43848	6264	11119.59
D11	SWC Kendupalli	125280	12528	18275.7
D7	OSWC Nagenpalli	290145	19343	23879.8
D3	CWC Kendupalli	183570	18357	19542.4
D6	FSD Hirakud	344550	22970	21937.04
D2	CWC Kalamati	198360	13224	23137.75

Table 7: Central Pool Data

Depot ID	Central Pool ID	Distance km	Cost per MT	Demand MT	Total Cost
D4	CP1	498	896	782.89	701783
D5	CP2	470	846	1949.53	1649302
D1	CP3	520	936	2740.14	2564771
D9	CP4	250	450	753.2	338940
D12	CP5	270	486	1882.98	915128
D8	CP6	516	929	908.21	843545
D10	CP7	500	900	1819	1637100
D11	**CP8**	500	900	2737.48	2463732
D7	CP9	264	475	1004.27	477229
D3	CP10	250	450	1631.99	734396
D6	CP11	500	900	2734.93	2461437
D2	CP12	500	900	2636.34	2372706

3.8 Cluster Analysis of FCI

Complementary to the multi-echelon optimization results, latent structural heterogeneity among depots has been unravelled by cluster analysis based on key operational indicators: storage capacity, average inventory levels, handling costs, utilization rates, and transportation costs. This cluster analysis is not comparative in algorithmic terms but aims at operationally meaningful groupings of depots that can support targeted managerial interventions and policy formulation within the Food Corporation of India supply chain.

The appropriate number of clusters was determined using the silhouette method. Figure 2 presents the silhouette plot for alternative cluster specifications and indicates that a three-cluster solution maximizes the average silhouette width. This result suggests that partitioning the depots into three groups yields the most internally cohesive and externally well-separated structure, while higher values of $k$lead to over-segmentation and diminished interpretability. Accordingly, a three-cluster configuration was adopted for subsequent analyses.

In order to facilitate the understanding of the multivariate phenomenon of depot performance, a representation based on clusters using the principal components is provided in Figure 3, where the top two principal components account for more than 80% of the total variability. Three clusters are identified based on this representation. A cluster that contains most of the facilities is identified in which facilities are closely grouped around the origin, thus suggesting that these facilities have a similar level of moderate performance. The second cluster contains only one facility, which is located in an extreme corner, thus suggesting the presence of an outlier or a facility that has an operating pattern that is quite different from others. The third cluster contains facilities that consistently differ from the Reference Group.

The operational interpretation of these clusters is further clarified in Figure 4, which maps depot utilization against average transportation cost. The analysis reveals three distinct performance profiles. One cluster is characterized by moderate to high utilization and relatively low transportation costs, identifying these depots as the most operationally efficient within the network. A second cluster exhibits lower utilization but comparatively stable cost performance, indicating underutilized yet operationally stable facilities. In contrast, the third cluster displays both low utilization and high transportation costs, signalling pronounced inefficiencies and potential structural or locational disadvantages that warrant targeted corrective action.

The hierarchical clustering outcome, as depicted in Figure 5, offers further evidence to substantiate clustering into three groups. The tree or dendrogram indicates sharp points of separation between high-efficiency, moderate-efficiency, and low-efficiency depots, gauged by the point where each depot is connected. Depots connected at low linkages show high levels of similarity and efficiency, whereas those connected at high points reveal high levels of dissimilarity with low efficiency.

Finally, the results are validated for their robustness with respect to the proposed clustering structure using Partitioning Around Medoids, and the results are given in Figure 6. The three-cluster solution is again recovered, and the difference between the large core cluster and the small cluster that has different operational features, and the outlier depot, is clearly marked. The fact that all four different analyses are paralleled gives a good indication that the three-cluster solution is robust.

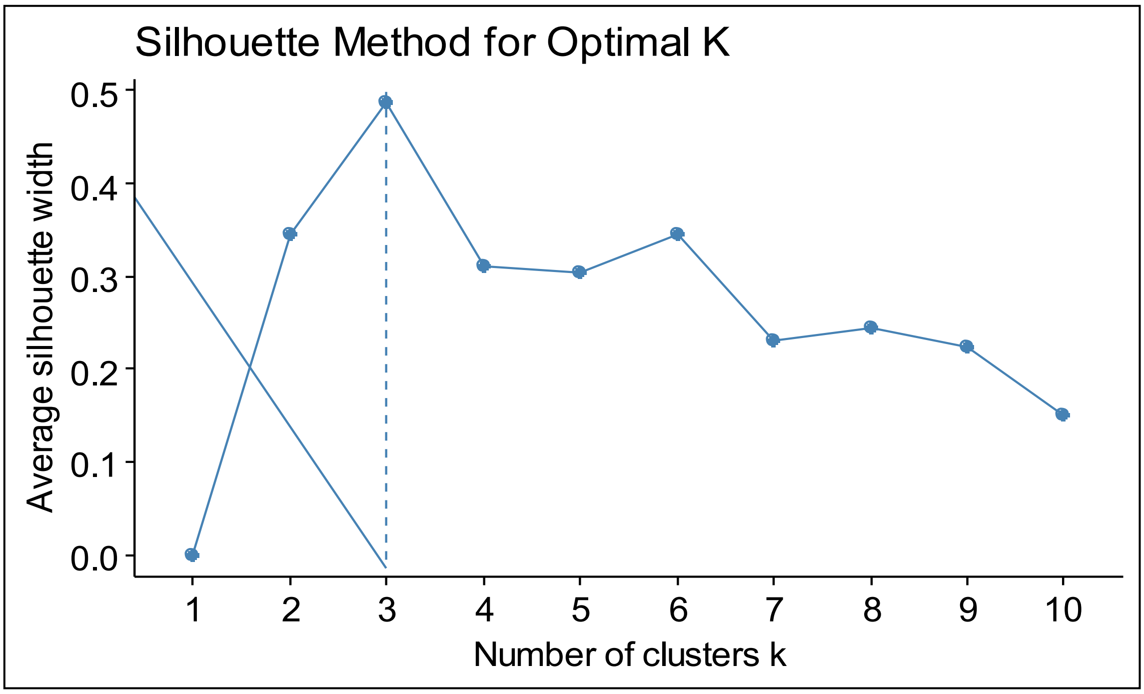

Figure 2: Silhouette Method

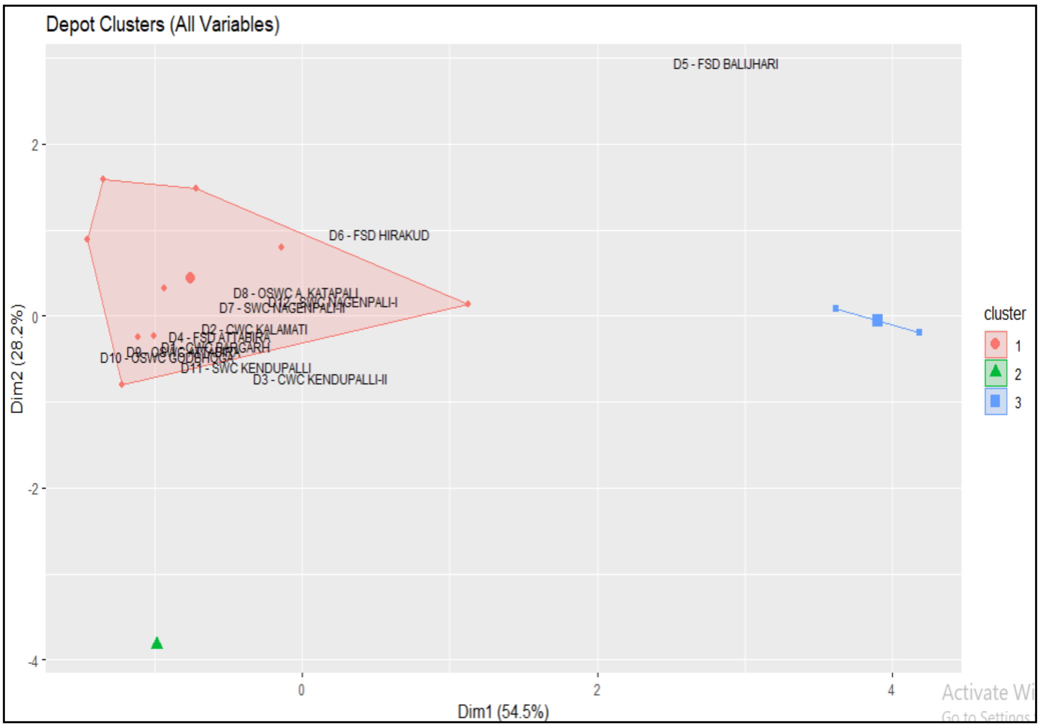

Figure 3: Multivariate Cluster analysis

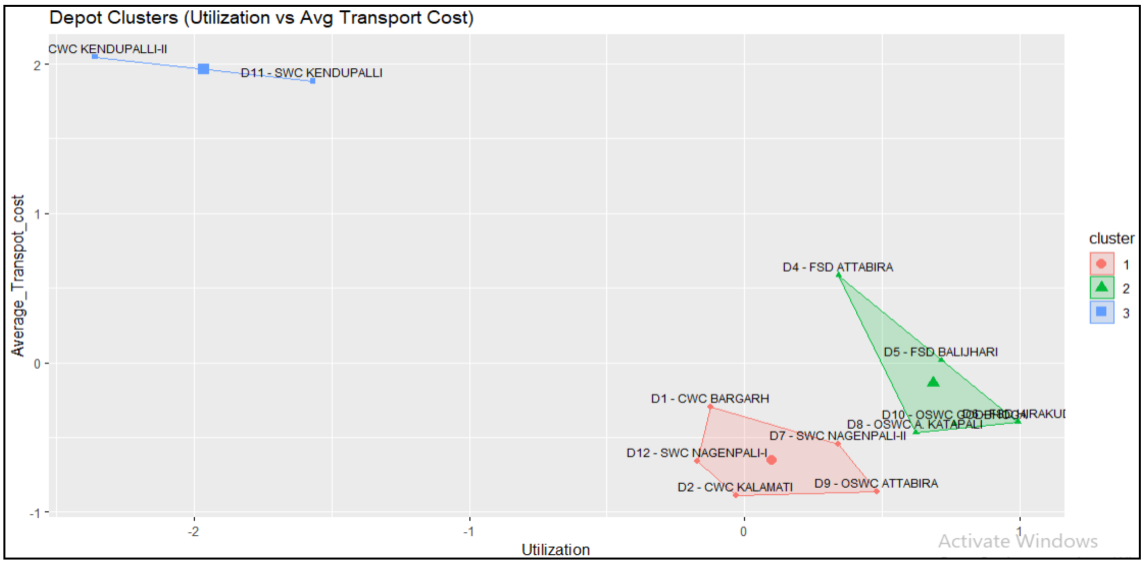

Figure 4: Depot Clusters (Utilization Vs Avg. Transport Cost)

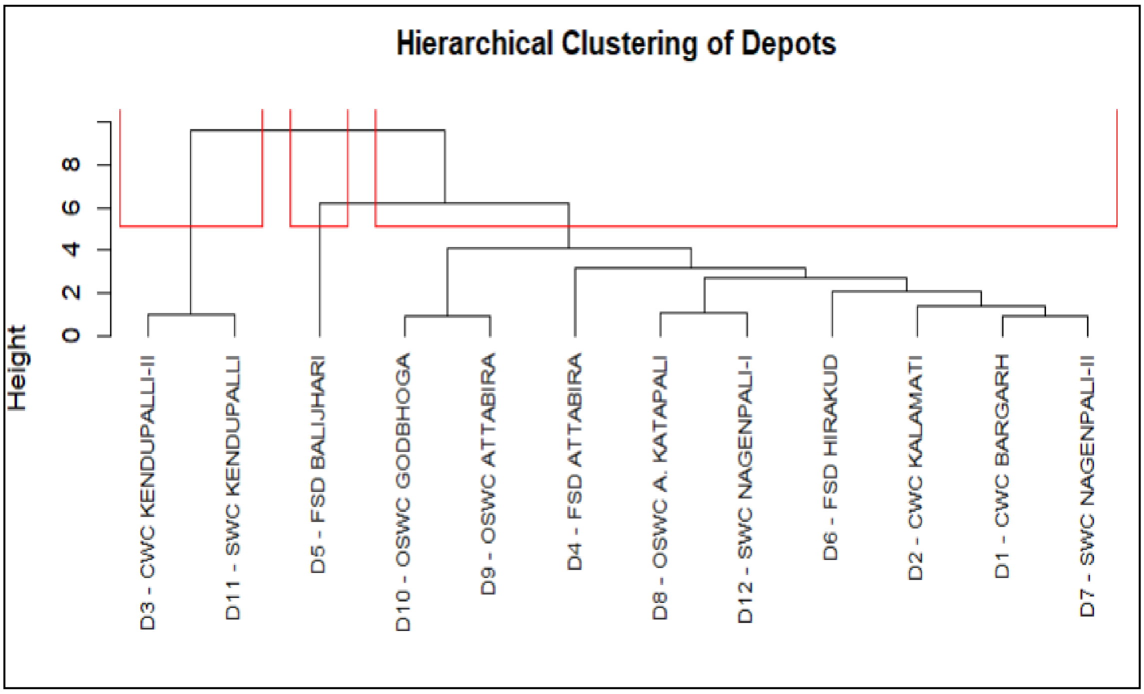

Figure 5: Hierarchical Clustering of Depots

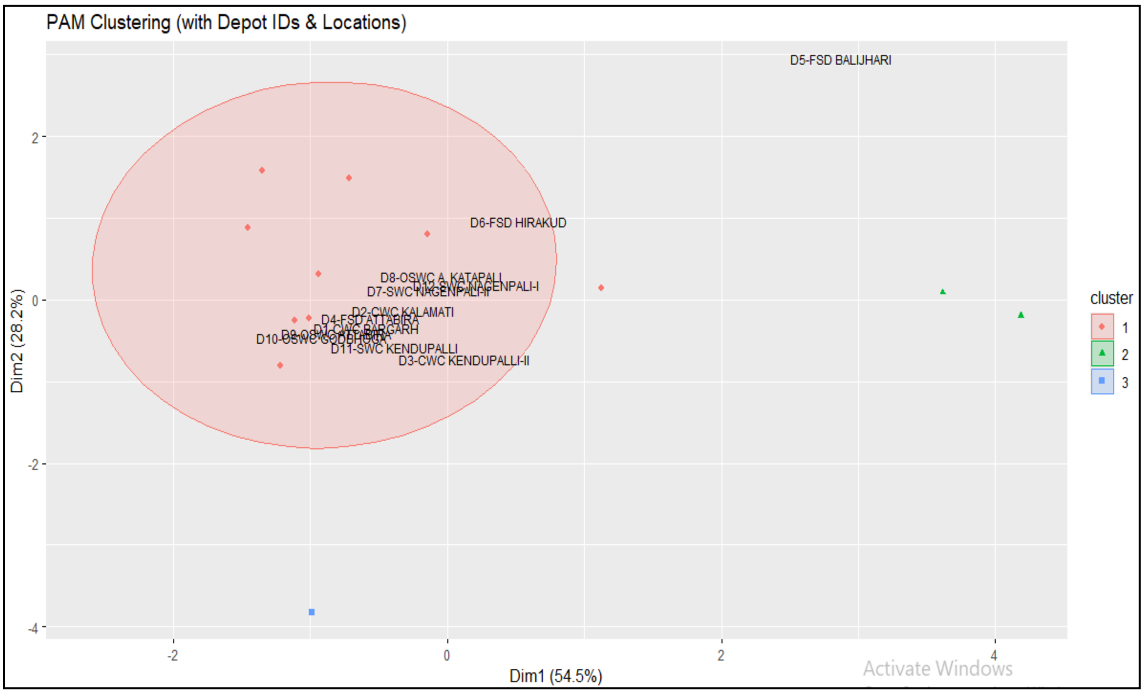

Figure 6: PAM Clustering

4.Customized Supply Chain Model of FCI

The operational dynamics of the FCI paddy distribution network are represented through a customized multi-echelon linear programming model. The formulation links procurement, storage, and distribution decisions within a unified cost-minimization framework.

$$\text{Min } Z= \sum_{i=1}^{12}\sum_{j=1}^{12} \boldsymbol{c_{ij}\, x_{ij}} + \sum_{j=1}^{12}\sum_{k=1}^{12} \boldsymbol{T_{jk}\, Y_{jk}} + \sum_{j=1}^{12} \boldsymbol{H_j} + (\sum_{j=1}^{12} \boldsymbol{X_{ij}})$$

The customized multi-echelon model developed for and applicable to the Food Corporation of India represents in a simplified linear programming format the stepwise movement of paddy from millers to depots and then to the central pool points. The purpose of formulation is to optimize and minimize system cost, thereby considering transportation between echelons and handling charges at depots related to material movement. The customized multi-echelon model is programmed to satisfy constraints related to supply, capacity, flow balance, and demand to provide an optimal structure to the FCI distribution system.

5.Results and Analysis

Empirical results derived from the multi-echelon linear programming model applied to the FCI paddy distribution network are discussed in this section. The findings illustrate consolidation behavior, flow patterns, and overall cost performance.

5.1 Multi-echelon Linear Programming Model

Results from the multi-echelon linear programming model are presented within this section for the relevant analytical investigations that involve optimization-related appraisals of material movements, relative analyses for general robustness measures of the solution, and cluster analyses complementing the performance assessment of the depot facilities.

The multi-echelon solution results in a strongly centralized and optimized solution in which all miller outputs are consolidated into a single common depot, D10, before being delivered to the central pool. Depot D10 is determined to be the only optimal consolidation point for minimization of cost due to its advantageous transport cost, handling, and storage capacity. All millers are utilized at capacity, and the minimum total system cost of ₹267,097,900 clearly portrays economies of scale, which have been supported in earlier research studies for two-echelon and multi-echelon networks with linear cost structures.

Tables 9 and 10 jointly indicate a fully centralized allocation pattern within the network. All millers direct their entire output to Depot D10, and D10 alone satisfies the complete demand of all central pools, with no flow routed through other depots. This configuration reflects a strongly consolidated structure in both inbound and outbound movements. The results imply that, under the prevailing cost and capacity parameters, D10 provides the most cost-efficient routing alternative. Consequently, D10 functions as the dominant hub in the optimized multi-echelon system.

The concentration of flows at Depot D10 emerges as a direct consequence of the model structure. Since transportation and handling costs are modelled as linear functions and no fixed operating costs are imposed on depot utilization, the optimization procedure allocates shipments to the location offering the lowest total marginal cost. Given that Depot D10 satisfies overall capacity requirements while exhibiting comparatively lower combined inbound and outbound costs, it becomes the preferred consolidation point. This outcome reflects the cost-minimizing behavior typical of linear multi-echelon supply chain models, where economies of consolidation are not offset by congestion or activation penalties. Therefore, the prominence of D10 represents an economically rational solution under the deterministic assumptions of the present formulation rather than an irregular computational artifact.

Table 8: Multi echelon Linear Programming Model

Division	Iterations	Elapsed runtime (sec)	Total Variables	Total Constraints	Total Non zeros	$x_{ij} \forall j = 7$	$x_{ij} \forall \neq 7$	$y_{ij} \forall j = 7$	$y_{ij} \forall \neq 7$	TSCC
Sambalpur	60	0.39	291	52	1158	[5244.960,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	0	[782.89,1949.30,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	0	267097900.00

Table 9: Optimized Inbound Depot Allocation

	D4	D5	D1	D9	D12	D8	D10	D11	D7	D3	D6	D2
M1	0	0	0	0	0	0	5244.960	0	0	0	0	0
M2	0	0	0	0	0	0	2756	0	0	0	0	0
M3	0	0	0	0	0	0	2085	0	0	0	0	0
M4	0	0	0	0	0	0	1873	0	0	0	0	0
M5	0	0	0	0	0	0	1546	0	0	0	0	0
M6	0	0	0	0	0	0	1536	0	0	0	0	0
M7	0	0	0	0	0	0	1373	0	0	0	0	0
M8	0	0	0	0	0	0	1192	0	0	0	0	0
M9	0	0	0	0	0	0	1131	0	0	0	0	0
M10	0	0	0	0	0	0	983	0	0	0	0	0
M11	0	0	0	0	0	0	943	0	0	0	0	0
M12	0	0	0	0	0	0	918	0	0	0	0	0

Table 10 : Optimized Outbound Depot Allocation

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
D4	0	0	0	0	0	0	0	0	0	0	0	0
D5	0	0	0	0	0	0	0	0	0	0	0	0
D1	0	0	0	0	0	0	0	0	0	0	0	0
D9	0	0	0	0	0	0	0	0	0	0	0	0
D12	0	0	0	0	0	0	0	0	0	0	0	0

D8	0	0	0	0	0	0	0	0	0	0	0	0
D10	782.89	1949.30	2740.14	753.2	1882.98	908.21	1819	2737.48	1004.27	1631.99	2734.93	2636.34
D11	0	0	0	0	0	0	0	0	0	0	0	0
D7	0	0	0	0	0	0	0	0	0	0	0	0
D3	0	0	0	0	0	0	0	0	0	0	0	0
D6	0	0	0	0	0	0	0	0	0	0	0	0
D2	0	0	0	0	0	0	0	0	0	0	0	0

5.2 Comparative Analysis

Comparative analysis will then be used to compare the relative sensitivity to structure of this multi-echelon model to that of other models within this context. Specifically, this tool will be used to assess how relaxing a set of constraints impacts this model versus other models. With this tool, one will be able to gain an understanding of which specific constraints play a bigger role in feasible and optimal models.

Table 11 presents the results of such a comparison. Relaxing miller supply constraints decreases total system cost but generates allocation patterns that are far from realistic operating conditions, which further suggests that the availability of supplies is a major driver behind feasible solutions. Conversely, relaxing depot capacity constraints does not affect the optimum solution, since available storage capacity at least around the primary depot is adequate under current conditions. Deleting central pool demand constraints yields infeasible solutions, which proves that demand satisfaction is a principal driver for defining network extent and flow direction. Similarly, the relaxation of the flow-balance constraints results in structurally incoherent solutions, which further underlines the need for conservation relationships to maintain coherence across the multi-echelon network.

Table 11: Comparative Analysis

Constraint	Iterations	Elapsed runtime (sec)	Total Variables	Total Constraints	Total Non zeros	x_{ij}	y_{jk}	TSCC
No Supply	49	0.14	291	40	1014	2158096	782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34	264736700.00
No Capacity	60	0.09	291	40	1014	5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918	782.89,1949.53,2740.14,753.2,1882.98,908.21,1819.9,2737.48,1004.27,1631.99,2734.93	267097900.00
No demand	0	0.09	291	40	1014	0	0	0
No inflow =no outflow	0	0.09	291	40	870	0	782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34	190277000.00

5.3 Sensitivity Analysis

Parametric sensitivity analysis is employed to analyse variations in key parameters of the model, which are supply, cost, and demand within the context of the optimal solution. The sensitivity of the network structure can be determined by identifying the parameters that have the maximum influence on cost behavior.

Table 12 presents a summary of how changes in the parameters related to miller supply, cost, and demand affect the optimal solution. The sensitivity analyses revealed that changes in miller supply resulted only in changes in the values related to flows. There was no structural sensitivity related to changes in transportation and handling cost, as indicated by insignificant changes in both allocation and total cost values. The changes in demand at a central pool level resulted in a high sensitivity value related to the total cost, indicating that demand is the source of sensitivity with a stable structural solution.

Table 13 presents the relative sensitivity impact of different parameters in the model on the value of the objective. Demand parameters have been found to have the maximum sensitivity impact, with minor changes resulting in comparatively large variations in the total system cost, thus indicating high sensitivity. Supply parameters were found to have a moderate impact in determining the level of costs, but not affecting the optimal networks. Transportation/handling parameters were found to have a negligible impact on allocation solutions as well as the value of the objective. In general,

these results suggest that the performance is demand-driven, but the optimal networks are insensitive to the variability in parameters

Table 12 : Sensitivity Table

Parameter	Decision Variables	-5%	-3%	0%	+5%	+10%
S_i	Iterations	60	60	60	60	60
	Elapsed runtime (sec)	.11	0.09	0.39	.11	.11
	Total Variables	291	291	291	291	291
	Total Constraints	52	52	52	52	52
	Total non-zeros	1158	1158	1158	1158	1158
	$x_{ij} \forall j = 7$	[6061.76,2618.2,1980.75,1779.35,1468.7,1459.2,1304.35,1132.4,1074.45,933.85,895.85,872.1]	[5735.04,2673.32,2022.45,1816.81,1499.62,1489.920,1331.81,1156.24,1097.07,953.51,914.71,890.46]	[5244.960,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[4428.16,2893.8,2189.25,1966.65,1623.3,1612.8,1441.65,1251.6,1187.55,1032.15,990.15,963.9]	[3611.36,3031.6,2293.5,2060.3,1700.6,1689.6,1510.3,1311.2,1244.1,1081.3,1037.3,1009.8]
	$x_{ij} \forall j \neq 7$			0	0	0
	$y_{ij} \forall j = 7$	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.30,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737,1004,1631,2734,2636]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]
	$y_{ij} \forall j \neq 7$	0	0	0	0	0

	TSCC	267307900.0	267223900.0	267097900.00	266887900.0	266678000.0
Cap_j	Iterations	60	60	60	60	60
	Elapsed runtime (sec)	.11	.11	0.39	.11	.10
	Total Variables	291	291	291	291	291
	Total Constraints	52	52	52	52	52
	Total Non zeros	1158	1158	1158	1158	1158
	$x_{ij} \forall j = 7$	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.960,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]
	$x_{ij} \forall j \neq 7$	0	0	0	0	0
	$y_{ij} \forall j = 7$	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.30,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2790.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]
	$y_{ij} \forall j \neq 7$	0	0	0	0	0
	TSCC	267097900.0	267097900.0	267097900.00	267097900.0	267097900.0
h_j	Iterations	60	60	60	60	60
	Elapsed runtime (sec)	.11	.13	0.39	.11	0.09
	Total Variables	291	291	291	291	291
	Total Constraints	52	52	52	52	52
	Total Non zeros	1158	1158	1158	1158	1158
	$x_{ij} \forall j = 7$	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.960,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.96,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]

	$x_{ij} \forall j \neq 7$	0	0	0	0	0
	$y_{ij} \forall j = 7$	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.30,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[782.89,1949.53,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]
	$y_{ij} \forall j \neq 7$	0	0	0	0	0
	TSCC	255099300	259898800	267097900.00	279096500	291095000
de_k	Iterations	60	60	60	60	180
	Elapsed runtime (sec)	.10	.10	0.39	.11	12.27
	Total Variables	291	291	291	291	291
	Total Constraints	52	52	52	52	52
	Total Non zeros	1158	1158	1158	1158	1158
	$x_{ij} \forall j = 7$	[4165.912,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[4597.531,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[5244.960,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[6324.008,2756,2085,1873,1546,1536,1373,1192,1131,983,943,918]	[6582,2756,2085,1873,1546,1536,1373,1192,1131,983,943]
	$x_{ij} \forall j \neq 7$	0	0	0	0	0
	$y_{ij} \forall j = 7$	[743.7455,1852.053,2603.133,715.5400,1788.831,862.7995,1728.050,2600.606,954.0565,1550.390,2598.184,2504.523]	[759.4033,1891.044,2657.936,730.6040,1826.491,880.9637,1764.430,2655.356,974.1419,1583.03,2652.882,2557.25]	[782.89,1949.30,2740.14,753.2,1882.98,908.21,1819,2737.48,1004.27,1631.99,2734.93,2636.34]	[822.0345,2047.006,2877.147,790.86,1977.129,953.6205,1909.95,2874.354,1054.484,1713.59,2871.677,2768.157]	[861.179,2144.483,3014.154,828.521,2071.278,999.031,2000.9,3011.228,1104.697,1795.189,3008.423,2078.918]
	$y_{ij} \forall j \neq 7$	0	0	0	0	0
	TSCC	253533000	258959000	267097900.00	280662800	821.0506

Table 13:Sensitivity Summary Table

Parameter	Iterations	Elapsed runtime	Total Variables	Total Constraints	Total non-zeros	$x_{ij} \forall j = 7$		$x_{ij} \forall j \neq 7$	$y_{ij} \forall j = 7$	$y_{ij} \forall j \neq 7$	TSCC
S_i	I	I	I	I	I	S		I	I	I	M
Cap_j	I	I	I	I	I	I		I	I	I	I
H_j	I	I	I	I	I	I		I	I	I	H
De_k	H	H	I	I	I	H		H	H	H	H

H = Highly Sensitive ,S = Sensitive, M = Moderately Sensitive, I = Insensitive

Figures 7 and 8 depict the sensitivity behavior of the optimum multi-echelon FCI supply chain subjected to demand and supply perturbations, respectively. From this, it can be seen that total system cost shows high sensitivity due to variations in central pool demand-the response is roughly linear with changing demand levels. On the other hand, the objective value varies comparatively moderately with fluctuations in miller supply. In all cases, the solution remains structurally invariant: Depot D10 is repeatedly identified as the unique cost-minimizing consolidation hub. Therefore, the main conclusions are that the overall system performance is basically driven by demand, while the optimized network topology appears highly robust with respect to supply-side uncertainty.

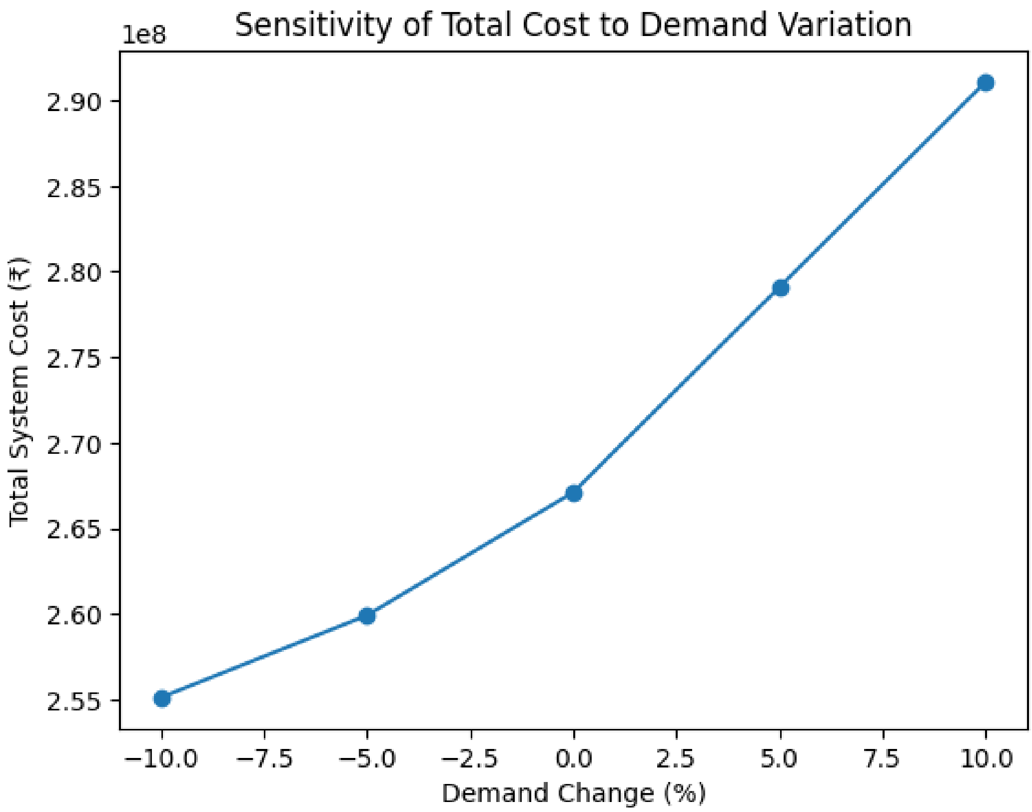

Figure 7: Demand Sensitivity

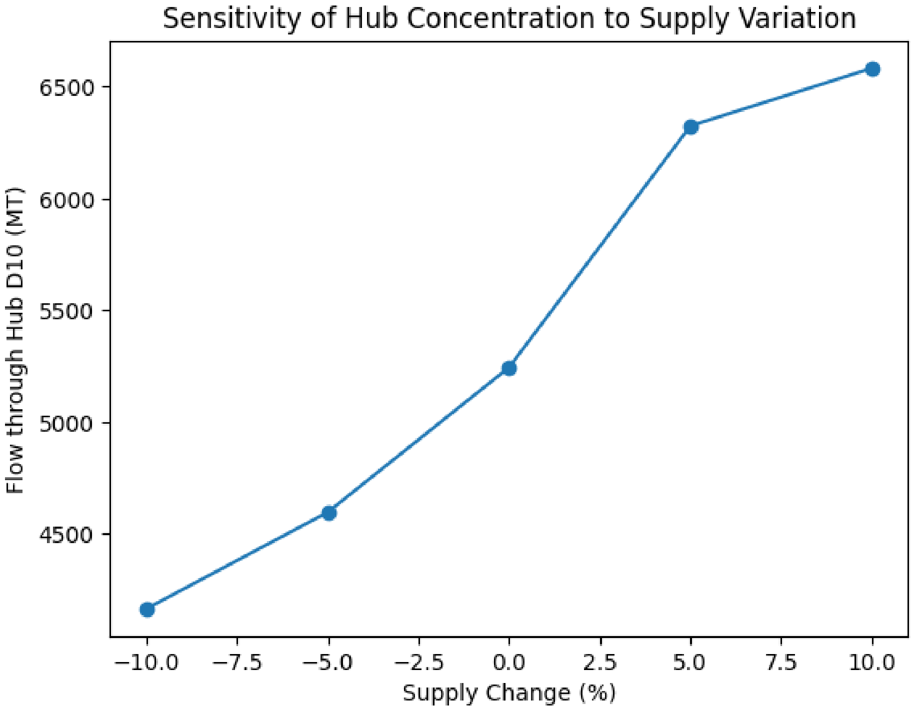

Figure 8: Supply Sensitivity

6.Implication of the study

The findings obtained from this analysis have important implications for society and management. At a society level, enhancements in cost efficiency, responsiveness to demand changes, and system structures would be helpful in facilitating reliable supply of food grains. Similarly, preventing wasteful inefficiencies in the Public Distribution System would be helpful in encouraging achievements in food security. At a management level, obtaining a cost-dominant structure, high variability in total system costs, and differences in depot-level performance provide important facts to decision-makers. There would be no inconsistencies between these results and those derived under different management contexts, such as new product businesses. For instance, it would not create confusion regarding new or established entities. Similarly, it would not be incongruent to enhance capacity utilization within supply chains, or to emphasize demand forecasts allied to new or established entities.

7.Conclusion

In this study, the efficacy of a holistic multi-echelon linear programming and cluster analysis approach is established for optimal cost-efficient and efficient public agri-food supply chains, using the Food Corporation of India's paddy distribution network in the Sambalpur region as a test example for validation purposes. From this, the following outcomes are derived: a strongly centralized and cost-efficient network architecture with a single consolidation point represented by a depot with optimal cost and capacity profiles, and a series of strong clustering patterns for the individual warehouses with marked levels of disparities exhibiting potential for operational and policy-based interventions for improving productivity and efficiency of individual warehouses for better public agri-food supply chain efficacy and outcomes, and through further sensitivity assessments, the major influence on system costs is determined to be demand volatility and change, and network architecture more or less insensitive to supply and cost coefficients trends, thus underlining for the need for precision in demand forecasts, especially in public and government-run agri-food supply chains and logistics networks for better efficacy, productivity, and outcomes.

8.Limitation and Future Scope of the study

This study adopts a deterministic, single-period optimization framework based on officially reported data for one operational year, which simplifies the analysis but does not explicitly represent temporal variations or uncertainty in demand and supply. The empirical application is confined to the Sambalpur region of Odisha, and therefore the numerical results may differ in settings with alternative logistical or institutional conditions. Additionally, the clustering exercise is grounded in static operational attributes rather than real-time or behavioral indicators. Despite these constraints, the modelling structure is flexible and can be readily extended to dynamic, stochastic, and multi-objective formulations in future research.

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