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High-Resolution Smart Card-Based OD Matrix for Optimizing Jakarta's LRT Operations

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Abstract. Efficient urban mobility is essential to support transportation planning and policy. However, traditional methods are often limited in data resolution, lacking the ability to describe passenger movement dynamics in detail. This study aims to analyze passenger mobility patterns using high-resolution tap-in/tap-out data from the closed-loop LRT system in Jakarta during January-February 2025. The methods used include constructing an origin-destination (OD) matrix based on 185,512 trip records, as well as temporal and spatial analysis of passenger flows. The results showed the existence of peak hour patterns on weekdays (07.00-09.00 and 17.00-19.00), trip spikes on weekends and holidays (14.00-18.00), and high flow concentrations at interchange stations such as Velodrome and North Boulevard. While data from the closed system allows for accurate trip tracking, potential data gaps due to technical errors or user behavior remain a concern for long-term analysis. The findings suggest that high-resolution smart card data can provide operationally relevant insights for short-term decision-making, such as schedule adjustments or fleet allocation. However, for long-term strategic planning, integration with predictive models and other planning tools remains necessary. This research fills a gap in the literature by showing that even limited-duration datasets can be leveraged to effectively support data-driven transportation management.

Keywords: Light Rail Transit (LRT), smart card, transit analysis, LRT performance metrics, transit demand estimation, urban mobility.

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1. Introduction

Jakarta's population is expected to reach 10,6 million, making it one of the most densely populated urban areas in Southeast Asia. This increase in population can lead to a higher demand for transportation. Furthermore, with the high growth of private vehicles that is not matched by the growth of existing road infrastructure, this can result in severe congestion that is economically costly [1]. To address this issue, the government has developed several public transportation systems in Jakarta. These include: TransJakarta BRT, which operates 14 main corridors covering a total of 244 km and connecting various areas of Jakarta and its surroundings; the Jakarta MRT, which currently operates one North-South corridor (Lebak Bulus-Bundaran HI, 15.7 km) and has another corridor under construction (Bundaran HI-Kota, 6.3 km); and the Jakarta LRT, which has one operational corridor (Pegangsaan Dua-Velodrome, 5.8 km) and is extending another segment (Velodrome-Manggarai, 6.4 km).

Based on the Jakarta-Bogor-Depok-Bekasi (Jabodetabek) Transportation Master Plan, the percentage of residents using urban public transportation must reach 60% [2]. One practical way to meet the mobility needs of urban communities is to build an urban rail system. It is estimated that the implementation of an urban rail system integrated with other public transportation networks will reduce traffic congestion. Urban railway systems are proven public transportation that can improve transportation efficiency by optimizing energy use, improving operational control, and contributing to economic and environmental benefits [3,9].

The Light Rail Transit (LRT) system is an urban rail transportation mode that is an important part of the public transportation network in Jakarta, one of the most densely populated cities in the world [10, 15]. The system is designed to integrate with other modes in the multimodal transit ecosystem, such as TransJakarta and Commuter Line, to improve connectivity and travel efficiency. However, in practice, the Jakarta LRT faces considerable operational challenges, especially in terms of dynamic adjustment between operational resources such as train travel frequency and the number of station staff with fluctuations in passenger demand that occur every day.

To deal with these challenges, a data-driven approach is needed that can provide a detailed picture of passenger mobility patterns. One commonly used tool is the origin-destination (OD) matrix, which can help map the flow of movements between stations and serve as the basis for optimizing transportation system operations [16].

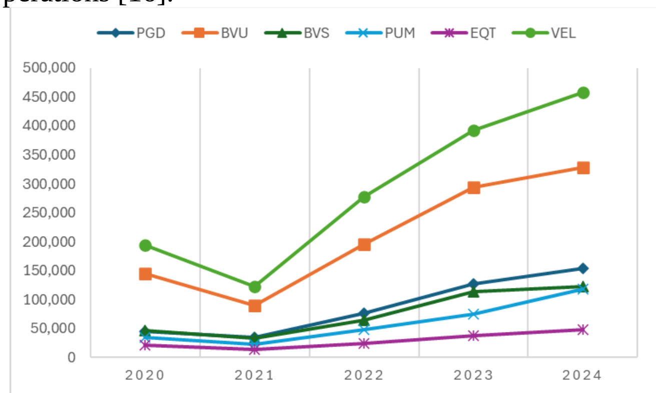

Figure 1. The number of passengers per station for the period from 2019 to 2024

Figure 1 shows the trend of Jakarta LRT ridership at all stations over the period 2020 to 2024. The data indicates significant growth in passenger volumes, especially after 2021. The decline in ridership in 2021 is thought to be the result of the COVID-19 pandemic which restricted mobility for a wide range of people. However, from 2022 to 2024, there was a sharp increase reflecting the recovery of activity and increased use of public transportation. In addition, the variation in ridership between stations is also quite striking. Velodrome (VEL) and North Boulevard (BVU) stations dominate passenger volumes during this period, indicating their role as key nodes of mobility. Travel fluctuations are not only seasonal, but also daily and weekly, depending on the time of day and type of day (weekday or weekend). Without an in-depth understanding of the origins and destinations of passenger trips, operators will find it difficult to adapt services adaptively, whether for train allocation, timetabling or other resource requirements.

The OD matrices are a critical component of public transportation management, not only for real-time operational decision making, but also for long-term strategic planning including annual trend analysis, service planning, and infrastructure investment justification [17,18]. High-resolution OD data provides the ability to analyze travel behavior in detail and identify spatial-temporal patterns that are not visible in aggregate data [19]. It has been used to adjust vehicle frequencies, dynamically estimate waiting times [20,22], and support the development of predictive models for travel demand [23]. Even in the short-term scope, high-resolution data enables rapid policy responses to changes in travel patterns or service disruptions [24].

However, there are several gaps in the literature that remain unaddressed. First, most OD matrix studies still focus on developed countries, such as the United States and Europe [17], while similar studies in developing countries, including Indonesia, are still very limited. Secondly, many previous studies rely on open fare collection systems that only record tap-in data, requiring complex inference algorithms to estimate travel destinations [25, 26]. Third, the use of high-resolution OD data to describe detailed temporal dynamics in a closed-loop LRT system like Jakarta has not been explored.

This study offers an update by utilizing the full tap-in and tap-out data of the Jakarta LRT system operating in a closed-loop environment, thus aiding the direct construction of the OD matrix without the need for additional estimation. In addition, this study uncovers previously unexplored daily and weekly temporal dynamics and establishes a data-driven framework for fleet allocation optimization. As such, this study makes an empirical and methodological contribution to data-driven transportation studies in developing countries, and strengthens the argument on the importance of using high-resolution data in closed systems as an alternative to the complex inference approaches commonly used in previous literature.

Methodologically, this research contributes by presenting a practical and efficient data-driven approach to construct the OD matrix of a closed system, and shows how this granular data can be directly utilized to develop a dynamic fleet allocation and scheduling framework. This approach offers an operational solution that is responsive to peak hour demand spikes as well as daily variations, and can be easily replicated in similar urban transportation systems that have full tap-in/tap-out data.

The contribution to the literature lies in filling the void of empirical studies on the utilization of smart card data in developing countries, particularly in closed-loop systems such as the Jakarta LRT. This study adds evidence that high-resolution data from closed systems is not only useful for short-term operational analysis, but can also be a solid basis for long-term strategic planning. The results of this study provide actionable insights for operators to improve real-time service efficiency and adapt to changing passenger mobility patterns.

2. Methods

2.1. Research Stages

This research was conducted through a series of systematic stages aimed at building an origin-destination (OD) matrix based on smart card data. The process starts with data acquisition from the closed Automatic Fare Collection (AFC) system of Jakarta LRT, followed by preprocessing and data validation to ensure data integrity and cleanliness. For the next steps can be seen in Figure 2, the data is then processed through the preprocessing stage to clean and categorize it based on parameters such as weekdays and weekends. Next, a descriptive analysis was conducted using visualizations (e.g., box plots) to identify trends and peak hours. These insights were then used to generate an Origin-Destination (OD) matrix by mapping passengers' origin and destination stations. The OD matrix results were further analyzed to uncover mobility patterns, including the busiest routes and differences in passenger volume between weekdays and weekends. The resulting insights offer potential support for operational decisions, such as service frequency adjustments and resource planning, although actual implementation would require further modeling or operator-level validation. The final output of this research process was a comprehensive OD matrix that served as a decision-support tool for managing the Jakarta LRT system.

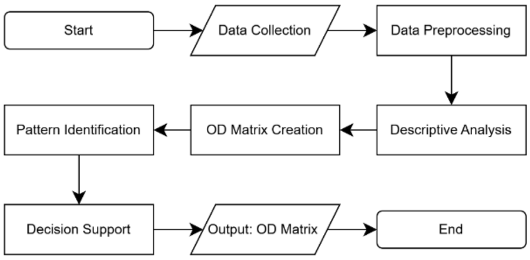

Figure 2. Research Stages

2.2. Study Location

Jakarta is home to about 10.6 million people despite covering only about 225 square miles, making it one of the most densely populated cities in the world. This condition demands a reliable public transportation system to reduce congestion and support community mobility. One of the efforts made by the government is the construction of the Jakarta LRT Phase 1, which is currently in operation serving a 5.8-kilometer route. The existence of LRT is expected to be an efficient and sustainable urban transportation solution, with plans for further line development in the future to expand coverage and improve connectivity between regions in the capital city.

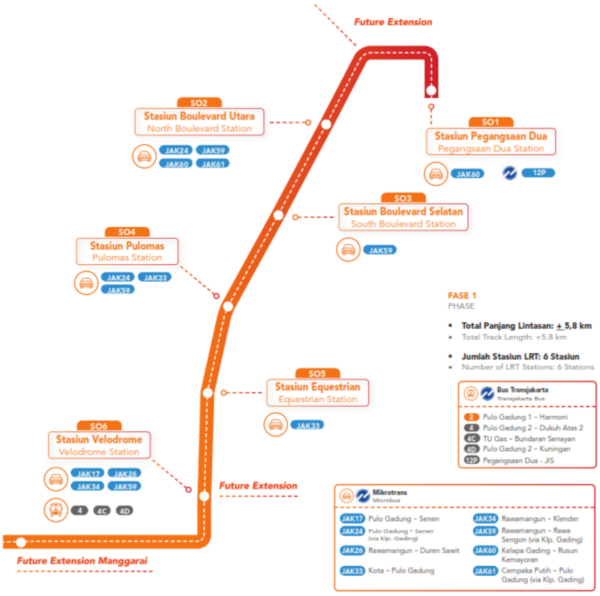

Figure 3. Jakarta LRT network phase 1 (PT LRT Jakarta Annual Report, 2023)

Table 1. Length of Track Between Stations

From	To	Length
Pegangsaan Dua (DPD)	Boulevard Utara (BVU)	1.550 km
Boulevard Utara (BVU)	Boulevard Selatan (BVS)	1.287 km
Boulevard Selatan (BVS)	Pulomas (PUM)	1.130 km
Pulomas (PUM)	Equestrian (EQT)	0.740 km
Equestrian (EQT)	Velodrome (VEL)	1.020 km

Figure 3 shows the map of the Jakarta LRT network, which includes two terminal stations and four transit stations. Each station featured indirect integration with Bus Rapid Transit (BRT) and angkot (micro transit), except Velodrome (VEL) station, which had direct BRT integration via the integrated AFC system. The data in Table 1 provided details on the length of the route between stations. This information provided an overview of the network scale and distance between stations, which was an important factor in operational planning and scheduling of LRT services.

2.3. Data Collection and Acquisition

Data were collected from transactions at six stations between January 1 and February 28, 2025. The dataset had high temporal resolution, with time recorded to the second, enabling granular analysis of passenger mobility patterns. The study covered 40 typical weekdays and 16 weekend days. Figure 4: Automatic Fare Collection (AFC) gates at Pegangsaan Dua (DPD) station, illustrating the closed-loop fare payment system utilized for accurate passenger tap-in and tap-out data collection in this study.

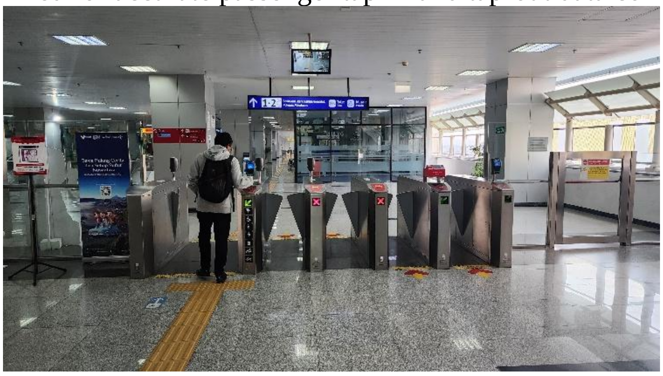

Figure 4. Automatic Fare Collection (AFC) gates at Pegangsaan Dua (DPD) station

2.4. Data Preprocessing and Validation

Data cleaning and validation steps are systematically performed to ensure the accuracy and reliability of subsequent analysis. The cleaning process includes removing duplicate transactions based on the combination of card ID and time, as well as checking the time logic to ensure that the tap-out time is always greater than the tap-in. Spatial validation is performed by ensuring that the origin and destination stations are within a geographically valid route network. Anomaly handling is performed using an interquartile range (IQR) approach to detect trips with extreme durations. Transactions that exhibit extremely short (<1 minute) or excessively long (>120 minutes) durations are flagged for manual analysis as they may indicate system errors or shared card usage. This procedure was performed to minimize noise and avoid misinterpretation of aberrant data.

2.5. Data Analysis and Tools

Following data acquisition, descriptive analysis was performed to generate box plots representing the hourly transaction distribution and identifying any outliers. These visualizations provided descriptive insights into peak periods and variations in passenger flow, which serve as preliminary indicators for further analysis. A combined method of box plots and visual comparisons of station-specific traffic on weekdays versus holidays ensured a comprehensive understanding of mobility trends. Subsequently, the data were used to construct an OD matrix that summarized passenger flows across stations and time intervals (e.g., weekdays vs. weekends).

2.6. Origin-Destination (OD) Matrix Model

Individual movements across geographic areas from origin (O) to destination (D) were captured using OD matrices, which illustrated passenger flows between stations or areas. Once OD matrices were created, further analyses on human mobility and transit demand were conducted. However, collecting OD matrices could be challenging due to hardware limitations at stations and infrastructure constraints within the transit system.

Table 2. Smart Card Data Specification

Variable	Format	Description
Card Type	String	Type of card used
Smart card ID	String	Identification number of a smart card
Time Gate In	Time	The card's tap-in time, i.e., date, hour, minute, and second
Time Get Out	Time	The card's tap-out time, i.e., date, hour, minute, and second
Station Code In	String	The card's tap-in location, i.e., the station's name
Station Code Out	String	The card's tap-out location, i.e., the station's name
Minimum Balance	Numeric: Real	Minimum balance that must be available on the card
Far (Rp)	Numeric: Real	Travel fare is charged based on distance
Balance Before (Rp)	Numeric: Real	The amount of credit (money) in the smart card
Deduct (Rp)	Numeric: Real	The amount deducted from the smart card balance to pay for travel
Balance (Rp)	Numeric: Real	Smart card balance after the transaction is made
Status Moda	String	Status or type of transportation mode used, i.e., multi-mode or single-mode.

Table 2 presents the detailed specifications of the Automatic Fare Collection (AFC) data used in this study. The data includes various important information, such as the smart card ID that is unique to each user, the time when the user taps-in and taps-out at the entry and exit gates, and information about the origin and destination stations of the trip. In addition, the table also contains data on the card balance before and after the trip, the amount of fare charged, and the integration status of the trip with other modes of transportation, which are important indicators in the analysis of travel patterns and the effectiveness of the transportation integration system.

2.7. Limitations and Bias Control

This study recognizes a number of limitations that may affect the accuracy of the results. Not all smart cards represent unique individuals due to possible shared use within a family or group. While the closed system minimizes data loss, there is still the possibility of unrecorded transactions due to tap-out failures. The absence of user demographic attributes also limits the ability to segment or analyze individual behavior. Therefore, the results of the OD matrix in this study better represent macro patterns of aggregate population movement. For more accurate policy or operational applications, additional validation through field surveys, integration with GPS data, or testing through limited operational simulations is recommended.

3. Results and Discussion

3.1. Descriptive Statistics

We conduct a descriptive analysis to get an initial overview of the transaction dataset and LRT operations. Figure 5 shows the total number of passenger transactions at each station in units of transactions (passengers), distinguishing between tap-in (In) and tap-out (Out) transactions. Typically, a single trip involves two transactions: a tap-in transaction at the origin station and a tap-out transaction at the destination station. Stations such as VEL and DPD showed a dominance of tap-in, indicating their characteristics as origin stations, while PUM, BVS, and BVU functioned as destination stations with a dominance of tap-out. The VEL station consistently had the highest passenger volume intensity, indicating its function as a major transportation node with the potential to become a transit center. However, the total number of tap-ins and tap-outs was the same, so there was no need to perform a validation method for missing data between tap-in and tap-out.

Figure 6 shows the distribution of average transactions per hour over the whole week (Sunday–Saturday). Figure 7 isolates the weekdays (Monday–Friday), where transactions peak at around 1,500 per hour per day during the evening rush hours from 5 p.m. to 8 p.m. A smaller peak is also observed during the morning peak hours between 7 a.m. and 9 a.m., indicating commuter activity toward central business areas. In contrast, the weekend pattern appears stable from 10 a.m. to 8 p.m., with a total of around 1,000 transactions per hour per day, and shows very little variation in the early morning hours.

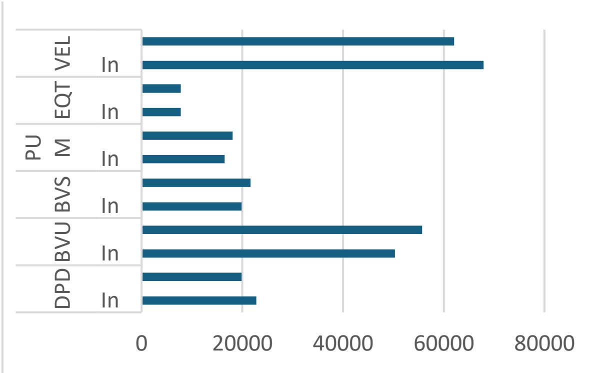

Figure 5. Passenger transactions between the Tap In and Tap Out period January-February 2025

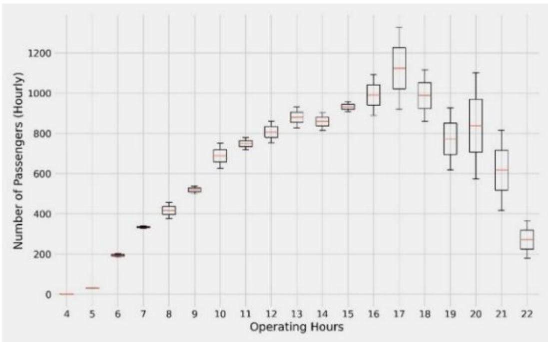

Figure 6. Distribution of passengers per hour on weekends

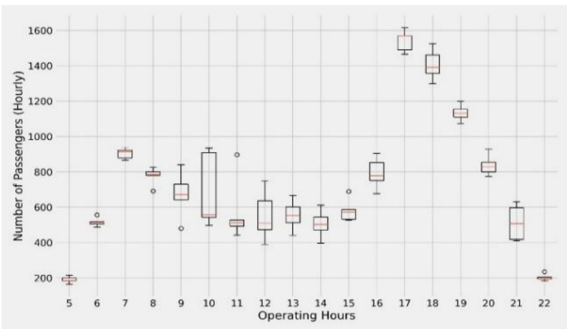

Figure 7. Distribution of passengers per hour on weekdays

The boxplot for weekdays at 10 a.m. shows a very large variation, indicating that the number of transactions at that time fluctuates more compared to other hours. This likely reflects the diverse behavior of passengers; some commuters depart early for work or appointments, while others delay their trips, resulting in a wider distribution. We also observe several outliers in the weekday data. These outliers are related to public holidays that fall on weekdays (e.g., New Year's Day on January 1 and Chinese New Year on January 29), when the number of passengers deviates significantly from the usual level. These anomalies help us distinguish routine operational peaks from extraordinary events that temporarily alter passenger flows.

The significant variations that occur at certain hours, such as 10am and visible through the boxplot visualization, indicate the existence of non-commuting and more flexible mobility patterns. This is in line with [27] findings, which show that smart card data can be used to identify passenger groups with diverse travel preferences. In addition, the presence of outliers on public holidays supports [28] research, which states that disruptions to daily routines such as holidays or extreme weather conditions can trigger spikes or drops in passenger volumes that deviate from the usual pattern.

3.2. Origin Destination (OD) Matrix Analysis

The output from the consolidation method is the main input for building the final OD matrix. The OD matrix is basically a modified version of the Aggregated Data Output (Table 3). As shown in Table 4, the OD matrix combines all passenger transactions that board and disembark at the station in the desired period. The OD matrix can be synthesized at the station level. The table shows a snapshot of the OD matrix at the station level during January-February 2025. Observing the table allows one to analyze the passenger volume between the origin and destination stations. The total number of trips during this period is 185,512 passengers or trips.

Table 3. Smart Card Transaction Record

Time Get In	**Time Get Out**	**Month**	**Station Code Out**	**Station Code In**	**Status Moda**
2025-01-07 15:25:11	2025-01-07 15:39:02	Jan	BVU	VEL	Single Moda
2025-01-07 15:25:31	2025-01-07 15:36:33	Jan	BVS	VEL	Single Moda
2025-01-07 15:26:06	2025-01-07 15:34:20	Jan	BVU	DPD	Single Moda
2025-01-07 15:27:24	2025-01-07 15:39:15	Jan	BVU	PUM	Single Moda
2025-01-07 15:27:24	2025-01-07 15:39:14	Jan	BVU	PUM	Multi Moda
2025-01-07 15:27:31	2025-01-07 15:39:08	Jan	BVU	PUM	Single Moda

Table 4. Station OD Matrix Jan-Feb 2025

Destination / **Origin**	**DPD**	**BVU**	**BVS**	**PUM**	**EQT**	**VEL**	**Grand Total**
DPD		1996	1421	3402	661	15271	22751
BVU	1771		5554	7475	3496	32384	50680
BVS	1189	5209		3313	558	9587	19856
PUM	2633	7454	2856		493	3044	16480
EQT	654	4092	640	491		1935	7812
VEL	13717	36958	11232	3455	2571		67933
Grand Total	19964	55709	21703	18136	7779	62221	185512

However, weekdays and weekends need to be distinguished because there are significant differences in passenger behavior under these conditions. Travel demand in typical LRT systems varies throughout the day, particularly during morning and evening peak periods. The OD matrix can be filtered according to specific time intervals, facilitating the analysis of the corridor's peak capacity. Examining the OD matrix in a tabular format may be tedious, particularly with extensive datasets. It is essential to present the OD matrix in a clear and comprehensible visual format.

	Weekday						Weekend					
	DPD	BVU	BVS	PUM	EQT	VEL	DPD	BVU	BVS	PUM	EQT	VEL
DPD		30	26	65	10	288		44	20	39	14	180
BVU	28		93	124	55	531	34		98	133	71	598
BVS	21	81		61	9	182	17	107		43	11	110
PUM	51	122	51		8	57	27	138	41		9	37
EQT	12	62	10	8		32	9	89	12	10		34
VEL	265	617	217	65	44		146	653	119	42	42	

Figure 8. Distribution of passenger trips per hour per station on weekdays and weekends

To / From	DPD	BVU	BVS	PUM	EQT	VEL
DPD		4	10	16	9	66
BVU			4	12	3	28
BVS	7	5		13		27
PUM	7	17	8		2	4
EQT	7	7	1	1		2
VEL	90	169	58	29	10	

Figure 9. Distribution of passenger trips in morning peak hour (07:00-09:00) per station on weekdays

To / From	DPD	BVU	BVS	PUM	EQT	VEL
DPD		3	7	8	1	69
BVU	7		29	59	15	199
BVS	7	21		22	2	97
PUM	23	36	17		5	29
EQT	4	5	5	1		17
VEL	69	167	110	34	19	

Figure 10. Distribution of passenger trips in peak hour (17:00-19:00) per station on weekdays

The OD matrix in Figure 8 shows that the VEL station has the highest passenger arrival and departure rates, both on weekdays and weekends. The data shows that on weekdays, 531 passengers are traveling from BVU to VEL, and 617 passengers are moving from VEL to BVU, making the BVU-VEL line the route with the highest movement volume. This trend even increased on weekends, with 598 passengers traveling from BVU to VEL and 653 passengers traveling from VEL to BVU.

Figure 9 reveals that passenger flows are highly centralized inbound toward a few key stations. BVU emerges as the dominant destination with 169 inbound passengers, followed by VEL with 90 inbound passengers. DPD served as a significant origin during this period, sending 66 passengers to VEL. These results indicate a pronounced convergence of morning commuters toward central hub stations. In contrast, the weekday evening peak OD matrix, as in Figure 10, exhibits more dispersed outbound travel patterns. VEL, BVU, and BVS are the primary destination stations in the evening, receiving approximately 199, 167, and 110 passengers, respectively. The distribution of origin stations is broader as well, with PUM and BVU identified as notable origins contributing 36 and 29 outbound passengers, respectively. This suggests a decentralization of flows in the evening, as passengers disperse from central areas to multiple outer stations.

Figure 11 presents a graphical representation of Origin-Destination (OD) station pairs using a circlepacking visualization technique. Each circle represents a specific OD pair, where the top station abbreviation indicates the origin (from) station, and the bottom abbreviation indicates the destination (to) station. For example, the label VEL BVU illustrates a passenger trip originating from VEL station and ending at BVU station. The size of each circle is proportional to the volume of trips between the corresponding OD pair, reflecting the relative intensity of passenger flows. Additionally, the color gradient ranging from light green to dark blue provides a visual cue for traffic density, with darker hues representing higher transaction volumes.

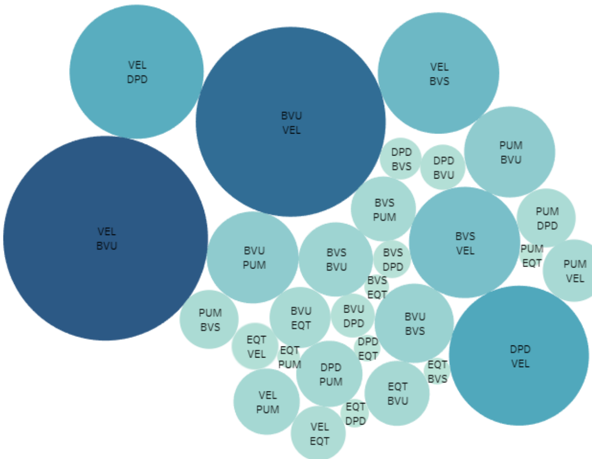

Figure 11. Visualization of Origin-Destination (OD) circles

This visualization offers a concise yet comprehensive overview of the most frequently used travel corridors. The largest and darkest circles, such as VEL BVU and BVU VEL, clearly indicate the highest-volume bidirectional flows within the network. Meanwhile, smaller and lighter-colored circles represent less-utilized connections. Such visual tools play a crucial role in supporting travel pattern analysis by enabling rapid identification of dominant travel links. Moreover, the insights derived from this diagram can inform targeted infrastructure improvements, capacity enhancements, and prioritization of service adjustments, particularly for OD pairs with consistently high demand.

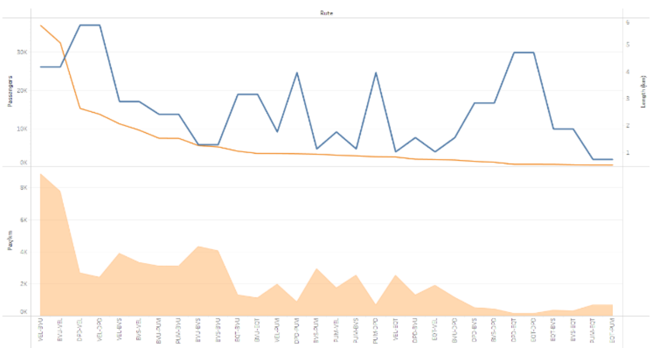

Figure 12. Number of Passenger Volume, Route Length, and Passenger per Kilometer (pnp/km) period Jan-Feb 2025

Figure 12 combines three key dimensions: passenger numbers, route length (km), and passengers per kilometer (passengers/km), which are visualized in a two-panel graph. The top panel compares passenger volume and distance for each OD pair, while the bottom panel displays spatial efficiency in pax/km units. The results show that the BVU–VEL and VEL–BVU routes have the highest passenger volumes with medium distances, making them priority routes. The DPD–VEL route, despite its length and high volume, shows moderate efficiency. In contrast, routes such as EQT–DPD and VEL–EQT have short distances and volumes with little contribution to the system load. The lower panel reinforces that passengers/km effectively identifies spatially dense routes. VEL–BVU is the most efficient, followed by BVS–VEL and PUM–VEL. Meanwhile, low-volume routes and passenger/km have limited optimization potential.

This finding confirms a previous study in [29] developing a predictive statistical model to estimate passenger density based on smart card data, emphasizing the importance of spatial and temporal aspects in evaluating the efficiency of transport systems. The bottom graph reinforces these findings, showing that the passenger per kilometer indicator is effective in identifying congested and spatially efficient routes, such as VEL-BVU, BVS-VEL, and PUM-VEL. In contrast, routes with low volumes and small passenger per kilometer values have limited optimization potential. Study, [30] also supports this data-driven approach, optimizing transport network design through smart card origin-destination data and considering criteria such as travel time, number of transfers, and service coverage.

However, for low-traffic routes, reducing service frequency is not always feasible especially on single-track systems such as the Jakarta LRT. Therefore, a number of studies offer alternative area-based solutions, such as Transit-Oriented Development (TOD) that encourages the integration of residential, business, and public facilities around transportation nodes, provision of park and ride facilities, and integration of micro-transit modes and adjustment of workforce zoning as strategies to increase ridership on low-utilization segments [31,33].

4. Conclusion

This research shows that utilizing smart card data from the closed-loop Jakarta LRT system can be used to construct origin-destination (OD) matrices directly without the need for complex estimation processes. By utilizing complete tap-in and tap-out records, the research constructs a deterministic framework that yields detailed insights into passenger flow patterns, including peak-hour congestion and flow imbalances during weekends. The findings demonstrate the great potential of OD analysis as a decision support tool in allocating resources and scheduling services more adaptively.

However, the results of this study are not intended to completely replace field surveys or predictive modeling. Validation of these findings through operational observations, cost-benefit analysis, and limited testing is required before widespread policy application. The limitations of this study lie in the limited temporal coverage of the data and have not considered external variables such as special events, weather, or ambient traffic conditions. Moving forward, the gradual integration of OD matrix-based analysis into the Jakarta LRT operational planning system may be a realistic strategic move. This approach should be complemented with additional data and predictive models that enable improved accuracy and responsiveness in service management. Thus, this research makes an initial contribution in strengthening the foundation of data-driven planning for public transportation systems in developing urban areas such as Jakarta.

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