SIMULATING RESILIENT LAST-MILE DELIVERY IN KOLKATA'S QUICK-COMMERCE: CLUSTERING INSIGHTS FOR FILL RATE AND ON-TIME DELIVERY UNDER DISRUPTIONS

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ABSTRACT

Purpose

The aim of the study is to perform a test on the strength of the clustering algorithms in improving the quality of last-mile delivery related to quick commerce (Q-commerce) in disruptive urban areas such as Kolkata, India. It measures the performance of clustering during disruption conditions after 30 days.

Design/Methodology/Approach

A simulation framework evaluates 15 clustering algorithms under 6 disruption scenarios and 5 disruption degrees (0%, 25%, 50%, 75%, 100%) and flexible operational settings. Based on the synthetic demands and urban road network of OpenStreetMap, 13,500 runs were done. The important metrics are On-Time Delivery (OTD) and fill rate, and the demand CAGR is in the range of 0-20%.

Findings

The flexibility in operations enhances delivery results in the occurrence of disturbances. FuzzyCMeans and KMedoids were also relatively resilient with an OTD up to 88.44% and fill rate to 0.936 at 75% disruption and a high tolerance (otd_std = 14.07, fill_std = 0.150). DBSCAN and GreedyClustering performed badly (OTD = 33.33%, fill rate = 0.333) and they had large variability (otd_std > 23). Hub optimization and proactive reallocation in spatial analysis is of importance to resilient logistics planning.

Originality

This study provides an innovative model of simulation combing real-life data of an urban street and dynamic processes to assess clustering resiliency in Q-commerce.

Practical Implications

The framework helps logistics planners to choose on robust clustering algorithms to

use when there are disruptions to the Q-commerce.

Keywords
Quick-commerce, last-mile delivery, Clustering algorithms, OTD, fill rate, Kolkata

INTRODUCTION

Quick-commerce (Q-commerce) has impacted urban consumption patterns by expanding the demand for fast last-mile delivery. The logistics of last-mile delivery have become complex due to the increase in e-commerce and Q-commerce, making it the most uncertain component of the supply chain (Escudero-Santana *et al.*, 2022). Customers have compelled an idea to receive goods within 30 minutes, and it exerts pressure on logistics services, which are forced to stay with the same level of service without adding anything to the cost. The problems with the environment are congested roads and city air pollution caused by deliveries, whereas traditional approaches lack effectiveness (Balaska et al., 2022; Xiao et al., 2017). Drones and electric vehicles can also be considered sustainable solutions because they can evade road traffic and have less environmental impact (Borghetti et al., 2022; Madani and Ndiaye, 2022).

By adding the Internet of Things (IoT) to the last-mile logistics flow, it becomes possible to make it more efficient owing to increased tracking, route optimization, and real-time decision-making, which allows for the enhancement of the overall quality of the offered services at a lower cost (Kafile and Mbhele, 2023). The autonomy of delivery tools, such as Autonomous Delivery Robots (ADRs) and Unmanned Aerial Vehicles (UAVs), provides uninterrupted availability and can counteract driver shortages, in addition to the ability to shorten delivery time (Engesser *et al.*, 2023). However, these technologies face challenges related to regulation and infrastructure (Balaska *et al.*, 2022). Delivery personalization with various delivery points and times increases serviceability (Escudero-Santana *et al.*, 2022), and to satisfy consumer demands, sophisticated arrangements of delivery chains must be adopted.

Although the growth of the q-commerce market poses problems for the last-mile delivery system, it opens new doors to innovation. A switch to sustainable technologies, IoT systems, and various alternative delivery strategies, such as drones, can address consumer needs and minimize discernible impacts on the environment; however, they need to be put into practice with caution and regulation factors in mind. Urban sprawl and leapfrogging development complicate last-mile delivery because roads are narrow, congested, and have aged infrastructure in densely populated cities, such as Kolkata. Electrified and autonomous aircraft (EAA) cargo shuttles are one of the solutions that could eliminate traffic and truck congestion (Bridgelall, 2024). To implement this, freight flow data must be studied and analyzed to optimize the deployment of EAA services.

Policies that advance public transport and control parking can reduce congestion and increase road security (Albalate and Fageda, 2019). As used in Isfahan, Iran, one-way traffic networks improve traffic by increasing speed and decreasing travel time by 9% (Karimi *et al.*, 2021). The interplay of movement and growth that congests the urban together with barriers to strategic transport challenges can be investigated by studying road networks and dynamics of growth (Lampo *et al.*, 2021). Last-mile delivery in dense cities must be addressed by technological improvements, better transportation, improved traffic routes, and knowledge of city development trends. These measures are aimed at enhancing efficiency in delivery as well as sustainable development. Delivery performance, when considering the level of disruption, space-based reassignment flexibility, and demand expansion, needs robustness owing to the possible disruption of supply chains regarding the availability of hubs and reassignment of affected customers.

Disruption Severity and Delivery Performance: Resilience helps supply chains survive disruptions. Resilience is improved through flexibility and redundancy, which reduce costs in the case of supplier and environmental disruptions (Kamalahmadi *et al.*, 2021). The disruption influence on upstream and downstream performance is higher for upstream performance (Parast and Subramanian, 2021). Active management, such as backup suppliers, lowers expenses and enhances responsive actions (Kamalahmadi and Mellat- Parast, 2015; Behzadi et al., 2017).

Spatial Reassignment Flexibility: Spatial flexibility enhances allocation in the case of threats to the market environment, providing greater profit and minimizing risks. Routability and allocation flexibility are effective in reducing disruption (Behzadi *et al.*, 2017). Flexible supplier capacity aids in contingency planning (Kamalahmadi and Mellat-Parast, 2015).

Rapid Demand Growth: The high velocity of demand growth increases the effects of disruption. The effect of digitalization and smart operations enhances efficiency in the face of increased customer expectations (Ivanov *et al.*, 2018). Predictive demand management assists in managing costs in the case of demand peaks (Kamalahmadi *et al.*, 2021).

Flexible strategies to respond to disruptions in delivery systems should consider the severity of the disruption, spatial redistribution, and quick spikes in demand to promote service delivery and supply chain performance. The complexity of supply chain challenges is better handled by incorporating innovative flexibility ideas. Hub location and customer zoning via optimal clustering optimize logistics processes by dividing the territory into clusters of individual cells based on logistical principles. The evaluated segmentation of capitals in EU27 uses a two-step cluster analysis that prioritizes logistics performance, congestion, and effects on the environment (Škultéty *et al.*, 2021). Digital technology has made new supply chains more resilient than inflexible manufacturing through systemic flexibility gains during and after COVID-19. Such digitized strategies create opportunities for real-time visibility and data-driven decision-making(Kashem *et al.*, 2024).

It is important to know how to handle uncertainties in urban logistics, and in the case of customer demands and travel time, which are stochastic factors. These variables are modeled using the Stochastic Dynamic Vehicle Routing Problem (SDVRP) approach, but the deterministic approach is typically insufficient (Mardešić *et al.*, 2023). Elastic logistics can be used more or less, and thereby responding to market forces dynamically improves the supply chain management of disruptions (Choi, 2020). Machine learning approaches enhance the accuracy of demand predictions and order confirmation and may have potential in forecasting high-risk shipments and customer segmentation (Pasupuleti *et al.*, 2024). Although clustering techniques have proven to be effective, they should be examined in an urban environment. Studies have shown that combining digital applications and analytical frameworks improves the effectiveness of logistics operations.This study fills these gaps by creating a simulation framework to test the resilience of clustering-based approaches to customer-hub assignment in Q-commerce networks during periods of disruption. Incorporating the synthetic demand data superimposed on real road networks in OpenStreetMap (OSM), the model evaluates 15 methods of clustering under six disruption scenarios, five severity degrees (0-100%), and two levels of operational flexibility (with/without customer reassignment). The level of performance is determined using two important service indicators: On-Time Delivery (OTD) and Fill Rate. In addition, the framework probes the scalability of the systems in the capacity of a forecasted 20 percent CAGR in the growth of demand in the system to model the future stress levels that may be experienced by the logistics planners.

Our paper offers four kinds of contributions on different levels: (1) we introduce an effective simulation framework that combines clustering, routing and disruption modeling in an urban logistics scenario; (2) we perform a comprehensive set of 13,500 simulations evaluating 15 clustering methods with regard to their ability to increase resilience of hubs under disruptions; (3) we expose the combined effects of operational flexibility and disruption severity on delivery performance; and (4) we offer regional views and performance-based design of logistics networks in disruption-suscept

The second part of the paper is organized as follows: Section 2 reviews the literature on urban logistics, clustering analysis, and disruption modeling. Part 3 describes the model specification, such as the model assumptions, data assumptions, disruption modeling, and model performance metrics. Section 4 explains the experiment and simulation plan. Section 5 presents the important findings and cross-comparisons of the performance of the clustering methods. Section 6 discusses the practical implications, design considerations, limitations, and future research. Section 7 concludes the paper.

LITERATURE REVIEW

Last-Mile Delivery Optimization in Urban Logistics

Urbanization, expansion of e-commerce, and infrastructure affect urban last-mile delivery (LMD) in Kolkata. Last-mile logistics has become an important supply chain issue owing to the increase in e-commerce and the popularity of quick delivery. The literature points to problems of last-mile logistics organizations in urban areas characterized by inefficiency, that is, technological insufficiency, lack of infrastructure, excessive cost, and management constraints (Bosona, 2020). Cities have other issues, such as traffic and parking shortages (Rosenberg *et al.*, 2021). Autonomous delivery solutions could be one of the innovations that hope to make humans less dependent on such crowded spaces but are burdened by regulatory and infrastructural shortcomings (Alverhed et al., 2024; Tadic et al., 2024). With electric and drone deliveries, sustainability is achieved owing to reduced emissions (Shuaibu *et al.*, 2025).

Crowdsourcing has emerged as an alternative, in which deliveries are directed to typical citizens, which is beneficial to society in cities. Nevertheless, such a model should be cost- effective for businesses (Seghezzi *et al.*, 2020). Micro-depot networks are common locations for parcel deliveries, lowering prices, and optimizing space in cities. In this model, collaboration between logistics providers and regulators is necessary because of the shared urban space (Rosenberg *et al.*, 2021). AI and IoT enhance LMD efficiency with respect to predictive analyses and dynamic routing; however, scalability is a problem (Giuffrida et al., 2022; Shuaibu et al., 2025). Although these are efficient LMD solutions in cities such as Kolkata, their implementation must solve regulatory and infrastructural challenges in collaboration with stakeholders. Infrastructure failures also influence the performance of the delivery of goods and services because the delivery chain is affected by disasters such as natural catastrophes or IT-related problems with unforeseen outcomes. Disruptive factors are necessary in a supply chain model. Inventory management of supplier selection is important when facing a disruption because delays and poor-quality goods are more expensive. Simulation techniques are used to update lead times in the case of disruptions (Saputro *et al.*, 2020). The nature of the network topology defines the robustness of the supply chain against failures, and disruptions that occur downstream in the chain lead to harsher consequences than those occurring upstream (Zhao et al., 2018; Olivares-Aguila and Elmaraghy, 2020).

The influence of technology disruptions can be viewed in terms of the role of supply chain management digitalization and IT systems. Network Data Envelopment Analysis (NDEA) reveals the impact of IT disruptions on logistics efficiency, which implies the vital role of preparation aimed at reducing efficiency losses (Klumpp and Loske, 2021). Diversifying supply chains increases resilience by reducing losses in sales and expenses. Backup suppliers have flexible characteristic strategies and increase responsiveness to disruptions (Kamalahmadi *et al.*, 2021). Although stochastic models have considered real-time data, they tend to overlook infrastructure imbalance, which should be considered to develop resilient supply chains (Snyder et al., 2006; Zhao et al., 2022).

To deal with complex road networks, such as those within cities such as Kolkata, it is important to introduce realistic conditions to the simulation modeling performed in the context of Last Mile Delivery. Urban freight systems are integrated with intelligent transport systems, and because it takes time to change the travel time, they cost less and produce fewer emissions (Taniguchi and Thompson, 2002). Urban logistics models combine passenger and freight networks to minimize pollution and service time to the minimum point(Pimentel and Alvelos, 2018). Logistics can be optimized using Digital Supply Chain Twins (Tasche *et al.*, 2023), and urban freight processes have been modelled in terms of distributed decision- making to reflect the practices of agents (Anand *et al.*, 2014).The application of metaheuristics solves logistics issues (Griffis *et al.*, 2012). In the two-echelon capacitated location-routing problem, the optimization of facility networks and vehicle fleets is considered to boost city freights (Winkenbach *et al.*, 2016). These methods enhance the simulation models of efficiencies in urban logistics studies in populated areas.

Disruption and Resilience in last-mile delivery

The issue of supply chain resilience has become relevant as disruptions to the supply chain have been on the rise. The major characteristics are robustness, network resilience, disruption modeling, flexibility, and structural redundancy. Enhanced resilience and robustness are related to the fact that supply chain connectivity and information sharing increase visibility (Brandon-Jones *et al.*, 2014). The mediation between technology utilization and resilience is achieved through digital technologies, making it easier to collaborate and enhance supply chain memory (Li et al., 2023; Alvarenga et al., 2023). Flexibility makes it possible to address disruptions in supply chains (Queiroz *et al.*, 2023), whereas structural redundancy, achieved by spare capacity mechanisms, guarantees persistence through interruptions (Mackay *et al.*, 2019). Awareness of the likelihood of disruption boosts resilience modeling processes and decisions (Ivanov, 2022). A culture of risk management and connection in the supply chain is essential for achieving resilience (Kumar and Anbanandam, 2019). An integrated strategy of robustness, flexibility, digitalization, and redundancy enhances supply chain resilience to shocks. The strength of last-mile delivery processes has become a topic of discussion in light of the increased demand for high-quality delivery services in urban areas. A simulation that focuses on disruption is essential in relation to how these systems deal with failures. The social- ecological system of last-mile delivery is a perspective in which social, ecological, and engineering perspectives are considered in the development of resilience. This methodology singles out strategic directions such as stabilization, adaptation, and transformation (Lin *et al.*, 2022). AI will help improve last-mile delivery through the achievement of transparency and limited impacts related to disruption. AI allows companies to apply dynamic capabilities and create nimble procurement strategies (Modgil *et al.*, 2021). Structural-aware simulation analysis combines the properties and operations of the network to simulate disruption recovery (Tan *et al.*, 2019). Such insights should be embedded into a disruption-centric simulation framework based on simulated scenarios and real-time data integration. It is possible to adjust the Networked Infrastructure Resilience Assessment framework to regional peculiarities and, therefore, to perform a complete assessment of transportation network resilience (Omer *et al.*, 2013).

Clustering Techniques for Hub Location and Customer Segmentation

Clustering algorithms streamline the last-mile delivery in cities by creating optimal delivery zones, allocating hubs, and creating routes. Instruments help solve the problem of last-mile logistics, which is regarded as the most inefficient supply chain segment (Bosona, 2020). Clustering customers on a sample base provides cost savings in terms of resource reduction because it is easy to transport to a closer customer. The flexibility of the assignment of loading bays increases routing efficiency and walking delivery stages (Letnik *et al.*, 2020). A model based on hard and soft clustering was used to discuss loading bay assignment, with soft clustering changing the degree of membership of the customers to the loading bays to minimize the distance. The growth of online shopping and, correspondingly, last-mile delivery is experiencing difficulties owing to worsening congestion and pollution (Alejandra Maldonado Bonilla *et al.*, 2024). Among the proposed solutions are urban consolidation centers and collaborative systems with shared transport and sustainable vehicles (Lyons and Mcdonald, 2022).

The reduction in the makespan and latency in delivery routes that depend on optimization algorithms and clustering techniques is imperative. Routing issues are effectively addressed by solutions based on heuristics and spatial indexing, such as hierarchically separated trees (Zeng *et al.*, 2019). Machine learning and AI, in combination with clustering algorithms, allow for improved decision-making in last-mile logistics, where big data are used to provide pattern analysis to achieve strategic operational models (Digiesi *et al.*, 2017). These methods enable urban logistics to respond to demand increases and environmental objectives. The harmful properties of K-means clustering are its sensitivity to initial centroid selection and monotropical cluster assumption, which affect its performance on irregular urban terrain (Ahmed et al., 2020; Qi et al., 2016). The algorithm must work with predetermined cluster numbers and has the problem of data noise (Ahmed *et al.*, 2020). Optimized versions, such as K-means, defend against random initializations by limiting them further with built-in hierarchical optimization (Qi *et al.*, 2016). The superior performance of genetic K-means is based on the principles of the genetic algorithm (Banerjee *et al.*, 2015). Such optimization methods based on natural inspirations, such as K-means with the CSA, minimize local optimum traps (Lakshmi *et al.*, 2018), and Bayesian hierarchical K-means is more acceptable for describing the real-world data structure (Liu and Li, 2020).

These enhancements show different ways to make clustering techniques more robust and flexible in the field of logistics to eliminate the shortcomings of the K-means algorithm. Non- convex clusters, sensitivity towards the initial centroid, and the logistics complex data computational efficiency can be dealt with more smoothly with high-level options (Tang and Khalid, 2016; Anchalia et al., 2013). K-medoids clustering in a high-density dynamic delivery setting provides information and issues. Although K-medoids is resistant to outliers because of its selection of actual data as cluster centers, unlike K-means, it has shortcomings in complex accuracy and preprocessing situations. The classic Partitioning Around Medoids (PAM) algorithm is computationally expensive, whereas its newest versions have accelerated its execution at the same level of quality (Schubert and Rousseeuw, 2021; Schubert and Rousseeuw, 2019). Generalized distance functions are important for characterizing various attributes of a delivery system, which K-medoids finds useful for dealing with mixed variable data (Budiaji and Leisch, 2019). It is robust to the outlying effect on dynamic data with variable demand (Arbin *et al.*, 2015), and novel methods increase the accuracy of dynamic delivery (Gullo *et al.*, 2008). Regardless of the developments, the application of effective K-medoids needs to consider both computational resources and the nature of the datasets. DBSCAN works best in places with natural barriers in an urban environment, but its sensitivity to parameterization may make it ineffective in locations with different customer densities.

The main problem with the use of DBSCAN is its sensitivity to data density changes. Therefore, an improved DBSCAN algorithm considers the local density differences of each cluster by computing the density variance of the core objects (Ram *et al.*, 2009). The altered DBSCAN process estimates the retail center extents in an urban setting by changing the radius parameter through a sparse graphical representation, thus properly determining the retail cluster of diverse shapes and densities (Pavlis *et al.*, 2017). The parallel process of DBSCAN with Spark or MapReduce addresses the limitations of load and scale when the dataset is large. To improve the efficiency of the processing capabilities, the MR-DBSCAN algorithm presents an additional data partitioning feature (He *et al.*, 2013). Detailed variants of DBSCAN have been optimized for use in embedded systems in automotive applications (Raj and Ghosh, 2020), and Ellipsoid DBSCAN makes dimension scaling available in real- world detection applications (Wagner *et al.*, 2015). Although parameter sensitivity is difficult to determine, it is continuously being worked on to provide a better application of DBSCAN in complicated settings. The overlapping of membership in common service areas is dealt with by fuzzy clustering techniques, especially Fuzzy C-Means. The dynamic fuzzy c-means algorithm is a novel algorithm that helps enhance customer satisfaction in a dynamic ride-sharing system to adapt fuzzy assignments (Munusamy and Murugesan, 2020) in real time.

The property of fuzzy logic to handle real-world imprecision and uncertainty is advantageous in the real world of telecommunications networks and dynamic systems (Ghosh *et al.*, 1998). It is possible to increase energy efficiency within the framework of wireless sensor networks through fuzzy clustering with the help of protocols such as energy- aware unequal clustering fuzzy (EAUCF) (Adnan et al., 2021; Singh et al., 2013). Nonetheless, fuzzy techniques have been confronted with problems such as high imbalance ratios, which make them impractical in places where workload equity is an issue. To solve these challenges, clustering strategies should be incorporated to accommodate system demands, but with quality clusters. FCM There are hyperplane partitioning techniques that can enhance the clustering accuracy of large datasets (Shen *et al.*, 2019). Although fuzzy clustering has advantageous characteristics in any application, it requires algorithm alterations to meet the challenges of dynamic environments. Spectral clustering performs well in clustering non-convex shapes and probabilistic shapes, as do Gaussian Mixture Models (GMM). Spectral clustering is based on graph Laplacians and affinity matrices and performs well for clustering high-dimensional data. It uses the diffusion distance on graphs, and is computationally expensive when applied to large datasets. Researchers have created approximate spectral clustering to increase speed without compromising accuracy (Wang et al., 2009; Nadler et al., 2008). GMMs provide probabilistic clustering, meaning that the data are assumed to be generated by different Gaussian distributions, which can be applied to ellipsoidal clusters and computer cluster membership probability. However, GMMs do not perform well on non-convex structures and may also be sensitive to parameter initialization. Both approaches have computational problems. The cost of spectral clustering affects scalability, but multiscale approaches are available to decrease the cost. GMM can be better scaled up with the help of the iteration of expectation-minimization; however, it is intense with regard to large data dimensions. The two techniques have different applications: spectral clustering is suitable for state-of-the-art relationships, whereas GMM has probabilistic modeling and processes elliptical clusters (Wang et al., 2009; Nadler et al., 2008).

Urban Delivery Challenges in Emerging Market Cities

Contextual solutions are needed to solve the challenges of urban logistics in emerging economies such as India. The logistics complexity that occurs in Kolkata is the unstructured addressing, high demand density, bad roads, and low warehousing (Arvianto *et al.*, 2021).Last-mile delivery is complicated by narrow alleys. Various practices deal with the challenges of urban logistics that revolve around optimization and partnerships. In accordance with sustainable urban mobility plans, mixed freight-passenger transporting systems should be introduced to achieve a better level of efficiency (Mazzarino and Rubini, 2019). The Stochastic Dynamic Vehicle Routing Problem (SDVRP) assists suppliers in gauging customer requests and travel durations under uncertain conditions (Mardešić *et al.*, 2023). Digital supply chain twin (DSCT) technology is designed to model logistics optimization. Its collaborative platform can improve resource management to optimize urban logistics, thus improving urban logistics despite implementation barriers (Tasche *et al.*, 2023). Research on air pollution in Kolkata demonstrates the pressure on the environment, which is why interventions are urgently needed in the sphere of urban planning (Kar *et al.*, 2024). Policies, infrastructure, and transport technology innovations continue to play critical roles in enhancing logistics and minimizing externalities (Ranieri *et al.*, 2018). The use of SDVRP to optimize the routes, DSCT, and implementation of sustainable mobility patterns are the factors that should be applied to address the logistical difficulties of the city of Kolkata. Local governance and community engagement are issues of success. The optimization of logistics in emerging economies such as India has a different approach compared to models in the West because of the unique infrastructure and market peculiarities. DSCTs provide advanced optimization solutions and tools; however, several barriers limit their implementation (Tasche *et al.*, 2023).

Logistics and supply chain practices in India are still in their developing stages, and the level of integration between systems is considered low, with issues regarding collaborative efforts, network design, and implementation of ICT. Logistics experts have pointed out the discordant aspects of the Indian industry (Srivastava, 2006). The termination of transportation and logistics in emerging markets due to the COVID-19 pandemic triggered the process of embracing blockchain and digital trucking technologies. Strategies such as contactless deliveries and the use of technology to manage drivers have become sustainable (Sumbal *et al.*, 2023).The need of the Indian supply chain management is streamlining with the business objectives and bringing into operation world's good practices to increase the efficiency (Sahay and Mohan, 2003). Cost and optimization of food grain procurement centers using a data-driven model of a supply chain employing mixed-integer linear programming (Mogale *et al.*, 2019). Innovations in last-mile logistics are crucial for decreasing urban traffic and air pollution, as delivery inefficiency is resolved with technology and transport optimization(Ranieri *et al.*, 2018).

RESEARCH GAP AND MODELING INNOVATION

Although significant progress has already been made in the areas of last-mile optimization and supply chain resilience approaches, there is still no available integrated and comparative framework that assesses the approaches to clustering schemes under conditions of possible disruption. *Specifically:*

- There are very few models in which graded hub disruption is simulated with flexible and inflexible reassignment policies.
- The concept of clustering techniques is seldom assessed through the measure of delivery performance in operational failures.
- Most studies do not consider road-constrained delivery routes and the

subsequent rise in demand.

In response, we developed a disruptive-resilience routing method that integrates road-based routing, synthetic demand modeling, and 15 clustering algorithms across 13,500 simulations. We provide a technically sound assessment of On-Time Delivery and Fill Rate in six disruptive circumstances, as well as the projection of 20 percent CAGR development rates in their assessments, which are truly applicable to planning logistics in a resilient and scalable method of delivering urban logistics.

Problem Description and Model

This study provides a mathematical modeling framework and simulation-based case study to assess the resilience of clustering-based last-mile delivery systems in urban quick- commerce (Q-commerce) operations, particularly under disruption scenarios. The focus is on a densely populated urban district in Kolkata, India, reflecting real-world complexities such as intricate road networks and fluctuating demand.

Mathematical Model Indices and Sets

- **Customers (C)**: Indexed by i
- **Hubs (H)**: Indexed by j
- **Days (D)**: Indexed by d, where $d = 1, \dots, 30$
- **Scenarios (S)**: Disruption types; $s = 1, \dots, 6$
- **Disruption %ages (P)**: $p \in \{0, 0.25, 0.5, 0.75, 1.0\}$

Table 1 Parameters

Parameter	Description
q_i^d	Demand for customer i on day d (Poisson, λ=2)
(lat_i, lon_i)	Coordinates of customer i
(lat_j, lon_j)	Coordinates of hub j
C_j	Hub j capacity: sum of assigned demand + 10% buffer
δ_p	Disruption severity (capacity reduction fraction)
C_j^p	Disrupted capacity: $C_j \cdot (1 - \delta_p)$
dist_{ij}	Road network distance between customer i and hub j
v	Vehicle speed: 40 km/h
$t_{\max}$	On-Time Delivery (OTD) threshold: 10 minutes (1/6 hour)
R_s	Reassignment policy (1 = reassignment enabled, 0 = not)
T_s	Disruption target: max, min, or all hubs
O_{ij}	Customer-hub assignment indicator

Decision Variables

- x_{ij}^d: 1 if customer i assigned to hub j on day d; 0 otherwise
- y_i^d: 1 if customer i's delivery is on-time on day d; 0 otherwise
- z_i^d: 1 if customer i's demand is fulfilled on day d; 0 otherwise
- r_j^d: Remaining capacity of hub j at end of day d

Objective

$$\text{Maximize} \sum_{s\in S}\sum_{p\in P}\sum_{d\in D}\sum_{i\in C} q_i^d \cdot z_i^d$$

Maximize total fulfilled demand across disruption scenarios and days.

Core Constraints

- **Hub Capacity**

$$\sum_{i\in C} q_i^d \cdot x_{ij}^d \le r_j^d \quad \forall j, d$$

- **Inventory Update**

$$r_j^d = \begin{cases} C_j^p, & d = 1 \\ r_j^{d-1} - \sum_{i\in C} q_i^d\, x_{ij}^d, & d > 1 \end{cases}$$

- **Customer Assignment**

$$\sum_{j\in H} x_{ij}^d = z_i^d \quad \forall i, d$$

- **Reassignment Policy**
  - If $R_s = 1$: If original hub lacks capacity, reassign to nearest hub with capacity.
  - If $R_s = 0$: Assign only to the original hub, otherwise demand unfulfilled.
- **On-Time Delivery**

$$y_i^d \le \begin{cases} [\text{illegible}]_{ij}\ \frac{dist_{ij}}{v}\ [\text{illegible}]\ \max \\ 0 \quad \text{otherwise} \end{cases}$$

- **Non-Negative Inventory**

$$r_j^d \ge 0 \quad \forall j, d$$

- **Binary Variables**

Hbbb nbnbbbn

$$x_{ij}^{d}, y_{i}^{d}, z_{i}^{d} \in \{0,1\}$$

Performance Metrics

- **Fill Rate**

$$\text{Fill Rate} = \frac{\sum_i q_i^d z_i^d}{\sum_i q_i^d}$$

Fraction of total demand fulfilled.

- **On-Time Delivery (OTD) %age**

$$\text{OTD} = \begin{cases} \frac{\sum_i y_i^d}{\sum_i z_i^d} \cdot 100 & \text{if fulfilled orders} > 0 \\ 0 & \text{otherwise} \end{cases}$$

%age of fulfilled orders delivered within 10 minutes.

Case Study: Application in Kolkata Urban

Context

Kolkata is a Tier-1 metropolis with over 14 million people, characterized by:

- **High density**: Crowded market centers, dense residential zones
- **Spatial complexity**: Narrow alleys, congested roads, frequent one-way restrictions
- **Diverse demand**: Centralized in markets, sparse on fringes

The model simulates a hub-and-spoke system within a bounded city district, using micro-fulfillment hubs to serve customer clusters for same-day Q-commerce.

Data Sources & Generation

Table 2

Component	Methodology/Tools
Customer Demand	Synthetic data: Poisson (λ=2) per customer, Normal spatial clusters centered on urban hubs
Demand growth	0-20% CAGR simulated for up to 30 days
Customer locations	Geospatial validation to keep within city boundary
Hub Locations	15 clustering algorithms (KMeans++, FuzzyCMeans, DBSCAN, others)
Road network	Downloaded from OpenStreetMap, processed with OSMnx & NetworkX
Travel times	Calculated at 40 km/h over shortest (road) paths

Assumptions and Parameter Table

Table 3

Parameter	Value
Delivery time threshold	10 minutes
Vehicle speed	40 km/h
Hub inventory buffer	Assigned demand +10%
Demand per customer	Poisson (λ=2)
Number of hubs	1-10
Disruption levels	0%, 25%, 50%, 75%, 100%
Scenario types (S1–S6)	Max/min/all hubs, with/without reassignment

Simulation Implementation

- **Programming Language**: Python 3.9
- **Key Packages**:
  - Geospatial: OSMnx, NetworkX, Folium
  - Clustering: scikit-learn, scipy, scikit-fuzzy, custom clustering modules
  - Simulation: numpy, pandas, multiprocessing
  - Visualization: matplotlib, seaborn
  - Statistical analysis: statsmodels, scipy.stats

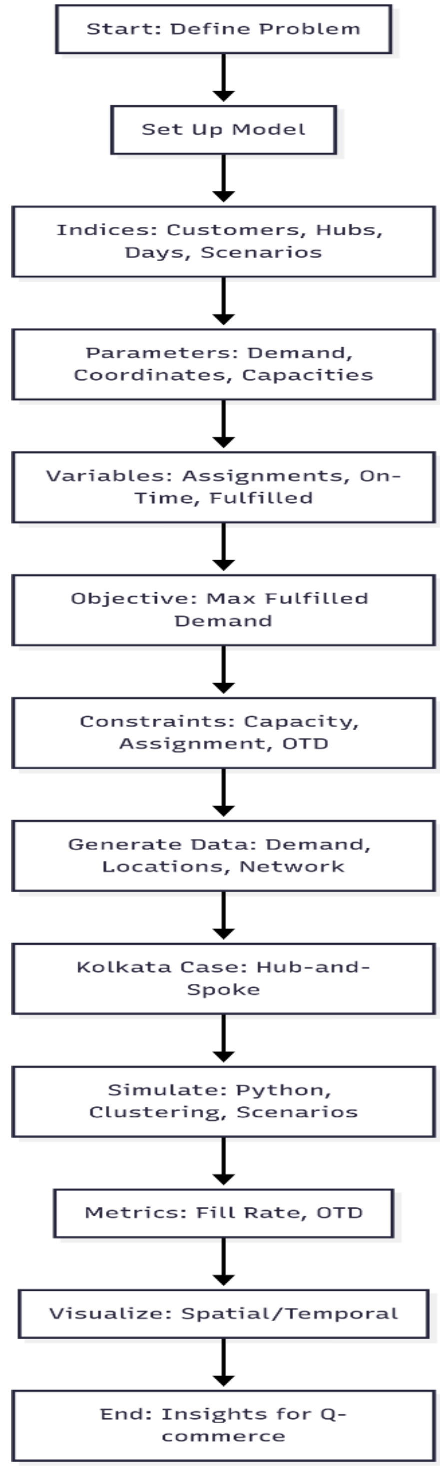
Synthetic Demand Generation

- **Order generation**: Each simulation day, customers are sampled, clustered, and assigned demand
- **Location generation**: Normal distribution centered on urban residential districts

Key Takeaways

- The two-stage simulation framework facilitates robust, granular assessment of urban last-mile delivery under varying levels of operational disruption.
- Clustering-based hub assignment, when coupled with geospatial routing, enables adaptive, disruption-resilient delivery even in Kolkata's complex urban topology.
- Metrics like fill rate and OTD, visualized spatially and temporally, guide both strategic planning and real-time response in Q-commerce operations.

Figure 1. Workflow for Urban Q-commerce Delivery System Analysis



RESULTS AND ANALYSIS

Overall Performance Trends under Disruption

When the four scenarios - full hub flexibility, no hub flexibility, and maximum/minimum inventory hubs- are assessed, different performance patterns are manifested through disruption levels varying between 0 and 100 percent. At 0% disruption, the clustering algorithms of KMeansPlusPlus, KMedoids and MultiCoG have 100% on-time delivery (OTD) and complete fill rates which implies ideal global performance. FuzzyCMeans shows an excellent resilience at less than 100 percent disruption, with OTD ranging between 83.27 percent and 90.91 percent and fill rates between 91.4 percent and 96.5, especially in the maximum/minimum inventory hub scenarios. At 0% level of disruption, CoG algorithm also works well in both full-flexibility and no-flexibility environments. Interestingly, the minimal inventory hub situation portrays the greatest endurance whereby, FuzzyCMeans and KMedoids yield their best in stress. The worst scenario emerges when there is no flexibility at all and no approach will allow operations to continue at a disruption level that is less than 100%. Still, KMeansPlusPlus/KMedoids gray remain comparatively strong to the extent of 75% disruption. The plan of customer locations and their allocated hubs is given in Fig. 2 that provides the basement of the following disruption analysis. The figures 3 to 8 show the results of six different scenarios of disruption varied according to the hub that is disrupted (i.e. full capacity, low capacity or all hubs) and the application of the customer reassignment model. In particular, Scenario 1 and 2 (Figures 3 and 4) depicts a situation with maximum and minimum capacity hub disruption in the case of reassignments being possible. An in depth multi-hub disruption including reassignment scenario is displayed in Figure 5. On the contrary, Figures 6-8 are associated with Scenarios 4-6 which model the disruptions with no reassignment. The latter cases are invaluable in terms of the comparative adaptability and resilience of the delivery system during a limited working operation environment.

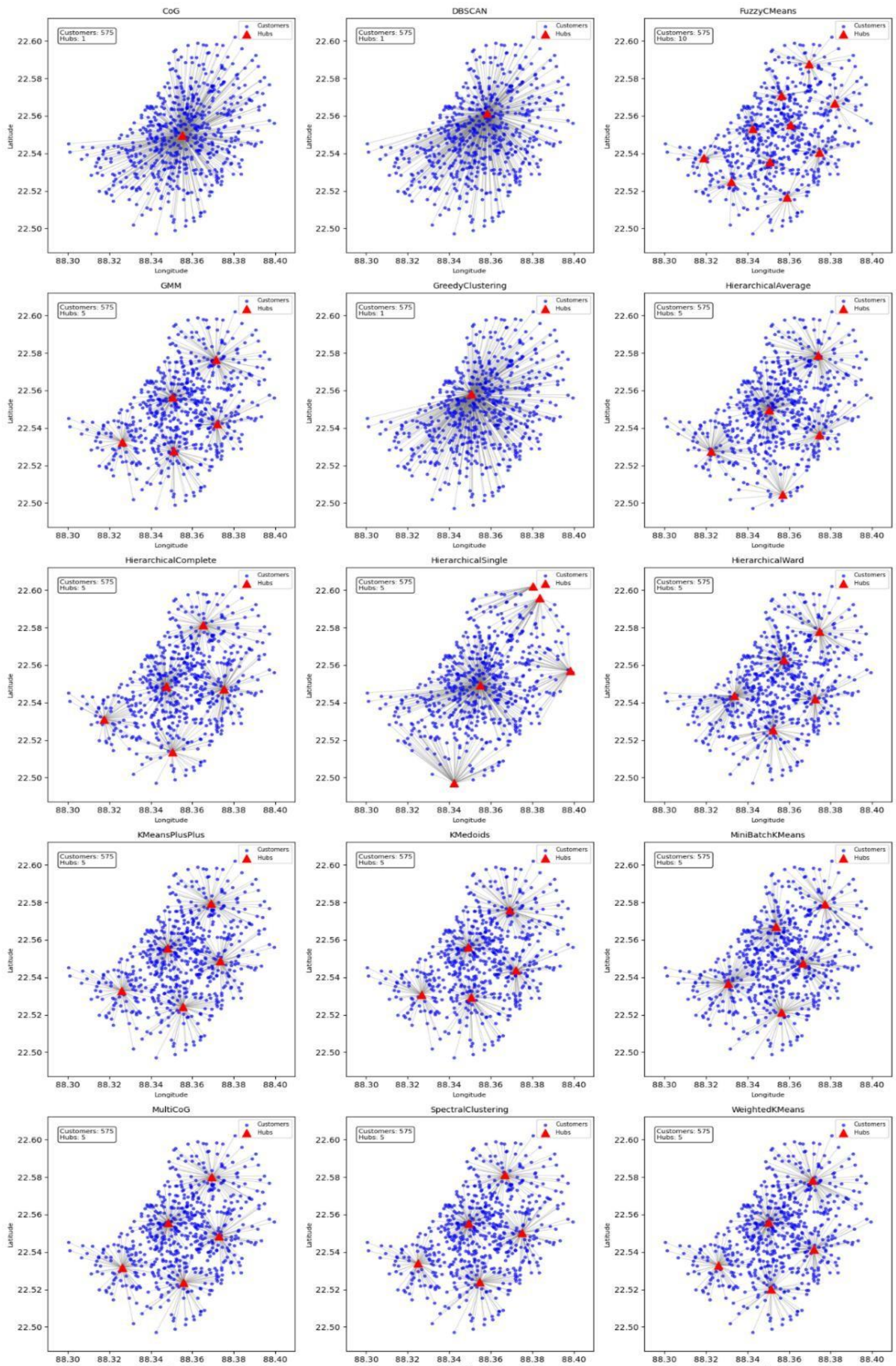


Figure 2. Visualization of customer location and hubs. –

Source: Authors own work

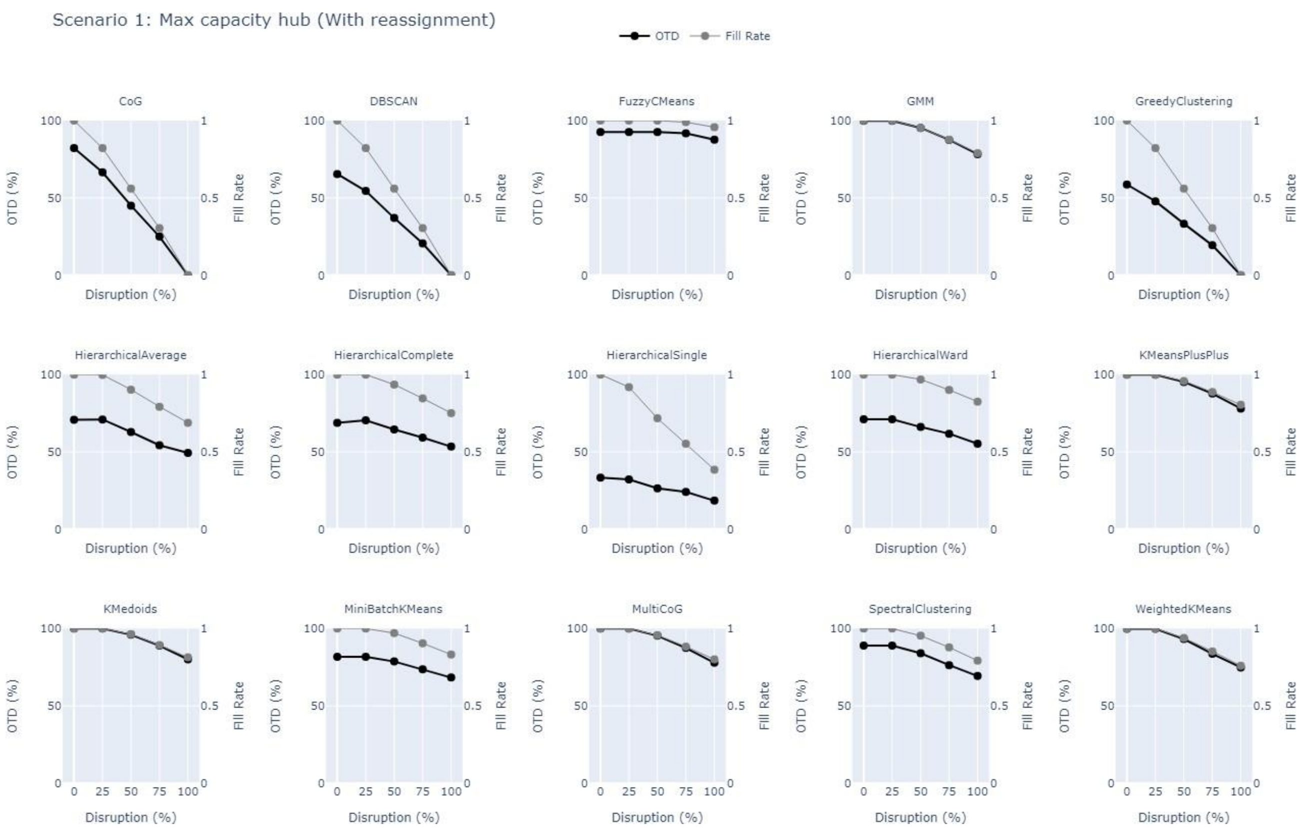


Figure 3. Scenarios 1: Disrupting hub with Max capacity (With reassignment) – **Source: Authors own work**

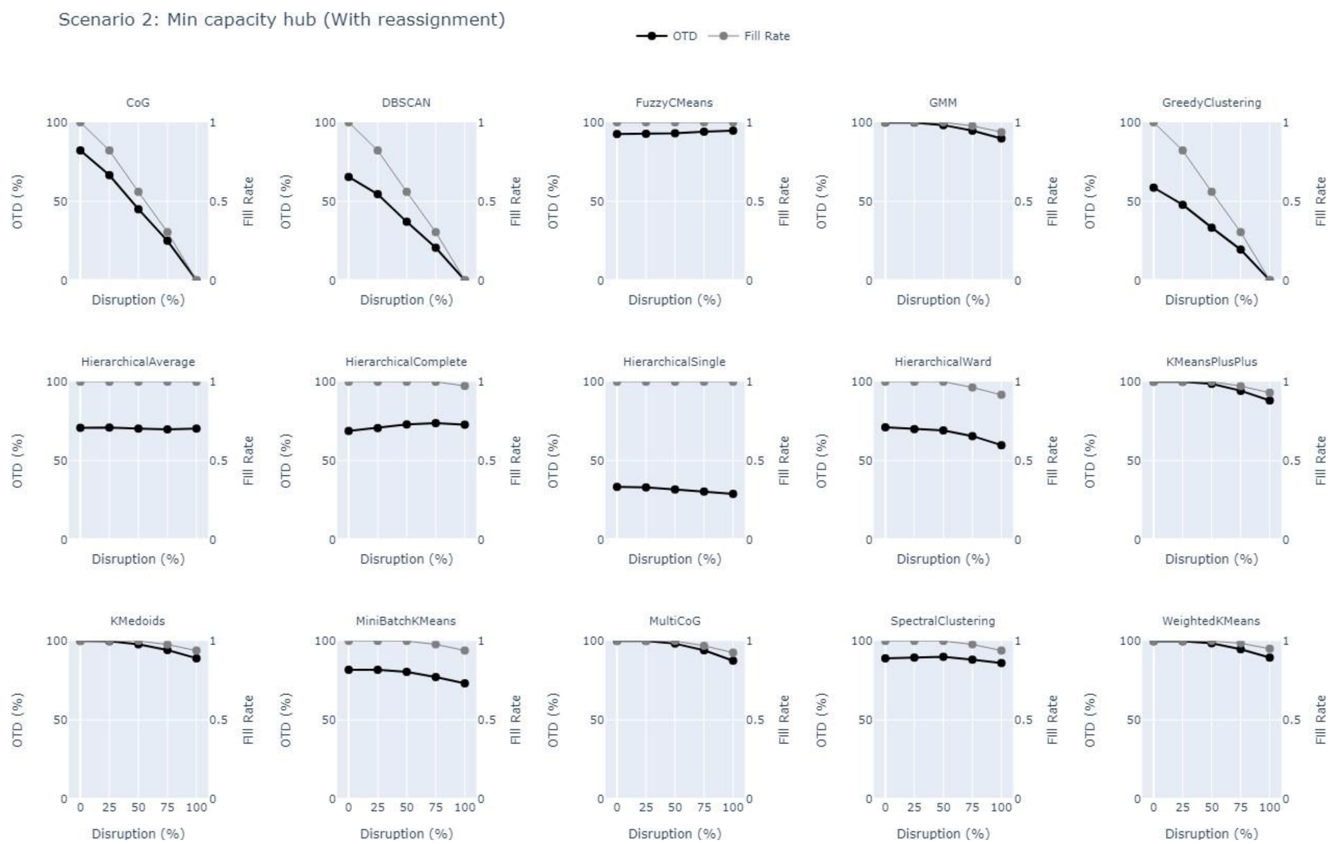


Figure 4. Scenarios 2: Disrupting hub with Min capacity (With reassignment) – **Source: Authors own work**

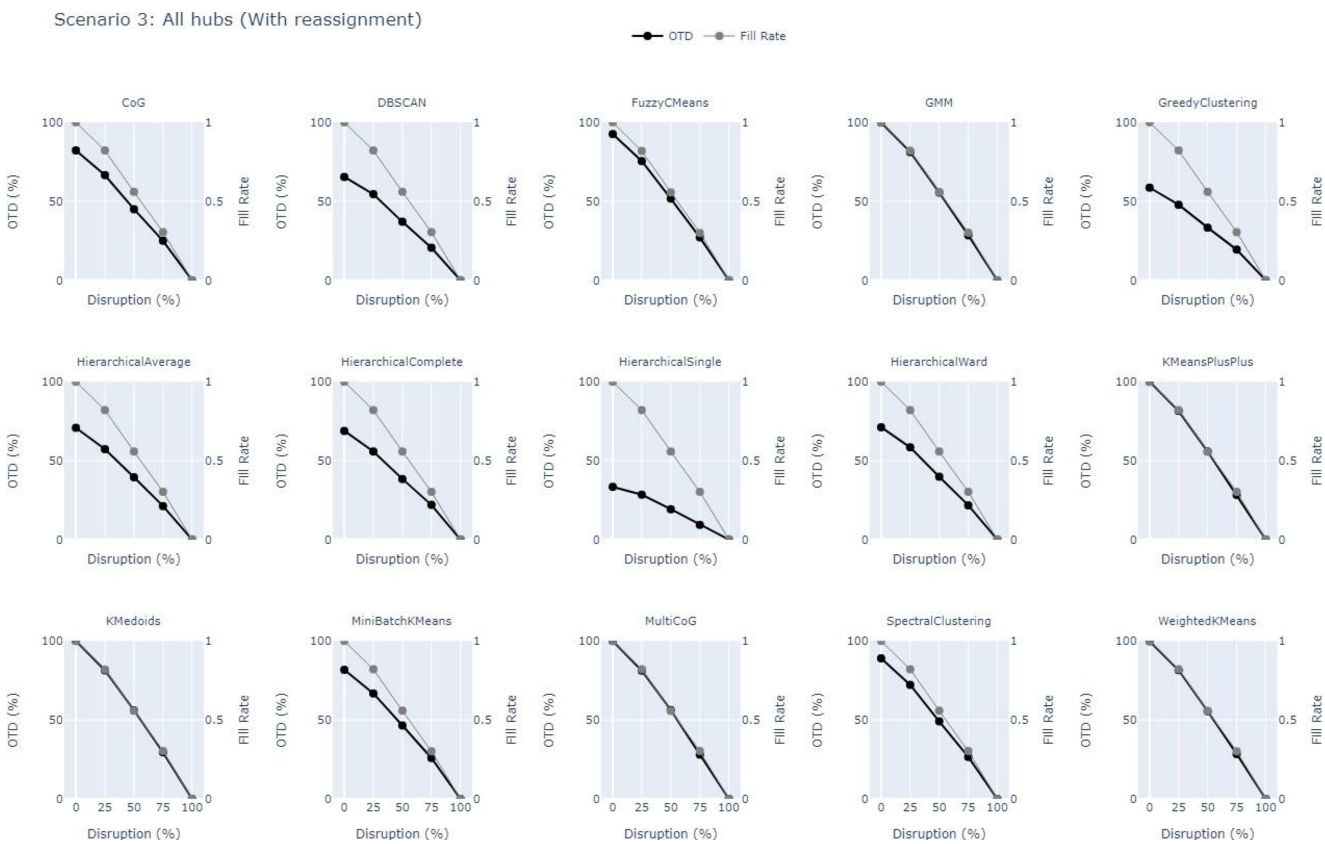


Figure 5. Scenarios 3: Disrupting hub with All hubs (With reassignment) –
Source: Authors own work

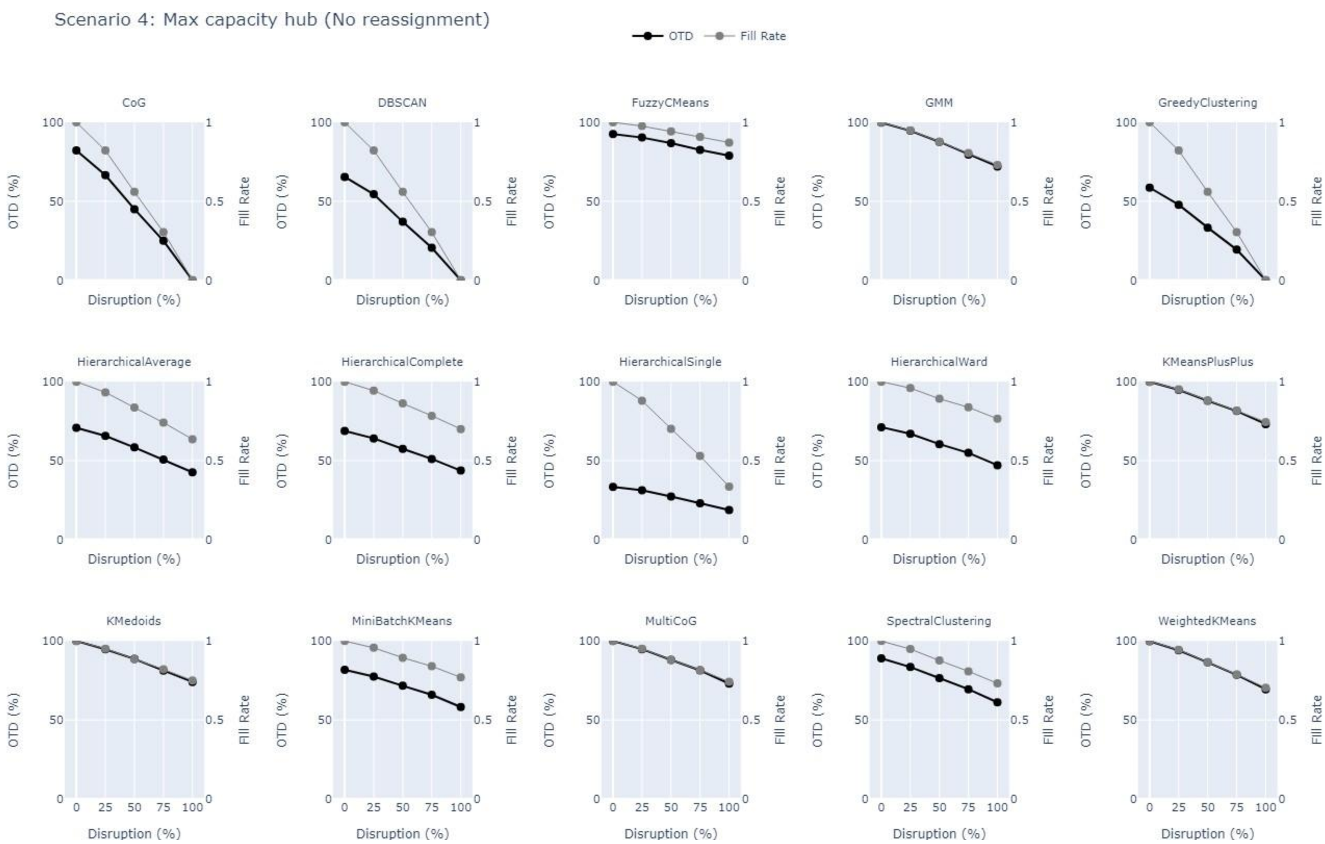


Figure 6. Scenarios 4: Disrupting hub with Max capacity (No reassignment) –
Source: Authors own work

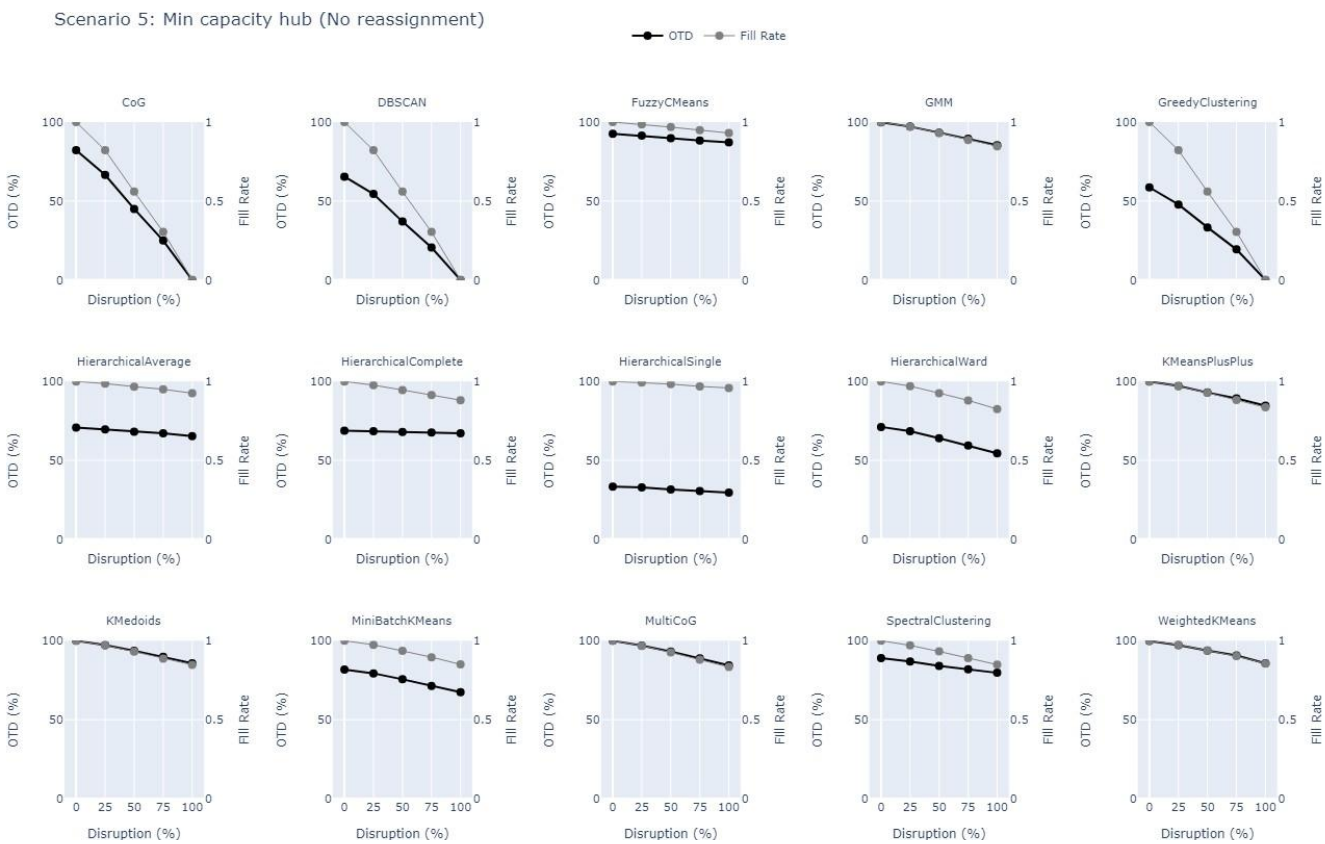


Figure 7. Scenarios 5: Disrupting hub with Min capacity (No reassignment) –
Source: Authors own work

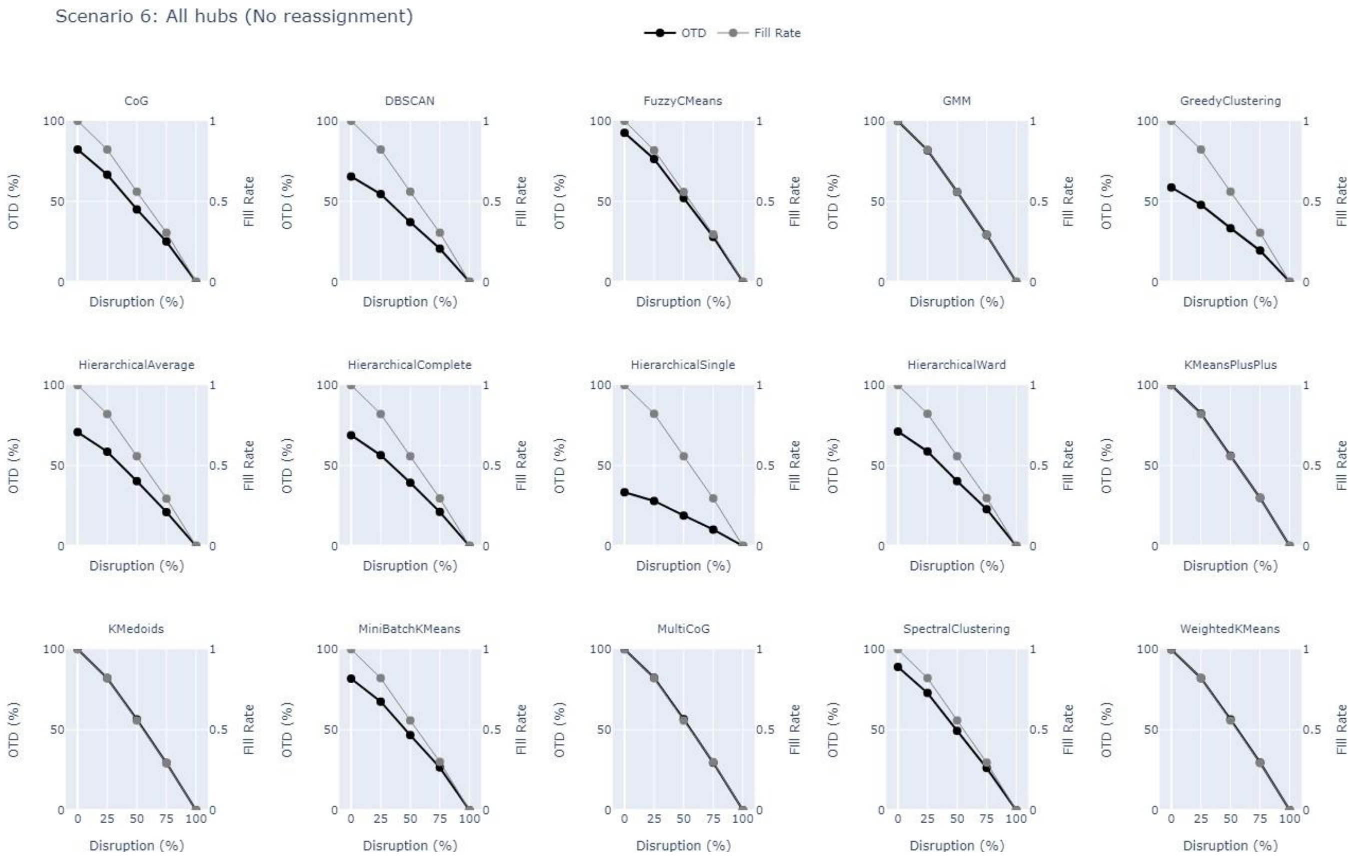


Figure 8. Scenarios 6: Disrupting hub with All hubs (No reassignment) –
Source: Authors own work

Fill Rate Resilience Across Scenarios

Stable Performers: The FuzzyCMeans is very resilient, as its fill rates remain high (between 91.4 and 96.5 percent), even under extreme disruption (100 percent). In a similar manner, KMedoids has stable performance, whereby fill rates remain at 89.3-93.2 with 100 percent disruption, and strong performance at intermediate disruptions (50 to 75 percent). Fragile Methods: On the other hand, CoG, DBSCAN and GreedyClustering result in the total failure under complete disruption, and the fill rates decrease to 0%. HierarchicalSingle varied widely when presented with identical conditions with a fill rate of 36.0-97.9, and this demonstrated unstable strength. The least inventory balanced situation presents itself as the most robust set up. In this environment, KMeansPlusPlus has a fill rate of 98.5 with 25 percent disruption and FuzzyCMeans proves to have a fill rate of 96.5 with 100 percent disruption. By contrast, the no flexibility case comes up with the poor results as the fill rates drop sharply to 29.4-0.4 at 75%, 0 at 100% disruption.

OTD Sensitivity and Robustness under Stress

Robust Methods: Relative to OTD measures, FuzzyCMeans is the most effective method especially in environment where inventory constraints prevail. It attains a 90.91 percent OTD with minimum inventory and 83.27 percent OTD with maximum inventory when disruption is at a full (100) percent and standard deviation of between 0.90 and 5.60, both of which denote a stable performance. KMedoids is also very robust, particularly when complete flexibility and minimal inventory are in effect, attaining an OTD level of 87.38 percent at 100 percent disruption (SD: 4.61-10.37) as well as high levels at 75 percent disruption. Sensitive Methods: CoG at the other extreme registers 0% OTD at full disruption which is a total failure to adapt. Single, DBSCAN and GreedyClustering are also sensitive to the stress with the widest OTD measures ranging between 9.33 and 29.24 percent (SD: 1.56 and 13.64). Again, no flexibility option would become the most susceptible where the whole system performance would significantly degrade. Both KMeansPlusPlus and KMedoids, nevertheless, demonstrate a certain robustness, in the sense that they operate effectively to up to 75 percent being disruptive. The smallest inventory hub case is the most robust one overall and FuzzyCMeans manages to deliver 90.91 percent OTD in the case of 100 percent disruption.

Stability Analysis of Clustering Techniques

The resilience of each clustering method is determined through the evaluation of the fluctuations in delivery levels on-time (OTD) and fill rate during interruption. FuzzyCMeans, although resilient, exhibits a little-unstable performance when completely (100 %) disrupted, especially in the minimum inventory hub setting, with standard deviation of 0.90 in OTD. Well, the absolute alteration of OTD and fill rate is not big and is between 0.000 and

0.051 that means that it is controlled and the changes are not big. HierarchicalSingle has moderate causes of variability so that OTD standard deviation is 1.86. On the other hand, the variability of CoG, DBSCAN, and GreedyClustering is the greatest one, the changes in the OTD are within the range of 23.15 to 32.66, and the changes in fill rate are 0.399-0.400 which clinical indicators of the low stability of the methods when subjected to stress. Interestingly, in the no flexibility case, the OTD variability of GMM and KMeansPlusPlus is really high (40.03-

40.15), which indicates high sensitivity to disturbance. Of all the configurations that were tested, the smallest inventory hub can be seen as the most stable, with OTD standard deviation never going above 5.31 and fill rate change never going above 0.040. Conversely, the no flexibility situation is the least resolute, the volatility of which is 13.64-40.15, which makes the strategic operational leeway extremely important.

Trade-offs and Managerial Insights

Performance Trade-offs: FuzzyCMeans exhibits an excellent tradeoff between performance and stability at full disruption, with 90.91 percent OTD and 96.5 fill rate, having smooth performance slopes and the very low variability. KMedoids is as well quite performing, offering 87.38% OTD and 89.3 % fill rate, but with fairly significant amounts of variability, being a stable choice albeit not as stable as the other options. Managerial Implications: FuzzyCMeans is a good choice of algorithm when working in an environment of high disruption because it exhibits good and robust metrics behavior. A good alternative is KMedoids which makes it a good trade-off between performance and variability. Although effective, KMeansPlusPlus is effective only in the low-disruption environments because it becomes vulnerable under stress. At mild disruption, CoG seems reliable, but completely unreliable at high disruption which means it experiences false reliability, thus not applicable on critical logistics situations. Strategic Recommendations: To plan the last-mile delivery in conditions of uncertainty and high disruptions: Rely on a hybrid method of FuzzyCMeans and KMedoids in order to further capitalize on their strengths. Possible response to contingency solutions with limited flexibility, i.e. there are no flexible seat or hub allocations, or flexibility of reassignments. Take resilience testing as part and parcel of logistics planning so as to ensure performance degradation under extreme conditions is detected beforehand and prevented.

DISCUSSION AND CONCLUSION

Key Findings and Insights

Complex forms of clustering techniques, including FuzzyCMeans, KMedoids and KMeansPlusPlus, show better ability to adapt to cumulative demand pressure over simpler clustering techniques. FuzzyCMeans is also an outstanding example with maximum disruption, Ott; and fill rates ranging between 83.27 and 90.91 percent; 91.40 and 96.50 percent; respectively, with the highest stability and performance loss (0.90 to 5.60). KMeansPlusPlus is best in low-disruption cases where there is 100 percent OTD and fill rates, whereas the KMedoids is stable in moderate to severe level of disruptive environments. The scenario with the minimum number of hubs in the inventory proves to be the most resilient to all others, as an extreme stress leads to a scenario with all OTD and fill rates at 0 percent; all other scenarios fail to handle such high levels of change without collapsing. Interestingly, CoG, although seems to be structurally robust at a full flexibility and no flexibility scenario, still shows a zero performance, pointing out a lack of coordination between structural stability and operational performance.

Practical Implications and Policy Relevance

The instilled resilience and stability of FuzzyCMeans and KMedoids can be powerful models to be implemented in stressful supply chain systems and especially in minimal inventory systems. The KMeansPlusPlus works better in low disruption cases on the other hand, and trustworthiness and performance are ensured with little strain. Such insights provide practical guidance on the implementation of logistics investment strategies, by providing the resources of computational and operational instructions on focusing on resilient clustering algorithms. The dysfunctional behavior of CoG in terms of its performance, its seemingly high resilience notwithstanding, begs the question that a robustness should always be tested with quantitative performance parameters, and not by the structural presumptions only.

Limitations

The present one has a very narrow scope of scenarios as it only deals with utter flexibility or utter rigidity. The binary categorization limits the possibility of zooming on the slight performances differences within intermediate working environments. Besides, the stability and trend measures give no clear indication of the number of trials involved or disruption periods, which lead to imprecise meanings of variability levels and slopes dynamics. The other weakness is the fact that the study will take a very short period that is limited to 30 days of simulation activities. This reduces the knowledge on the long-term of performance- changing dynamics, in a way preventing the potential of generalizing findings to the wider temporal and contextual landscape.

Future Research Directions

To facilitate analysis under spatial and locational dependencies, integration of spatial data must appear in future literature in order to perform spatially-aware performance analysis.

A more finely-grained scenario taxonomy, having intermediary levels of flexibility, would assist in exposing the finer performance gradients amid clustering strategies. Further the work to be followed must define clearly the extent of replication as well as the frequency of trials, as far as non linear trend patterns in stability measures are concerned. Long-term resilience of algorithms may benefit by extending timeframe or replicating more times of the simulation. Finally, the resilience properties of CoG in the case of radical disruption are paradoxical enough to be investigated further by examining more specific parameters with the help of modifications to the parameter set. These suggested changes imply reassessment of the evaluation criteria and eliminate inconsistencies, as well as making the discussion methodologically more rigorous.

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