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Assessing Travel Time Reliability and Route Clustering in Urban Metro Systems: A Case Study of Tehran Metro Using AFC Data

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As rail transportation becomes increasingly vital for daily commuting, reliability has emerged as a crucial factor influencing passengers' travel preferences and overall experience. Reliability, defined by consistent travel times, is a key metric for assessing the quality of rail services. This is especially important in metropolitan transit systems, where punctuality significantly impacts mode selection and the economic viability of transportation networks. This study is organized into three phases. The first phase involves collecting Automatic Fare Collection (AFC) data from the Tehran Metro (May 2018), including an overview of the data architecture and preparation procedures. In the second phase, travel time reliability is evaluated using two metrics: buffer time and the planning time index, with particular emphasis on the buffer time index as a primary indicator of route reliability. The final phase applies the k-means clustering method to categorize routes, determining the optimal number of clusters using the Silhouette criterion. The findings reveal that the buffer time index is a more accurate measure of travel time reliability compared to the planning time index. The analysis identifies routes with high and low reliability, highlighting that 90% of routes originating from transfer stations exhibit low average travel time reliability.

1. Introduction

In transportation systems, travelers may face several criteria to select the routes. Some travelers select routes to minimize their reliable travel time which consists of travel time and travel time reliability according to their past experience, such as the commuters, who travel regularly between the same OD pair daily .some travelers would like to select the routes with minimum travel time or travel distance using the vehicle navigation system [1, 2]. Reliability optimization problems, which employ methods to enhance system reliability, aim to optimize objective functions related to reliability. These objectives may involve maximizing system reliability or minimizing resource requirements while adhering to specific design constraints [3]. Time reliability not only reflects the service quality of

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transportation networks, but also affects passengers' route choices [4].

The concept of Travel Time Reliability (TTR) was initially addressed by Asakura and Kashiwadani (1991), by examining the daily traffic flow fluctuation on the network. Asakura (1999) has also established reliability measures in a deteriorated link for an OD pair with variable traffic flow parameters[5]. Travel time reliability on urban road networks has been documented extensively in the literature, for both buses and private vehicles[6, 7]. However, metro systems have long been considered punctual to timetables (except during service interruptions/disruptions) and metro travel time reliability has attracted little attention in the literature. This is likely due to the lack of empirical observations regarding metro travel time reliability, which has now become available with the emergence of smart card data [8]. As a result reliability is the most important performance indicator of a time-dependent system, and the reliability of a system has a significant impact on its efficiency, capacity utilization, and economic benefits [9].

The main idea of this paper is divided into three parts. The first part focuses on collecting and preparing Automatic Fare Collection (AFC) data from the Tehran Metro. This section explains how the data, collected from smart cards in May 2018, was organized, including the times of entries and exits recorded between 5:30 AM and 10:30 PM, along with customer IDs. The second part examines how travel time reliability is measured using two leading indicators: the buffer time index and the planning time index. The buffer time index is highlighted as the primary tool for assessing the reliability of different routes. In the third part, the paper discusses how routes are grouped using the K-means clustering method, with the best number of groups determined by the Silhouette criterion. This clustering helps in categorizing passenger travel routes based on how reliable they are.

The remainder of this paper is structured as follows: Section 2 offers an overview of recent studies on travel time reliability, emphasizing the various indicators employed for assessing reliability. In Section 3, we will analyze and visualize the data utilized in our research. Section 4 will delve into the results, and finally, we will end with conclusions and recommendations for future research.

2. Literature review

Travel time reliability is a key to ensuring consistent and predictable travel experiences, making it essential for effective transportation planning and management. In broad terms, reliability relates to the ability of a system to perform to expectations under a given set of conditions. With more precision, reliability can be described as the probability that a system, device or component will perform adequately for the period, time intended under the operating conditions encountered [10, 11]. In similar definition travel time reliability was 'the variations in journey time that travelers cannot predict' [12].

Several publications have addressed the state of the travel time reliability. Lomax and Margiotta. [13] categorized travel time reliability metrics into statistical range measures, buffer time measures, and tardy trip indicators. Building on this foundation, Li et al. [14] developed models to evaluate travel time reliability across various levels—origin-destination pairs, transit lines, and entire networks—by employing travel time distributions that deviate from normality, as confirmed by the Kolmogorov-Smirnov test. To address the challenge of non-normal distribution, they introduced a kernel density estimation algorithm, revealing significant impacts from factors such as departure time, travel distance, and interchange frequency on reliability outcomes. Similarly, Yang et al. [15] proposed advanced methodologies for estimating travel time distributions using Kernel Density Estimation and the HL-RF algorithm, based on empirical traffic data from Saint Louis. Their method, which captures more significant variability compared to the Florida reliability method during peak hours, proved more effective across different roadway levels.

In another innovative approach, Sun et al. [16] explored novel data visualization techniques to analyze passenger trips and evaluate travel time reliability in the Shanghai Metro, demonstrating the potential of visualization in uncovering significant patterns within large datasets. Bhouri et al. [17] focused on managed lane operations on a French motorway, critically assessing travel time reliability indicators during rush hours and highlighting the challenges associated with interpreting skewed travel time distributions. Swierstra et al. [18] examined multiple model specifications for Travel Time Reliability (TTR) in public transport, concluding that the reliability buffer time indicator is more effective than standard deviation measures. However, its significance varies across different user classes.

Li et al. [19] investigated the interplay between travel time reliability and in-vehicle crowding on mode choice among various transport users, finding that neglecting mode-specific factors can result in biased demand estimates, particularly in scenarios with high reliability. Bimpou and Ferguson [20] incorporated travel time reliability into accessibility measurements, using real-time data from Glasgow's Queen Elizabeth University Hospital to illustrate how variability in travel times affects accessibility. Sen et al. [21] evaluated the travel time reliability of different public transport modes in Kolkata, identifying the metro railway as the most reliable mode compared to buses and minibusses. The connection between Total Travel Time Risk (TTRR) and Conditional Value at Risk was further explored by Li [22], leading to the development of a nonparametric estimation method for TTRR, which proved more robust against distributional assumptions. Kathuria et al. [23] provided a comprehensive review of public transport reliability measures, applying these concepts to a case study of Ahmedabad's Bus Rapid Transit System. Singh et al. [24] analyzed journey time performance on the London Underground, identifying key metrics for service quality assessment under both normal and incident-affected conditions.

Jose and Ram [9] reviewed travel time reliability (TTR) in airport access, emphasizing the significance of value of time, value of reliability, and reliability ratio across different networks, while Brands et al. [25] highlighted the societal benefits of transportation infrastructure investments through ex-post evaluations of Amsterdam's north-south metro line. Liu et al. [26] utilized Monte Carlo simulations to estimate Passenger Travel Reliability, linking it with associated costs and influential factors through regression analysis. Finally, Xu et al. [27] applied station travel time reliability metrics to optimize train operation plans in the Beijing metro, demonstrating the broader applicability of their framework across metro systems equipped with AFC infrastructure. Soza-Parra et al. [28] underscored the importance of incorporating service reliability into transport modeling, showing that bus users prioritize reliability over shorter travel times to avoid irregular headways. Table 1 presents a summary of these studies.

Table 1. Summary of past studies

Authors	Year	Case Study	Indicator	Data
Lomax and Margiotta	2003	-	Standard Deviation of Travel Time, Buffer Time Index, Time Index	Travel Time and Speed Data, Traffic Volume Count Data
Li et al.	2013	Beijing city rail transportation system	Possible travel time, Buffer time index, program time index	AFC
Yang et al.	2014	Westbound from Highway K to Prospect Road, Westbound from Chesterfield Parkway to Research Park Drive	HLRF algorithm, The TR index of a system is calculated by a function of statistically independent variables.	ITS
Sun et al.	2016	Shanghai Metro	Travel time reliability index	AFC
Bhouri et al.	2016	Highway in France	Statistical range methods, buffer time methods, Travel delay	-
Swierstra et al.	2017	-	Standard deviation index, Buffer time index	SP-RP
Li et al.	2017	Shanghai urban construction	Standard deviation	RP Survey

		transportation development		
Sen et al.	2018	Kolkata Bus Public Transport	Buffer time index, Planning time index	Data Hence on Board
Li	2019	Lankershim Street in Los Angeles	A nonparametric approach to estimate TTRR	Camera during morning rush hour
Singh et al.	2019	London Underground	Statistical Range Criteria, Buffer time Criteria, Travel delay Criteria	AFC
Bimpou and Ferguson	2020	Queen Elizabeth University Hospital (QEUH) in Glasgow	Real-Time Travel Times, Accessibility Indicator	Google Distance Matrix API (GDMA)
Kathuria et al.	2020	Ahmedabad Bus Rapid Transit System India	Planning time index, Variance index, Buffer time index	ITS
Jose and Ram	2020	Access to airports by metro in India	Travel time index, Buffer time index, Planning time index	Airport Authority of India monthly air traffic reports GPS
Brands et al.	2020	North-South subway line in Amsterdam	standard deviation	AVL
Liu et al.	2021	Rail transit network of Wuhan, China	Buffer time index	Monte Carlo simulation
Xu et al.	2021	Beijing subway network	Cumulative probability of NSTTR, LSTTR and STTR values based on real-time and standard travel time	AFC
Soza-Parra et al.	2022	Santiago's public transport system is called Transantiago	Travel time reliability index, Standard deviation	Transactions and GPS information

3. Data analysis

3.1. Reliability calculation indicators

Previous studies have introduced several metrics to evaluate the reliability of travel time, each offering a unique perspective on this issue. Key examples of these indicators underscore the significance of consistency and dependability in travel duration. By analyzing these metrics, researchers can better understand the efficiency and predictability of transportation systems. Gaining insights into these measures is essential for improving travel reliability for commuters and enhancing the overall experience of public transit. In the following, several examples of the most important indicators are explained.

3.1.1. Buffer time indicator

Buffer time indicator (BTI) is the extra period added to schedules to manage potential delays or disruptions. This additional time helps ensure that tasks are completed accurately and punctually, especially when forecasts are off or unexpected events arise. Ultimately, buffer time plays a crucial role in time and project management, enabling individuals and organizations to navigate unpredictable circumstances more effectively. The indicator measures the percentage of extra time a passenger should allocate beyond the average travel duration, T_{mean}, to arrive on time T_{95} which is 95% of all travel duration is at this value or less. This indicator is defined by Equation (1)[29].

$$BTI = \frac{T_{95} - T_{mean}}{T_{mean}} \tag{1}$$

3.1.2. Planning time indicator

The Planning Time Index (PTI) measures the time individuals allocate for planning a journey. This includes the expected departure time and an additional buffer to accommodate potential delays, or unexpected route changes. The index evaluates travel efficiency across a traveling path throughout the planning time, e.g., day or week, irrespective of peak or off-peak periods. Defined by Equation (2)[29], it provides a comprehensive overview of travel planning dynamics, where T_{90} and T_{15} is 90% or 15% of all travel duration is at this value or less, respectively.

$$PTI = \frac{T_{90}}{T_{15}} \quad (2)$$

3.1.3. Standard deviation indicator

Standard deviation is a crucial metric for assessing travel time reliability. It measures how much travel times deviate from the average. A higher standard deviation indicates more significant variability, which translates to reduced reliability for that route's travel times. In essence, the more inconsistent the travel times, the less dependable the route becomes. Understanding this metric is essential for evaluating and improving travel efficiency[30, 31].

3.1.4. Skewness indicator

Skewness Indicator (SI) is a term in statistics used to describe asymmetry from the normal distribution and it is outlined in Equation (3)[29].effectively highlights the asymmetry of travel duration experienced by individuals, where T_{50} is 50% of all travel duration is at this value or less, respectively

$$SI = \frac{T_{90} - T_{50}}{T_{50} - T_{15}} \quad (3)$$

3.1.5. Travel time indicator

Travel Time Indicator (TTI) measures the ratio of peak travel time, i.e., T_{PK}, to the time taken under ideal conditions, i.e., T_{FF}. Since peak travel times differ across cities, the index may not be universally applicable. This indicator is represented mathematically by Equation (4)[29].

$$TTI = \frac{T_{Pk}}{T_{FF}} \quad (4)$$

3.2. Data preparation

This section offers an overview of the Tehran Metro network and outlines the initial database. The data for this study was collected in May 2018, during which the Tehran Metro network included five operational lines and a total of 113 stations. Detailed specifications can be found in Table 2, while the network layout is illustrated in Figure 1.

Table 2. Specifications of Tehran metro lines in 2018

Line	Year of Establishment	Length (Km)	Number of Stations	Number of Intersection Stations
1	2001	70	31	5
2	1999	26	19	6
3	2012	37	28	5
4	2008	22	21	6
5	1998	42	14	1
6	2017	33	23	5
7	2018	22	22	5

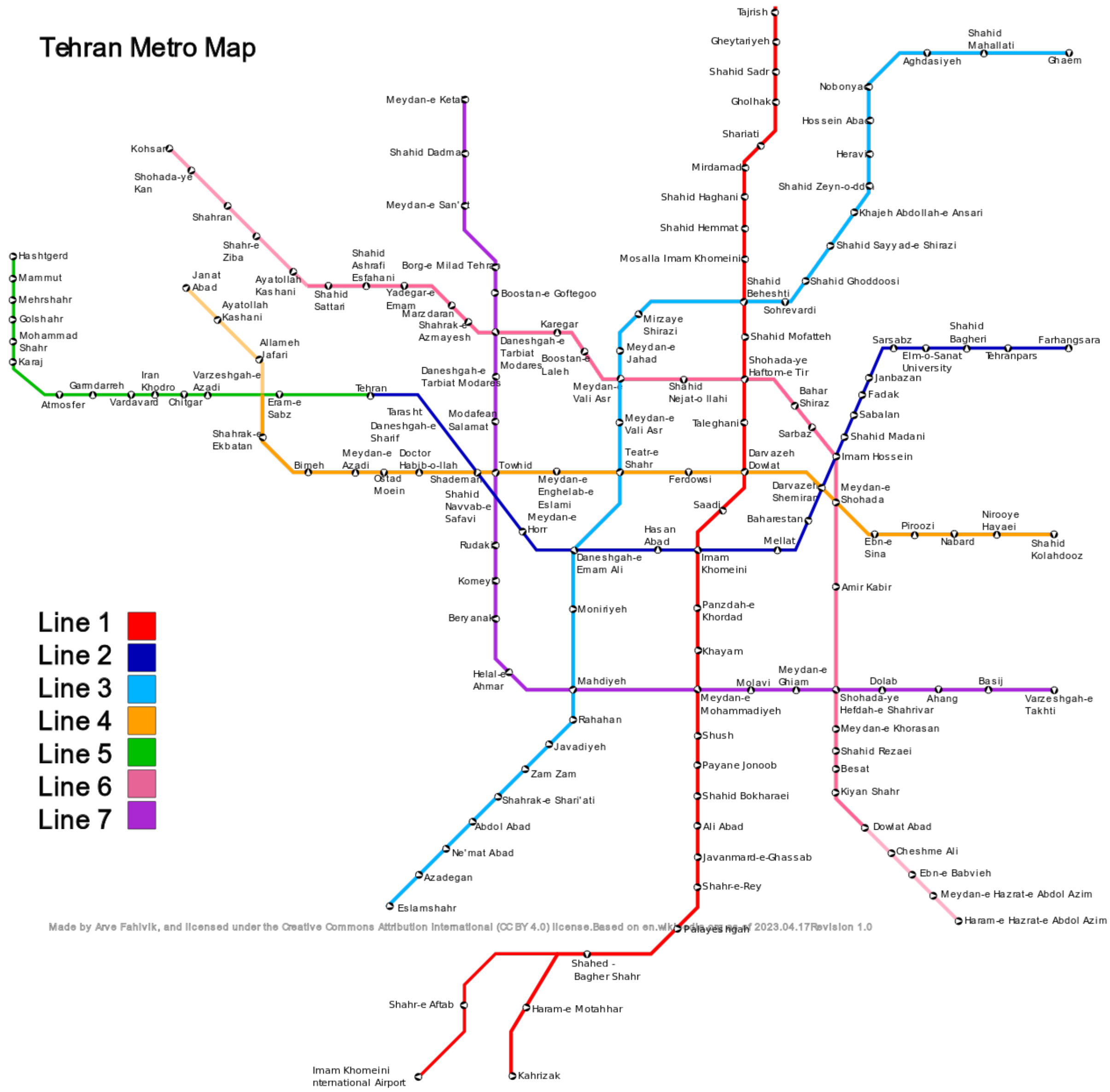

Figure 1. Tehran metro map [32]

The initial data structure is in the form of an Excel file (Figure 2), which contains data collected through smart cards used for fare transactions from line 1 to line5. The available data includes all recorded transactions from May 1, 2018, to May 31, 2018, covering the period from 5:30 AM to 10:30 PM. The rows in this dataset represent the number of trips made. Each row is structured such that every time a transaction occurs in the system, a new row is added to the dataset. By transaction, we refer to using a card at the entry or exit gates of the metro. The initial database comprises nine columns and a total of 62,779,771 rows, organized as follows:

- The first column indicates the row number, denoted index.
- The second column lists the customer IDs and unique for all users, denoted id.
- The third column records the unique card numbers associated with each transaction, logged during station entry and exit, denoted card id.
- The fourth column provides the station codes, denoted station code.
- The fifth column details the transaction date according to the Persian calendar,

- capturing the date of each entry or exit, denoted date.
- The sixth column specifies the exact time of each transaction, marking the moment of entry or exit, denoted time.
- The seventh column is binary, where a value of 1 indicates an entry at the station, and a value of 0 indicates an exit, denoted direction.
- The eighth column enumerates the transaction number, denoted transactionnum.
- The ninth column records the exact minute of the transaction, specifying the precise time of entry or exit, denoted minute time.

	index	id	cardid	stationcode	date	time	direction	transactionnum	minutetime
0	0	406888	2.227399e+09	175	13970201	1823	1	50	1103
1	1	406889	1.192048e+15	129	13970201	1517	1	121	917
2	2	406910	9.152126e+06	240	13970201	2231	0	193	1351
3	3	406935	1.212732e+09	132	13970201	1858	0	164	1138
4	4	406971	2.525895e+09	105	13970201	1614	0	182	974
...	...	...	...	...	...	...	...	...	...
62779766	62779766	56764648	4.266704e+08	179	13970231	2104	1	229	1264
62779767	62779767	56764660	2.221322e+09	206	13970231	1440	1	232	880
62779768	62779768	56764691	2.446871e+09	210	13970231	1832	0	46	1112
62779769	62779769	56764714	2.225149e+09	220	13970231	1841	1	75	1121
62779770	62779770	56764719	9.183164e+08	124	13970231	726	0	5	446

Figure 2. Initial Data

First, data entries recorded between 10:30 PM and 5:30 AM were removed, (as Tehran Metro operates from 5:30 AM to 10:30 PM), and any data outside of these hours was mistakenly logged. Subsequently, columns deemed unnecessary were deleted from the database. The second column, based on customer IDs, was also deleted and instead using the third column, which displays the unique customer card numbers. The eighth column, which showed the transaction number, was deemed redundant and was therefore removed from the database.

To address ambiguities in data storage formats, a data transformation technique was employed to prepare the data. A preprocess was developed to consolidate the separate rows for a card's entry and exit into a single row, recording both entry and exit times and locations in one row. Data entries where the exit was not recorded or where the entry and exit stations were the same were also removed.

Ultimately, the data cleaning and preparation process significantly reduced the dataset's volume, making it more manageable for subsequent algorithms. Regarding missing data, given that the number of missing entries was minimal compared to the overall dataset, any row containing missing data was removed. Following the data cleaning process, the number of rows in the dataset was reduced by 63%. In Figure 3, the modified data is shown, consisting of 8 columns and 23,805,982 rows.

	cardid	date	entrance_stationcode	exit_stationcode	entrance_time	exit_time	entrance_minutetime	exit_minutetime
1	1.212732e+09	13970201	132	153	1858	1922	1138	1162
2	1.212732e+09	13970201	124	132	1002	1025	602	625
3	2.525895e+09	13970201	105	210	1614	1644	974	1004
4	4.399757e+06	13970201	206	212	727	752	447	472
5	4.399757e+06	13970201	212	207	1744	1802	1064	1082
...	...	...	...	...	...	...	...	...
24112069	2.443822e+09	13970231	132	98	1901	1938	1141	1178
24112070	9.076116e+08	13970231	154	127	1848	1912	1128	1152
24112071	2.446644e+09	13970231	103	106	746	758	466	478
24112072	2.050789e+08	13970231	92	219	1335	1438	815	878
24112073	4.269857e+08	13970231	98	105	1018	1038	618	638

Figure 3. Data cleared

To calculate travel time reliability, it is essential to compute both buffer time, (1), and planning time, (2), which have been addressed in this study. The buffer time requires the 95th percentile of travel time for each route, while planning time necessitates the calculation of the 90th and 15th percentiles for each route. These calculations were performed using Python programming language (Figure 4). After calculating buffer time and planning time using equations (1) and (2), the final dataset is presented in Figure 5 and Figure 6.

cardid	entrance_minutetime	exit_minutetime	travel_minutetime	95th_percentile_travel_time	90th_percentile_travel_time	15th_percentile_travel_time
1.212732e+09	1138	1162	24	30.0	27.0	21.0
1.212732e+09	602	625	23	84.0	82.0	22.0
2.525895e+09	974	1004	30	39.0	32.0	20.0
4.399757e+06	447	472	25	31.0	27.0	19.0
4.399757e+06	1064	1082	18	27.0	24.0	17.0
...	...	...	...	...	...	...
2.443822e+09	1141	1178	37	43.0	40.0	32.0
9.076116e+08	1128	1152	24	38.0	31.0	22.0
2.446644e+09	466	478	12	19.0	16.0	9.0
2.050789e+08	815	878	63	76.0	72.0	58.0

Figure 4. Calculation of the 95th, 90th, and 15th percentiles

cardid	entrance_minutetime	exit_minutetime	travel_minutetime	mean_traveltime	95th_percentile_travel_time	buffer_time_index
1.212732e+09	1138	1162	24	24.282379	30.0	23.546378
2.525895e+09	974	1004	30	26.645389	39.0	46.366789
4.399757e+06	447	472	25	23.342604	31.0	32.804377
4.399757e+06	1064	1082	18	21.055839	27.0	28.230466
9.149616e+08	1185	1268	83	81.209480	103.0	26.832483
...	...	...	...	...	...	...
2.443822e+09	1141	1178	37	36.124183	43.0	19.033834
9.076116e+08	1128	1152	24	27.328151	38.0	39.050756
2.446644e+09	466	478	12	12.997776	19.0	46.178853
2.050789e+08	815	878	63	64.626204	76.0	17.599356
4.269857e+08	618	638	20	22.192802	28.0	26.167035

Figure 5. Calculation of buffer time

	cardid	entrance_minutetime	exit_minutetime	travel_minutetime	90th_percentile_travel_time	15th_percentile_travel_time	planning_time
0	1.212732e+09	1138	1162	24	27.0	21.0	1.285714
1	1.212732e+09	602	625	23	82.0	22.0	3.727273
2	2.525895e+09	974	1004	30	32.0	20.0	1.600000
3	4.399757e+06	447	472	25	27.0	19.0	1.421053
4	4.399757e+06	1064	1082	18	24.0	17.0	1.411765
...	...	...	...	...	...	...	...
23805977	2.443822e+09	1141	1178	37	40.0	32.0	1.250000
23805978	9.076116e+08	1128	1152	24	31.0	22.0	1.409091
23805979	2.446644e+09	466	478	12	16.0	9.0	1.777778
23805980	2.050789e+08	815	878	63	72.0	58.0	1.241379
23805981	4.269857e+08	618	638	20	25.0	19.0	1.315789

Figure 6. Calculation of planning time

4. Results

4.1. Macro results

In this section, the buffer time indicator, a crucial indicator of route reliability, was analyzed and is represented as a percentage in the terms of Route%, i.e., the percentage of routes where the buffer time indicator is lower than the value on the chart. Lower indicators indicate higher reliability for a given route. The distribution of the buffer time indicator, as visualized in Figure 7, ranges from 0 to 100 (Buffer Time), with most routes falling between 20% and 40%. Only a few routes exhibit indices below 20% or above 40%, reflecting varying levels of reliability across different routes. Figure 8 further elaborates on this distribution with two histograms positioned at the top and right margins. The top margin details the density of routes within the 20% to 40% buffer time range, while the right margin illustrates that most routes have travel times ranging from 15 to 60 minutes, segmented by minute intervals. This comprehensive visualization highlights the variability in both buffer time and travel time across the analyzed routes. In Figure 9, the correlation matrix is depicted, where varying colors indicate the strength of correlations between data points. A deep brick-red hue reflects strong self-correlation among the variables, while a lighter brick-red suggests a relatively strong correlation between the buffer time index and the planning time index. In contrast, darker shades of blue signify a lack of correlation between the variables.

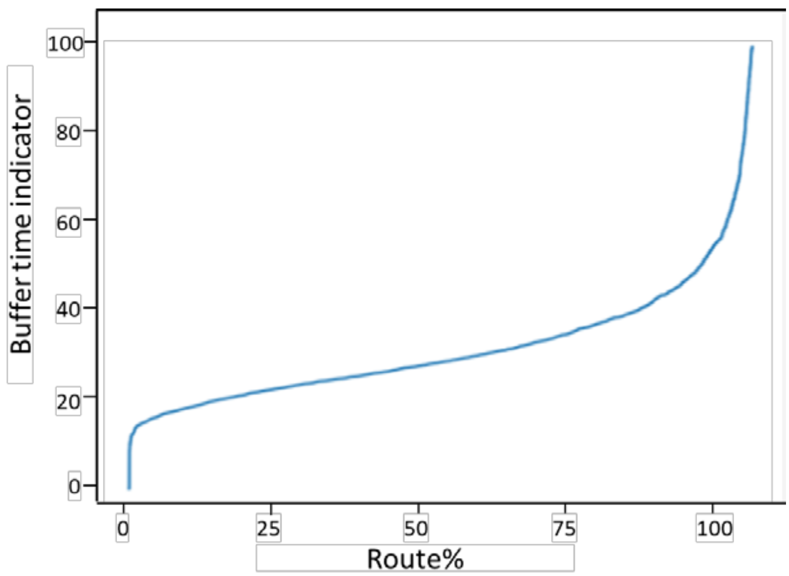

Figure 7. The distribution chart of the buffer time index

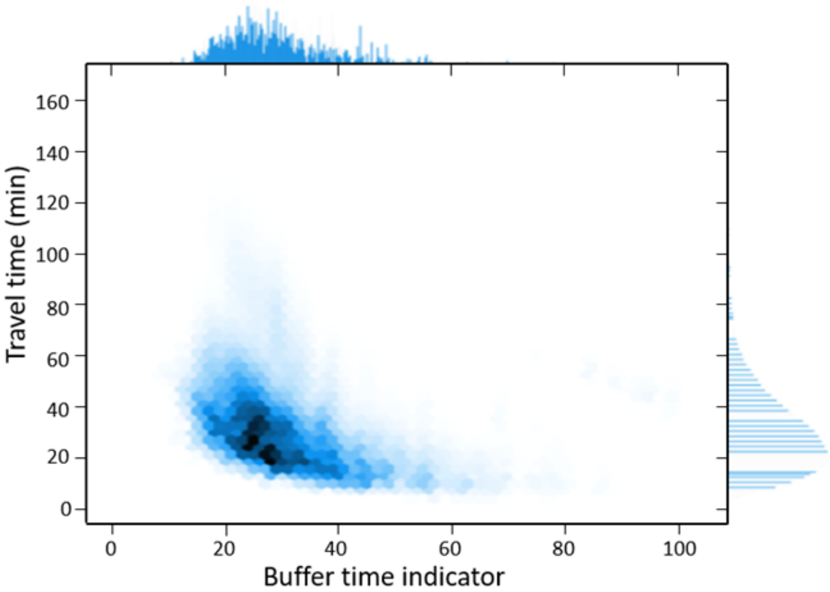

Figure 8. Distribution chart of buffer time and travel time

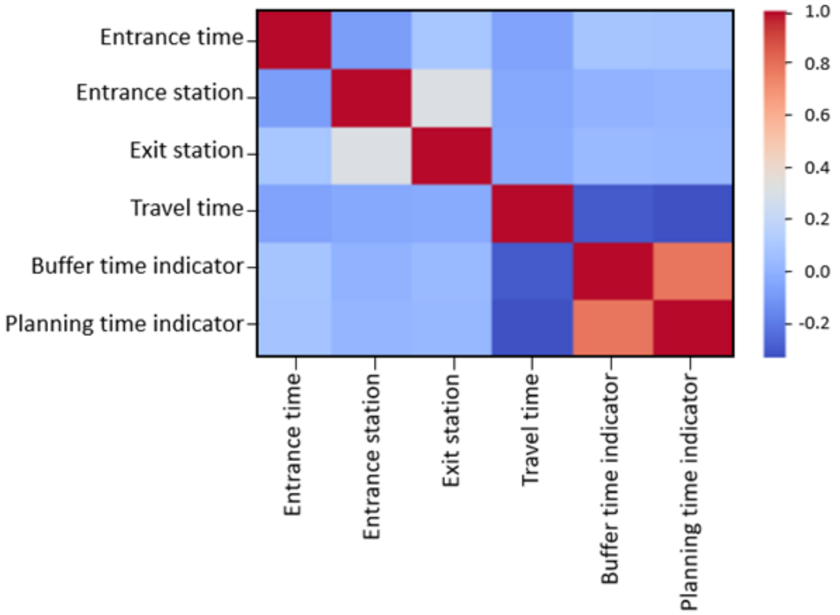

Figure 9. Correlation of data

4.2. Micro result

In this section, we present the micro results for the Tehran metro data, which is divided into two parts. In the first part, we analyze the reliability of the stations across various lines in order to calculate the reliability of each station within the five lines of the Tehran metro system. In the second part, we focus on the categorization or clustering of the collected data to determine the optimal number of clusters.

4.2.1. Reliability of the stations

Based on the literature review, the buffer time index has emerged as the most commonly used metric in previous studies, indicating its greater applicability compared to other indices. Consequently, in this paper, the buffer time index has been selected as the primary criterion for evaluating route reliability. Routes were ranked according to their buffer time, identifying the top 10 routes with the lowest buffer time, signifying high reliability, and the 10 routes with the highest buffer time, indicating lower reliability. Figure 10 illustrates the routes that exhibit high reliability, characterized by their lower buffer time index and Figure 11 illustrates the routes characterized by low reliability, as indicated by their elevated buffer time index.

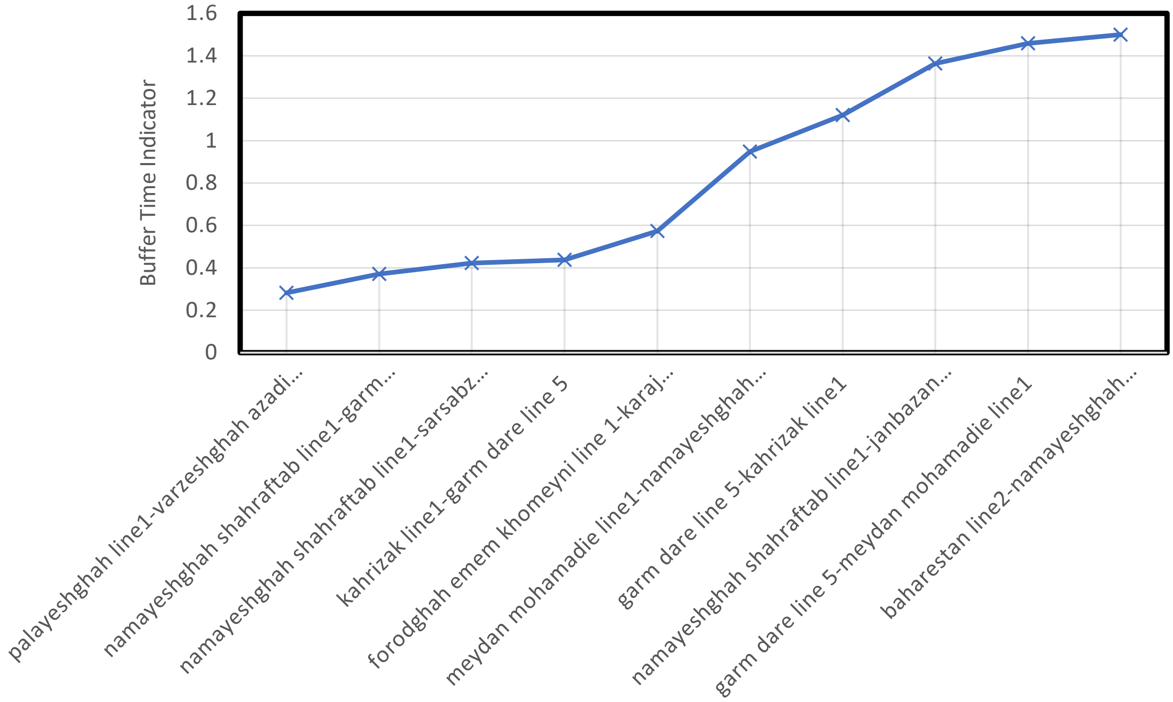

Figure 10. Line graph of routes that have high reliability

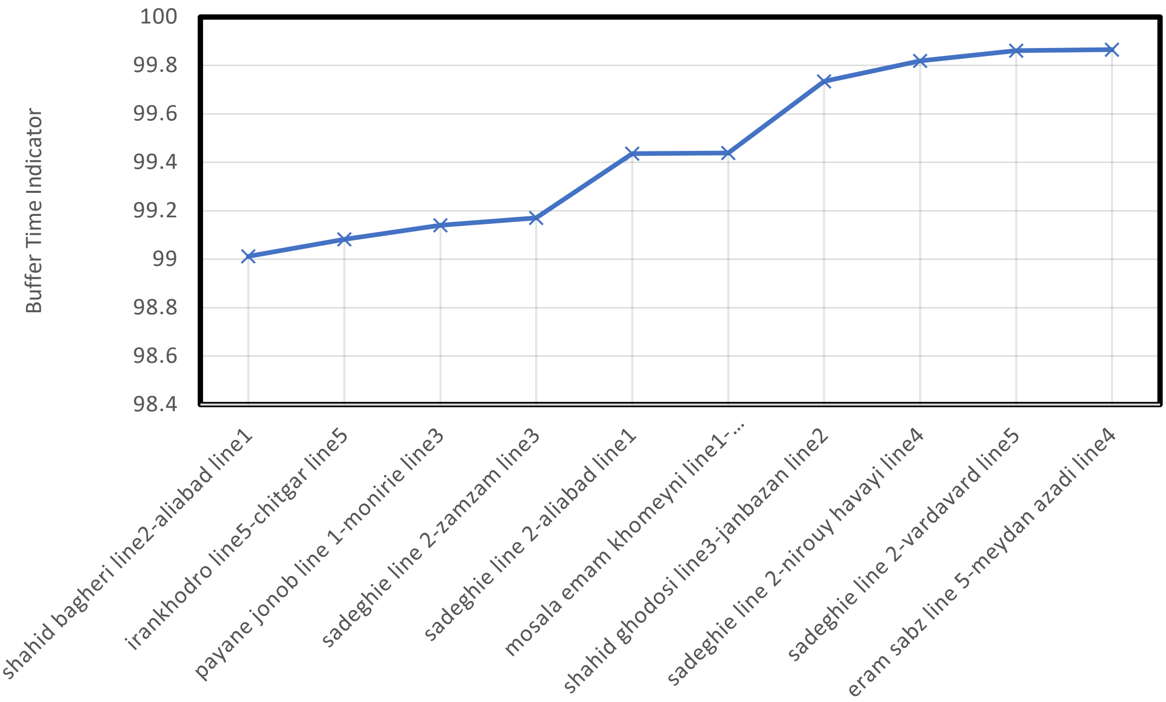

Figure 11. Line graph of routes that have low reliability

Figure 12 through 16 present a comprehensive analysis of the average travel time reliability across various stations on Tehran Metro Lines 1 through 5. Starting with Line 1, Figure 12 illustrates that Tajrish Station (station code 95) achieves the highest travel time reliability at 23.19%. In contrast, Shahid Beheshti Station (station code 104) records the lowest reliability at 39.23%, which could be attributed to its role as a central transfer station. Moving to Line 2, as shown in Figure 13, Farhangsara Station (station code 145) leads with the highest average reliability of 21.19%. On the other hand, Imam Khomeini Station (station code 132), another critical transfer hub, shows the lowest reliability at 37.48%. Figure 14 provides insights into Line 3, where Qaem Station (station code 170) stands out with the highest reliability at 18.62%. Conversely, Meydan Vali Asr Station (station code 185), also serving as a transfer station, has the lowest reliability at 37.83%.

For Line 4, Figure 15 reveals that Shahid Kolahdooz Station (station code 221) exhibits the highest reliability at 22.73%, while Theater Shahr Station (station code 211), a significant transfer point, has the lowest reliability at 37.99%. Finally, Figure 16 analyzes Line 5, highlighting that Mohammadshahr Station (station code 153) maintains the highest travel time reliability at 28.86%. In stark contrast, Sadeghieh Station (station code 124), a crucial transfer station, reports the lowest reliability with an average of 86.80%. This detailed analysis underscores the impact of transfer stations on travel time reliability across the Tehran Metro network.

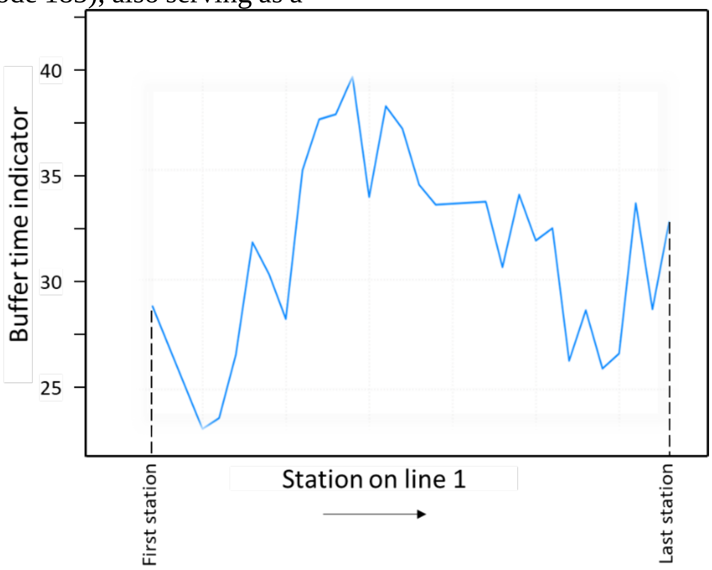

Figure 12. Linear diagram of the average reliability of stations in line 1 of Tehran Metro

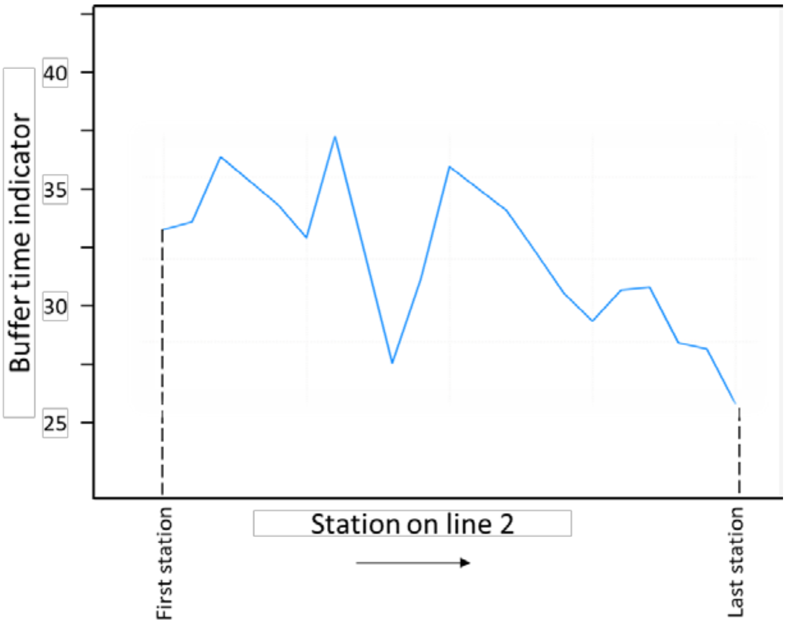

Figure 13. Linear diagram of the average reliability of stations in line 2 of Tehran Metro

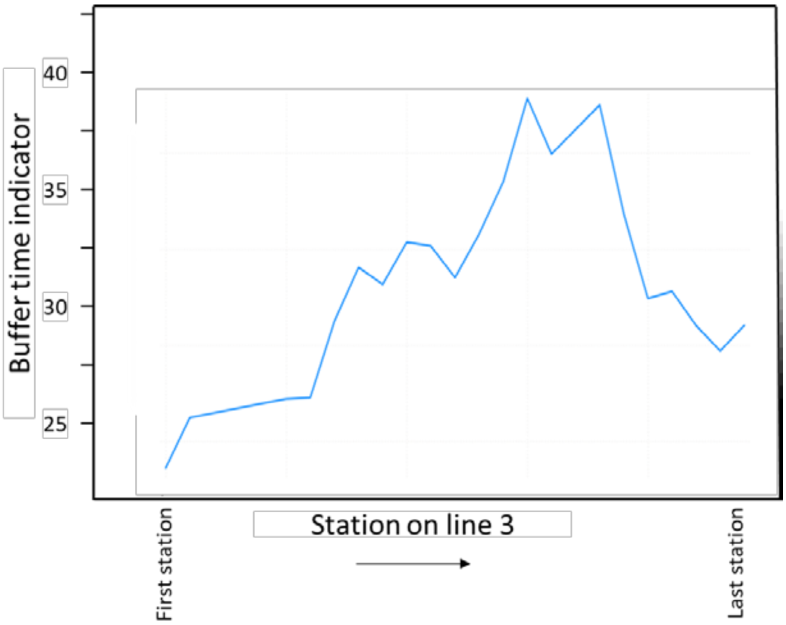

Figure 14. Linear diagram of the average reliability of stations in line 3 of Tehran Metro

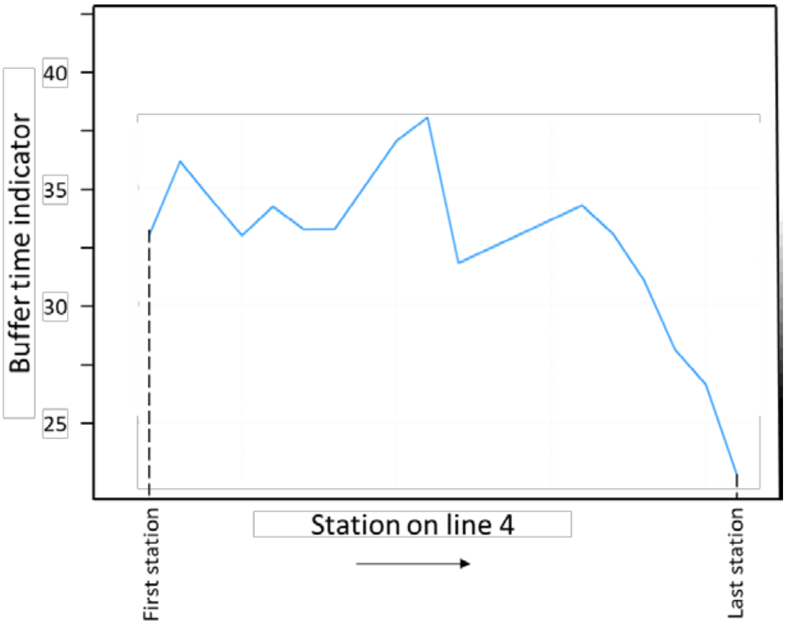

Figure 15. Linear diagram of the average reliability of stations in line 4 of Tehran Metro

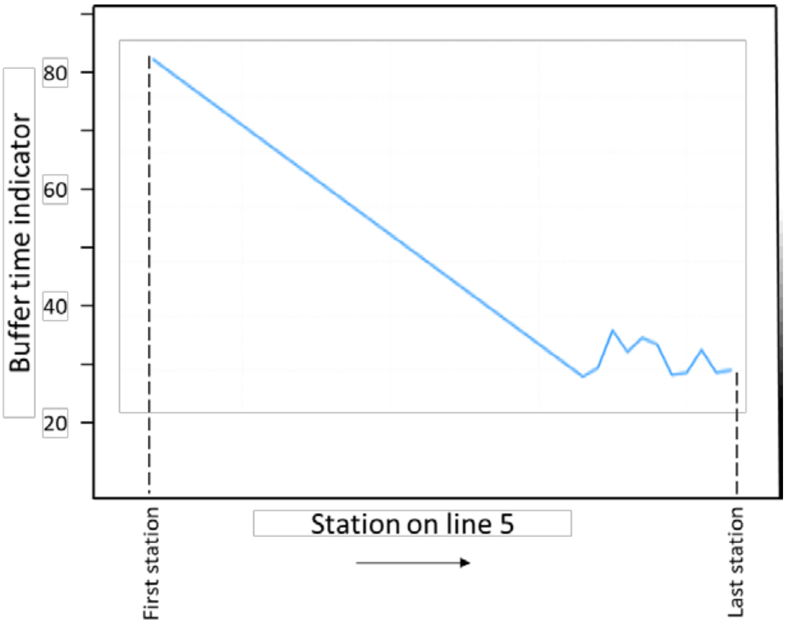

Figure 16. Linear diagram of the average reliability of stations in line 5 of Tehran Metro

4.2.2. Clustering of routs

In this section, route clustering was conducted using two input metrics: the buffer time index and the planning time index, employing the k-means clustering method. Routes were grouped into 2, 3, 4, and 5 clusters based on these indices. Standard scaling was applied to normalize the data, which adjusts the features to have a mean of zero and a variance of one. Unlike min-max scaling, which fixes the minimum and maximum values to a specific range, standard scaling focuses on normalizing the mean and variance of the data.

To evaluate the model, both scaled and unscaled scenarios were examined, with results displayed in Figure 17. The findings reveal that in the unscaled scenario, outliers were included within clusters, leading to reduced clustering accuracy. Conversely, in the scaled scenario, outliers were isolated into a separate cluster, significantly improving the accuracy of the clustering process. This distinction is particularly noticeable in cases with a higher number of clusters. For instance, in the five-cluster scenario, the unscaled method grouped distant or non-similar data points into the same cluster, whereas the scaled method successfully isolated outliers into their own cluster, enhancing the overall clustering precision. The improved performance of the scaled approach is visually demonstrated in Figure 18, while the challenges of the unscaled approach are evident in Figure 19.

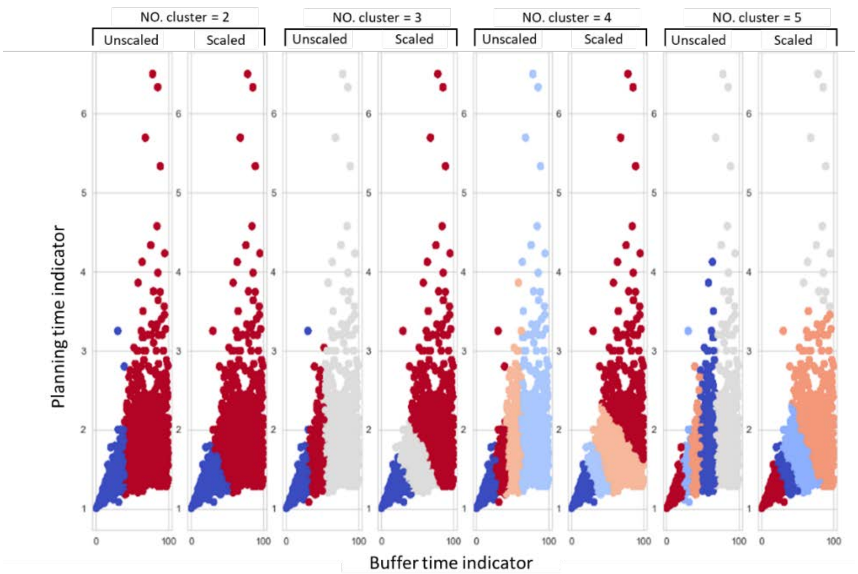

Figure 17. Skilled mode and unskilled mode

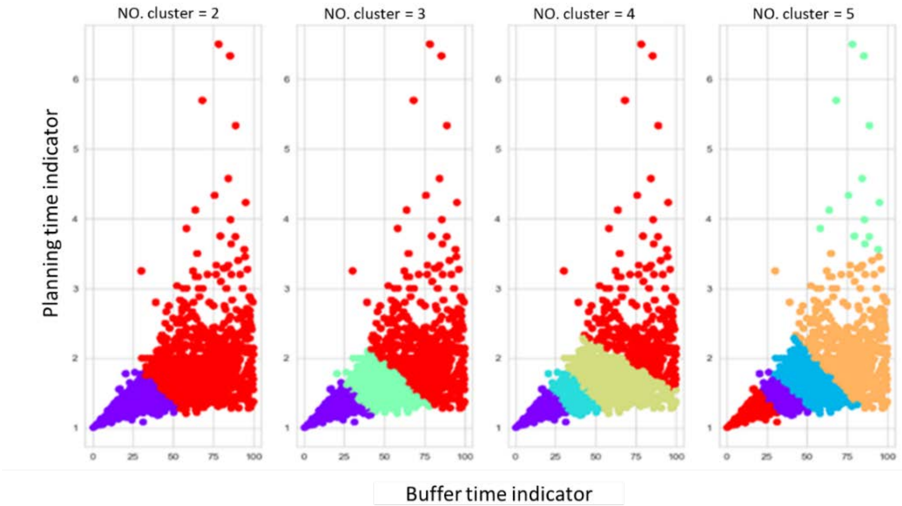

Figure 18. Scaled approach

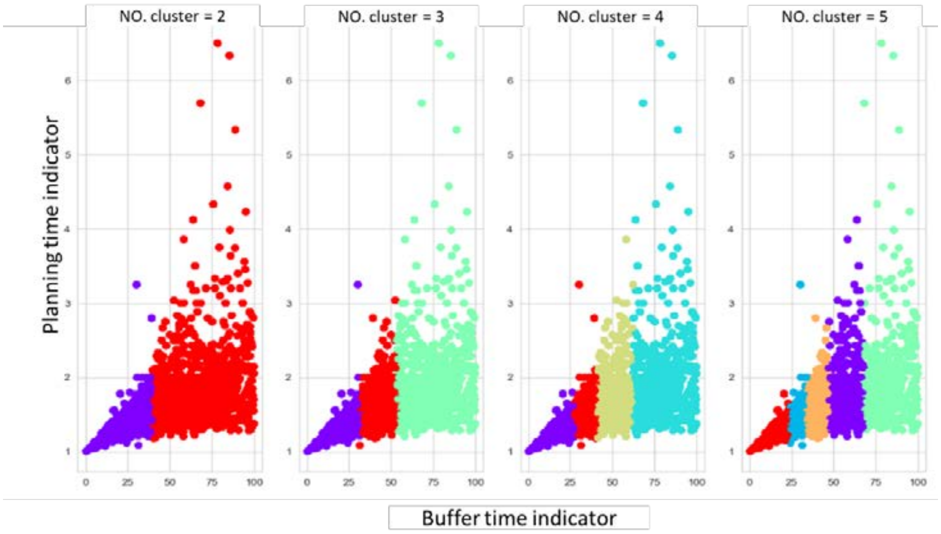

Figure 19. Unscaled approach

5. Conclusion and discussion

The literature underscores the critical importance of travel time reliability for passengers utilizing metro systems. Uncertainty in travel times can significantly diminish service quality, prompting passengers to modify their routes even when the average travel time remains low. To combat this issue, new metrics for measuring travel time reliability are being developed to help maintain passenger satisfaction in rail transit systems and alleviate urban traffic congestion. The accurate assessment of reliability depends heavily on the availability of Automatic Fare Collection (AFC) data. However, the absence of recorded exit data often results in incomplete datasets, highlighting the necessity for mandatory exit registrations to ensure data integrity and, consequently, more reliable analyses.

In this study, AFC data was leveraged to calculate travel time reliability using the buffer time index and the planning time index. The buffer time index served as the primary metric for evaluating route reliability, effectively distinguishing routes with high and low reliability. Routes were subsequently clustered based on these indices using the k-means clustering method, with the Silhouette criterion identifying three as the optimal number of clusters.

The literature review and analysis show that the buffer time index is a more precise indicator of travel time reliability than the planning time index and other metrics. The buffer time index alone is sufficient to assess route reliability, whereas the planning time index lacks accuracy due to its failure to consider distance. Further analysis reveals that the presence of transfer stations does not necessarily imply lower route reliability. However, 90% of routes originating from transfer stations were found to have low average travel time reliability. The optimal number of clusters for grouping routes, as determined by the Silhouette criterion, is three.

Future research can be explored from the following directions:

1. Investigate the differences between stations with high and low reliability, considering factors such as the presence of escalators, population density, and train schedules.
2. Develop a hybrid model that incorporates passenger flow data from both bus and metro systems.
3. Analyze the characteristics of routes within different clusters to determine the factors contributing to high reliability.
4. Examine the influence of weather and passenger volumes from other transportation modes on route reliability and metro station clustering quality.
5. Conduct separate analyses for weekdays, Thursdays, and Fridays to account for variations in passenger demand, thereby enhancing model accuracy.
6. Perform separate analyses for peak and off-peak hours to better capture the impact of

passenger demand variations on model precision.

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