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Integrating Freight Distribution into Urban Rail Transit Networks: Hotspot and Accessibility Mapping in Greater Jakarta

Muhammad Efando Haryadi*, Nahry, Andyka Kusuma
Universitas Indonesia
Email: muhammad.efando@ui.ac.id*, nahry@eng.ui.ac.id, andyka.k@ui.ac.id

Abstract

Urban freight transport in Jakarta remains heavily reliant on road-based networks, leading to severe traffic congestion and environmental degradation. Integrating freight distribution into existing passenger rail networks through Freight-on-Transit (FOT) concepts offers a sustainable alternative. This study aims to identify spatial urban freight demand hotspots within the Greater Jakarta Metropolitan Area (Jabodetabek) and evaluate their accessibility to commuter rail (KRL) stations for potential logistics node development. Utilizing one-day parcel delivery transaction data, K-Means clustering was applied to isolate 20 distinct demand centroids across major urban corridors. A network-based shortest path analysis via the Open-Source Routing Machine (OSRM) was subsequently conducted to measure actual road-network distances and compute accessibility scores for each hotspot–station pair. The findings reveal significant spatial heterogeneity in logistics demand. Several stations within dense urban corridors, notably Stasiun Angke (Cluster 19) and Stasiun Sudirman (Cluster 5), exhibited the highest potential for rail-integrated logistics due to high demand concentration and close physical proximity of under 3.2 km. Conversely, suburban clusters showed lower feasibility due to substantial network distances. This study provides a practical decision-support framework combining spatial data analytics and infrastructure routing, offering valuable insights for logistics operators and policymakers in planning rail-based micro-consolidation depots to improve last-mile delivery efficiency.

Keywords: Urban Freight Transport; Freight-on-Transit; K-Means Clustering; Accessibility Analysis; Jabodetabek

INTRODUCTION

Urban freight transport plays a highly important role in sustaining economic activity, especially in metropolitan areas, yet remains heavily dependent on road-based distribution systems. In many large urban regions, including Jakarta, freight movement is dominated by trucks, contributing disproportionately to congestion, greenhouse gas emissions, air pollution, and noise (Climate Watch Data: Indonesia, 2022; Dablanc & Rodrigue, 2017). Although freight vehicles represent only a relatively small share of total traffic volume, their impact on urban transport systems remains significant.

In response to these challenges, increasing attention has been directed towards alternative approaches to freight distribution. One such approach is the integration of freight transport into existing passenger transport systems, particularly urban rail networks. Concepts such as Freight-on-Transit (FOT), shared-use public transport, and integrated passenger–freight systems propose utilizing underused capacity in passenger services, specifically during off-peak periods, to accommodate freight flows (Cochrane et al., 2017; Derse & Van Woensel, 2024). Previous empirical studies suggest that such integration can help reduce congestion, lower emissions, and improve system efficiency (Bruzzone et al., 2023; Xue et al., 2024). However, implementing an integrated passenger–freight system requires a precise understanding of where logistics demand is concentrated to ensure effective consolidation.

Demand hotspot identification has therefore become an important component of urban logistics planning (Markou et al., 2019). Spatial clustering methods can be used to identify concentrated areas of delivery activity and reveal underlying spatial demand patterns (Ducret et al., 2016; Liu et al., 2019). Among various clustering approaches, K-Means clustering is widely applied due to its computational simplicity and effectiveness in partitioning spatial data into homogeneous groups based on geographic proximity (Johansson et al., 2024; Miller, 2018; Nassar et al., 2023). In the context of logistics and facility planning, clustering techniques can assist decision-makers in identifying candidate service areas, evaluating spatial concentrations of demand, and supporting infrastructure expansion strategies (Foroozanfar et al., 2026; Uddin & Warnitchai, 2020).

Previous studies in urban freight transportation have explored topics such as city logistics, facility location optimization, and accessibility-based freight planning (Elbert & Rentschler, 2022; Halim, 2023). Crainic et al. (2004) emphasized the importance of advanced freight transportation systems in addressing congestion in urban environments, while Cui et al. (2015) highlighted the role of city logistics in the smooth functioning of urban transport networks. Additionally, accessibility analysis has been widely adopted in transportation planning to evaluate the relationship between demand locations and transport infrastructure. Despite these developments, limited studies have specifically examined the integration potential between urban freight demand hotspots and commuter rail station infrastructure in the Jabodetabek region.

This study aims to identify spatial freight demand hotspots in the Jabodetabek area using K-Means clustering based on parcel delivery coordinates. The resulting demand centroids are subsequently analyzed in relation to commuter rail (KRL) stations to evaluate potential accessibility and suitability for supporting urban logistics activities. By combining spatial demand clustering with transport accessibility analysis, this research contributes to the development of a decision-support framework for identifying potential rail-integrated logistics nodes in metropolitan areas. The findings of this study are expected to provide both academic and practical contributions. Academically, this research extends the application of spatial clustering methods within the context of urban freight accessibility analysis. Practically, the results may support logistics operators and policymakers in identifying strategic locations for depot expansion and rail-based freight integration in highly urbanized regions such as Jabodetabek.

METHODS

Study Area and Data Collection

This study focuses on the Greater Jakarta Metropolitan Area (Jabodetabek), Indonesia, which represents one of the largest urban agglomerations in Southeast Asia with high logistics activity intensity. The analysis utilizes parcel delivery transaction data obtained from logistics operations. The dataset includes geographic coordinates (longitude and latitude) representing delivery locations, as well as shipment demand information.

Prior to analysis, the dataset underwent preprocessing stages, including coordinate cleaning, removal of missing values, and spatial filtering to ensure that only observations within the Jabodetabek operational area were included. Geographically distant outliers outside the study area were excluded to avoid distortion in the clustering process.

Spatial Demand Analysis

To identify spatial demand hotspots, K-Means clustering was applied to the geographic coordinates of delivery demand points. K-Means partitions observations into several clusters by minimizing within-cluster variance based on Euclidean distance. The clustering process was conducted using longitude and latitude coordinates as spatial variables.

The general objective function of K-Means clustering is expressed as:

$$J(C)=\sum_{k=1}^{K}\sum_{x_i\in c_k}\|x_i-\mu_k\|^2$$

where:

k represents the number of clusters

C_k represents cluster k

x_i represents data point i

μ_k represents the centroid of cluster i.

Determination of Number of Clusters

The Elbow Method was employed to evaluate the relationship between the number of clusters and the Within-Cluster Sum of Squares (WCSS). The analysis showed a significant reduction in WCSS values at lower cluster numbers, followed by a gradual flattening trend.

Although the Elbow Method indicated an initial optimal range at lower cluster values, this study adopted a higher number of clusters to achieve finer spatial granularity and better representation of heterogeneous freight demand patterns across the Jabodetabek metropolitan region. The final number of clusters was selected based on a combination of statistical indication, spatial interpretability, and operational relevance for logistics hotspot identification.

Accessibility Analysis Using Shortest Path

Following the identification of demand hotspots through K-Means clustering, an accessibility analysis was conducted to evaluate the spatial relationship between hotspot centroids and commuter rail (KRL) stations. The analysis aimed to identify stations with the highest potential to support rail-integrated urban logistics operations.

Shortest path analysis was performed using the Open Source Routing Machine (OSRM) based on the OpenStreetMap road network. Unlike Euclidean distance, the network-based approach considers actual road connectivity and provides more realistic accessibility measurements for logistics operations.

For each hotspot centroid, the shortest road-network distance to all KRL stations was calculated, and the nearest station was identified based on the minimum travel distance. The resulting accessibility values were subsequently used to rank hotspot–station pairs according to their operational potential.

An accessibility score was calculated using the following equation:

Accessibility Score=Total Demand/Shortest Path Distance

where:

Total Demand represents the aggregated parcel demand within each hotspot cluster,

Shortest Path Distance represents the minimum road-network distance between the hotspot centroid and the nearest KRL station.

Higher accessibility scores indicate areas with relatively high logistics demand and shorter access distance to commuter rail infrastructure, suggesting stronger potential for logistics integration.

Visualization and Analytical Tools

Spatial clustering, accessibility analysis, and visualization were conducted using the R programming language. Several packages were utilized, including:

ggplot2 for spatial visualization (Wickham, 2016),

ggmap for basemap integration (Kahle & Wickham, 2013),

sf for spatial data processing (Pebesma, 2018),

osrm for shortest path routing analysis, and

dplyr for data manipulation.

OpenStreetMap-based road networks were accessed through the OSRM routing engine to estimate shortest path distances between hotspot centroids and KRL stations.

RESULTS AND DISCUSSION

Spatial Distribution Of Demand

Figure 1 illustrates the spatial distribution of parcel delivery demand in the Jabodetabek metropolitan area based on one-day operational data obtained from a parcel delivery company. The distribution shows that delivery activities are highly concentrated within Jakarta and surrounding urban areas, including Bekasi, Tangerang Selatan, Depok, and Bogor.

Figure 1. Spatial Distribution of Parcel Delivery Demand in Jabodetabek Based on One-Day Operational Data

Source: Parcel delivery transaction data from a logistics operator (one-day operational dataset, 2025); visualization by the author using R (ggplot2, ggmap)

The spatial pattern indicates several dense delivery zones, particularly along major urban corridors and suburban residential areas. This uneven distribution suggests the presence of demand concentration areas that may potentially support logistics consolidation and integration with commuter rail (KRL) infrastructure.

Prior to clustering analysis, spatial filtering was applied to remove geographically distant observations outside the Jabodetabek operational area to improve clustering consistency and hotspot identification accuracy.

Elbow Method Analysis

The Elbow Method was applied to determine the appropriate number of clusters for the K-Means clustering process. Figure 2 shows the relationship between the number of clusters (k) and the Within-Cluster Sum of Squares (WCSS). The graph indicates a substantial decrease in WCSS values at lower cluster numbers, followed by a more gradual decline as the number of clusters increases.

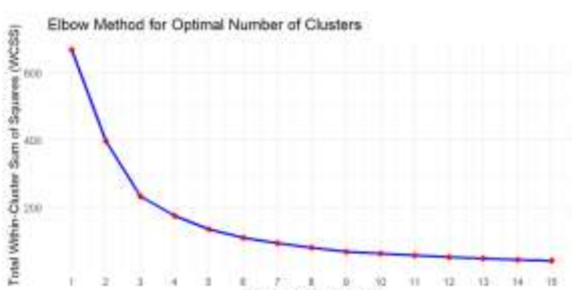

Figure 2. Elbow Method for Determining the Number of Clusters

Source: Author's calculation based on parcel delivery data (WCSS values for k = 1 to 15)

The elbow point appears around k=4 to k=5, indicating the initial optimal clustering range based on statistical compactness. However, this study adopted a higher number of clusters to capture the heterogeneous spatial characteristics of parcel delivery demand within the Jabodetabek metropolitan area. A larger cluster configuration was considered more suitable for providing finer hotspot segmentation and supporting operational-level logistics analysis.

Demand Hotspot Identification

Figure 3 illustrates the spatial distribution of freight demand hotspots identified using K-Means clustering. The blue points represent parcel delivery locations, while the red points indicate the centroid of each cluster, representing the spatial center of demand concentration.

Figure 3. Spatial Distribution of Demand Hotspots Identified Using K-Means Clustering
Source: K-Means clustering results (author's analysis); basemap from OpenStreetMap; visualization by the author using R

The clustering results reveal that delivery demand is concentrated along major urban corridors within the Jabodetabek metropolitan area, particularly in Jakarta and surrounding suburban regions such as Bekasi, Tangerang Selatan, Depok, and Bogor. Several clusters exhibit higher demand accumulation, indicating areas with strong logistics activity and potential suitability for freight consolidation or depot development.

Compared to lower cluster configurations suggested by the Elbow Method, the selected cluster configuration provides finer spatial segmentation and better representation of heterogeneous urban freight demand patterns. This allows more detailed identification of localized demand hotspots and supports operational-level accessibility analysis toward commuter rail (KRL) stations.

Table 1 summarizes the centroid coordinates and total demand associated with each identified cluster.

Table 1. Spatial Demand Cluster Centroids and Associated Demand

Cluster	Longitude	Latitude	Total Demand (kg)	Number of Delivery Points
1	106.9667	-6.4076	862	794

Cluster	Longitude	Latitude	Total Demand (kg)	Number of Delivery Points
2	106.9991	-6.2007	1026	943
3	107.1046	-6.2446	897	866
4	106.9077	-6.1458	1790	1685
5	106.8259	-6.2161	2291	2021
6	106.8587	-6.1545	1688	1522
7	106.8349	-6.4770	880	854
8	106.8038	-6.2864	1445	1210
9	106.6353	-6.2256	1117	845
10	106.9857	-6.2934	1168	1066
11	107.0956	-6.3732	590	550
12	106.8612	-6.3643	1325	1195
13	106.9068	-6.2422	1447	1300
14	106.6942	-6.3024	1277	1032
15	106.7725	-6.3915	764	700
16	106.6878	-6.5568	509	496
17	106.7302	-6.1344	1354	1170
18	106.7550	-6.1999	1504	1154
19	106.7946	-6.1389	2151	1735
20	106.8016	-6.5843	1500	1285

Source: Author's calculation based on K-Means clustering of parcel delivery coordinates (one-day operational data, 2025)

Acessibility Analysis Between Hotspots And Krl Stations

Table 2 summarizes the shortest path accessibility results between identified demand hotspots and the nearest KRL stations. The analysis reveals varying accessibility characteristics across the Jabodetabek metropolitan area.

Table 2. Shortest Path Accessibility Between Demand Hotspots and Nearest KRL Stations

Cluster	Longitude	Latitude	Total Demand (kg)	Number of Delivery Points	Nearest Station	Distance (km)	Accessibility Score
19	106.7946	-6.1389	2151	1735	Stasiun Angke	2.842	756.9
5	106.8259	-6.2161	2291	2021	Stasiun Sudirman	3.158	725.5
6	106.8587	-6.1545	1688	1522	Stasiun Rajawali	3.801	444.1
3	107.1046	-6.2446	897	866	Stasiun Metland Telaga Murni	3.045	294.6
12	106.8612	-6.3643	1325	1195	Stasiun Univ. Indonesia	4.738	279.7
13	106.9068	-6.2422	1447	1300	Stasiun Buaran	5.923	244.3

Cluster	Longitude	Latitude	Total Demand (kg)	Number of Delivery Points	Nearest Station	Distance (km)	Accessibility Score
18	106.7550	-6.1999	1504	1154	Stasiun Bojong Indah	6.518	230.7
7	106.8349	-6.4770	880	854	Stasiun Cibinong	4.038	217.9
20	106.8016	-6.5843	1500	1285	Stasiun Bogor	7.157	209.6
17	106.7302	-6.1344	1354	1170	Stasiun Rawa Buaya	6.533	207.3
2	106.9991	-6.2007	1026	943	Stasiun Bekasi	5.097	201.3
4	106.9077	-6.1458	1790	1685	Stasiun Buaran	9.581	186.8
14	106.6942	-6.3024	1277	1032	Stasiun Rawa Buntu	6.956	183.6
9	106.6353	-6.2256	1117	845	Stasiun Tangerang	7.086	157.6
10	106.9857	-6.2934	1168	1066	Stasiun Bekasi	7.451	156.8
8	106.8038	-6.2864	1445	1210	Stasiun Duren Kalibata	9.417	153.4
15	106.7725	-6.3915	764	700	Stasiun Depok	6.97	109.6
1	106.9667	-6.4076	862	794	Stasiun Nambo	12.706	67.8
16	106.6878	-6.5568	509	496	Stasiun Bogor	15.177	33.5
11	107.0956	-6.3732	590	550	Stasiun Cikarang	19.823	29.8

Source: Network-based shortest path analysis using OSRM (Open Source Routing Machine) and OpenStreetMap road network; accessibility scores computed by the author

Several hotspot clusters exhibit relatively high accessibility scores due to the combination of high parcel demand and short road-network distances to nearby stations. Cluster 19, associated with Stasiun Angke, achieved one of the highest accessibility scores with a shortest path distance of approximately 2.84 km and a total demand of 2,151 kg. Similarly, Cluster 5, located near Stasiun Sudirman, demonstrated strong accessibility performance with a distance of approximately 3.16 km and the highest recorded total demand of 2,291 kg.

These clusters demonstrate relatively balanced conditions between demand concentration and proximity to commuter rail infrastructure, indicating strong potential for supporting urban logistics activities.

Conversely, several clusters exhibited lower accessibility scores due to relatively long network distances despite moderate demand levels. For example, Cluster 11 associated with Stasiun Cikarang recorded the lowest accessibility score, primarily due to its long shortest path distance of approximately 19.82 km. Similar conditions were observed in peripheral suburban clusters connected to Stasiun Bogor and Stasiun Nambo.

Overall, the findings indicate that several KRL stations located within high-demand urban corridors possess significant potential to function as supporting logistics nodes or micro-consolidation facilities. The integration of freight demand hotspots with commuter rail infrastructure may contribute to improving last-mile distribution efficiency and reducing dependency on road-based logistics operations (Savelsbergh & Van Woensel, 2016; Taniguchi et al., 2016).

Implication For Urban Logistics Planning

The combination of spatial demand clustering and network-based accessibility analysis provides a useful framework for identifying strategic logistics locations within metropolitan regions. The results demonstrate that hotspot areas with high parcel demand and strong accessibility toward commuter rail stations may serve as potential candidates for rail-integrated logistics operations.

The findings also highlight the importance of considering actual road-network accessibility rather than relying solely on geographic proximity. Several hotspot clusters that appeared spatially close to stations exhibited relatively longer network distances due to urban road connectivity constraints.

From a practical perspective, the identified hotspot–station pairs may support:

a. depot expansion planning,
b. micro-fulfillment center development,
c. multimodal freight integration strategies, and
d. sustainable urban logistics initiatives.

The analytical framework developed in this study may also assist policymakers and logistics operators in evaluating future rail-based freight distribution opportunities within rapidly growing metropolitan regions such as Jabodetabek.

CONCLUSION

This study identified spatial parcel delivery demand hotspots within the Jabodetabek metropolitan area using K-Means clustering based on one-day operational data from a parcel delivery company. The clustering results revealed heterogeneous freight demand patterns distributed across major urban corridors in Jakarta and its surrounding suburban areas. The Elbow Method was initially used to evaluate cluster compactness, while a larger cluster configuration was ultimately selected to provide finer spatial segmentation and improve operational interpretability for logistics planning purposes.

Subsequently, shortest path accessibility analysis was conducted using OpenStreetMap-based road-network routing through the OSRM framework. The analysis identified several hotspot clusters with strong accessibility to nearby KRL stations, particularly around Stasiun Angke, Stasiun Sudirman, and Stasiun Rajawali. The findings suggest that integrating urban freight demand hotspots with commuter rail infrastructure may offer opportunities for developing rail-supported urban logistics systems and improving last-mile delivery efficiency within metropolitan areas. Overall, the study demonstrates that combining spatial clustering and network-based accessibility analysis can provide a practical decision-support framework for identifying potential logistics nodes and supporting sustainable urban freight planning in Jabodetabek.

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