A Case Study of Urban Rail Transit Network in Klang Valley

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UNIVERSITI TUNKU ABDUL RAHMAN

A Case Study of Urban Rail Transit Network in Klang Valley

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Civil Engineering with Honours

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

I certify that this project report entitled **"A CASE STUDY OF URBAN RAIL TRANSIT NETWORK IN KLANG VALLEY"** was prepared by **NICHOLAS BRYAN LEE ZHI YI** has met the required standard for submission in partial fulfilment of the requirements for the award of Bachelor of Civil Engineering with Honours at Universiti Tunku Abdul Rahman.

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ABSTRACT

The urban rail transit networks worldwide are experiencing a growing disparity between supply and demand. In the context of Klang Valley, travelling with the urban rail transit network results in significant journey time between origin and destination (OD) compared to private vehicles due to the mature road network. The current Klang Valley urban rail transit network consists of radial lines, necessitating transfers at central business district (CBD) interchange stations and leading to bottleneck congestion. This study aims to assess the quantitative improvement of the forecasted network, which includes the introduction of LRT 3 and MRT Circle Line, in comparison to the existing operational network. Additionally, the compatibility of the available urban rail transit network infrastructure with passenger flow demand is evaluated. A comprehensive analysis was conducted with quantitative indicators including average shortest path length, betweenness centrality, closeness centrality, degree centrality, and clustering coefficient. Results indicate the important stations are predominantly located around CBD areas. The results indicate significant improvements in the forecasted network across various weighted analysis. The global average shortest path length decreased by 5.38% in unweighted network, while increased by 6.23% in time-weighted and 4.71% in distance-weighted network analysis. Similarly, global closeness centrality decreased by 5.16% in the unweighted network but increased by 6.06% and 3.50% in the time-weighted and distance-weighted analyses, respectively. Betweenness centrality showed overall increases of 16.05% (unweighted), 17.89% (time-weighted), and 18.75% (distance-weighted). Global degree centrality shows 0.83% increment while significant decrease of 18.53% was observed in global clustering coefficient. Strong regression values of compatibility analysis between network infrastructure and passenger flow based on average shortest path length and closeness centrality, with regression values ranging from 63.49% to 78.97%, while betweenness centrality shows lower regression ranging from 17.58% to 29.61%. The forecasted network demonstrates enhanced connectivity and reduced significance of individual stations with the additional shorter routes between OD pairs, effectively addressing congestion and long journey times.

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

With the acceleration of urbanisation and population growth, urban rail transit has been widely adopted in many countries, given its efficiency and effectiveness in reducing traffic congestion (Huang et al., 2016). Urban rail transit is a general term to describe the various types of passenger-carrying rail systems that primarily operate around urban and suburban areas. It provides an alternative transportation mode for commuters travelling back and forth between their origin and destination (OD) on daily basis. Many of the densely populated major cities experienced extreme traffic congestion, with the rapid increment of population moving to urban areas for job opportunities, the traditional mode of transportation where commuters rely on private vehicles and low-capacity buses that can only carry limited number of passengers at the same time is just not sustainable. The number of vehicles on the road increases with the population growth which leads to a much worsening traffic congestion situation.

Urban rail transit is a rail based, fast, reliable, high-capacity, and energy efficient transportation mode that operates on dedicated tracks, capable of mobilising high volume of passengers from one point to another. This can reduce the number of vehicles on the road, thus alleviating the traffic congestion in the city centre. These independent transit lines interconnect with one another, connecting multiple important areas of a city, forming a complex urban rail transit network with high connectivity.

Rathbone (2023) agreed that owning a private vehicle is somehow a necessity rather than a luxury in some cities due to the availability and efficiency of a public transportation system. A highly car-dependent cities promotes horizontal growth and endless road infrastructure expansion, and expressway is needed to solve traffic congestion, which is not a viable option for a city with scarce land resources (Price, 2017). Countries with limited energy reserves limit their dependency on fuel imports by reducing inefficient private vehicle usage and focusing on the development of energy-efficient urban rail transit network. A well-designed network with suitable implementation of the network pattern can encourage optimised connectivity of a system that encourages ridership, reduces the need to use a vehicles and traffic congestion.

The efficiency and connectivity of the public transport system is greatly enhanced and interrelated to the design of the network. A well-designed urban rail transit network can reduce the number of transfers and unnecessary movements of passengers while changing to different lines at interchange stations, reducing the total journey times of passengers during their daily commute between OD. Saidi (2016) mentioned that a high connectivity complex urban rail transit network can reduce the vulnerability of a network with alternative route options for passengers to reach their destination in case of a breakdown of a transit line. The network pattern is the configuration of several rail transit lines designed to complement each other to form a complex rail network.

The urban rail transit network worldwide adopted 3 types of network patterns in the network design, which include radial, circular, and grid network. A radial network with starting and terminating stations located in peripheral areas of a city was adopted to improve the connectivity of the city. Radial lines are more direct for passengers moving from suburban areas to the city centre, as there is less, or no transfer needed to reach their destination. Saidi (2016) mentioned that the main problem with radial lines is that trips between suburban areas cause unnecessary additional transfer loads and additional travel distance as passengers need to commute to interchange stations located in the CBD before heading to their destinations by transferring to other lines, increasing the total journey time taken to reach their destination. The additional passenger load generated may cause unnecessary congestion in interchange stations in the CBD, resulting in more crowded station platforms and trains that lead to increased journey times.

Ring lines are transit lines circulating around the CBD of a city. The transit lines can be a full circle loop without terminus, or a partial circle line intercepting the existing transit lines to create shorter transit path and improve connectivity between suburban areas. As most countries first introduced urban rail transit, aiming to relieve traffic congestion on roads connecting the core areas of the CBD and suburban areas. Walker (2015) agreed that most cities start implementing their rail transit network with a radial line that is effective to address this scenario, providing direct access without transfer to the central area. It is less likely to observe countries adopting a ring line transit pattern before a radial transit pattern, as a ring only transit line is inefficient in relieving the traffic congestion in the CBD area.

Figure 1.1 shows the London Underground transit network designed by adopting radial and ring configurations. The network adopts radial lines to connect suburban areas with direct access to the CBD located at the heart of London, and a ring line circulating around the city centre providing direct access between the peripheral areas of the city.

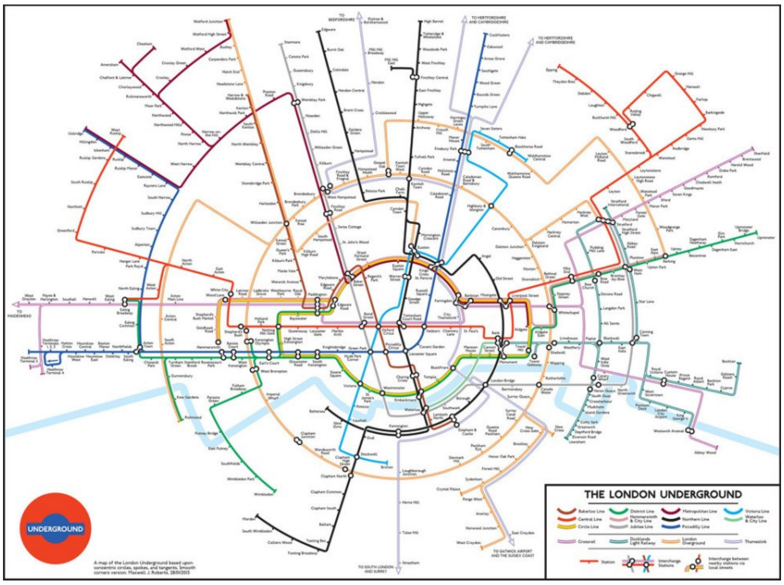


Figure 1.1: London Underground Map (Transit Maps, 2013)

Grid networks are formed by transit lines that intersect perpendicularly to provide multiple transfer points throughout the network. The network provides direct connections that reduces the need for transfers (Walker, 2015). Figure 1.2 shows the New York City subway map shows a densely intersected transit lines forming a grid network that follows the grid street nature of the city.

Figure 1.2: New York City Subway Map (Coneybeare, 2019)

1.1.1 Overview on Klang Valley Urban Rail Transit Network

The rapid urbanisation of the Klang Valley in the past few decades has attracted professionals from various locations for career development. Burdett (2018) categorised the development movement of an urban city into centrifugal movement, where population moves away from a city centre, and centripetal movement, where population moves towards the urban area. He mentioned that cities may experience centripetal movement and slowly shift towards centrifugal movement towards peripheral areas around the urban area due to congestion, social issues, and environmental pollution.

The urban sprawl development in Klang Valley was catalysed by the availability of cheaper peripheral land and the unavailability of growth limits in the city (Naeema, Shamsuddin, and Sulaiman, 2016). He added that the sprawling development has increased energy consumption and the time spent commuting to CBD as it encourages horizontal development that has a lower population density. A high-density transit-oriented development that encourages vertical mixed development around a transit station can help increase the viability of urban rail transit networks. A well-designed urban rail transit network and the implementation of transit-oriented development in

Klang Valley can greatly increase the range of locations accessible via the rail transit network and, therefore, increase ridership.

The implementation of Malaysia’s urban rail transit network is relatively late compared to other cities. With the effort of improving Klang Valley’s connectivity while reducing the reliance on private vehicles, Malaysia has implemented transit systems, namely Keretapi Tanah Melayu (KTM), Light Rapid Transit (LRT), Monorail, and Mass Rapid Transit (MRT).

According to the Ministry of Transportation (2024), KTM commuter was the first electrified rail transit service in the Klang Valley. KTM has an extensive network stretching beyond Klang Valley, connecting Klang Valley to suburban areas. However, it has limited frequency and a slower travel speed, leading to a longer journey time. LRT, on the other hand, offers a much more frequent and faster train speed with a shorter route, connecting major residential areas and business districts around Klang Valley. It may face occasional disruption due to a lack of maintenance on trains and ageing infrastructure. Monorail KL uses a smaller fleet that runs on a single-rail system, requiring less space to operate. It primarily operates around the CBD in KL, given the flexibility to reach into a congested urban environment. The smaller fleet with lower capacity and limited coverage are among the drawbacks of the transit system. The recently launched MRT Kajang Line and Putrajaya Line in Klang Valley offer comfortable and reliable transportation services with higher capacity compared to other train services. The driverless train system is capable of travelling at higher speeds, offering a shorter journey time. As cited by Azhar (2022), the CEO of MRT Corporation, Zarif Hashim, said that the MRT Circle line is the last transit line under the 2010 urban rail development blueprint after the MRT Kajang Line and MRT Putrajaya Line, becoming the backbone of Klang Valley’s Urban Rail Transit Network, improving connectivity with 31 stations, including 10 interchange stations connecting 8 existing lines. He added that the new urban rail development blueprint emphasises the west part of Kuala Lumpur, including Klang, Shah Alam, Petaling Jaya, and underserved areas like Selayang, Batu Caves, and Gombak.

The existing operational urban rail transit network consists of a radial line primarily connects suburban areas with urban areas in the Klang Valley.

The upcoming MRT Circle Line is set to introduce a ring line to significantly enhance the connectivity of the region with direct linkage between suburban areas and reduce traffic congestion in the central area, providing a more efficient travel experience. The details of each operating rail system in the Klang Valley, along with the number of interchange stations to indicate connectivity, are tabulated in Table 1.1 below.

Table 1.1: The Urban Rail Transit Network in Klang Valley (mrt.com.my, n.d.)

<table>
<tr><th>Types</th><th>Num</th><th>Transit Lines</th><th>Start Operate</th><th>Length (KM)</th><th>Stations Number</th><th>Interchange</th></tr>
<tr><td rowspan="3">KTM</td><td>1</td><td>KTM Seremban</td><td>1995</td><td>135</td><td>26</td><td>7</td></tr>
<tr><td>2</td><td>KTM Port Klang</td><td>1995</td><td>126</td><td>34</td><td>11</td></tr>
<tr><td>10</td><td>KTM Skypark Link</td><td>2018</td><td>24</td><td>3</td><td>1</td></tr>
<tr><td rowspan="4">LRT</td><td>3</td><td>LRT Ampang</td><td>1996</td><td rowspan="2">45.1</td><td>18</td><td>13</td></tr>
<tr><td>4</td><td>LRT Sri Petaling</td><td>1998</td><td>31</td><td>15</td></tr>
<tr><td>5</td><td>LRT Kelana Jaya</td><td>1998</td><td>46.4</td><td>37</td><td>12</td></tr>
<tr><td>11</td><td>LRT 3</td><td>2024</td><td>38</td><td>26</td><td>2</td></tr>
<tr><td rowspan="2">ERL</td><td>6</td><td>ERL KLIA Ekspres</td><td>2002</td><td>57</td><td>3</td><td>1</td></tr>
<tr><td>7</td><td>ERL KLIA Transit</td><td>2002</td><td>57</td><td>6</td><td>3</td></tr>
<tr><td>Mono rail</td><td>8</td><td>Monorail</td><td>2003</td><td>8.6</td><td>11</td><td>6</td></tr>
<tr><td rowspan="3">MRT</td><td>9</td><td>MRT Kajang</td><td>2016</td><td>51</td><td>31</td><td>10</td></tr>
<tr><td>12</td><td>MRT Putrajaya</td><td>2022</td><td>57</td><td>39</td><td>9</td></tr>
<tr><td>13</td><td>MRT Circle</td><td>2032</td><td>50.8</td><td>31</td><td>10</td></tr>
</table>

Figure 1.3 shows the forecasted Klang Valley urban rail transit network. The forecasted network includes the provisional stations, the under-construction LRT 3 transit line, and the proposed MRT Circle Line that is set to operate in 2032 (MRT Corp, 2024). The implementation of the new transit lines increases the connectivity of the overall urban rail transit network of Klang Valley with the increment of number of interchange stations.

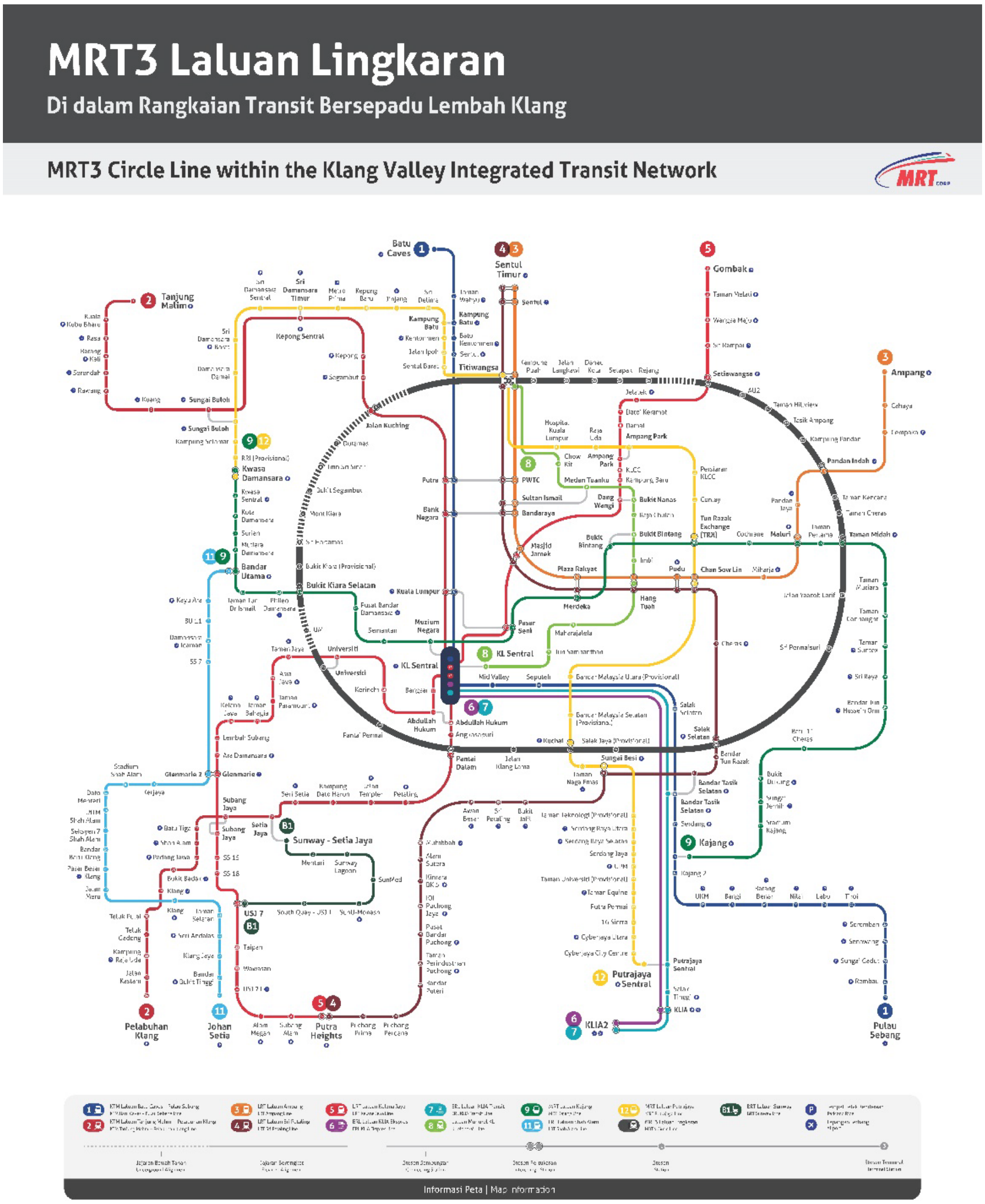


Figure 1.3: Klang Valley Urban Rail Transit Network (MRT Corp, n.d.)

1.2 Importance of the Study

The implementation of urban rail transit networks worldwide has gained popularity in recent years. The study of the performance and connectivity of urban rail transit networks enhances the understanding of the strengths and weaknesses of the current network for future improvement strategies. The analysis enhances the efficiency and sustainability of transportation by optimising the topological connections among the stations to align with the passenger flow demand. The goal of enhancing the connectivity of the urban rail transit network is to promote ridership of the public transportation system and reduce traffic congestion by reducing the dependency on private vehicles.

1.3 Problem Statement

Urban rail transit describes the various types of passenger-carrying rail systems that operate between urban and suburban areas, serving as alternative travel options for passengers commuting to work daily. These rail systems were first introduced in Klang Valley in the late 1990s and were intended to relieve the traffic congestion in the CBD area by reducing the total number of vehicles that commute between urban and suburban areas by providing a transport option that is punctual, fast, reliable, energy efficient, and has a high mobility rate. However, the total journey time between OD is significantly higher than the journey time between the same OD with private vehicles, especially for underserved area like OD between suburban areas (Litman, 2024). The current layout of the urban rail transit network in Klang Valley consists of 7 transit lines with stating and terminating stations in suburban areas and are passing through the CBD of Klang Valley; thus, these lines can be classified as radial transit lines. The common problem for a radial line is longer travel time between OD and bottleneck congestion at the interchange station located in CBD. The improvement in travel time and efficient transfer between multiple transit lines were analysed with the inclusion of the proposed MRT Circle Line by comparing the current and forecasted Klang Valley urban rail transit network in this study. There is a significant disparity between the available urban rail transit network infrastructure and passenger flow demand. The study analyses the compatibility of supply and demand quantitatively.

1.4 Aim and Objectives

This study aims to assess the performance and connectivity of weighted Klang Valley urban rail transit network with quantitative indicators.

The objectives of this study include:

1. To quantitatively compare performance and connectivity of the current operational network with the forecasted network.
2. To compare the compatibility of network's infrastructure and the passenger flow demand.
3. To compare the performance and connectivity of Klang Valley network with multiple major cities around the world.

1.5 Scope and Limitation of the Study

The scope of this study focuses on the topological analysis of the current and forecasted Klang Valley urban rail transit network with the assumption that passenger route choice is not affected by the transit trip cost. The scope of the network excludes Express Rail Link (ERL) KLIA Ekspress Line and KLIA Transit Line that primarily connect the airports and the suspended Skypark Link. The limitations of the study include the availability of passenger flow data for all KTM transit lines for compatibility comparison of the overall network and the actual time and distance data for new transit lines in forecasted network. The limitation in the data collection is the transfer time is subject to change due to date and time of collection and the speed of walking. Another limitation of the study is the MRT Circle Line alignment identification for distance collection is assumed based on the limited available information to the proposed transit line.

1.6 Contribution of the Study

The study aims to contribute insight to the performance through topological analysis of the Klang Valley urban rail transit network with widely used quantitative indicators. The study assesses the improvement impact of the proposed MRT Circle Line and the compatibility of the supply and demand of the network quantitatively, facilitating the feasibility study of the proposed transit network.

1.7 Outline of the Report

The study consists of 5 chapters as follows:

Chapter 1: Introduction

The chapter provides purpose of the studies and the general introduction to the design and patterns of urban rail transit network adopted worldwide. This chapter also outlines the scope and limitations of the study.

Chapter 2: Literature Review

This chapter provides insight to the types of design patterns of urban rail transit networks. The different methods and considerations in performing topological and robustness analysis of the urban rail transit network were presented in this chapter.

Chapter 3: Methodology

This chapter presents the methodology of the study in analysing Klang Valley urban rail transit network. Methods and consideration of time, distance and passenger flow data collections were presented. The steps to analyse the data and the computation method of each quantitative indicators were displayed accordingly.

Chapter 4: Results and Discussion

This chapter displays the results obtained from the calculations of quantitative indicators of the performance of urban rail transit network in the form of tables and graphs. The chapter also includes discussions on the findings in fulfilling the aims and objectives of the study.

Chapter 5: Conclusion and Recommendations

The chapter concludes the overall findings of the study in which fulfil the aim and objectives of the study and proposed recommendations on future research extended from this study.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In this chapter, the literature review was discussed based on the topological analysis and robustness analysis of an urban rail transit network. Numerous studies were conducted to analyse the performance of an urban rail transit network with indicators that were proposed based on graph theory and complex network theory to quantify the performance and importance of each station in the network. The findings of the research were reviewed.

2.2 Network Patterns

Alternative Transport (2018) illustrates the route types of urban rail transit network patterns, which include radial, circular (ring), and grid networks. Radial lines are transit lines with starting and terminating stations built away from the city centre, usually in the suburban areas. These lines pass through the Central Business District (CBD) area, serving commuters who work in the CBD and reside in suburban areas (Saidi, 2016).

2.2.1 Radial Network

Radial lines can be separated to two types, Figure 2.1 shows radial lines that only resemble the radius of a circle where the transit line terminates at the city centre, and Figure 2.2 shows the diameter where both stations are located out of the city centre and passing through the CBD.

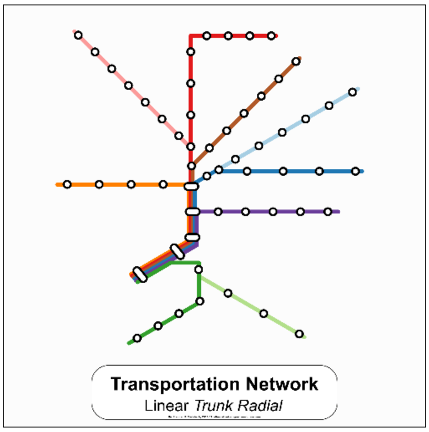


Figure 2.1: Radial Transit Line (Alternative Transport, 2018)

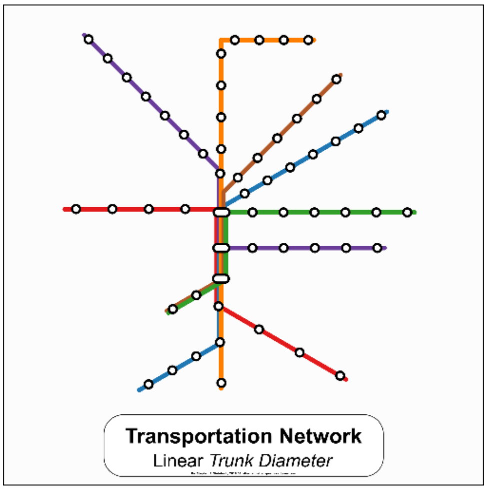


Figure 2.2: Diameter Transit Line (Alternative Transport, 2018)

Design models adopt the radial transit approach of emphasising the directness of a transit line and reducing the number of transfers or limiting the number of transfers to encourage ridership by reducing the transit user cost, which includes the time spent waiting, in the ride, and in the transfer (Zhao, 2006). The same report quantifies the directness of a transit line by the additional travel time when the most direct route between OD is not chosen. However, radial lines only focus on the connectivity between CBD and suburban areas, the transit line has inadequate connectivity and increases the number of paths between non-central areas.

2.2.2 Ring Network

The second configuration of transit pattern is the ring transit line shown in Figure 2.3.

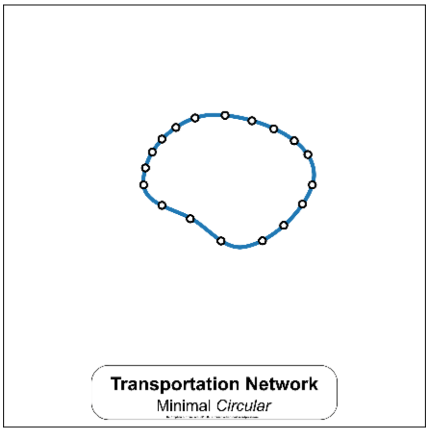


Figure 2.3: Ring Transit Line (Alternative Transport, 2018)

A ring transit line intercepts radial lines, forming interchange stations away from the central area for passengers to transfer between different transit lines. Figure 2.4 shows the radial-ring transit network configuration.

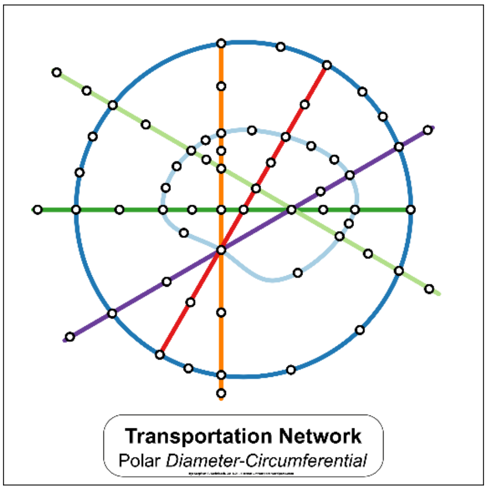


Figure 2.4: Polar Diameter-Circumferential (Radial-Ring) Transit Line (Alternative Transport, 2018)

A ring line can provide direct linkage between peripheral areas of a CBD and suburban areas, enhancing the connectivity of the rail transit network. The additional options allow passengers with non-central destinations to commute directly towards their destination without needing to transfer at an interchange station in the city centre. Saidi (2016) mentioned that the introduction of a ring line to an existing rail transit network can improve connectivity with the addition of interchange stations. He also noted that the additional transfer stations can provide flexibility for passengers to transfer to the nearest transit lines to their destinations in case of service breakdowns on any lines, and the redundancy of the interchange can reduce the vulnerability of the overall rail transit network. It was mentioned by Yang et al. (2015) that vulnerability is a useful index to quantify the capability of an urban rail transit network to handle service disruption in the event of a disaster. By providing an additional route option for passengers with no intention of entering the central area, the passenger load at the interchange stations located in the CBD can be reduced. The original passenger load from these stations dispersed to multiple new interchange stations resulting from the intersections of the ring and radial lines.

2.2.3 Grid Network

The third urban rail transit network pattern is grid network. A grid network is a transit system with arrangement of multiple rail lines intersecting each other to form a grid-like structure. This network pattern is more common in cities with well-designed street grids that allow rail lines to align with the major roads. Figure 2.5 shows the grid network transit line configuration.

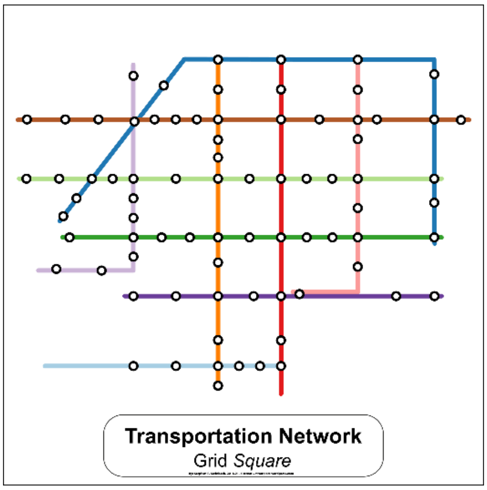


Figure 2.5: Grid Network Transit Line (Alternative Transport, 2018)

Grid network transit lines have a set of parallel transit lines running from one end to another that intersect with another set of transit lines parallel to the other set, each spaced at a walkable distance, allowing passengers to access a station from any point within the urban rail transit network in the city centre. With this pattern of network coupled with optimised frequency, passengers can commute from one point to another on a relatively direct path that has similar travel time compared to driving. Walker (2015) mentioned that a grid network pattern is much preferable for dense cities with a large CBD area and multiple important points scattered along the city. He also mentioned that the highly connected grid network increases the number of locations passengers can reach with minimal transfers, the route is a direct L-shaped with just one transfer in an ideal grid transit network. Therefore, the coverage and accessibility of the grid network have reduced the total journey time by limiting the waiting time during transfers. The redundancy of the densely spaced stations reduces the network's vulnerability in case of disruption, as there are alternative lines to accommodate the route between the OD.

2.3 Graph Theory and Complex Network Theory

Researchers have widely adopted graph theory and complex network theory to quantitatively analyse the performance of an urban rail transit network for decades. Numerous indicators are proposed by researchers based on the two theories to assess the network from various aspects. Extensive research is applied to analyse the topological characteristics of various types of transportation, including airports, bus networks, and rail networks (Lin et al., 2020).

2.3.1 Graph Theory

With the first introduction in the eighteenth century, intended to solve transportation problems, graph theory has evolved for more than 200 years. Derrible and Kennedy (2009) and Quintero-Cano (2011) have reviewed the evolution and application of graph theory from its early days to recent applications on the urban rail transit network.

The authors concluded that there are five types of graphs represented with graph theory, as shown in Figure 2.6. The theory represents a network with a directed graph when the direction of movement is limited to one direction and an undirected graph when the movement happens in both directions. An undirected graph can be segmented into a tree graph, where no loops were formed, and the total number of edges is always less than the total number of nodes or vertices. Another graph classified by the theory is a planner graph, where the edges or links only intersect at the nodes, while a non-planner graph can converge between edges.

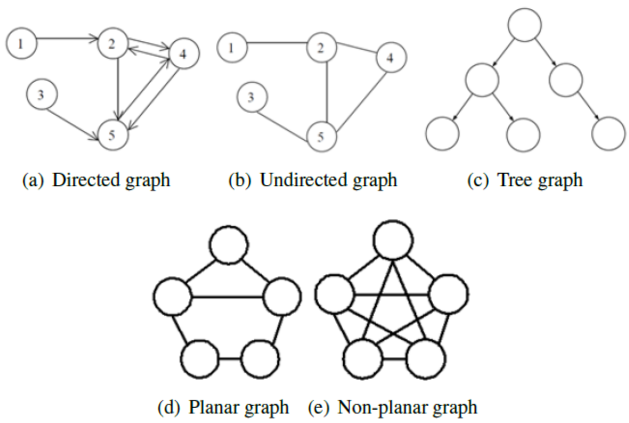


Figure 2.6: Types of Graphs (Quintero- Cano, 2011)

The application of graph theory in the mid-19th century focused on road transportation systems that emphasised economic aspects. As more intensive models were developed, several indicators were introduced that focused on the nodal connectivity of a network (Derrible and Kennedy, 2009). In the early 1980s, the approach of graph theory shifted from mathematical to computational systems, and during this period, the application of the theory began to focus on urban transport systems and bus networks, with more indicators being proposed (Derrible and Kennedy, 2009). With the first introduction based on graph theory to analyse human communications, Tu (2013) mentioned the centrality indicators, including degree, betweenness, and closeness, that were efficient to analyse and evaluate the importance of nodes from different points of view. Indicators proposed decades ago are still being used as supporting indicators today, these researchers have laid the foundation for transportation network structure optimisation.

2.3.2 Complex Network Theory

Networks comprised of nodes and edges are becoming more complex with increased network size, and more dynamical aspects are being considered when analysing a network. Meng et al. (2020) have summarised that with the increasing complexity of networks, complex network theory is now more crucial to analysing the local and global characteristics of urban public transportation. The paper also mentioned that recent studies revolve around the multiple indicators that were continuously evaluated and optimised over time to better reflect and produce useful insight into the urban rail transit network. The indicators involve the static topological characteristics of the connections between nodes and the dynamic characteristics of passenger flow to analyse the performance of the network from a local and global perspective.

Soh et al. (2010) highlighted the significance of studying a network from a topological and dynamical perspective to understand the network holistically. The study has proved that dynamic analysis enhances the insights obtained from traditional topological analysis. With the advancement of complex network theory research and computational power in recent years, researchers have been able to analyse intricate networks with up to millions of nodes and edges. Complex network theory has gained popularity in analysing the safety management and robustness of an urban rail transit network given its efficiency in analysing the scale-free and small-world characteristics of a network (Yang et al., 2015). Complex networks with scale-free characteristics are robust and follow a power law distribution where most nodes have a low degree and only a few nodes have disproportionately more connections, while small-world networks tend to have a short average path length and high local clustering where most nodes are reachable from other nodes in a relatively small number of steps despite the large size of the network (Meng et al., 2020). Pu, Li, and Ma (2022) concluded that the research on single-layer transportation systems based on complex networks has been refined over years of evolution and mentioned the possibility and efficiency of analysing and optimising multi-layer transportation networks by including multiple modes of transportation at once.

2.3.3 Summary

The long history of graph theory has paved the foundation for modern transportation system analysis. The increasingly popular complex network theory can address the limitations of the traditional graph theory in the analysis requirements of the increasingly complex urban rail transit network structure (Li, 2023). While graph theory mainly focuses on analysing physical and topological relationships of a network with simplified nodes and edges, complex network theory, which is very much interrelated with graph theory, includes the weighted dynamic characteristic to better reflect the real-world condition of a large-scale and increasingly complex network. Graph theory considers the classical indicators to reflect the connectivity and complex network theory dives deeper considering the centrality and clustering characteristics of the network. Combination of both theories in analysing an intricate urban rail transit network can complement each theory and provide comprehensive insight.

2.4 Analysis Model

Multiple research papers have adopted the Space L and Space P analytical models to construct and represent the complex urban rail transit network to analyse and compare networks from different aspects.

2.4.1 Space L

Meng et al. (2020) and Lin et al. (2020) described the Space L model as the schematic layout of a transit network that represents a station as a node and the connection between adjacent nodes as an edge. It is supported by Ma, Sallan, and Lordan (2023) that the Space L model, which better reflects reality, represents the physical layout and characteristics of the urban rail transit network, including the number of stations and distance between adjacent stations. The Space L model emphasises the relationship between adjacent nodes and is suitable to perform analysis with interest related to the physical structure of the network, such as network coverage and shortest path length.

2.4.2 Space P

Ma, Sallan, and Lordan (2023) describe the Space P model as more aligned with public cognitive behaviour as the model represents travel routes between two nodes through multiple modes of transportation. The authors also mentioned that the Space P model can perform path planning and path search to determine the fastest path within a network. Meng et al. (2020) and Lin et al. (2020) supported the above statement that the Space P model considers the connections between two stations as edges, whether they are connected directly with the same line or through transfer between multiple lines in the network. The Space P model emphasises the dynamic and transfer characteristics of passenger flow in the network.

2.4.3 Summary

Space L and Space P analytical models in urban rail transit networks serve complementary roles in analysing the network from different aspects. Space L focuses on the physical connection between stations in the network, while Space P considers the dynamic properties of the passenger flow in a network.

Figure 2.7 shows the topological network representation modals adopted by researchers in analysing an urban rail transit network.

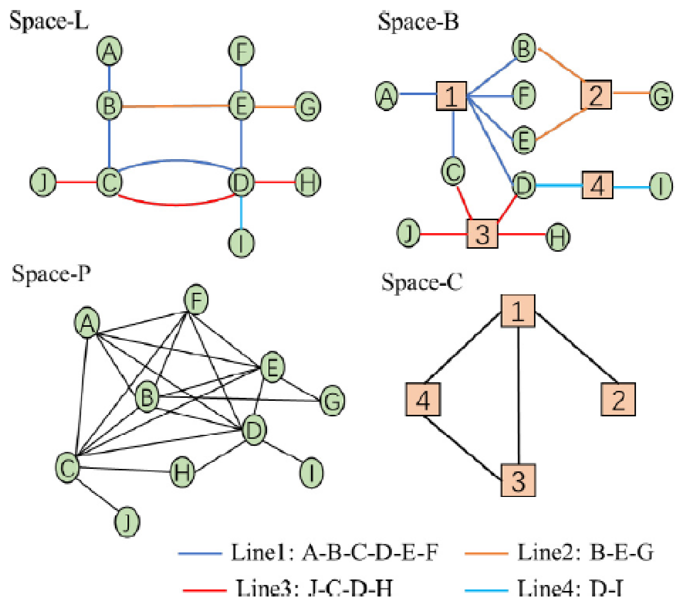


Figure 2.7: Topological Network Representation Models (Meng et al, 2020)

Meng et al. (2020) have further categorised public transportation into Space B model, which does not connect the same kind of nodes, and the Space C model, which represents each line as network nodes and connected nodes as links. However, the authors agreed that the Space L and Space P models are more aligned with the actual rail transit network, making them more suitable to analyse the network.

2.5 Network Performance Indicators

In the study of urban rail transit network planning and design, the evaluation of the network's performance is crucial. Researchers have proposed multiple indicators based on graph theory and complex network theory to quantify and assess the network structure's connectivity from different perspectives. This section discussed the widely used indicators in the study of urban rail transit networks.

2.5.1 Complexity

Various analysis models propose different methods to represent nodes and edges. The complexity indicator is useful to compare different representations of the same complex transit network. This indicator is efficient in comparing the level of complexity among different networks to analyse the network we are interested in. Chen (2023) and Ding et al. (2015) assess the network's complexity by dividing the number of edges by the number of nodes. A network with a higher number of edges than nodes yield a higher complexity value.

2.5.2 Connectivity

The connectivity indicator measures the ratio of the actual connected edges to the possible maximum number of edges in a network (Chen, 2023). This is a useful indicator to analyse the extent of connectivity between the stations and compare different networks. A highly connected network increases accessibility and reduces passenger costs while using network services. The higher the value of the connectivity indicator, the greater the extent of network development and travel convenience (Chen, 2023; Ding et al., 2015).

2.5.3 Clustering Coefficient

The clustering coefficient indicator can reflect the efficiency of transfer and connectivity of the local rail transit network by assessing the relationship between a node and its neighbour. Meng et al. (2020) explain that the indicator represents the possibility that two neighbouring nodes of a node are also adjacent in a network, which measures the extent of aggregation among the stations in a network. The statement is supported by Ding et al. (2015) and Ma, Sallan, and Lordan (2023), who say that the indicators measure the extent of clustering among nodes of a network. Researchers also utilise the average clustering coefficient to assess the network by taking the mean clustering coefficient for all nodes. The higher the clustering coefficient, the better the connectivity of the entire urban rail transit network and the higher the robustness of the network with the presence of alternative routes connecting the neighbouring stations.

2.5.4 Degree Centrality

The degree centrality indicator is useful in quantifying the importance of a node from a local perspective. Ding et al. (2015) and Lin et al. (2020) defined the indicator as the number of direct connections from a node; the greater the number of edges a node is connected to, the more important and influential the node is. A network is said to be scale-free when the degree distribution follows power law, indicating most stations have less degree centrality while a few stations have disproportionately high values (Meng et al., 2020). The network's average degree of centrality can be calculated as the mean value of all nodes. A node with a higher degree of centrality is more important within the network.

2.5.5 Closeness Centrality

Closeness centrality assesses the connectivity of a rail transit network with the actual distance between the nodes to identify the station that can be efficiently accessed from the rest of the network. It is calculated as the inverse of the average shortest path length between two nodes. Meng et al. (2020) describe closeness centrality as a positive indicator that can reflect the level of difficulty of reaching a node from another node. The indicator can reflect the degree of concentration of the adjacent nodes around a node; the more concentrated and closer the nodes are, the more important the node is (Ding et al., 2015). An effective distance metric that took into account passenger flow data and the mobility of the network was proposed by Lin et al. (2020) in response to the claim that distance alone is ineffective for measuring the distance between nodes in a network. A higher value of closeness centrality signifies that this node is important and can be easily reached from any other node in the same network.

2.5.6 Betweenness Centrality

Betweenness centrality measures how often a node is used as a link connecting two other nodes from a global perspective. It refers to the number of shortest paths that connect any two nodes of the network that pass through a single node. Stations with higher betweenness centrality tend to have higher passenger flow when the shortest path is chosen, which indicates the higher passenger carrying capacity of the station (Lin et al., 2020). Ding et al. (2015) and Meng et al. (2020) agreed that stations with higher the betweenness centrality have greater passenger flow; this means that the nodes have higher control power over the traffic flow of the entire network. Any disruption to an important station may cause chain effects throughout the network. Since a station with higher centrality tends to have higher traffic flow, the station is more likely to experience bottlenecks and overwhelming traffic flow, especially during peak hours. This indicator can assist urban planners in emphasising the design of stations with higher centrality to cope with the higher traffic volume.

2.5.7 Average Shortest Path Length

Meng et al. (2020) mentioned that the path length between a given OD is described as the number of edges connecting the two nodes. It determines the connectivity and accessibility of the urban rail transit network. The average shortest path length value of a node is the mean value of the shortest path length between the given node and all other nodes. The smaller the average shortest path length value, the more extensive the connectivity of the network, with less travel required to reach another node (Meng et al., 2020). The network diameter is often referred to as the maximum shortest path length between two nodes (Ding et al., 2015).

2.5.8 Summary

In short, various researchers adopted graph theory and complex network theory to propose multiple indicators to quantitatively assess and compare the performance of multiple urban rail transit networks worldwide, or the changes in performance of a network before and after the development of new rail lines. These indicators were adopted by many researchers, which implies the reliability of the indicators to assess the urban rail transit network. These indicators can assist urban planners in identifying the important nodes to select potential stations as interchange stations for future transit lines. Moreover, it allows maintenance teams to highlight important stations to prevent catastrophic disruption to the station, which may affect the operation of the network. Quantitatively comparing the global value of each indicator can help reflect the percentage performance difference between any two networks, facilitating the performance and connectivity forecasting and analysis of network expansion.

2.6 Topological Analysis

The urban rail transit network comprises multiple nodes and edges. Topological analysis is important to study the connections between the components of the network and optimise the network structure design, improving future rail transit development planning and connectivity optimisation. The analysis utilises mathematical tools to study the relation between space and object, providing helpful decisions for design, operation, and maintenance with the insight of nodal distribution in the network. This section explored how researchers analyse the topology of urban rail transit networks with graph theory and complex network theory.

2.6.1 Network Expansion Performance

Ding et al. (2015) have performed topological analysis on the Klang Valley urban rail transit network with complex network theory. Despite decades of implementations and improvements, the authors concluded that there is still insufficient research performed on rail transit networks to analyse the relationship between the network expansion process and network performance.

An important point to note is that the expansion of an urban rail transit network not just meet the local needs of public transportation in an area; more importantly, it improves overall efficiency through the optimisation of the transportation capacity of the entire network in the long run. The Kuala Lumpur urban rail transit network is represented with the space-L method to describe its topological performance. The performance of the network is calculated and tested with classical traffic indicators, which include number of nodes and edges, complexity, connectivity, network loops, and availability of loops, while also considering indicators based on complex network theory, which include connection, clustering, and centrality. Using the year increment as a variable, Ding et al. (2015) analyse the changes to the performance of the network from 1995 to 2017, from the introduction of Keretapi Tanah Melayu (KTM) to the Mass Rapid Transit (MRT) Kajang line.

The result of the paper concluded that there is a linear relationship between the number of nodes and edges in the network with a high fitting confidence coefficient, whereas network complexity, connectivity, and availability of loops shoot up during the early years but gradually deteriorate. This paper performed an in-depth study on the network expansion process and found that the maximum value of node degree increased from 3 in 1995 to 9 in 2017, indicating the increased connection of a single node with the network. Although more connections are formed, a large proportion have a relatively low node degree value of 2, referring to the fact that the rapid development of network connections cannot keep up with the speed of the overall physical expansion of the network. The largest portion of node degree remains at 2, despite gradual increment in maximum node degree. The degree distribution graph shifted from a normal distribution towards a heavy-tailed distribution over the years. Data shows the network had a peak global clustering coefficient in 2004 and gradually became loose over time, with KL Sentral Station being the most distinct cluster node in general. The average degree of centrality falls as the network grows, and the closeness degree value obeys the normal distribution, while the average betweenness centrality reduces with the increase of stations, and the value best fits the exponential distribution. Simulating the network growth process allows urban planners to observe changes with the addition of nodes to the existing urban rail transit network, which is useful in identifying potential stable growth points for the network (Ding et al., 2015).

2.6.2 Travel Time Data Weighted Analysis

Time weighted network analysis provides a comprehensive approach to the understanding of connectivity of the urban rail transit network. Jia et al. (2021) performed a study on identifying important stations of an urban rail transit network to understand the transmission path of COVID-19 by taking Beijing as case study. The study utilises various parameters to weigh the network. utilising travel time weighted network analysis provides a more realistic representation of the network dynamics, considering the real-world constraints including travel time between OD, waiting time and transfer time at interchange stations. The indicators used in the case study include degree centrality, betweenness centrality, clustering coefficients, and PageRank to analyse the network from multiple aspects. Considering weighted parameters in the urban rail transit network analysis captures the intricacy of the real-world scenario where passengers may have their personal preferred route.

2.6.3 Distance Data Weighted Analysis

Distance is another commonly used parameter to analyse the connectivity of an urban rail transit network. Tan et al. (2022) performed analysis to evaluate the utilisation of distance to weigh the network's edge, then, the Nearest Transport Point indicator is computed to evaluate the possible alternative route and accessibility of switching between metro lines if any edge connecting two stations experiences disruptions. The findings of the paper include capturing the impact of proposed future transit lines when compared to the existing operational network using the multiple quantitative indicators including betweenness centrality. The study provides contribution to the analysis of urban rail transit network with the introduction of assessing the resilience of network considering the distance between two stations. The methodology used in the study is able to apply to any other urban rail transit network for similar analysis.

2.6.4 Passenger Flow Data Weighted Analysis

Lin et al. (2020) concluded that the results of many research papers are not applicable for the operation and management of an urban rail transit network as the papers solely focused on topological analysis of the structural elements of the network without including the dynamic interaction among passenger flow and network structure. The paper assesses the urban rail transit network by incorporating passenger flow data based on complex network theory to identify important stations and sections and measure the interaction and linkage between stations. The approach of the research obtained insight into the static properties and dynamic patterns produced by passenger movement to assist future infrastructure design and operational decisions.

A weighted network was used to represent the Beijing rail transit system with passenger flow data obtained from Automated Fare Collection (AFC) of the network. The results suggest that stations with a high degree of centrality experience a high level of transfer, boarding, and alighting volume; these stations are mostly located within a large residential area or commercial office area with high passenger flow volume, supporting the reliability of the indicator. Stations with a high betweenness centrality value concentrate around loop lines or transfer stations that intersect between loop lines and radial lines. While these stations are important for bridging commuters between suburban and urban areas, they often show a high risk of congestion during peak hours.

The stations located in the city centre of Beijing generally have high closeness centrality, but this gradually reduces when moving towards the surrounding suburban areas. The important stations identified using the PageRank Index are among the busiest stations of the network, and the route that involves these stations is also among the busiest. The research also assesses the connection or edge between stations. The average passenger flow for the top 10 stations with the highest value of edge weight and betweenness centrality for edge exceeds 20,000, with the highest volume reaching 34,000. The top stations correlate to the high volume of passenger flow, indicating the reliability of the indicators to assess the rail network. The results also show that certain stations do not appear at the top of the list of other indicators despite having high betweenness centrality, confirming the unique roles of each indicator. In short, the result values of degree centrality, PageRank Index, betweenness centrality for node, betweenness centrality for edge, and edge weight were plotted on probability distribution graph according to the respective indicators, and the results obey power low, with only a very tiny portion of the stations or links having disproportionately high passenger flow volume and playing an important role in the entire network, while the results of closeness centrality follow normal distribution, indicating the network possesses the characteristics of the small world where most stations have high clustering and are closely connected to each other. Stations located in areas with high passenger flow volumes are usually important, and having the value of the indicator align with the passenger flow volume further reinforces the credibility of the above indicator.

A similar result is obtained in research by Xing, Lu and Chen (2016) on the weighted complex network analysis of urban rail transit networks by taking Shanghai Rail Transit System as case study. Weekday peak hour passenger flow data obtained from Shanghai Shentong Metro Company is used to weigh the edge between nodes of the network. Analysis with passenger flow data reflects the actual traffic dynamics of the network. The findings of the study reflect multiple indicators calculated with passenger flow weighted network captures a more meaningful analysis compared to unweighted topological network analysis as it considers the number of passengers commuting around the network.

2.6.5 Analytical Model Comparison

While most research uses indicators to analyse the network represented by Space L, Meng et al. (2020) took a different approach by comparing the significance of multi-space modelling based on six parameters. The topological analysis of Shenzhen Metro (SZM) in the paper has concluded that the degree centrality distribution of SZM has a severe heavy-tailed distribution with a large proportion of nodes in Space L representation having a value less than 2, and Space P representation having a large proportion of nodes with a value less than 30. This is due to the network representation in Space P, which considers connections between any two nodes, which significantly increases the number of edges. The cumulative degree distribution of SZM was mentioned to obey power law distribution, and the network is said to be scale-free, indicating the robustness of the network in resisting random failure. The clustering coefficient data shows nodes are more connected when analysed with Space P compared to Space L. Betweenness centrality and closeness centrality data observe dramatic differences in station ranking lists in different representation models. This signifies that a station has a different controlling role when represented in the 2 models.

The authors concluded the centrality indicators have highly corelated mathematical connections in Space P, while distinct fluctuations of data are observed in Space L representations. The standardised data can be compared and ranked equally between Space L and Space P. The analysis revealed that stations with high scores are primarily transfer stations with higher probability as the risk point of the network, and the top stations are more decentralised in Space P but more centralised in Space L (Meng et al., 2020).

2.7 Robustness Analysis

With increasing urbanisation and rapid population growth, the implementation of an urban rail transit network has become the most effective solution to traffic congestion in densely populated cities around the world. Nonetheless, the regular incidents of random failure and malicious attacks represent a significant challenge to the security and reliability of the network. Much research based on complex network theory has been done in recent years, focusing on quantitative analysis of the robustness of an urban rail transit network to handle different failures and attacks, as well as preventing cascading failures from happening.

2.7.1 Network Element Failure Scenario

An urban rail transit network generally encounters two types of failure scenarios, which include random failure and malicious attacks (Yang et al., 2015; Xing et al., 2017; Cats and Krishnakumari, 2020). Random failure of a node or edge often happens unintentionally or as an unexpected event that disrupts the normal operation of an urban rail transit network, while malicious attacks involve the intentional and deliberate actions of individuals that cause harm to the network. Yang et al. (2015) mentioned that the disruptive power of a random failure is minimal compared to a malicious attack that could cease the operation of an urban rail transit network for a long period of time. Another difference between the two scenarios is that the probability of a random failure is uniform across all stations within the network, while malicious attacks tend to occur at targeted stations, which is more important with a higher degree of betweenness. The authors also mentioned that natural disasters were not considered in their study as the disruption can cause catastrophic damage to the whole network, which is not practical to simulate with just several stations. Table 2.1 shows the common behaviours of urban rail transit networks in various kinds of failures and attacks.

Table 2.1: Summary of Common Behaviours of Failures and Attacks for an Urban Rail Transit Network (Yang et al, 2015).

Categories	Precursors	Description
Random Failure	Technical malfunctions	Broken rail, Broken wheels, Brake failure, Gear Failure, Signal failures, Power failure, Crack rail, Line fault, Exceeding speed
	Passengers actions	Congestion, Suicide in platform, Fall onto track, Falls on escalators, Group fighting, Unconscious destruction due to drunkenness, Smoke in station/train, Wrong operation by driver, Passenger carrying dangerous goods, Passenger carrying pets, Riot caused by rumours, Caught in train doors
	Official actions	Temporary disruption of service, Temporary line maintenance, Temporary closure for safety inspection, Temporary closure for special activity, Decision error
Malicious attacks	Targeted destruction	Deliberate destruction, Passenger carrying dangerous/flammable goods, Passenger carrying poisonous goods, Kidnapping, Trespass, Manual destruction on rail, Manual destruction on train, Explosion in purpose, Set fires, Gun shooting, Derailment caused by human, Deliberate assassination to raise riot and etc.

2.7.2 Robustness Indicators

The efficiency and connectivity of an urban rail transit network typically depend on the topological completeness of the network (Yang et al., 2015). The robustness analysis model assesses the global performance of the network when subjected to various types of failures and attacks. Two indicators adopted by various researchers to quantify the robustness of an urban rail transit network are the Relative Size of the Maximal Connected Sub-graph

(RSMCS) and Global Network Efficiency (GNE) (Yang et al., 2015; Xing et al., 2017; Cats and Krishnakumari, 2020).

The first indicator is the Relative Size of the Maximal Connected Sub-graph (RSMCS). The removal of one or more nodes in a network disintegrates the graph into multiple sub-graphs, and the sub-graph with the maximum number of connected nodes is identified as the maximal connected sub-graph (Yang et al., 2015). The RSMCS indicator evaluates the robustness of the network that is under attack by evaluating the ratio of the largest remaining intact sub-graph with respect to the initial undisrupted network (Cats and Krishnakumari, 2020). Thus, evaluating the extent of disintegration of the network under various failure conditions.

The second indicator is Global Network Efficiency (GNE). The shortest path length between two nodes is a common measurement of the efficiency of a network. However, the shortest path length between two unconnected neighbouring nodes within a network that is under attack yields an infinite value and cannot be computed (Yang et al., 2015; Xing et al, 2017). Rerouting and possible detours that affect the shortest path length may be required for a given OD due to the removal of nodes. GNE is proposed to assess the effect on the network (Cats and Krishnakumari, 2020).

2.7.3 Methodology

The performance of an urban rail transit network that is under various attacks is analysed with RSMCS and GNE indicators. In the robustness analysis where nodes are deleted to simulate the performance of a network under failure, Space L can represent the intuitiveness of physically adjacent nodes where these stations are directly connected in the most simplified manner compared to other representation models (Xing et al., 2017; Cats and Krishnakumari, 2020).

A random failure happens at equal probability for all nodes, while malicious attacks happen to more important nodes within a network. As discussed previously, two of the topological indicators that are effective in evaluating the importance of a node within a network are degree centrality, which assesses the local connectivity, and betweenness centrality, which assesses the connectivity globally. Here, researchers use these indicators to develop attacking strategies to simulate the worst-case scenario by precisely attacking the most important stations to evaluate the robustness of a network. Various attacking strategies were used by researchers to simulate the attacking strategies by removing nodes according to the importance ranking obtained from the network performance indicator. These strategies remove one node at a time from a network and reevaluate the centrality indicators, as well as the RSMCS and GNE indicators, to evaluate the performance of a disrupted network and compare the functionality loss globally in percentage (Yang et al., 2015; Xing et al., 2017; Cats and Krishnakumari, 2020). Figure 2.8 shows the structure of the connected graph before and after the removal of a node.

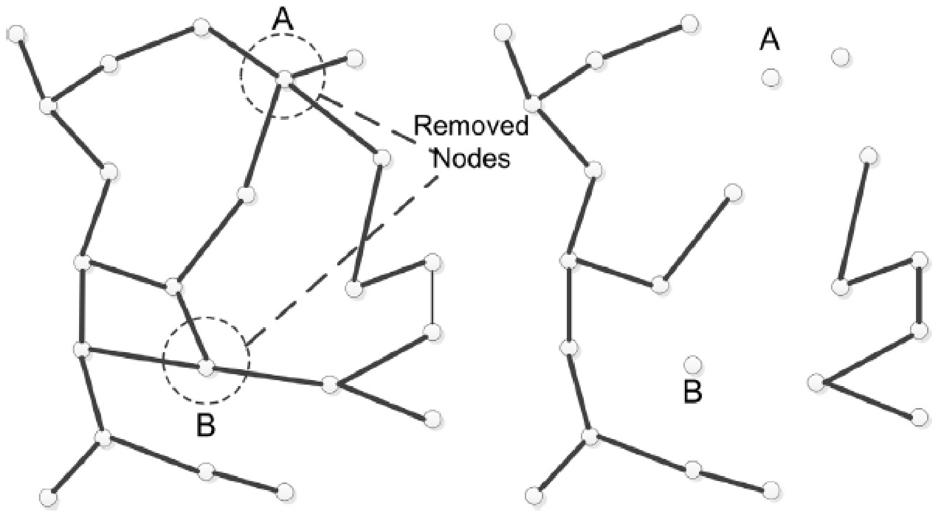


Figure 2.8: Structure of the Connected Graph Before and After Node Removal (Yang et al, 2015)

In short, random failure follows a sequence where nodes are deleted randomly while malicious attacks target the most important nodes based on indicators including degree centrality and betweenness centrality. The performance of the global network is recalculated and compared. A rapid decrease in RSMCS and GNE presents a vulnerable characteristic of a network (Xing et al., 2017).

2.7.4 Findings

Various researchers concur that malicious attacks are more likely to target an urban rail transit network than random failures. The decline of RSMCS when the network is under random failure is insignificant, and minimal fragmentation is observed compared to rapid deterioration when under malicious attacks (Xing et al., 2017). Cats and Krishnakumari (2020) concluded that at 40% of nodes or 50% of links removed based on degree and betweenness centrality removed in malicious attack simulation, the network exhibits a high degree of fragmentation, with no subgraph containing more than 1% of the original network, whereas about 80% nodes or links removal is required to achieve the same severity for random failure. Additionally, their findings indicate that when nodes or links are removed based on importance, particularly betweenness centrality, the RSMCS decreases rapidly and significantly. The degradation of network connectivity was twice as rapid when links were removed based on betweenness centrality compared to degree centrality, indicating the importance of global connectivity over local connectivity in identifying the critical links (Cats and Krishnakumari, 2020).

A similar pattern was seen by the GNE indicator. In the case where just 10% of the nodes were removed from the network, the GNE recorded a slight decrease under random failure but a much more severe decline when the network is under malicious attack (Xing et al., 2017). Cats and Krishnakumari (2020) found that networks are considerably more susceptible to deliberate attacks than to random failures, with the most devastating consequences observed when targeting network elements characterised by the highest betweenness centrality values. In a scenario involving targeted removal of nodes, it was observed that even with the removal of just 5% of nodes, GNE is subjected to a rapid increase, indicating that even if the network is still intact, as indicated by RSMCS for both failures, the impact is severe, requiring significant detours and resulting in a substantially longer path within the network (Cats and Krishnakumari, 2020).

Yang et al. (2015) mentioned that studies assumed the transfer station as a simple spatial point where the internal distance between multiple lines was not considered. A malicious attack is more likely to cause disruption to whole stations regardless of the size and distance apart between different lines, while a random failure is less likely to cause widespread disruption to other lines connected to a station.

The significance of a station varies within an urban rail transit network. While traditional research often assesses node importance using degree centrality and betweenness centrality, there's a lack of studies considering damage as a measure of node importance (Xing et al., 2017). Robustness analysis with the aforementioned indicators can analyse the functionality loss of a network when nodes are removed. RSMCS and GNE exhibit a more rapid decrease in network efficiency when nodes are removed based on betweenness centrality. A simulation that confirms the simultaneous failure of the top 5 stations with the highest indicators reveals that betweenness centrality-based removals impact network efficiency more than degree and strength centrality-based removals (Xing et al., 2017).

The author stated that these findings provide insight for urban planners to consider potential locations to increase interchange stations, increase node redundancy to provide alternative routes for passengers to connect the OD, and prioritise limited resources to protect and enhance station structure. The findings from the research show most of the stations with the most damage to the network when removed are connected to a circle line, indicating the importance of the circle line. The circle line is effective in creating new transfer stations that serve as linkages between urban and rural areas to provide multiple alternative routes between given OD, thus increasing the connectivity and robustness of the network (Xing et al., 2017).

While Cats and Krishnakumari (2020) credited the presence of ring lines intercepting radial lines with enhancing the network's robustness by providing transfer opportunities, the authors doubted the direct relationship between network structure and the robustness of the network. While decentralised networks are generally more resilient to targeted attacks, a polycentric urban agglomeration does not always necessarily lead to a distributed network in terms of centrality indicators. In the case study of the paper, a Randstad network with a polycentric structure was found to be the least robust in terms of network performance, which contradicts the general expectation that polycentricism enhances network robustness. The network structure of the Randstad network presents a fragile fork-like structure with key stations located outside the urban cores, which makes it more susceptible to breakdowns between the key stations. Previous studies often assumed that the impacts of network element breakdowns were confined to the respective element. However, in practice, breakdown consequences can extend beyond the primary disruption and disrupt operations further upstream or downstream (Cats and Krishnakumari, 2020).

2.8 Summary

In recent years, there have been increasing studies adopting graph theory and complex network theory to introduce indicators to quantify the topological connectivity and robustness of the urban rail transit network in a weighted network. These networks are constructed with Space L and Space P representations, incorporating factors such as passenger flow data, distance, and travel time to mirror real-world complexities and obtain intuitive results. Network performance is comprehensively assessed through a range of metrics, including degree centrality, closeness centrality, betweenness centrality, clustering coefficient, and average shortest path length, which each assess the functionality and connectivity of the network from different aspects.

Robustness analysis simulates random attacks by replicating unexpected disruptions, while targeted attacks focus on high-importance nodes based on degree centrality and betweenness centrality. Importantly, these indicators enable the ranking of station importance from various perspectives, with the understanding that constructing weighted networks with different parameters can yield distinct ranking lists, allowing urban planners to highlight important stations as potential growth points for the network.

The global value when assessing a network can help quantitatively compare performance and connectivity of any two networks. The calculations of quantitative indicators help predict the performance of network expansion in assessing the impact and feasibility of the proposal of new transit lines when incorporating to the existing rail network.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter have discussed the methodology of analysing the Klang Valley urban rail transit network with quantitative indicators.

3.2 Flowchart

Figure 3.1 shows the steps conducted in this study.

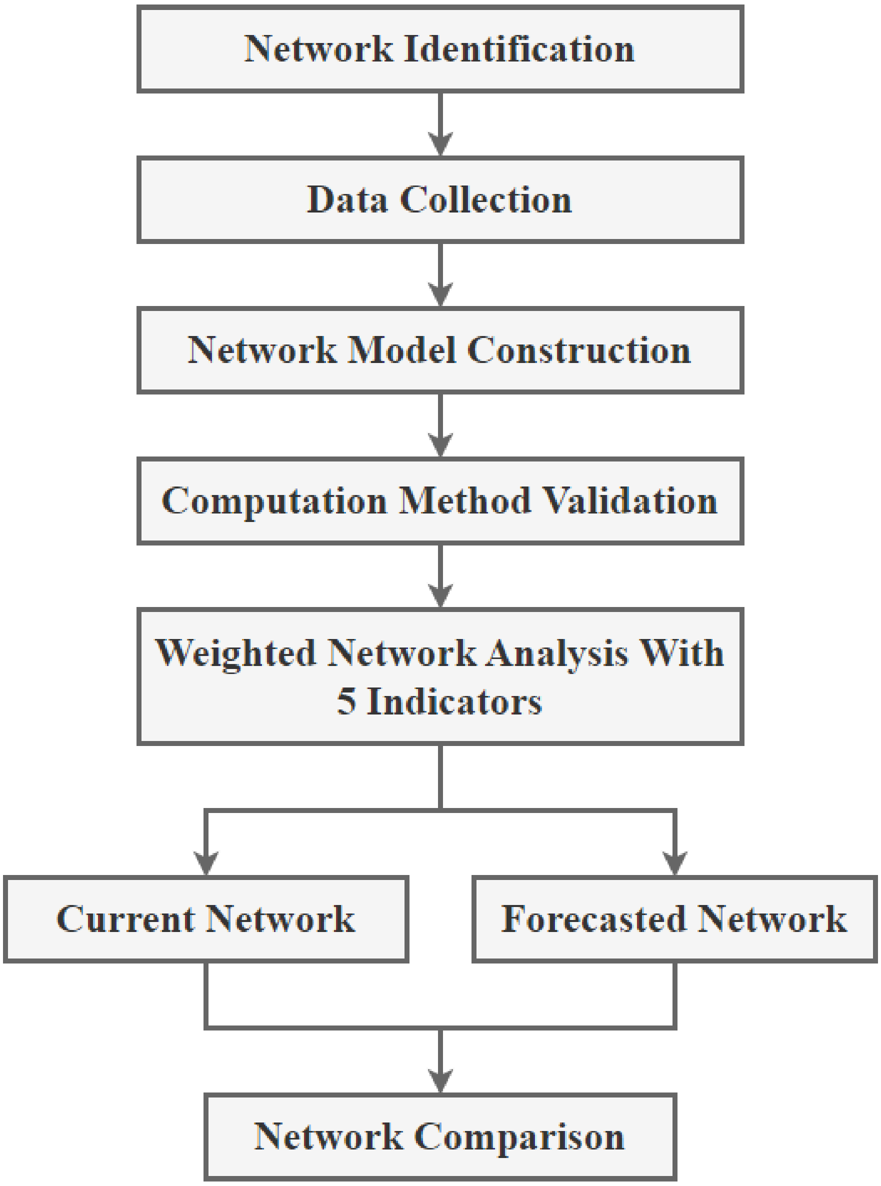


Figure 3.1: Flowchart of Methodology

Based on the flowchart above, the study started with the data collection of time intervals and distance between stations, transfer time and distance between different platforms of an interchange station and passenger flow data between stations. Then the current operational network and forecasted network with the inclusion of new transit lines were constructed to confirm the topological connections of the network. After that, the Python code used to compute the values of indicators was validated with a small sample and verified with hand-calculated values. Next, the Klang Valley urban rail transit network is analysed based on average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient with different parameters that include unweighted, time-weighted, distance-weighted and passenger flow weighted network. The results, discussions, conclusion and recommendations were prepared and documented in the report. The details of the procedure are described in following sub-sections.

3.3 Data Collection

The methodology employed in the data collection on the urban rail transit network in Klang Valley Malaysia includes desktop study and on-site survey with the aim of providing a comprehensive understanding of the performance and connectivity. The data collection involves identifying the direct connections of a same transit line and the interchange connection that connects multiple lines. The availability of the data provides a fundamental understanding on how the stations are connected for the following analysis.

Distance and time between each station are chosen as the parameters in this study due to the availability and reliability of the parameters in reflecting the users' commuting experience. Multiple logical assumptions were made to the expanded forecasted network to obtain the time and distance between stations to facilitate the analysis of the impact with the inclusion of LRT 3 and MRT Circle Line. Passenger flow data is collected to further analyse connectivity of the urban rail transit network to compare the from supply and demand perspective. However, the passenger flow data is limited to LRT, MRT and Monorail lines only.

Efficient inter-platform connectivity is crucial for commuter transfer effectiveness within interchange stations. Interchange stations that undergo comprehensive planning prior to construction typically have direct and straightforward connections, where the station seamlessly aligns with other lines, thus facilitating a smooth transfer experience. However, the Klang Valley urban rail transit networks observed majority interchange stations require long transfer time and distance due to multiple constraints such as land availability. The interconnection pathways between platforms may incorporate with escalators, particularly when linking underground platforms with elevated alignment stations, aiming to facilitate vertical passenger movement. Moreover, certain interchange stations feature platforms interconnected via linking bridges. Additionally, platforms within an interchange station that are situated at considerable distances, require passengers to exit the station and re-enter to access connecting transit line station. Table 3.1 shows the connecting lines of each interchange station and the remarks on the amount of traverse required when moving between different platforms within the interchange stations.

Table 3.1: Connections Between Different Platforms of Interchange Stations

No.	Interchange Station	Connecting Lines	Remarks
1	Kampung Batu	KTM Batu Cave MRT Putrajaya	• Proximity connection with minimal traverse. • Exit and re-enter to the network is required.
2	Bandar Tasik Selatan	KTM Batu Cave LRT Sri Petaling	• Proximity connection with minimal traverse. • Exit and re-enter to the network is required.
3	Kajang	KTM Batu Cave MRT Kajang	• Proximity connection with minimal traverse. • Exit and re-enter to the network is required.
4	Sungai Buloh	KTM Tg Malim MRT Putrajaya	• Facilitated with link bridge for long walking distance. • Exit and re-enter to the network is required.
5	Kepong Sentral / Sri Damansara Timur	KTM Tg Malim MRT Putrajaya	• Facilitated with link bridge for long walking distance. • Exit and re-enter to the network is required
6	Abdullah Hukum	KTM Tg Malim LRT Kelana Jaya	• Facilitated with link bridge for long walking distance. • Exit and re-enter to the network is required
7	Subang Jaya	KTM Tg Malim LRT Kelana Jaya	• Proximity connection with minimal traverse. • Exit and re-enter to the network is required
8	Sentul Timur	LRT Ampang LRT Sri Petaling	• Direct Interchange with minimal transverse.
9	Sentul	LRT Ampang LRT Sri Petaling	• Direct Interchange with minimal transverse.
10	Pudu	LRT Ampang LRT Sri Petaling	• Direct Interchange with minimal transverse.
11	Maluri	LRT Ampang MRT Kajang	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for long walking.

(continued)

12	Sungai Besi	LRT Sri Petaling MRT Putrajaya	• Proximity connection with minimal traverse.
13	Putra Height	LRT Sri Petaling LRT Kelana Jaya	• Proximity connection with minimal traverse. • Interchange at the end of transit lines.
14	Ampang Park	LRT Kelana Jaya MRT Putrajaya	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Notable walking distance between platforms. • Exit and re-enter to the network is required.
15	Dang Wangi	LRT Kelana Jaya Monorail	• Notable walking distance between platforms • Exit and re-enter to the network is required.
16	Bukit Bintang	MRT Kajang Monorail	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Exit and re-enter to the network is required.
17	Kwasa Damansara	MRT Kajang MRT Putrajaya	• Proximity connection with minimal traverse. • Interchange at the end of transit lines.
18	Tun Razak Exchange	MRT Kajang MRT Putrajaya	• Direct Interchange with minimal transverse.
19	Sultan Ismail / Medan Tuanku	LRT Ampang LRT Sri Petaling Monorail	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for notable long walking distance. • Exit and re-enter to the network is required.
20	Masjid Jamek	LRT Ampang LRT Sri Petaling LRT Kelana jaya	• Proximity connection with minimal traverse.

(continued)

21	Plaza Rakyat / Merdeka	LRT Ampang LRT Sri Petaling MRT Kajang	• Comprises of underground and elevated alignment. • Facilitated with escalators and travelator for traverse between platforms.
22	Hang Tuah	LRT Ampang LRT Sri Petaling Monorail	• Proximity connection with minimal traverse. • Exit and re-enter to the network is required between LRT and Monorail lines.
23	Chan Show Lin	LRT Ampang LRT Sri Petaling MRT Putrajaya	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for long walking distance.
24	Titiwangsa	LRT Ampang LRT Sri Petaling MRT Putrajaya Monorail	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for long walking distance. • Exit and re-enter to the network is required between Monorail and other transit lines.
25	Kuala Lumpur / Pasar Seni	KTM Batu Cave KTM Tg Malim LRT Kelana Jaya MRT Kajang	• Comprises of underground and elevated alignment. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for long walking distance between KTM and other transit line. • Exit and re-enter to the network is required between KTM and other transit line.

(continued)

26	Putra / PWTC	KTM Batu Cave KTM Tg Malim LRT Ampang LRT Sri Petaling	• Facilitated with link bridge for notable long walking distance between KTM and LRT lines. • Exit and re-enter to the network is required between KTM and LRT lines.
27	Bank Negara / Bandaraya	KTM Batu Cave KTM Tg Malim LRT Ampang LRT Sri Petaling	• Facilitated with link bridge for notable long walking distance between KTM and LRT lines. • Exit and re-enter to the network is required between KTM and LRT lines.
28	KL Sentral / Muzium Negara	KTM Batu Cave KTM Tg Malim MRT Kajang LRT Kelana Jaya Monorail	• Comprises of underground MRT station and elevated alignment of other transit lines. • Facilitated with escalators for vertical movement. • Facilitated with link bridge for notable long walking distance between Monorail linking to other platforms through NU Sentral Mall. • Relatively shorter distance between LRT and KTM stations located within same building. • Exit and re-enter to the network is required for all transit lines.

It is noted that all interchange connecting to both KTM transit lines requires exiting and re-entering to the network to transfer. This is due to the different operators of the transit lines where KTM lines are operated by Keretapi Tanah Melayu (KTMB) and LRT, MRT and Monorail are operated by Prasarana Malaysia Berhad. All monorail stations also require exiting and re-entering to the network due to remoteness of station location and extensively longer walking distance between connecting transit lines.

3.3.1 Time Data

Time data collection throughout Klang Valley urban rail transit network involves different methodologies due to constraints faced by each transit line.

The following sections explain the detailed steps of time data collection in each distinct transit line.

3.3.1.1 LRT and MRT Stations

The time interval data between each station are collected through sourcing data from the official websites of the urban rail transit network operators, which include Prasarana Malaysia Berhad and Keretapi Tanah Melayu Berhad (KTMB). The websites present the departure time of the last train at each station. Subsequently, the time interval between two stations in a same transit line is determined by computing the time difference with precision to minutes.

The time for the last train leaving each station on Monday to Saturday has slight variation with Sunday due to the commuter demand. There is typically higher demand from Monday to Saturday due to regular work and school schedules. Figure 3.2 shows the time which the last train leaving the station in both directions. The time taken for the train to move to subsequent station can be computed. Since the time might have slight difference for trains moving towards Kajang and Kwasa Damansara directions, time interval for both directions are calculated and the maximum value between the same stations is considered. The sample time interval for both directions and maximum time interval between stations are shown in Table 3.2. A similar computation method is performed for all LRT and MRT stations.

Figure 3.2: Operating Hours sample for MRT Kajang Line (MyRapid, 2024)

Station	Station Name	Last train (SB) towards Kajang	Last train (NB) towards Kwasa Damansara	Station Closing Time
4	Kwasa Damansara	11:35 PM	12:41 AM	11:25 PM
5	Kwasa Sentral	11:37 PM	12:38 AM	11:25 PM
6	Kota Damansara	11:41 PM	12:35 AM	11:35 PM
7	Surian	11:43 PM	12:32 AM	11:35 PM
8	Mutiara Damansara	11:45 PM	12:29 AM	11:35 PM
9	Bandar Utama	11:47 PM	12:27 AM	11:45 PM
10	TTDI	11:50 PM	12:24 AM	11:45 PM
12	Phileo Damansara	11:53 PM	12:21 AM	11:45 PM
13	Pusat Bandar Damansara	11:56 PM	12:17 AM	11:45 PM
14	Semantan	11:58 PM	12:15am	12:00 AM

Table 3.2: Travel Time Between Stations for MRT Kajang Line

Station Name		Time Taken (minute)		
From	To	Towards Kajang	Towards Kwasa Damansara	Maximum time taken
Kwasa Damansara	Kwasa Sentral	2	3	3
Kwasa Sentral	Kota Damansara	4	3	4
Kota Damansara	Surian	2	3	3
Surian	Mutiara Damansara	2	3	3
Mutiara Damansara	Bandar Utama	2	2	2
Bandar Utama	TTDI	3	3	3
TTDI	Phileo Damansara	3	3	3
Phileo Damansara	Pusat Bandar Damansara	3	4	4
Pusat Bandar Damansara	Semantan	2	2	2

3.3.1.2 Monorail Line

The last train leaving each station schedule of Monorail Line is not available on the official website of the operator Prasarana Malaysia Berhad. Therefore, the time interval between Monorail Line stations is collected with Google Map features. First, the station names of two adjacent monorail stations are entered into the search box of Google Map and the transit mode is selected as shown in Figure 3.3. Then, the time interval between two adjacent stations is displayed as shown in Figure 3.4 where the time interval between

Monorail Line KL Sentral station and Monorail Line Tun Sambanthan station is 3 minutes.

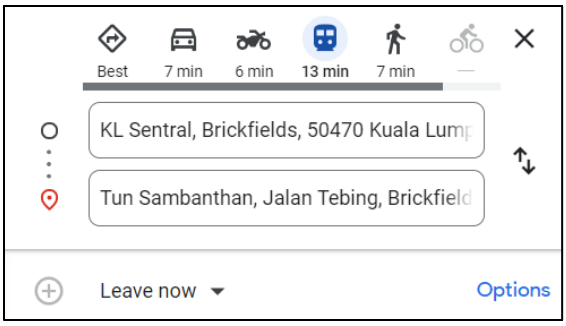


Figure 3.3: Transit Route Between Monorail KL Sentral and Monorail Tun Sambanthan Station.

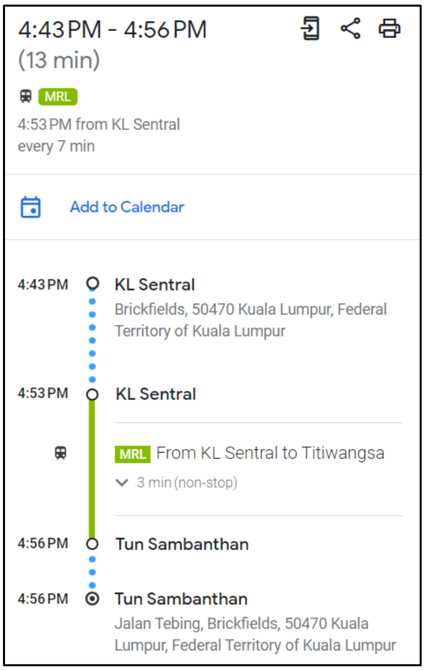


Figure 3.4: Time Interval Between Monorail KL Sentral and Monorail Tun Sambanthan Station.

3.3.1.3 Interchange Stations

However, the time interval data available on the websites is limited to the interval between stations of the same transit line. The time required for transfers between different transit lines within an interchange station is not available on the said websites. To address the incomplete data, an on-site survey was conducted at all interchange stations to collect data of transfer time between different transit lines within an interchange station. A binomial coefficient formula is used to identify the number of combinations based on the number of intersecting transit lines within an interchange station as shown in Equation 3.1.

$$^{n}C_{r} \tag{3.1}$$

Where:

$n = Total\ number\ of\ intersecting\ transit\ lines$

$r = Number\ of\ transit\ lines\ involved\ in\ a\ particular\ combination$

The transfer time calculations involve the utilisations of a stopwatch to measure the total time taken to move from platform of one transit line to another platform within the interchange station. The inter-platform connectivity and the mode of transfer involved in each interchange station presented in Table 3.1 facilitate the calculation of transfer time. The transfer time between platforms is calculated with Equation 3.2 with the components of the interchange stations identified during the site data collections.

$$\begin{aligned} Transfer\ Time = {} & Walking + Escalator \\ & + Travelator + Link\ Bridge \\ & + Exiting\ and\ Reentering \end{aligned} \tag{3.2}$$

Where:

$Walking = Walking\ time\ taken$

$Escalaor = Time\ taken\ traversing\ vertically\ with\ escalator$

$Travelator = Time\ taken\ traversing\ horizontally\ with\ travelator$

$Link\ Bridge = Time\ taken\ walkng\ along\ a\ link\ bridge$

$Exiting\ and\ Reentering = Time\ taken\ exit\ and\ reenter\ the\ network$

Pedestrian movement during escalator and travelator operations was intentionally omitted during the data collection process to simulate the condition during the crowded peak hours, where spaces of escalators are filled, leaving no room for additional pedestrian movement. The walking speed is kept constant for all traversing to ensure consistent data collection. The collected data is rounded up to the nearest minutes to ensure standardised and cohesive representations of the transfer time to facilitate the analysis.

The transfer time data is collected on 5th January 2024. A total of 28 interchange stations are visited for transfer time collection. The interchange stations have a total of 67 pairs of transfer paths between different platforms within interchange stations. Each pair is identified, and the transfer time is calculated and shown in Appendix A. The time period of transfer time data collection at interchange stations for each transit line is shown in Table 3.3.

Table 3.3: Time Data Collection Period of Each Transit Line

Transit Lines	Time Data Collection Period
MRT Putrajaya	10am – 11.30am
LRT Sri Petaling	12pm – 2.30pm
LRT Ampang	12pm – 2.30pm
KTM Batu Cave	2pm – 3pm
Monorail	3pm – 4pm
MRT Kajang	4pm – 6pm
LRT Kelana Jaya	7pm – 9pm
KTM Tanjung Malim	7pm – 9pm

3.3.2 Distance Data

The data collection procedure for distance between stations includes the identification of coordinates for all stations with the help of Google Maps to precisely locate their positions. The estimated distance between each station pair along the railway are measured with the distance measurement feature available on Google Maps. The iterative processes are repeated systematically to collected distance data between all pairs of stations within the network. Data collected is documented in an Excel file with information including station names and distances between the station pairs.

The data collection of the transfer time between multiple transit lines within an interchange station involves measuring the time interval to traverse between platforms of one transit line and another. As such, the specific day in a week and the time in a day have minimal impact to the data collection. The collection of time interval and distance data between stations on the same transit line is not constrained by specific day and time. The flexibility enables the data collection to be conducted at any given moment with contingent of availability of computers and internet access.

The estimated distance is facilitated with Google Map transit route feature. The OD station is keyed in into Google Map as shown in Figure 3.5. Then the actual alignment is traced and shown on the aerial view of Google Map as shown in Figure 3.6. The same figure also showcases the distance measuring feature of Google Map where the alignment of MRT is traced to measure the distance.

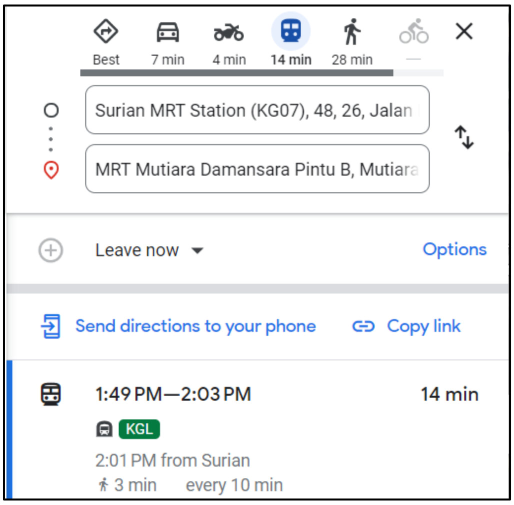


Figure 3.5: Transit Route from Station MRT Surian to MRT Mutiara Damansara.

Figure 3.6: Measuring Estimated Distance Between Station MRT Surian and MRT Mutiara Damansara.

3.3.3 Forecasted Network Data

The analysis of the Klang Valley urban rail transit network includes the improvement analysis between the current operational network and the forecasted network that includes the provisional stations of the existing line, the under-construction LRT 3 and the proposed MRT Circle Line. Due to the unavailability of the travel time and distance between stations of LRT 3 and MRT Circle Line, multiple logical assumptions were made to facilitate the analysis of the impact of the new transit line to the network.

The station location and the alignment of the under-construction LRT 3 transit lines were confirmed as shown in Figure 3.7. The location and alignment of the LRT 3 are located with Google Map to measure the distance between stations.

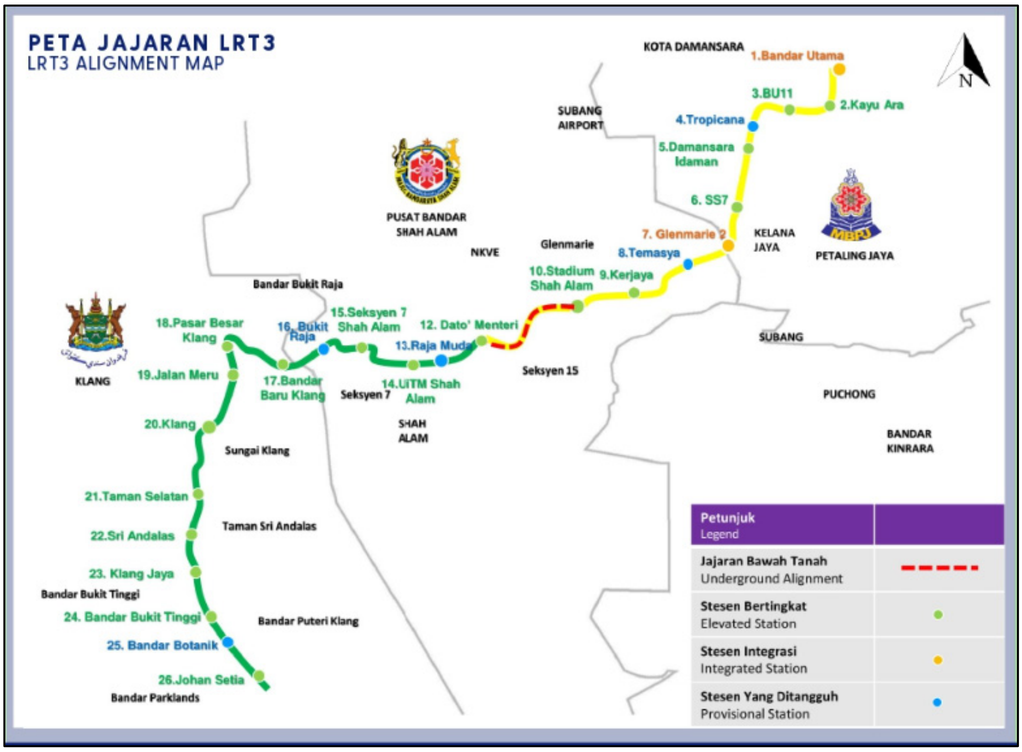


Figure 3.7: LRT 3 Alignment Map (LRT 3, 2024).

The exact location and alignment of stations not shown in aerial view of Google Map. The exact coordinates of the station and the alignment is confirmed by using Street View feature of Google Map as shown in Figure 3.8. Street View features is helpful to identify station locations where aerial view map is not updated.

Figure 3.8: Street View of Station Jalan Meru

Then, the distance between each station can be obtained by measuring with distance measuring features of Google Map by tracing the alignment as shown in Figure 3.9. The LRT 3 alignment is measured to have a total length of 37.57 km, aligns with the 37 km total alignment length (LRT 3, 2024).

Figure 3.9: Measuring Estimated Distance Between Station Kayu Ara and BU 11

However, MRT Circle Line was still in the proposal stage and the exact location of station and alignment of the MRT Circle Line were not confirmed as at the date of analysis. Therefore, the location of the station was estimated based on the map of proposed alignment of MRT Circle Line as shown in Figure 3.10.

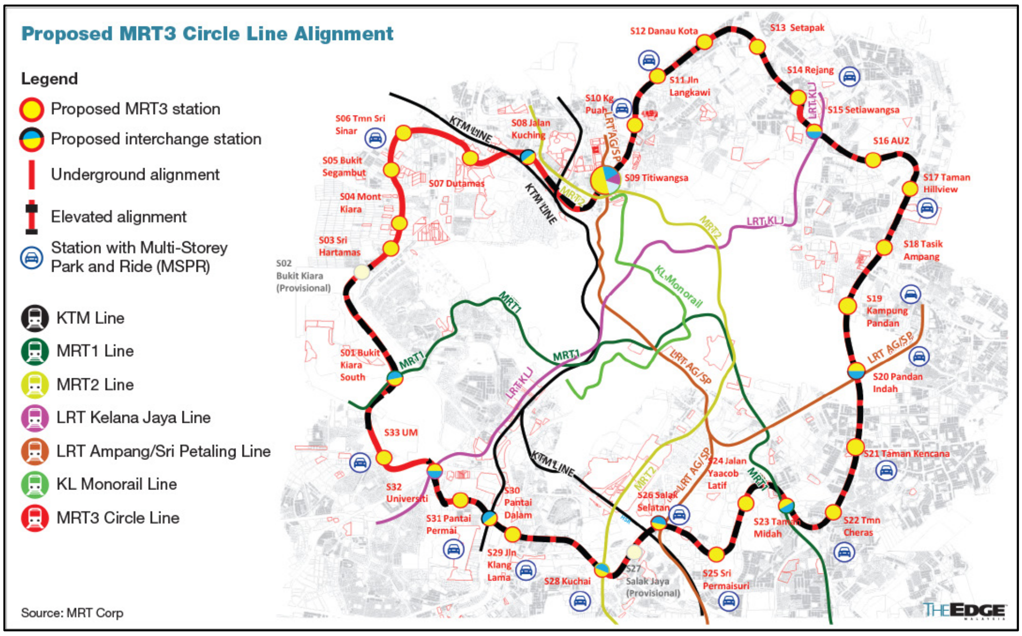


Figure 3.10: Proposed Alignment of MRT Circle Line (Seah, 2022).

In the data collection of the distance between stations of MRT Circle Line, an estimated alignment of the transit line was drawn on Google Map as shown in Figure 3.11 to facilitate an accurate estimation of the edge weight. To ensure a reliable and logical assumptions, the station location was estimated to be constructed on empty land and the alignment of the transit lines follows the empty available road network with a reasonable spacing between stations. The MRT Circle Line alignment is measured to have a total length of 50.93 km, aligns with the 51km total alignment length (MRT Corp, 2024).

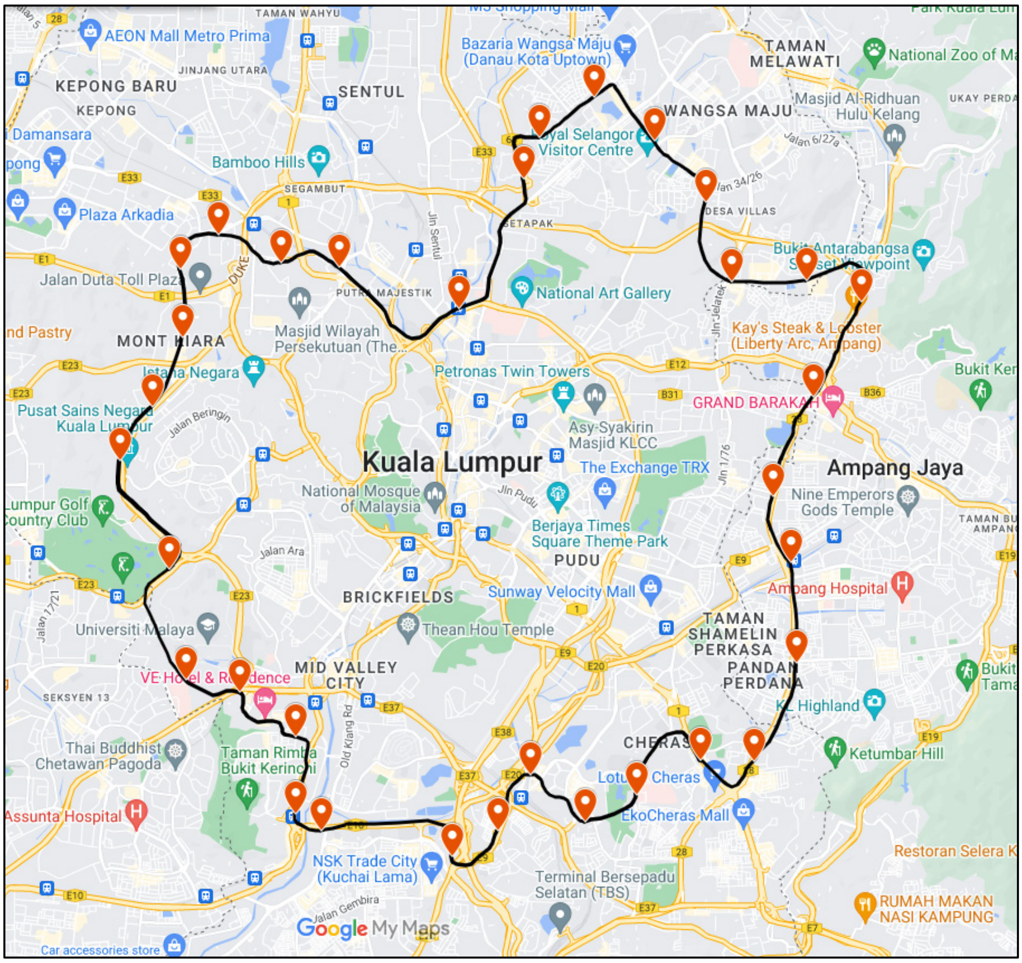


Figure 3.11: Estimated Alignment of MRT Circle Line Drawn on Google Map

The time data of both LRT 3 and MRT Circle Line were not available. Therefore, the data were estimated based on the distance between stations with an average train speed assumed to be 50km/h considering the acceleration and deceleration of train coaches when departing and approaching a station. The travel time between stations was calculated and rounded up to the nearest minute.

A total of 11 new interchange stations were created with the inclusion of the new transit lines. Assumptions to the distance and travel time data between different platforms within the same interchange stations were made due to the unavailability of the data. Taking the average value of the actual collected distance and time traversing between different platforms of the available interchange stations, the distance between stations was assumed to be 0.2km and the time taken was assumed to be 5 minutes.

3.3.4 Passenger Flow Data

The analysis includes using passenger flow data as the parameters to analyse the urban rail transit network. The passenger flow data is available on the official government website with data provided by Prasarana (Government of Malaysia, 2024). The website provides the number of passengers flowing between any two stations. The number of passengers traverse between any two stations is used to construct a weighted network to analyse the urban rail transit network. However, the limitation of the website is the unavailability of passenger flow data for all KTM stations. Therefore, the analysis of passenger flow data includes only all MRT, LRT and monorail lines.

The selection of time frame for passenger flow data is important to ensure the reliability and accuracy of the data collection and analysis. Passenger flow data for July 2023 is chosen for this study as the observation period has minimal disruption from school holidays and public holidays that may affect the number of passengers on certain stations, ensuring a more stable representation of regular commuter patterns. In addition, by selecting for monthly data instead of specific daily data can provide a consistent urban rail transit network usage trend as it prevents the potential inconsistency caused by variation between weekdays and weekends.

The passenger flow data between any pairs of stations is obtained from the official government website. The OD station was selected accordingly as shown in Figure 3.12. Then, the passenger flow data for July 2023 is collected. The website displays the passenger flow data for both directions, data for both directions was collected, and the maximum value is selected to weigh the network.

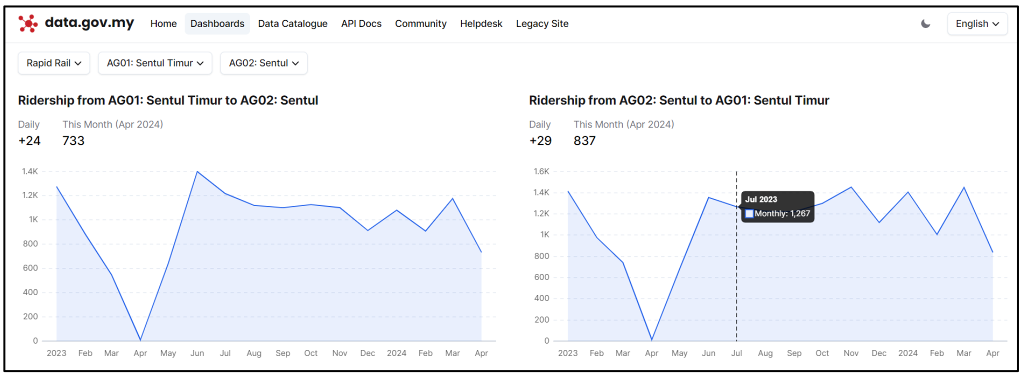


Figure 3.12: Ridership Data Between LRT Sentul and LRT Sentul Timur (Government of Malaysia, 2024)

3.4 Data Analysis

This section explains the methodology in the analysis of the raw data with the aid of python code. Python code is used to process the iterative data analysis to ensure efficiency and reliability.

3.4.1 Data Pre-processing

To facilitate the evaluation of the performance of the Klang Valley urban rail transit network that is characterised by multiple lines with distinct colours, a systematic temporal naming of 4-digit station code is employed. The first two digits denote the specific transit line the station belongs to, and the subsequent two digits signifies the specific station. The coding mechanism facilitates the identification of both line and station by referencing the station node code.

In the input data excel file, the first column is named "Node 1", and the second column is named "Node 2". The third column denotes the weight between the 2 nodes in the same row. This study considers analysis of unweighted network, time data weighted network, distance data weighted network, and passenger flow data weighted network.

3.4.2 Network Construction

Network construction can facilitate and enhance the development of network models that is used to evaluate the networks connectivity and dynamics over time (Scharler and Borrett, 2021). The authors also mentioned that collection of necessary data and parameterising of the network model is important in ensuring a reliable network construction.

The representation gives a better representation of the actual network and displays the relationship between nodes, the weight of the edge, and interchange stations. Network construction can also help to cross check the input data file with the actual network to ensure reliable analysis in this study. The Klang Valley urban rail transit network is weighted with time data, distance data and passenger flow data. The current network and forecasted network are represented with Pyvis, a Python library used to create interactive network graph, as shown in Figure 3.13 and Figure 3.14 respectively. Pyvis map can display the name of each station and show the edge weight represented by the line thickness with the respective colour according to the Klang Valley urban rail transit network map.

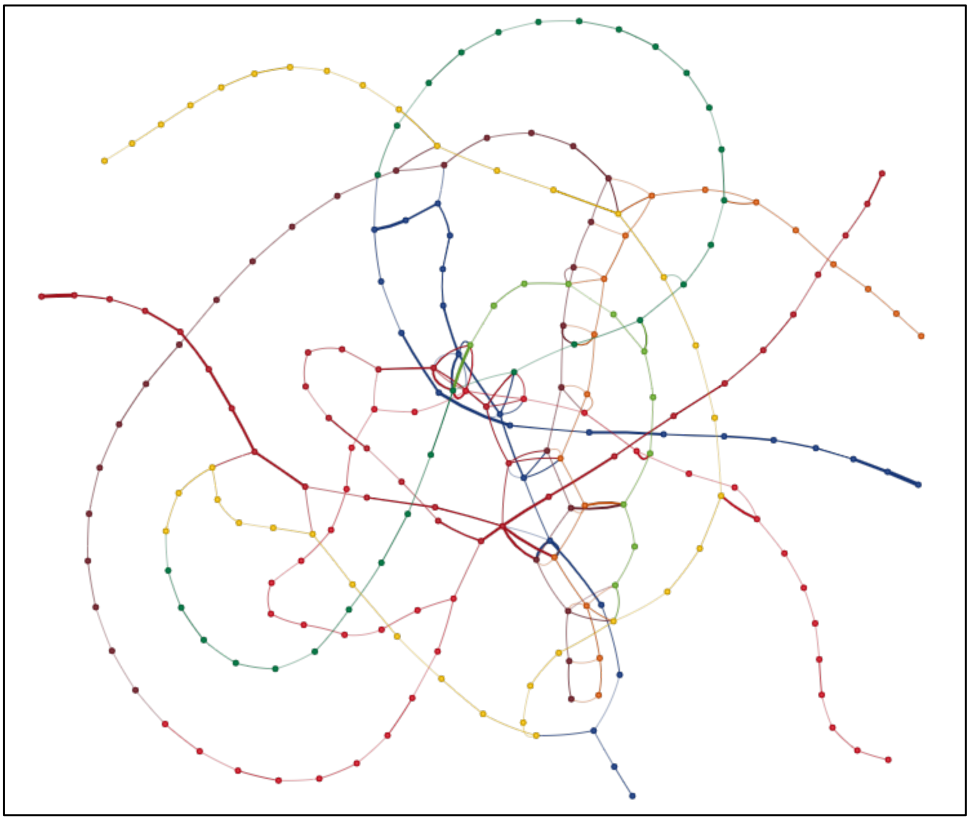


Figure 3.13: Network Construction of Current Network with Pyvis.

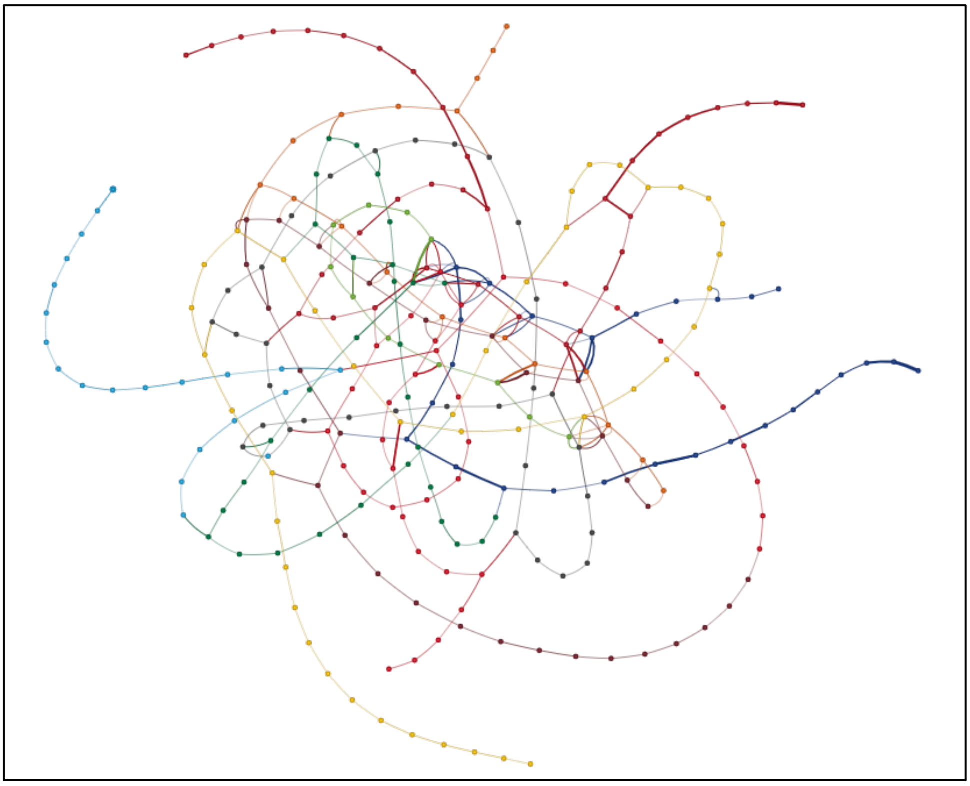


Figure 3.14: Network Construction of Forecasted Network with Pyvis.

3.4.3 Validation of Computation Method

A comprehensive validation process was conducted to ensure the accuracy and reliability of the output result of each indicator computed with the Python code in analysing the urban rail transit network. A small sized sample network was randomly created with edge weights between each node pair is equal to 1 as shown in Table 3.4. Then the network is visualised with Pyvis to ensure correct connection among the nodes as shown in Figure 3.15. The process involves running the Python code with the input data and obtain the results to test the functionality of the code that returns the local and global values of the 5 indicators. Then, the result values of each indicator of the same sample network were also manually computed using the formula presented in Section 3.5. Results from both computations were cross-checked to verify consistency and accuracy. The validation process can help identify and address any discrepancy or error on the Python code before the computation of the actual network data.

Table 3.4: Input Data for Small Sample Network

Node 1	Node 2	Distance	Colour Node 1	Colour Node 2
0101	0102	1	#315090	#315090
0101	0107	1	#315090	#315090
0102	0107	1	#315090	#315090
0102	0106	1	#315090	#315090
0102	0103	1	#315090	#315090
0103	0106	1	#315090	#315090
0103	0104	1	#315090	#315090
0104	0105	1	#315090	#315090
0105	0106	1	#315090	#315090
0106	0107	1	#315090	#315090
0107	0108	1	#315090	#315090
0108	0109	1	#315090	#315090
0109	0105	1	#315090	#315090
0109	0110	1	#315090	#315090
0110	0111	1	#315090	#315090

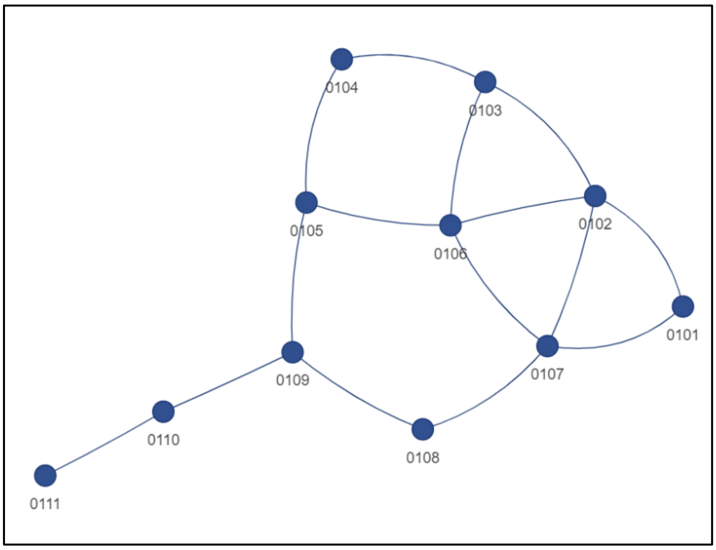


Figure 3.15: Network Construction of Small Sample Network.

3.4.4 Computation of Indicators

The network performance value is computed based on the respective formulas of the 5 indicators which include average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. The increasing number of nodes and edges of the urban rail transit network increases the complexity of the calculation of the selected indicator that involves high volume of repeated iterations. To ensure efficiency and accuracy Python code is used to perform the calculations of the indicators. The calculations and explanations to each of the selected indicators is broken down in section 3.5.

3.4.5 Presentation of Results

The results of 5 indicators for each individual node under different parameters weighted network analysis is computed. The values are categoriesed into equal size classes according to indicator values of each node. Next, the frequency of the indicator that falls under each of the classes is calculated. The corresponding probability of occurrence is computed by dividing the frequency of each class by the total frequency. Then, the probability of each class and the upper boundary value of each class is plotted on the graph. Then the x-axis and y-axis of the graph is changed to logarithmic scales. The graph is compared to a power law graph trendline.

Street (2017) explains the rate of change of variable can be affected by the exponent of a power law equation. The power law equation is represented with a general equation $Y = MX^B$. The exponent of the equation, B value, represents the rate of change of Y variable in respect of X variable. Positive B value indicates rate of increase of Y variable in respect to the increase of X variable, while a negative B value indicates the rate of decrease of Y variable with respect of the increase of X variable. The magnitude of B indicates the steepness of the increase or decrease.

3.5 Network Performance Indicators Applied

The network performance indicators are used to analyse the performance of the network quantitatively. The selected indicators quantitatively reflect the actual topological characteristics of the network. This subsection breaks down the computation of the indicators.

3.5.1 Average Shortest Path Length

Average shortest path length (L) measures the average distance or path between all pairs of nodes in a network. Local average shortest path length is the average number of paths the station requires to move to any other station of the network. The lower the value of average shortest path length indicates a more connected network and efficient network with less path required to reach another node. Equation 3.3 shows the formula to calculate the average shortest path length (Ding et al., 2015; Lin et al., 2020; Meng et al., 2020).

$$L(i) = \frac{2}{N(N-1)} \sum_{i \neq j} d_{ij} \tag{3.3}$$

$Where$:

$L(i) = Average\ shortest\ path\ length\ of\ node\ i$

$N = Total\ number\ of\ nodes$

$d_{ij} = Shortest\ distance\ between\ node\ i\ and\ j$

3.5.2 Betweenness Centrality

Betweenness centrality (B) reflects the number of shortest paths connecting any two nodes that pass through a node. The greater betweenness centrality indicates the greater importance of the node acting as a mediator or a bridge in a network. The indicator is calculated by dividing the number of shortest paths passing through a node by the total number of shortest paths in the network. Equation 3.4 shows the formula to calculate betweenness centrality (Ding et al., 2015; Lin et al., 2020; Meng et al., 2020).

$$B_i = \sum_{s \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{3.4}$$

$Where$:

$B_i = Betweenness\ Centrality\ of\ node\ i$

$\sigma_{st} = Total\ number\ of\ shortest\ path\ connecting\ node\ s\ and\ t$

$\sigma_{st}(i) = Total\ number\ of\ shortest\ path\ connecting\ node\ s\ and\ t$
$through\ node\ i$

3.5.3 Closeness Centrality

Closeness centrality (C) reflects the difficulty of other nodes from the network reaching a node. The greater the closeness centrality, the more connected the node to the entire network. The indicator is calculated with the reciprocal of the average shortest path length. Equation 3.5 shows the formula to calculate closeness centrality (Ding et al., 2015; Lin et al., 2020; Meng et al., 2020).

$$C_i = \frac{N-1}{\sum_{i \neq j} d_{ij}} \tag{3.5}$$

$Where$:

$C_i = Closeness\ centrality\ of\ node\ i$

$N = Total\ number\ of\ nodes$

$d_{ij} = Shortest\ distance\ between\ node\ i\ and\ j$

3.5.4 Degree Centrality

Degree centrality (D) is the index to reflect the connectivity of a node compared to another node. The degree of a node is calculated with the number of edges radiating outward from the node. The higher the degree indicates the greater connections the node has to another node in the network.

3.5.5 Clustering Coefficient

Clustering coefficient (CC) reflects the tendency of the neighbouring nodes of a node also connected to each other directly in a network. The greater the coefficient indicates the network is highly connected to enhance passenger transfer convenience. Equation 3.6 shows the formula to calculate clustering coefficient (Ding et al., 2015; Ma, Sallan, and Lordan, 2023).

$$CC(i) = \frac{2e_i}{k_i(k_i - 1)} \tag{3.6}$$

$Where$:

$CC(i) = Clustering\ Coefficient\ of\ node\ i$

$e_i = Number\ of\ edges\ connecting\ neighbour\ of\ node\ i$

$k_i = Degree\ value\ of\ node\ i$

3.6 Summary

This chapter summarises the methodology used in analysing the performance and connectivity of Klang Valley urban rail transit network. The urban rail transit network weighted with multiple parameters to yield the desired output analysis data. The parameters employed in this study include time data, distance data, and passenger flow data. The unweighted and weighted networks is analysed with the computation of quantitative indicators that include average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. The output analysis data ranks the stations based on the computed indicator value.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter discusses the results obtained from the methodology. The urban rail transit network of Klang Valley is analysed with quantitative indicators that include average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. While most research focuses on analysing the network with unweighted network, this study analyses the network with 3 realistic parameters that include time, distance, and the passenger flow data.

The Klang Valley urban rail transit network is analysed from both supply and demand aspects. In the supply assessment, the current configuration of the network is analysed and compared with the forecasted network with the inclusion of provisional stations of the existing lines, the under-construction LRT 3, and the proposed MRT Circle Line to yield insight on the percentage improvement of the extended network. In the demand assessment, the network is analysed with passenger flow data and compared with the findings of the current network analysis to evaluate the compatibility between the supply of existing infrastructure with the current demand. The unweighted analysis of the current and forecasted Klang Valley urban rail transit network is compared with 8 major cities' network to identify strengths and weaknesses for future improvement.

The probability distribution graph of 5 indicators and the top 10 performing stations are presented accordingly. The results for betweenness centrality, closeness centrality and clustering coefficients are normalised to standardise the values within the range of 0 and 1 for a fair comparison between networks of different sizes.

4.2 Validation of Python Code

In the analysis of Klang Valley urban rail transit network, Python code is used to compute the values for 5 quantitative indicators including average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. To validation process involves comparing the indicator values obtained by the code and hand calculations as explained in Section 3.4.4. The validation process of the Python code with a small size sample network is crucial in ensuring the credibility and reliability of the actual analysis of the Klang Valley network. Validation of the code can avoid potential discrepancies of the results and mitigate the risk of pointless efforts and contributions in this study. The verified code can ensure reproducibility of the singular code to apply to various analysis scenarios including different size networks and different parameter-weighted network analysis. Table 4.1 shows the indicator value of the small size sample network based on the input data in Section 3.4.4 calculated with Python code. The values of each node were verified with hand-calculation based on the formula explained in Section 3.5.

Table 4.1: Indicator Value of Small Sample Network with Python Code

Node	Average Shortest Path Length	Betweenness Centrality	Closeness Centrality	Clustering Coefficient	Degree Centrality
0101	2.6	0	0.38	1.0	2
0102	2.2	4.33	0.45	0.5	4
0107	2.0	9.50	0.50	0.3	4
0106	1.9	8.17	0.53	0.3	4
0103	2.4	3.17	0.42	0.3	3
0104	2.4	2.00	0.42	0	2
0105	1.9	12.33	0.53	0	3
0108	2.1	7.50	0.48	0	2
0109	2.0	18.00	0.50	0	3
0110	2.7	9.00	0.37	0	2
0111	3.6	0	0.28	0	1
Global	2.3	6.73	0.44	0.2	2.72

4.3 General Findings

The general findings and observations are explained in this section. The longest OD pairs of both current and forecasted networks are identified and compared with the time taken to drive between the same OD. The driving time data are taken based on weekday peak hour on 9am Wednesday. The findings are presented separately based on overall network and urban network for better observation on the connectivity of stations located around central area of Klang Valley. The overall network observes the top 5 longest OD considering the whole network, while the urban network omits stations located significantly away from CBD area. The stations omitted in the urban network include Station Tanjung Malim to Station Sungai Buloh and Station Batu Tiga to Station Pelabuhan Klang from KTM Tanjung Malim Line, and Station Kajang 2 to Station Pulau Sebang from KTM Batu Cave Line.

4.3.1 Current Network

The top 5 longest pairs of OD of current network were identified and shown in Table 4.2. The top 5 longest OD generally takes more than 240 minutes of transit time as compared to around 130 minutes of driving time, almost two times the time taken to transit. The stations shown in the table are at the end of the radial KTM transit line station that located at suburban area that usually located at significant distance away from the CBD. There is minimal improvement to the longest OD of the current network with the inclusion of LRT 3 and MRT Circle Line in the forecasted network. This is because the alignment and interchange stations of the new transit lines provide minimal influence on the shortest path between the longest OD pairs.

Table 4.2: Top 5 Longest OD of Overall Current Network

Station		Time (min)		
From	To	Transit (Current)	Transit (Forecasted)	Driving
Pulau Sebang	Tanjung Malim	257	257	160
Pulau Sebang	Pelabuhan Klang	248	235	130
Pulau Sebang	K Kubu Bharu	242	242	160
Pulau Sebang	Jalan Kastam	241	228	130
Rembau	Tanjung Malim	240	240	150

Table 4.3 shows the top 5 longest OD of urban current network where several suburban area stations were omitted to analyse the connectivity of the central part of the Klang Valley. Generally, the top 5 longest OD times of urban areas is significantly lower, with around 106 minutes. The stations shown in the table are located towards the end of the radial MRT Putrajaya Line and LRT Sri Petaling Line stations that located at peripheral area of Klang Valley with notable distance away from the CBD. Significant improvements were observed to the time taken to transit between the longest pair of OD of current network with the inclusion of LRT 3 and MRT Circle Line in the forecasted network. In general, a 30 minute or 30% reduction in transit time is observed. The shortest path between the OD initially passes through the CBD area along MRT Putrajaya Line, in the forecasted network, the shortest path switched to travelling along LRT 3. However, the time taken to drive between the OD is still significantly shorter compared to transit time. With about 3 times the driving time taken in the current network, reduced to around 2 times in forecasted network.

Table 4.3: Top 5 Longest OD of Urban Current Network

Station		Time (min)		
From	To	Transit (Current)	Transit (Forecasted)	Driving
Sungai Buloh	Puchong Prima	108	77	45
Sungai Buloh	Putra Heights	107	75	35
Kampung Selamat	Puchong Prima	106	73	45
Kampung Selamat	Putra Heights	106	71	35
Sungai Buloh	Puchong Perdana	106	79	40

4.3.2 Forecasted Network

The top 5 longest pairs of OD of forecasted network were identified and shown in Table 4.4. The top 5 longest OD in overall forecasted network generally from similar locations compared to overall current network. The longest OD takes around 235 minutes of transit time compared to around 130 minutes of driving time, almost twice the time taken to transit. The stations shown in the table are at the end of the radial KTM transit line station that located at suburban area that usually located at significant distance away from the CBD. The OD pairs with maximum time taken to transit in overall network remain at 258 minutes between KTM Pulau Sebang and KTM Tanjung Malim stations. This is due to the alignment and interchange stations of LRT 3 and MRT Circle Line provides minimal influence on the shortest path between the OD pairs. A similar observation where transit has almost double the time taken compared to driving between same OD.

Table 4.4: Top 5 Longest OD of Overall Forecasted Network

Station		Time (min)	
From	To	Transit	Driving
Pulau Sebang	Tanjung Malim	258	160
Pulau Sebang	K Kubu Bharu	243	160
Rembau	Tanjung Malim	241	150
Pulau Sebang	Rasa	237	150
Pulau Sebang	Pelabuhan Klang	235	130

Table 4.5 shows the top 5 longest OD of urban forecasted network where several suburban area stations were omitted to analyse the connectivity of the central part of the Klang Valley. Generally, the longest OD pair in forecasted network takes longer time to transit compared to in the current network, with about 17 minutes difference. The table of longest OD pairs in urban forecasted network shows stations from LRT 3. The implementation of LRT 3 intended to serve the underserved areas around Klang. However, due to the radial characteristics and the station location at notable distance from the CBD area has increased the time taken to travel. With that said, the average shortest path length of the network still reduces notably with the inclusion of LRT 3 and MRT Circle Line. A similar observation where transit has almost doubled the time taken compared to driving between same OD.

Table 4.5: Top 5 Longest OD of Urban Forecasted Network

Station		Time (min)	
From	To	Transit	Driving
Johan Setia	Kajang	125	60
Johan Setia	Stadium Kajang	124	60
Johan Setia	Putrajaya Sentral	123	55
Johan Setia	Sungai Jernih	122	60
Bandar Bukit Tinggi	Kajang	122	60

4.3.3 Summary

In short, the inclusion of LRT 3 and MRT Circle Line in the forecasted network has decreased the total time taken of the longest OD pairs observed in current urban network while minimal improvements to the overall network. Time taken to transit between the same OD is consistently around 2 to 3 times the time taken to drive.

4.4 Current Network Operational Analysis

This section evaluates the operational efficiency of the current Klang Valley urban rail transit network that consists of operational transit lines. The network is evaluated with unweighted, time weighted and distance weighted network to yield a comprehensive analysis of the network. The current operational network consists of 177 stations with 15,576 pairs of OD.

Degree centrality and clustering coefficients are not considered in the time-weighted and distance-weighted network analysis. These two indicators primarily focus on the topological connection of a network without considering the weighted parameters like time and distance. Degree centrality measures the number of direct connections of a node, and clustering coefficient measures the tendency of a node cluster together in a network. Calculating the indicators with time and distance data does not provide relevant insight into the network. Focusing the analysis of time and distance weighted networks with average shortest path length, betweenness centrality and closeness centrality effectively addresses the key considerations of the analysis.

4.4.1 Unweighted Network

Table 4.6 shows the top 10 results of the unweighted network analysis of the 5 indicators which include the average shortest path length, betweenness centrality, closeness centrality, degree centrality, and clustering coefficient of the current operational network.

Table 4.6: Top 10 Ranking Station of Unweighted Current Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality		Degree Centrality		Clustering Coefficient	
1	Kuala Lumpur / Pasar Seni	8.64	MidValley	0.214	Kuala Lumpur / Pasar Seni	0.116	KL Sentral / Muzium Negara	9	KL Sentral / Muzium Negara	0.440
2	KL Sentral / Muzium Negara	8.70	Seputeh	0.210	KL Sentral / Muzium Negara	0.115	Kuala Lumpur / Pasar Seni	8	Titiwangsa	0.350
3	MidValley	9.04	Salak Selatan	0.206	MidValley	0.111	Bank Negara / Bandaraya	8	Kuala Lumpur / Pasar Seni	0.300
4	Bank Negara / Bandaraya	9.06	Bandar Tasik Selatan	0.204	Bank Negara / Bandaraya	0.110	Putra / PWTC	8	Bank Negara / Bandaraya	0.300
5	Plaza Rakyat / Merdeka	9.26	Angkasapuri	0.189	Plaza Rakyat / Merdeka	0.108	Titiwangsa	7	Putra / PWTC	0.300
6	Masjid Jamek	9.32	Pantai Dalam	0.183	Masjid Jamek	0.107	Plaza Rakyat / Merdeka	6	Plaza Rakyat / Merdeka	0.167
7	Seputeh	9.50	Petaling	0.176	Seputeh	0.105	Masjid Jamek	6	Masjid Jamek	0.167
8	Bank Rakyat - Bangsar	9.55	Jalan Templer	0.170	Bank Rakyat - Bangsar	0.105	Hang Tuah	6	Hang Tuah	0.167
9	Abdullah Hukum	9.59	Kg Dato Harun	0.164	Abdullah Hukum	0.104	Sultan Ismail / Medan Tuanku	6	Sultan Ismail / Medan Tuanku	0.167
10	Putra / PWTC	9.62	Seri Setia	0.157	Putra / PWTC	0.104	Chan Show Lin	6	Chan Show Lin	0.167
	Global	14.09	Global	0.052	Global	0.075	Global	2.41	Global	0.014

The global average shortest path length of the unweighted network is 14.09, indicating the network requires 14.09 steps to move from any node of the network to any other node on average. The results table shows notable consistency among average shortest path length, closeness centrality, degree centrality and clustering coefficients. In total, there are 6 stations concurrently appeared on the top 10 stations of the 4 indicators, namely Kuala Lumpur/Pasar Seni, KL Sentral/Muzium Negara, Bank Negara/Bandaraya, Putra/PWTC, Plaza Rakyat/Merdeka, and Masjid Jamek Station. These stations are among the interchange stations that intersect multiple transit lines of the network.

However, results of betweenness centrality show rather different stations appeared on the list with MidValley and Seputeh stations topping the list of average shortest path length, betweenness centrality and closeness centrality concurrently. It is observed that stations that appear at the top list of betweenness centrality often do not appear elsewhere. Stations located in the CBD tend to have high redundancy in terms of the connections. Therefore, in the calculation of betweenness centrality, there is often multiple route choices to move around among the stations in the CBD. This dilutes the number of shortest paths passing through a station, which then leads to lower betweenness centrality of each station. In contrast, stations adjacent to the CBD stations have only singular route, increasing the number of shortest paths passing through, yielding a higher local betweenness centrality.

It is observed that a limited number of stations exhibit high degree centrality and clustering coefficient values in the network analysis. This suggests the network has unequal distribution and lack of redundancy of interchange stations to reduce bottleneck congestion.

4.4.2 Time Weighted Network

Table 4.7 shows the top 10 results of the time-weighted network analysis of the current operational transit lines with average shortest path length, betweenness centrality and closeness centrality.

Table 4.7: Top 10 Ranking Station of Time-weighted Current Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality	
1	Masjid Jamek	35.70	Bank Rakyat - Bangsar	0.225	Masjid Jamek	0.028
2	Plaza Rakyat / Merdeka	35.83	Tun Razak Exchange	0.216	Plaza Rakyat / Merdeka	0.028
3	Tun Razak Exchange	35.91	Abdullah Hukum	0.176	Tun Razak Exchange	0.028
4	Kuala Lumpur / Pasar Seni	36.09	Cochrane	0.143	Kuala Lumpur / Pasar Seni	0.028
5	Bank Rakyat - Bangsar	37.33	Sungai Besi	0.133	Bank Rakyat - Bangsar	0.027
6	Conlay	37.59	Kuchai	0.128	Conlay	0.027
7	Hang Tuah	37.67	Kuala Lumpur / Pasar Seni	0.124	Hang Tuah	0.027
8	Bukit Bintang	37.75	Kerinchi	0.123	Bukit Bintang	0.027
9	KL Sentral / Muzium Negara	37.75	Taman Naga Emas	0.123	KL Sentral / Muzium Negara	0.027
10	Cochrane	37.89	Conlay	0.122	Cochrane	0.026
	Global	58.65	Global	0.060	Global	0.019

The global average shortest path length of the time-weighted network is 58.65 minutes, which is considerably long travel period due to the extended KTM lines. From table 4.2, 5 out of the top 10 stations with high betweenness centrality values appeared in the top list of average shortest path length and closeness centrality list.

Time-weighted network analysis considers the actual time taken to walk and traverse between different platforms of an interchange station. Results reveal top performing station in betweenness centrality list predominantly from CBD area. The shortest path length between any pair of stations in time-weighted analysis differs from unweighted network analysis. Stations revolved around CBD areas tend to have lower values of average shortest path length and closeness centrality due to the centric location and dense interconnection with other transit lines, requiring less time to move to any other stations in the network.

It is worth noting that KTM stations rarely top the list in time weighted network due to the longer journey time between stations and the longer transfer time between different platforms in the interchange stations compared to other transit lines.

4.4.3 Distance Weighted Network

Table 4.8 shows the top 10 results of the distance-weighted network analysis of the current operational transit lines with average shortest path length, betweenness centrality and closeness centrality.

Table 4.8: Top 10 Ranking Station of Distance-weighted Current Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality	
1	Masjid Jamek	15.63	Angkasapuri	0.187	Masjid Jamek	0.064
2	Plaza Rakyat / Merdeka	15.65	Pantai Dalam	0.181	Plaza Rakyat / Merdeka	0.064
3	Kuala Lumpur / Pasar Seni	15.71	Petaling	0.175	Kuala Lumpur / Pasar Seni	0.064
4	Hang Tuah	15.83	Jalan Templer	0.168	Hang Tuah	0.063
5	KL Sentral / Muzium Negara	15.98	Kg Dato Harun	0.162	KL Sentral / Muzium Negara	0.063
6	Pudu	16.04	Abdullah Hukum	0.159	Pudu	0.062
7	Bukit Bintang	16.09	Bandar Tasik Selatan	0.156	Bukit Bintang	0.062
8	Bank Negara / Bandaraya	16.10	Seri Setia	0.156	Bank Negara / Bandaraya	0.062
9	Dang Wangi	16.18	Setia Jaya	0.150	Dang Wangi	0.062
10	Imbi	16.20	Sungai Besi	0.141	Imbi	0.062
	Global	28.48	Global	0.058	Global	0.042

The global average shortest path length of the distance-weighted network is 28.48 kilometres. The 10 stations that top the betweenness centrality list do not appear in average shortest path length and closeness centrality lists. The edge weight of the distance-weighted network analysis considers the actual distance between stations. As such, the transfer distance between different platforms in an interchange station seemed relatively short when compared to the overall distance between stations. Therefore, the shortest path may pass through the multiple supplementary interchange stations to reach the destinations without considering the actual traverse time between platforms and the boarding and alighting time required. Stations with high betweenness centrality mainly located adjacent to KL Sentral/Muzium Negara station and along KTM Tanjung Malim line, rather similar to the top 10 stations of betweenness centrality of unweighted network analysis in Section 4.2.1.

4.4.4 Graph

Probability distribution graphs were used to analyse the likelihood of stations in the network exhibits high importance over other stations based on the quantitative indicators.

4.4.4.1 Probability Distribution Graph of Unweighted Current Network

This subsection discusses the probability distribution graphs of the unweighted current network based on 5 indicators that include average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. Figure 4.1 shows the probability distributions of current network based on average shortest path length follows power law distribution, with an exponent of -3.945 and a regression value of 0.5863. Figure 4.2 shows the probability distributions of current network based on betweenness centrality follows power law distribution, with an exponent of -1.471 and a regression value of 0.7081. Figure 4.3 shows the probability distribution of current network based on closeness centrality follows normal distributions. Figure 4.4 shows the probability distributions of current network based on degree centrality follows power law distribution, with an exponent of -2.912 and a regression value of 0.9986. Figure 4.5 shows the probability distributions of current network based on clustering coefficient follows power law distribution, with an exponent of -2.892 and a regression value of 0.9885.

Probability distribution graph of current network based on average shortest path length, betweenness centrality, degree centrality and clustering coefficients follows a power law distribution with a negative exponent ranging from -3.945 to -1.471. A negative exponent in power law distribution indicates an inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggests that only few number of stations have great influence and exhibits significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network. The probability distribution graph for average shortest path length has the greatest magnitude of exponent compared to other indicators, indicates the less likelihood of a node with extreme high average shortest path length while most stations generally have lower shortest path length to move around the network. The probability graph exhibits high regression value ranging from 0.5863 to 0.9986. This indicates a great adherence of the distribution of each indicator value with the power law distribution.

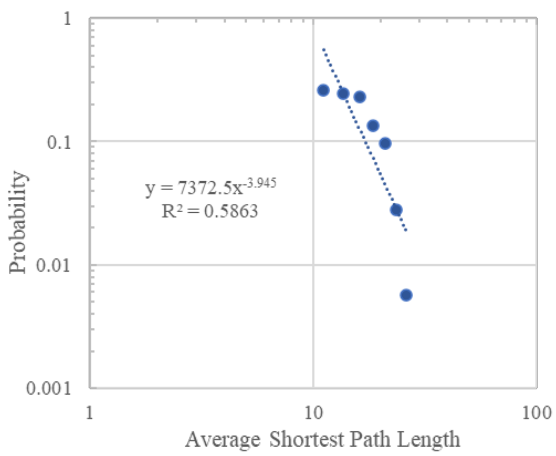


Figure 4.1: Probability Distribution Graph of Average Shortest Path Length of Unweighted Current Network

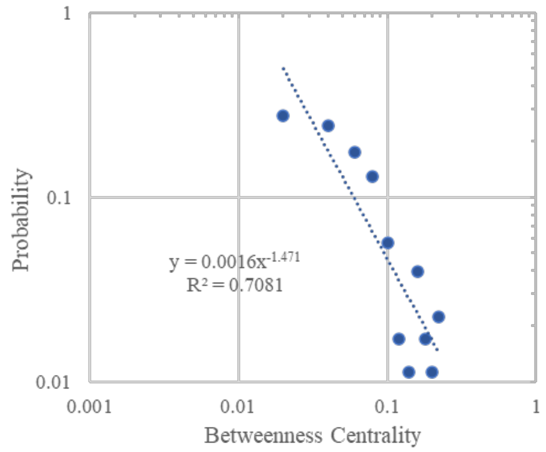


Figure 4.2: Probability Distribution Graph of Betweenness Centrality of Unweighted Current Network

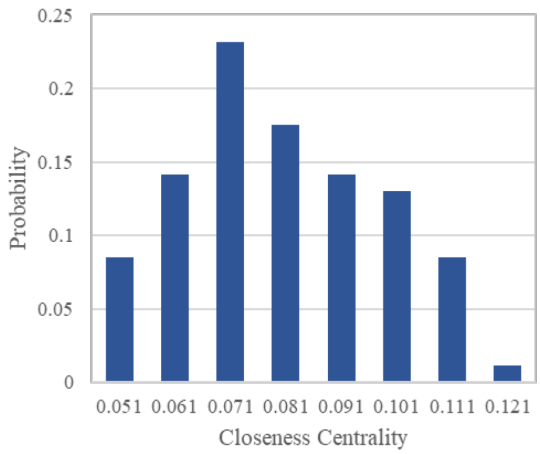


Figure 4.3: Probability Distribution Graph of Closeness Centrality of Unweighted Current Network

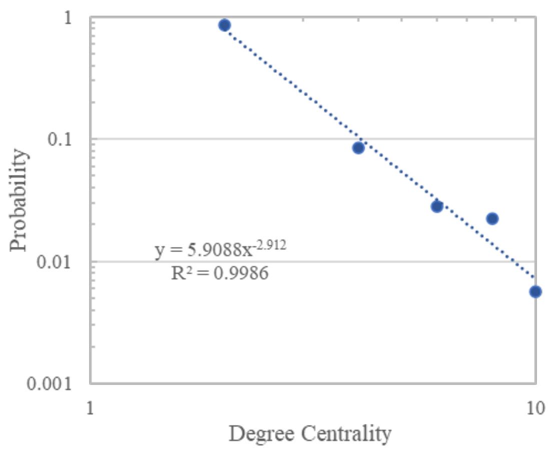


Figure 4.4: Probability Distribution Graph of Degree Centrality of Unweighted Current Network

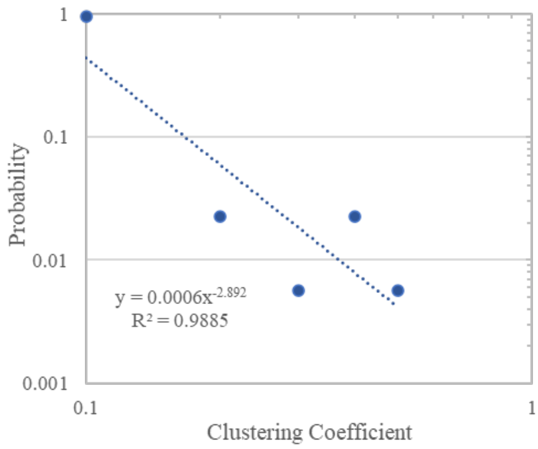


Figure 4.5: Probability Distribution Graph of Clustering Coefficient of Unweighted Current Network

4.4.4.2 Probability Distribution Graph of Time-weighted Current Network

This subsection discusses the probability distribution graphs of the time-weighted current network based on 3 indicators that include average shortest path length, betweenness centrality, closeness centrality. Figure 4.6 shows the probability distributions of current network based on average shortest path length follows power law distribution, with an exponent of -3.466 and a regression value of 0.8536. Figure 4.7 shows the probability distributions of current network based on betweenness centrality follows power law distribution, with an exponent of -2.747 and a regression value of 0.6735. Figure 4.8 shows the probability distribution of current network based on closeness centrality follows normal distributions.

The probability distribution in time-weighted network analysis is similar with graphs in unweighted network analysis with similar negative exponent values for average shortest path length and betweenness centrality, while closeness centrality follows normal distribution. The explanation for a negative exponent in power law distribution is the inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggests that only few number of stations have great influence and exhibit significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network. The probability graph exhibits high regression value ranging from 0.6735 to 0.8536. This indicates a great adherence of the distribution of each indicator value with the power law distribution.

The probability distribution graph for average shortest path length in time-weighted network analysis has slightly lower magnitude value of exponent compared to unweighted current network, suggests that the likelihood of having station with higher average shortest path length in time-weighted network analysis is higher. Whereas the probability distribution of betweenness centrality in time-weighted network analysis has higher exponent magnitude compared to unweighted network analysis, this indicates a steeper decline and the decreased likelihood of stations having high betweenness centrality value.

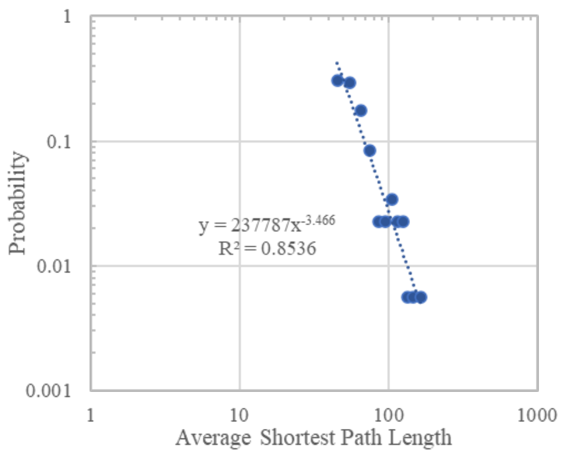


Figure 4.6: Probability Distribution Graph of Average Shortest Path Length of Time-weighted Current Network

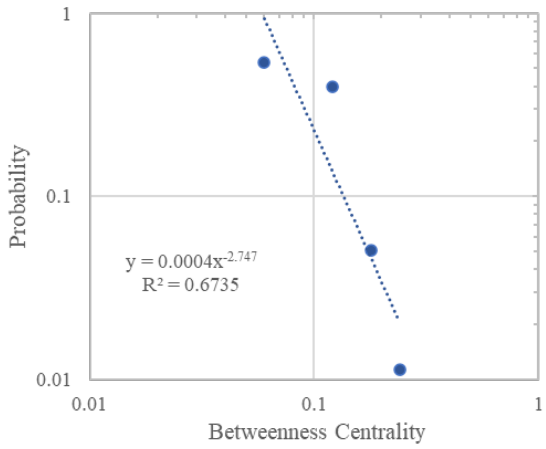


Figure 4.7: Probability Distribution Graph of Betweenness Centrality of Time-weighted Current Network

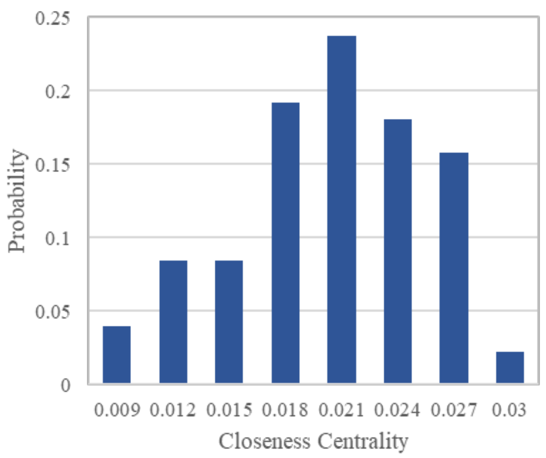


Figure 4.8: Probability Distribution Graph of Closeness Centrality of Time-weighted Current Network

4.4.4.3 Probability Distribution Graph of Distance-weighted Current Network

This subsection discusses the probability distribution graphs of the distance-weighted current network based on 3 indicators that include average shortest path length, betweenness centrality, closeness centrality. Figure 4.9 shows the probability distributions of current network based on average shortest path length follows power law distribution, with an exponent of -3.745 and a regression value of 0.9959. Figure 4.10 shows the probability distributions of current network based on betweenness centrality follows power law distribution, with an exponent of -2.609 and a regression value of 0.8765.

Figure 4.11 shows the probability distribution of current network based on closeness centrality follows normal distributions.

The probability distribution in distance-weighted network analysis is similar with graphs above with similar negative exponent values for average shortest path length and betweenness centrality, while closeness centrality follows normal distribution. The explanation for a negative exponent in power law distribution is the inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggest that only few number of stations have great influence and exhibit significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network. The probability graph exhibits high regression value ranging from 0.8765 to 0.9959. This indicates a great adherence of the distribution of each indicator value with the power law distribution.

The probability distribution graph for average shortest path length in distance-weighted network analysis has slightly lower magnitude value of exponent compared to unweighted network analysis, suggests that the likelihood of having station with higher average shortest path length in time-weighted network analysis is higher. Whereas the probability distribution of betweenness centrality in time-weighted network analysis has higher exponent magnitude compared to unweighted network analysis, this indicates a steeper decline and the decreased likelihood of stations having high betweenness centrality value. The regression value of average shortest path length probability distribution in distance-weighted network analysis is close to 1, indicating the great adherence to power law distribution. This is due to the presence of few limited number of KTM stations located distanced away and beyond Klang Valley and these stations have significantly higher average shortest path length when analysed with distance as parameter.

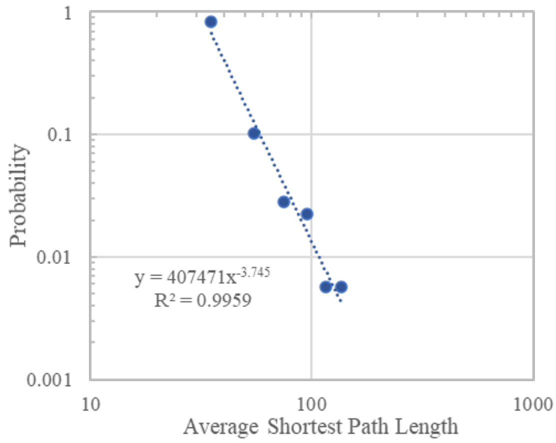


Figure 4.9: Probability Distribution Graph of Average Shortest Path Length of Distance-weighted Current Network

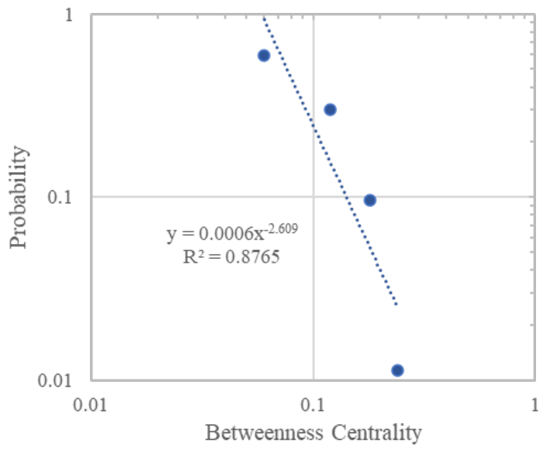


Figure 4.10: Probability Distribution Graph of Betweenness Centrality of Distance-weighted Current Network

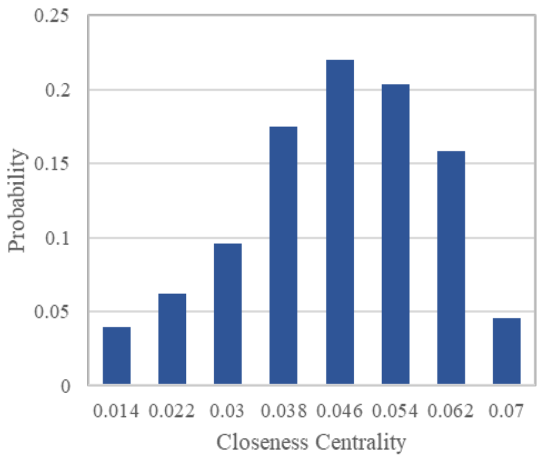


Figure 4.11: Probability Distribution Graph of Closeness Centrality of Distance-weighted Current Network

4.4.4.4 Graph Overview of Current Network

All probability distribution graphs in current network analysis, except for closeness centrality, follow power law distribution, indicates the heterogeneous and scale-free characteristic of the network (Meghanathan, n.d.).

Average shortest path length graph shows that majority of the stations have low value, indicating less steps to move between any pair of nodes with only few stations requires high number of paths to move to any other station, especially thoses station located at the end of the radial transit lines. Betweenness centrality graph shows most stations have low value, indicating limited influence on the network while only few stations have significantly higher value, suggesting the role as critical hubs with large number of shortest paths passing through. Degree centrality graph shows only few stations have high connections in the network and most stations only have two connections. Clustering coefficient graph shows only few stations have high number of supplementary connections between the neighbouring stations, while majority of the stations exhibit zero in clustering coefficient. Degree centrality obeys power law with great regression value, indicating the network exhibits scale-free properties.

All power law distribution graphs have negative exponent value, suggesting the rate of decrease of probability is higher than the rate of increase in network size. A higher magnitude of exponent indicates a more heterogeneous network, with only few stations having high indicator value and most of the stations having low value. The high regression value of each graph indicates the great adherence of the data distribution with power law distribution model. Closeness centrality distribution graph for 3 networks follows a normal distribution pattern, indicates evenly distributed network with minimal extreme values. The unweighted closeness centrality graph observed a left skewed normal distribution graph while time-weighted and distance-weighted graphs observed a right skewed normal distribution graph.

4.4.5 Summary

Stations appeared on the top list of indicators show the importance of the station in the network. Stations that appeared on multiple indicator top list in different parameters weighted networks repeatedly show greater importance and influence over the network.

The shortest path between same pair of OD may change when network is weighted with different parameters, causing changes to the importance ranking of stations in the network quantified by different indicators. The topological analysis reveals the important node and serves as key protected station.

All power law distribution graphs have negative exponent, indicating the probability distribution decreases at a rate higher than the increase of network size. However, closeness centrality distribution follows a normal distribution pattern. The current network can be categorised as scale-free network.

4.5 Forecasted Network Operational Analysis

This section evaluates the operational efficiency of the forecasted Klang Valley urban rail transit network that included the provisional stations of the existing lines, the under-construction LRT 3, and the proposed MRT Circle Line. The network is evaluated with unweighted, time-weighted, and distance-weighted to yield a comprehensive analysis of the expanded network. The number of stations increased from 177 to 225 number of stations in the analysis of the forecasted network with 25,200 pairs of OD.

The analysis of the forecasted network aims to predict the operational efficiency improvement with the implementation of the new transit line compared to the current operational urban rail transit network of Klang Valley.

4.5.1 Unweighted Network

Table 4.9 shows the top 10 results of the unweighted network operational analysis of the 5 indicators that include the average shortest path length, betweenness centrality, closeness centrality, degree centrality, and clustering coefficient of the forecasted network with the inclusion of LRT 3 and MRT Circle Line.

Table 4.9: Top 10 Ranking Station of Unweighted Forecasted Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality		Degree Centrality		Clustering Coefficient	
1	Kuala Lumpur / Pasar Seni	9.45	Petaling	0.175	KL Sentral / Muzium Negara	0.106	KL Sentral / Muzium Negara	9	KL Sentral / Muzium Negara	0.440
2	KL Sentral / Muzium Negara	9.45	Jalan Templer	0.170	Kuala Lumpur / Pasar Seni	0.106	Titiwangsa	9	Titiwangsa	0.440
3	MidValley	9.90	Kg Dato Harun	0.166	MidValley	0.101	Kuala Lumpur / Pasar Seni	8	Kuala Lumpur / Pasar Seni	0.300
4	Bank Negara / Bandaraya	9.93	Seri Setia	0.162	Bank Negara / Bandaraya	0.101	Bank Negara / Bandaraya	8	Bank Negara / Bandaraya	0.300
5	Angkasapuri	10.05	Bandar Tasik Selatan	0.158	Angkasapuri	0.100	Putra / PWTC	8	Putra / PWTC	0.300
6	Abdullah Hukum	10.07	Setia Jaya	0.158	Abdullah Hukum	0.099	Plaza Rakyat / Merdeka	6	Plaza Rakyat / Merdeka	0.167
7	Semantan	10.12	Pantai Dalam	0.155	Semantan	0.099	Masjid Jamek	6	Masjid Jamek	0.167
8	Plaza Rakyat / Merdeka	10.16	MidValley	0.155	Plaza Rakyat / Merdeka	0.098	Hang Tuah	6	Hang Tuah	0.167
9	Bank Rakyat - Bangsar	10.22	Seputeh	0.151	Bank Rakyat - Bangsar	0.098	Chan Show Lin	6	Chan Show Lin	0.167
10	Pantai Dalam	10.24	Subang Jaya	0.150	Pantai Dalam	0.098	Sultan Ismail / Medan Tuanku	6	Sultan Ismail / Medan Tuanku	0.167
	Global	14.85	Global	0.043	Global	0.071	Global	2.43	Global	0.012

The global average shortest path length of the unweighted forecasted network increased to 14.85. Interestingly, the inclusion of LRT 3 and MRT Circle line increased the difficulties to move from any node of the network to any other node. The implementation of a radial LRT 3 line with only 2 interchange stations increased overall network size and the number of steps to move around in the network despite the inclusion of MRT Circle line that provides 10 interchange stations to provide alternatives routes to the network. A similar scenario of increment in average shortest path length with the network expansion is observed in unweighted network analysis by (Ding et al., 2015). The unweighted network analysis of the paper observes a smaller connectivity and less efficient with the expansion of stations in LRT Sri Petaling and LRT Kelana Jaya Lines of Klang Valley urban rail transit network. Scaggs (2021) mentioned that as the number of nodes and edges of a network increases, the density of the network decreases, causing the network to be considered as sparse network. The author mentioned that with the number of paths between OD increases as the density of the network decreases. The betweenness centrality list shows the stations mainly located around KTM Batu Cave Line and KTM Tanjung Malim Line, with Pantai Dalam station is the new interchange station connecting MRT Circle Line.

The results table of the forecasted unweighted network analysis shows 4 same stations appeared on the top list of average shortest path length, closeness centrality, degree centrality and clustering coefficients, namely Kuala Lumpur/Pasar Seni, KL Sentral/Muzium Negara, Bank Negara/Bandaraya, and Plaza Rakyat/Merdeka station, a decrement from 6 stations of the current operational unweighted network analysis. The stations that concurrently topping the list of average shortest path length, betweenness centrality and closeness centrality is left with MidValley station. Suggesting the forecasted network exhibits a decentralised characteristic with less singular stations toping all list concurrently.

Minimal changes to the degree centrality list with only Titiwangsa station have increment of degree centrality due to the inclusion of MRT Circle Line. The inclusion of the interchange station from the two transit lines increases the global degree centrality from 2.41 to 2.43. The clustering coefficient of the forecasted network reduces from 0.014 to 0.012 due to the growing size of the network. This suggests the rate of growth of connections among station cannot keep pace with the network size growth rate as the additional stations do not offer increment of supplementary connections around a node, and instead relatively sparse distribution, which reduces the average clustering coefficient (Ding et al., 2015). The unweighted network analysis shows a generally decrement in multiple indicators in the forecasted network analysis. The possible explanation is the less accurate representation of each edge weight with 1 in the analysis compared to more realistic time and distance weighted network analysis.

4.5.2 Time Weighted Network

Table 4.10 shows the top 10 results of the time-weighted network operational analysis of the 3 indicators that include average shortest path length, betweenness centrality and closeness centrality of the forecasted network with the inclusion of LRT 3 and MRT Circle Line.

Table 4.10: Top 10 Ranking Station of Time-weighted Forecasted Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality	
1	Masjid Jamek	36.08	Jalan Klang Lama	0.147	Masjid Jamek	0.028
2	Tun Razak Exchange	36.16	Kuchai	0.146	Tun Razak Exchange	0.028
3	Kuala Lumpur / Pasar Seni	36.19	Pantai Dalam	0.129	Kuala Lumpur / Pasar Seni	0.028
4	Plaza Rakyat / Merdeka	36.20	Glenmarie 2	0.123	Plaza Rakyat / Merdeka	0.028
5	Bank Rakyat - Bangsar	36.53	Bandar Utama	0.117	Bank Rakyat - Bangsar	0.027
6	Universiti	36.65	Universiti	0.117	Universiti	0.027
7	Pantai Permai	36.73	Tun Razak Exchange	0.116	Pantai Permai	0.027
8	Jalan Klang Lama	36.98	Phileo Damansara	0.115	Jalan Klang Lama	0.027
9	UM	37.09	Taman Naga Emas	0.115	UM	0.027
10	Kerinchi	37.23	Bukit Kiara Selatan	0.114	Kerinchi	0.027
	Global	55.00	Global	0.050	Global	0.020

The global average shortest path length of the time-weighted forecast network is 55 minutes, a reduction of 3.65 minutes from the current network layout despite the increasing overall network size. The reduction of global average shortest path length signifies the improvement in travelling efficiency of the overall network in terms of travelling duration, requiring less travelling time between OD.

A network with lower global betweenness centrality values indicates a more decentralised and resilient network. The global betweenness centrality value decreased from 0.060 to 0.050 in the network expansion. Although a higher local betweenness centrality value means a node is important in a network, but an overly high value indicates higher possibility of bottleneck congestion at few critical nodes. The statement above is supported by the research done by Derrible (2012) where the betweenness centrality of central stations decreases with the additional number of nodes and edges, resulting in a more uniformly distributed centrality of stations, reducing the possibility where few stations dominate the network. The paper also mentioned that the decrease in dependency on specific nodes increases robustness of the network in handling unexpected disruptions and reduces the possibility of congestion at central stations.

The new interchange stations alleviate the probability of congestion which can be observed with the reduction of local betweenness centrality values of each station in forecasted network from the current network. The alternative shortest path route emerged from the inclusion of LRT 3 and MRT Circle Line distributes traffic flow of the network to reduce the dependency on specific node. The global closeness centrality values increased from 0.019 to 0.020 with the network expansion. This indicates that it is more efficient when connecting any node to any other node within the network.

In the forecasted network analysis, 8 distinctive new stations from LRT 3 and MRT Circle Line appeared on the top list in time-weighted network analysis. This indicates the strategic station location and efficient routing of the new transit lines can effectively integrate with the existing rail lines. Bandar Utama and Glenmarie 2 station are the only 2 interchange stations that integrate LRT 3 with the current network. Therefore, both interchange stations may experience bottleneck congestion and appear on the top 10 list of betweenness centrality due to the scarcity of connection of the transit line with the network. Time-weighted network analysis shows the inclusion of LRT 3 and MRT Circle Line can effectively improve the overall connectivity of the network as suggested by the improvement on the global values of multiple indicators and the emergence of multiple stations from new transit lines as the top important stations in the top ranking.

4.5.3 Distance Weighted Network

Table 4.11 shows the top 10 results of the distance-weighted network operational analysis of the 3 indicators that include average shortest path length, betweenness centrality and closeness centrality of the forecasted network with the inclusion of LRT 3 and MRT Circle Line.

Table 4.11: Top 10 Ranking Station of Distance-weighted Forecasted Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrality	
1	Masjid Jamek	15.62	Sungai Besi	0.150	Masjid Jamek	0.064
2	Kuala Lumpur / Pasar Seni	15.66	Pantai Dalam	0.148	Kuala Lumpur / Pasar Seni	0.064
3	Plaza Rakyat / Merdeka	15.66	Petaling	0.147	Plaza Rakyat / Merdeka	0.064
4	KL Sentral / Muzium Negara	15.87	Jalan Templer	0.142	KL Sentral / Muzium Negara	0.063
5	Hang Tuah	15.88	Kg Dato Harun	0.138	Hang Tuah	0.063
6	Bank Negara / Bandaraya	16.09	Subang Jaya	0.135	Bank Negara / Bandaraya	0.062
7	Pudu	16.11	Seri Setia	0.134	Pudu	0.062
8	Bukit Bintang	16.15	Setia Jaya	0.130	Bukit Bintang	0.062
9	Dang Wangi	16.20	Glenmarie 2	0.129	Dang Wangi	0.062
10	Bank Rakyat - Bangsar	16.26	Jalan Klang Lama	0.127	Bank Rakyat - Bangsar	0.062
	Global	27.14	Global	0.047	Global	0.043

A pattern is observed whereby stations located at CBD areas tend to top the list of average shortest path length and closeness centrality, while stations located near to residential areas along KTM lines top the list of betweenness centrality.

As explained in the methodology chapter, the distance between each node of LRT 3 and MRT Circle Line is measured with Google Map with the estimated route planning and station location while the time interval is calculated by multiplying the distance with an estimated 50 km/h average speed of train. Despite the linear relationship between time data and distance data which shall yield a similar result, the analysis shows significant difference. None of the new stations from LRT 3 and MRT Circle Line appeared at the top list of average shortest path length and closeness centrality, and just 3 new stations top the list of betweenness centrality list. This indicates the lack of influence from the new stations on the efficiency of the network when analysed with distance data. The possible explanation to the disparity between time-weighted and distance-weighted analysis is the unique characteristic of interchange stations in both analyses.

The distance data between platforms within an interchange station appears to be relatively short when compared to the distance between nodes, the shortest path between any node pair may pass through multiple interchange stations consisting of multiple transit lines to find the shortest distance route. In contrast, the time data between platforms within an interchange station captures the real traverse time that is similar to the interval time between pairs of nodes, the shortest path between any nodes may be limited to few paths with lower interval time. The time-weighted analysis shows the stations from forecasted network can provide a shorter time interval path. This suggests that the inclusion of MRT Circle Line offers route with shorter time interval but may not necessarily be a shorter distance route.

A similar positive result was obtained from distance weighted network analysis. The global average shortest path length decreased from 28.48 kilometres in the current network to 27.14 kilometres in the forecasted network, indicates that the shortest path length between any pair of nodes reduced by 1.34 kilometres on average. The inclusion of the MRT Circle Line provides shorter alternative route between any two nodes, facilitating a more efficient travelling around the network. A similar decreasing pattern for both local and global betweenness centrality is observed in distance-weighted network analysis. The global betweenness centrality decreased from 0.058 to 0.047 in the distance-weighted analysis indicating the distribution of shortest path between any pair of nodes to passing through more nodes rather than concentrating at several crucial nodes. This reduces the dependency on several important nodes which in turn reduces the potential of bottleneck congestion. The global closeness centrality of the network increased from 0.042 to 0.043 with the network expansion, indicating slight improvement to the distance connectivity of the network.

4.5.4 Graph

Probability distribution graphs were used to analyse the likelihood of stations in the network exhibit high importance over other stations based on the quantitative indicators.

4.5.4.1 Probability Distribution Graph of Unweighted Forecasted Network

This subsection discusses the probability distribution graphs of the unweighted forecasted network based on 5 indicators that include average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient. Figure 4.12 shows the probability distributions of forecasted network based on average shortest path length follows power law distribution, with an exponent of -4.316 and a regression value of 0.7109. Figure 4.13 shows the probability distributions of forecasted network based on betweenness centrality follows power law distribution, with an exponent of -1.878 and a regression value of 0.8145. Figure 4.14 shows the probability distribution of forecasted network based on closeness centrality follows normal distributions. Figure 4.15 shows the probability distributions of forecasted network based on degree centrality follows power law distribution, with an exponent of -3.615 and a regression value of 0.9994. Figure 4.16 shows the probability distributions of forecasted network based on clustering coefficient follows power law distribution, with an exponent of -2.839 and a regression value of 0.9872.

Probability distribution graph of forecasted network based on average shortest path length, betweenness centrality, degree centrality and clustering coefficients follows a power law distribution with a negative exponent ranging from -4.316 to -1.878. A negative exponent in power law distribution indicates an inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggests that only few number of stations have great influence and exhibit significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network.

The probability distribution graph for average shortest path length in unweighted forecasted network also has the greatest magnitude of exponent compared to other indicators, indicating the less likelihood of a node with extreme high average shortest path length while most stations generally have lower shortest path length to move around the network. The magnitude of exponent of average shortest path length, betweenness centrality and degree centrality in forecasted unweighted network has higher value compared to current network analysis, suggesting reduced tendency of a station having extreme high average shortest path length, betweenness centrality and degree centrality in comparison. This indicates the inclusion of new transit lines in forecasted network reduced the probability of stations having extreme long average shortest path length compared to the current operational network. The probability graph exhibits high regression value ranging from 0.7109 to 0.9994. The forecasted unweighted network has higher regression value compared to current unweighted network, indicating a greater adherence of the distribution of each indicator value with the power law distribution.

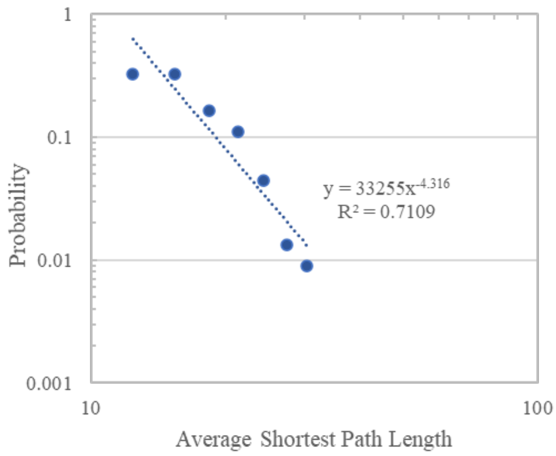


Figure 4.12: Probability Distribution Graph of Average Shortest Path Length of Unweighted Forecasted Network

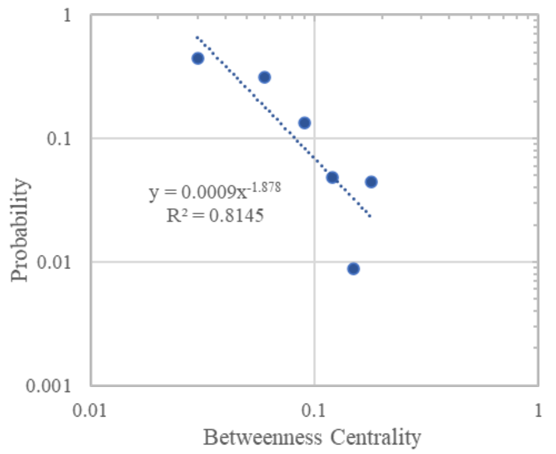


Figure 4.13: Probability Distribution Graph of Betweenness Centrality of Unweighted Forecasted Network

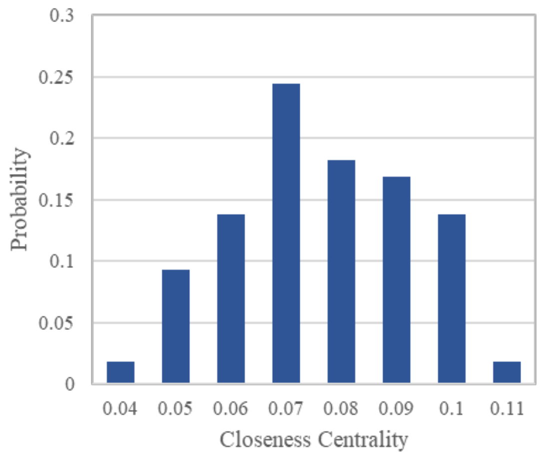


Figure 4.14: Probability Distribution Graph of Closeness Centrality of Unweighted Forecasted Network

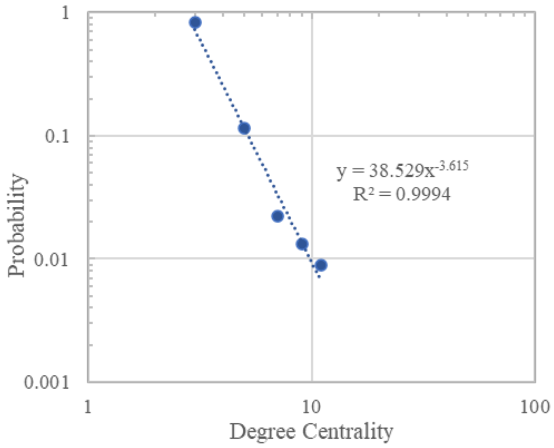


Figure 4.15: Probability Distribution Graph of Degree Centrality of Unweighted Forecasted Network

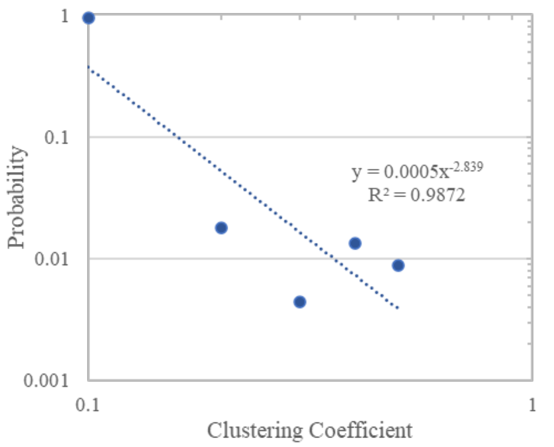


Figure 4.16: Probability Distribution Graph of Clustering Coefficient of Unweighted Forecasted Network

4.5.4.2 Probability Distribution Graph of Time-weighted Forecasted Network

This subsection discusses the probability distribution graphs of the time-weighted forecasted network based on 3 indicators that include average shortest path length, betweenness centrality, closeness centrality. Figure 4.17 shows the probability distributions of forecasted network based on average shortest path length follows power law distribution, with an exponent of -4.326 and a regression value of 0.9845. Figure 4.18 shows the probability distributions of forecasted network based on betweenness centrality follows power law distribution, with an exponent of -1.753 and a regression value of

0.7136. Figure 4.19 shows the probability distribution of forecasted network based on closeness centrality follows normal distributions.

The probability distribution in time-weighted network analysis is similar with graphs in unweighted network analysis with similar negative exponent values for average shortest path length and betweenness centrality, while closeness centrality follows normal distribution. The explanation for a negative exponent in power law distribution is the inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggests that only few number of stations have great influence and exhibit significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network. The probability graph exhibits high regression value ranging from 0.7136 to 0.9845. This indicates a great adherence of the distribution of each indicator value with the power law distribution.

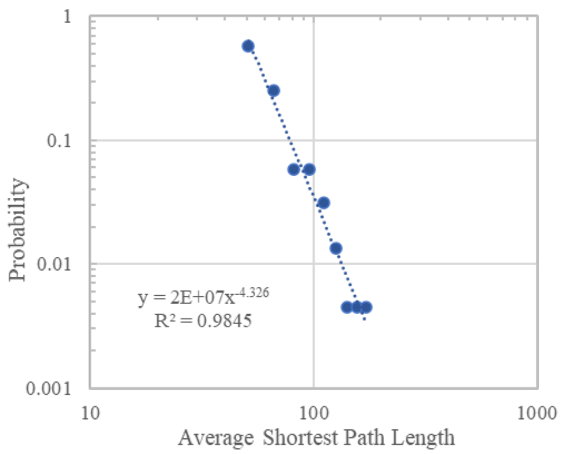


Figure 4.17: Probability Distribution Graph of Average Shortest Path Length of Time-weighted Forecasted Network

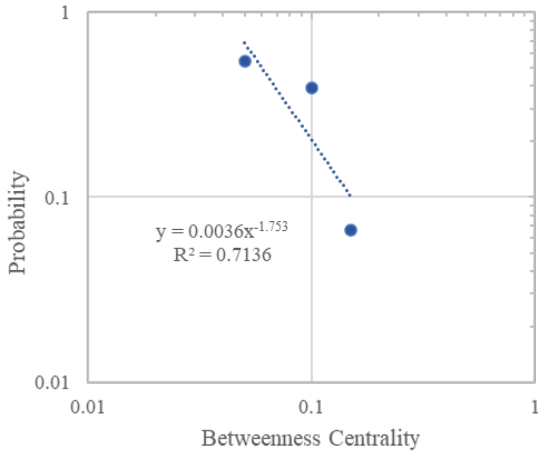


Figure 4.18: Probability Distribution Graph of Betweenness Centrality of Time-weighted Forecasted Network

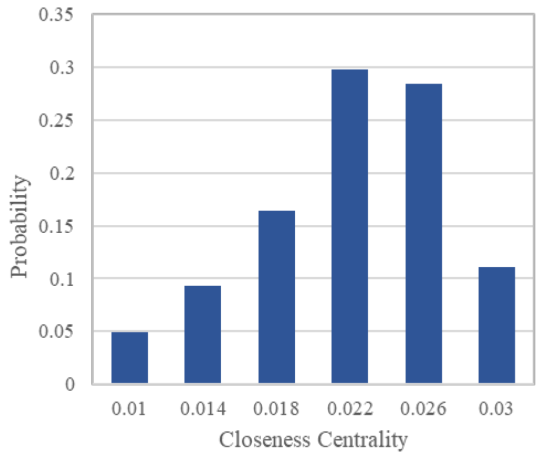


Figure 4.19: Probability Distribution Graph of Closeness Centrality of Time-weighted Forecasted Network

4.5.4.3 Probability Distribution Graph of Distance-weighted Forecasted Network

This subsection discusses the probability distribution graphs of the distance-weighted forecasted network based on 3 indicators that include average shortest path length, betweenness centrality, closeness centrality. Figure 4.20 shows the probability distributions of forecasted network based on average shortest path length follows power law distribution, with an exponent of -3.981 and a regression value of 0.9984. Figure 4.21 shows the probability distributions of forecasted network based on betweenness centrality follows power law distribution, with an exponent of -1.601 and a regression value of

0.7799. Figure 4.22 shows the probability distribution of forecasted network based on closeness centrality follows normal distributions.

The probability distribution in distance-weighted forecasted network analysis is similar with graphs above with similar negative exponent values for average shortest path length and betweenness centrality, while closeness centrality follows normal distribution. The explanation for a negative exponent in power law distribution is the inverse relationship between the increase in indicator values and the corresponding probability. The probability of occurrence decreases exponentially as the indicator value increases. This suggests that only few number of stations have great influence and exhibit significant importance over the majority stations in the network. A higher magnitude of the exponents indicates a steeper decline in probability distribution of a node with higher indicator value and greater heterogeneity presence in the network. The probability graph exhibits high regression value ranging from 0.7799 to 0.9984. This indicates a great adherence of the distribution of each indicator value with the power law distribution.

The regression value of average shortest path length probability distribution in distance-weighted forecasted network analysis is similarly close to 1, indicating the great adherence to power law distribution. This is due to the presence of few limited number of KTM stations located distanced away and beyond Klang Valley and these stations have significantly higher average shortest path length when analysed with distance as parameter.

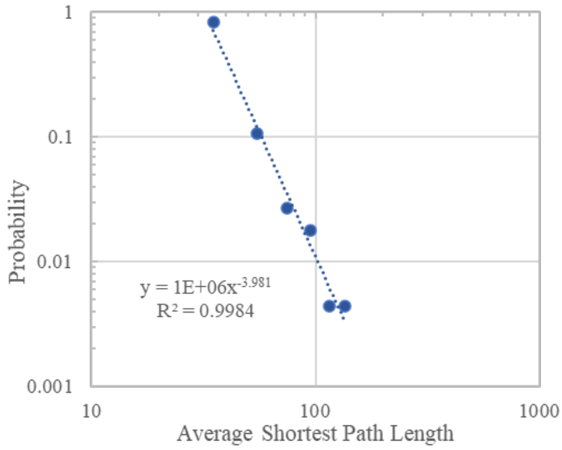


Figure 4.20: Probability Distribution Graph of Average Shortest Path Length of Distance-weighted Forecasted Network

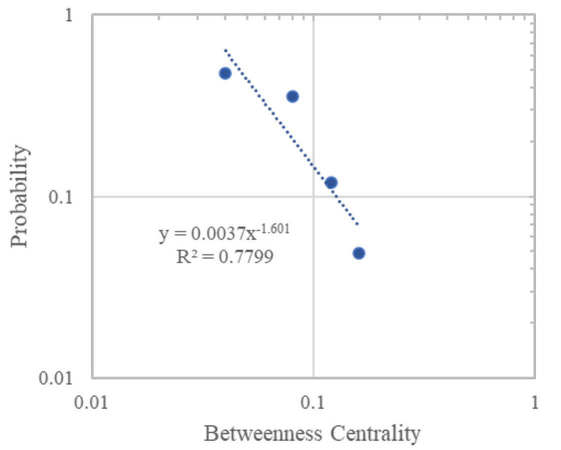


Figure 4.21: Probability Distribution Graph of Betweenness Centrality of Distance-weighted Forecasted Network

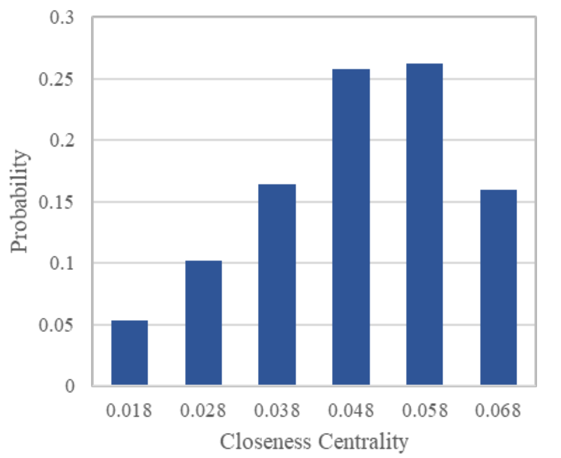


Figure 4.22: Probability Distribution Graph of Closeness Centrality of Distance-weighted Forecasted Network

4.5.4.4 Graph Overview of Forecasted Network

All graphs, except for closeness centrality in the forecasted network analysis, follow power law distribution, indicating the heterogeneous and scale-free characteristic of the network.

The forecasted network analysis observes a similar trend across the indicators in different parameter-weighted networks. The average shortest path length graph reveals that most stations maintain low values, indicating shorter travel distances between them. Similarly, the betweenness centrality graph shows that most stations have low values, implying limited influence on the network, while few stations act as critical hubs with many shortest paths passing through them. The degree centrality graph reveals that only a few stations have high connectivity, with most stations having only two connections. Clustering coefficient graph illustrates that only a few stations have a high number of supplementary connections among neighbouring stations, while the majority exhibit zero clustering coefficient. Similarly, the forecasted network shows scale-free characteristic as evident by significant regression value of power law distribution of degree centrality graph.

The power law distribution graphs in both current and forecasted network analysis show a negative exponent value, suggesting the rate of decrease of probability is higher than the rate of increase in network size. The high regression value of each graph suggests great adherence of the data distribution with power law distribution model. The exponent values in forecasted network analysis have some differences compared to current network analysis. The magnitude of average shortest path length and degree centrality graph exponents have slight increase while for betweenness centrality and clustering coefficient graphs decrease.

Closeness centrality distribution graph for 3 networks follows a normal distribution pattern, indicates evenly distributed network with minimal extreme values. The unweighted, time-weighted, and distance-weighted closeness centrality graphs observed a left skewed normal distribution graph.

4.5.5 Summary

The inclusion of LRT 3 and MRT Circle Line in the forecasted network shows improvement in time-weighted and distance-weighted network analysis, while unweighted analysis shows slight decrement in multiple indicators due to the less accurate and realistic representation of the edge weight.

Although the distance and time between LRT 3 and MRT Circle Line stations are estimated based on 50km/h train speed, which shall return a linear relationship between the time and distance data, the new transit line stations having greater influence over the network in time-weighted network compared to distance-weighted network as evidenced by new stations superseding existing stations as the important stations in multiple indicator value ranking list.

Similar to current network analysis, all power law distribution graphs in forecasted network have negative exponent value, suggest the probability distribution decreases at a rate higher than the increase of network size. Conversely, closeness centrality observes left skewed normal distribution pattern. The forecasted network can be categorised as scale-free network.

4.6 Passenger Demand Analysis

With the increasing disparity between the supply and demand of the worldwide urban rail transit network, the compatibility of the network infrastructure with the passenger flow demand of Klang Valley urban rail transit network is evaluated.

The current network is weighted and analysed with the available passenger flow data obtained from the operator website. However, data for KTM lines are not available. The network is modified with 131 stations with 8,515 pairs of OD.

Analysis in Section 4.2 and 4.3 focus on existing and forecasted network infrastructure and the topological connection. The analysis with passenger flow weighted network aims to obtain performance and connectivity insight of the network with quantitative indicators and compare with the existing network infrastructure to yield the compatibility between the supply and demand of the urban rail transit network.

4.6.1 Unweighted Network

Table 4.12 shows the top 10 results of the unweighted network operational analysis of the 4 indicators that include average shortest path length, betweenness centrality, closeness centrality and degree centrality of current operational urban rail transit network of Klang Valley excluding both KTM lines.

Table 4.12: Top 10 Ranking Station of Unweighted Modified Network Analysis

	Average Shortest Path Length		Betweenness Centrality		Closeness Centrallity		Degree Centrality	
1	Tun Razak Exchange	8.65	Tun Razak Exchange	0.366	Tun Razak Exchange	0.116	KL Sentral / Muzium Negara	5
2	Bukit Bintang	8.72	Chan Show Lin	0.366	Bukit Bintang	0.115	Chan Show Lin	5
3	Chan Show Lin	8.89	KL Sentral / Muzium Negara	0.343	Chan Show Lin	0.112	Titiwangsa	5
4	Plaza Rakyat / Merdeka	8.94	Sungai Besi	0.321	Plaza Rakyat / Merdeka	0.112	Tun Razak Exchange	4
5	Kuala Lumpur / Pasar Seni	9.14	Kuchai	0.299	Kuala Lumpur / Pasar Seni	0.109	Kuala Lumpur / Pasar Seni	4
6	Pudu	9.15	Taman Naga Emas	0.291	Pudu	0.109	Bukit Bintang	4
7	Masjid Jamek	9.16	Kuala Lumpur / Pasar Seni	0.268	Masjid Jamek	0.109	Maluri	4
8	Hang Tuah	9.20	Bukit Bintang	0.244	Hang Tuah	0.109	Sungai Besi	4
9	Conlay	9.21	Maluri	0.236	Conlay	0.109	Masjid Jamek	4
10	Dang Wangi / Bukit Nanas	9.22	Bank Rakyat - Bangsar	0.199	Dang Wangi / Bukit Nanas	0.109	Hang Tuah	4
	Global	13.73	Global	0.099	Global	0.078	Global	2.18

The urban rail transit network with the inclusion of both KTM lines provided additional 9 interchange stations around the network. The unweighted analysis of the modified network observes the effect of the exclusion of the interchange stations to facilitate the fair comparison with the passenger flow weighted network in the following section.

The average shortest path length reduced to 13.73 compared to 14.09 of the current networks with both KTM lines in Section 4.2. However, with 9 interchange stations excluded in this analysis, the global degree centrality decreased to 2.18 as well.

The results show 4 same stations toping lists of all 4 indicators, namely Tun Razak Exchange, Chan Show Lin, Kuala Lumpur / Pasar Seni, and Bukit Bintang stations. These stations are among the most crucial stations in the network and located around CBD areas.

4.6.2 Passenger Flow Weighted Network

Table 4.13 shows the top 10 results of the passenger flow weighted network demand analysis of the 4 indicators that include average shortest path length, betweenness centrality, closeness centrality and degree centrality of current operational urban rail transit network of Klang Valley excluding both KTM lines.

Table 4.13: Top 10 Ranking Station of Passenger Flow Weighted Modified Network Analysis

	Average Distance		Betweenness Centrality		Closeness Centrality		Degree Centrality	
1	Bukit Bintang	3.63	Tun Razak Exchange	0.547	Bukit Bintang	0.276	KL Sentral / Muzium Negara	130126
2	Dang Wangi / Bukit Nanas	3.64	Bukit Bintang	0.493	Dang Wangi / Bukit Nanas	0.275	KLCC	78205
3	Tun Razak Exchange	3.64	KL Sentral / Muzium Negara	0.440	Tun Razak Exchange	0.275	Kuala Lumpur / Pasar Seni	76762
4	Raja Chulan	3.65	Masjid Jamek	0.400	Raja Chulan	0.274	Bukit Bintang	74579
5	Imbi	3.66	Kuala Lumpur / Pasar Seni	0.394	Imbi	0.273	Ampang Park	72698
6	Plaza Rakyat / Merdeka	3.66	Dang Wangi / Bukit Nanas	0.365	Plaza Rakyat / Merdeka	0.273	Bank Rakyat - Bangsar	56797
7	Masjid Jamek	3.67	Chan Show Lin	0.345	Masjid Jamek	0.272	Imbi	41182
8	Cochrane	3.69	Cheras	0.312	Cochrane	0.271	Tun Razak Exchange	39583
9	Kuala Lumpur / Pasar Seni	3.70	Salak Selatan	0.304	Kuala Lumpur / Pasar Seni	0.270	Maluri	37452
10	Chan Show Lin	3.71	Sungai Besi	0.299	Chan Show Lin	0.270	Surian	36967
	Global	6.35	Global	0.112	Global	0.183	Global	12225

An anticipated analysis outcome suggests that most top-ranking stations in passenger flow weighted analysis located around CBD. The stations around CBD areas are often associated with economic activities that attracts significant number of commuters. The results of the passenger flow weighted network analysis shows that 6 stations concurrently top the list of average shortest path length, betweenness centrality and closeness centrality; namely Kuala Lumpur / Pasar Seni, Chan Show Lin, Masjid Jamek, Bukit Bintang, Dang Wangi / Bukit Nanas, and Tun Razak Exchange stations. These are among the stations with great influence on the overall network when considering the number of passengers passing through each node on daily basis. Stations with high betweenness centrality value may be susceptible to nodal attacks, which can jeopardise the connectivity of the network.

Degree centrality in passenger flow weighted network analysis represents the number of passengers flowing through a single node. It is observed that 4 stations having high number of passengers flow despite not serving as an interchange station. The possible explanation is that these stations are the important destination stations where most passengers disembark the train to work. The top stations with high numbers of passengers are all located at CBD of Kuala Lumpur, passengers from peripheral area around Klang Valley commute to the top-ranking stations located at the city centre. As such, stations with high number of connections does not necessarily mean high passenger flow.

The result tables show most of the top stations of the current network operational analysis in section 4.2 and the unweighted analysis of the modified network excluding all KTM lines matches with the top stations of the passenger flow weighted network analysis. This indicates the network's infrastructure effectively aligns with the passenger flow demand and usage pattern, which contributes to the overall connectivity and functionality of the network.

Individual station may have different ranking in topological analysis and passenger flow weighted analysis. Stations that rank high in both section 4.2 and passenger flow weighted network analysis illustrate the strong alignment and correlation between the supply and demand of the network. Indicating effectiveness of the network in facilitating passenger movement.

Stations that rank high in Section 4.2 but low in passenger flow weighted network analysis exhibit underutilization of the station in the network. This can be caused by unoptimized station location or inadequate accessibility around the station. Whereas station that ranks low in section 4.2 but significant in passenger flow weighted network analysis shows overutilization of the station. These stations were potentially built before urbanisation, which cause exponential increase in passenger flow over time. These stations shall be closely monitored to mitigate potential capacity constraints and bottleneck congestion.

4.6.3 Graph

Linear graphs are plotted to facilitate the quantitative compatibility comparison between current network infrastructure and the passenger flow demand. The comparison was conducted for the average shortest path length, betweenness centrality and closeness centrality ranking of unweighted network, time-weighted network, and distance-weighted network between the current operational network analysis and passenger demand analysis.

The results for the passenger flow analysis are sorted in ascending and the station name is represented with the ranking of the list. This yielded a linear line for the passenger flow weighted indicator ranking with regression line equal to 1. The results for unweighted network, time-weighted network, and distance-weighted network analysis are treated similarly and the rankings are then sorted out. Both data are then plotted on the same graph to observe the changes of the station ranking in different parameter weighted analysis and the compatibility of the station ranking between supply and demand. The analysis facilitates the identification of underutilisation and overutilisation of stations in the network.

The passenger flow weighted analysis ranking is compared with topological analysis of network that is unweighted, time-weighted, and distance-weighted. Graphs for average shortest path length and closeness centrality shows relatively high correlation in different parameter-weighted network analysis with minimal fluctuation of station ranking. This indicates that from the perspective of average shortest path length and closeness centrality, the currently available urban rail transit network infrastructures align effectively with the passenger flow demand. In contrast, the graphs for betweenness centrality shows relatively low regression value with significant fluctuations of station ranking in 3 different parameter weighted analysis. This indicates that stations that is important in topological analysis may not necessarily have high passenger flow passing through. Figure 4.23 to Figure 4.31 shows the compatibility between supply and demand for unweighted, time-weighted and distance-weighed network analysis.

4.6.3.1 Compatibility Comparison of Average Shortest Path Length

This subsection discusses the compatibility between passenger flow weighted analysis with unweighted, time-weighted and distance-weighted current network analysis based on average shortest path length. Figure 4.23 shows the ranking comparison between demand based on passenger flow weighted network analysis with unweighted network analysis based on average shortest path length, with regression value of 0.6349. Figure 4.24 shows the ranking comparison between demand based on passenger flow weighted network analysis with time-weighted network analysis based on average shortest path length, with regression value of 0.8137. Figure 4.25 shows the ranking comparison between demand based on passenger flow weighted network analysis with distance-weighted network analysis based on average shortest path length, with regression value of 0.7897.

The regression value of the compatibility graph based on average shortest path length was relatively high with minimal fluctuations between station rankings based on supply and demand. This indicates that from the perpective of average shortest path length, the currently available urban rail transit network infrastructures align effectively with the passenger flow demand.

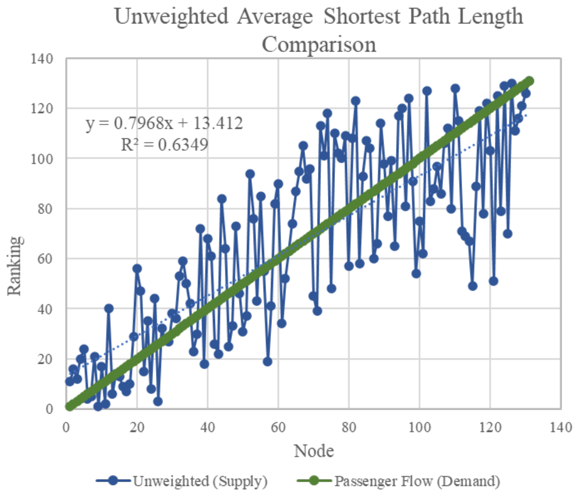


Figure 4.23: Compatibility Comparison of Average Shortest Path Length of Unweighted Network

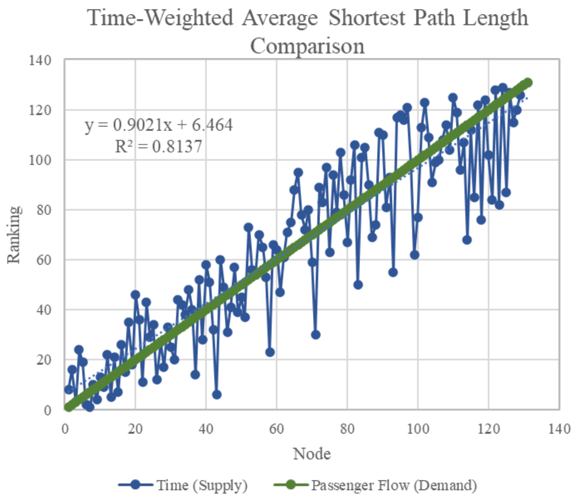


Figure 4.24: Compatibility Comparison of Average Shortest Path Length of Time-weighted Network

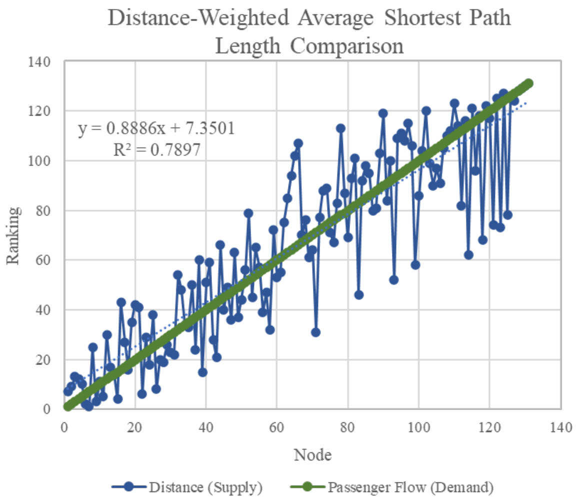


Figure 4.25: Compatibility Comparison of Average Shortest Path Length of Distance-weighted Network

4.6.3.2 Compatibility Comparison of Betweenness Centrality

This subsection discusses the compatibility between passenger flow weighted analysis with unweighted, time-weighted and distance-weighted current network analysis based on betweenness centrality. Figure 4.26 shows the ranking comparison between demand based on passenger flow weighted network analysis with unweighted network analysis based on betweenness centrality, with regression value of 0.1758. Figure 4.27 shows the ranking comparison between demand based on passenger flow weighted network analysis with time-weighted network analysis based on betweenness centrality, with regression value of 0.2961. Figure 4.28 shows the ranking comparison between demand based on passenger flow weighted network analysis with distance-weighted network analysis based on betweenness centrality, with regression value of 0.2616.

The regression value of the compatibility graph based on betweenness centrality was relatively low with notable fluctuations between station rankings based on supply and demand. This indicates that from the aspect of betweenness centrality, significant improvement on the currently available urban rail transit network infrastructures were required to align effectively with the passenger flow demand. Stations that is important in topological analysis may not necessarily have high passenger flow passing through.

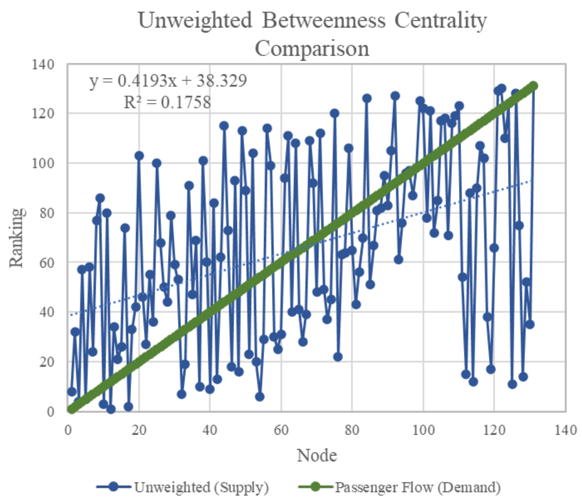


Figure 4.26: Compatibility Comparison of Betweenness Centrality of Unweighted Network

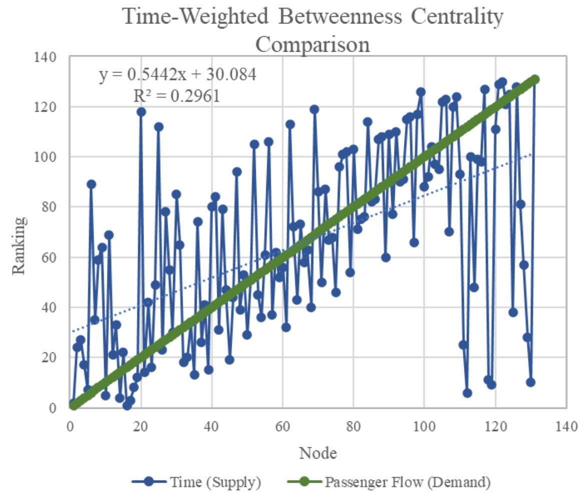


Figure 4.27: Compatibility Comparison of Betweenness Centrality of Time-weighted Network

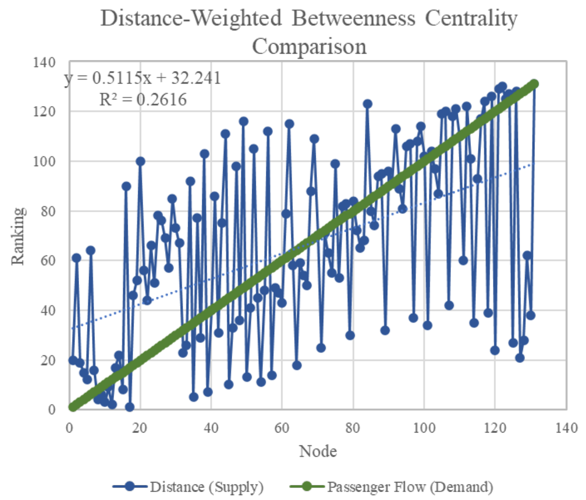


Figure 4.28: Compatibility Comparison of Betweenness Centrality of Distance-weighted Network

4.6.3.3 Compatibility Comparison of Closeness Centrality

This subsection discusses the compatibility between passenger flow weighted analysis with unweighted, time-weighted and distance-weighted current network analysis based on average shortest path length. Figure 4.29 shows the ranking comparison between demand based on passenger flow weighted network analysis with unweighted network analysis based on closeness centrality, with regression value of 0.6349. Figure 4.30 shows the ranking comparison between demand based on passenger flow weighted network analysis with time-weighted network analysis based on closeness centrality, with regression value of 0.8137. Figure 4.31 shows the ranking comparison between demand based on passenger flow weighted network analysis with distance-weighted network analysis based on closeness centrality, with regression value of 0.7897.

The regression value of the compatibility graph based on closeness centrality has similar results with graphs based on average shortest path length, both have relatively high values with minimal fluctuations between station ranking based on supply and demand. This indicates that from the aspect of closeness centrality, the currently available urban rail transit network infrastructures align effectively with the passenger flow demand.

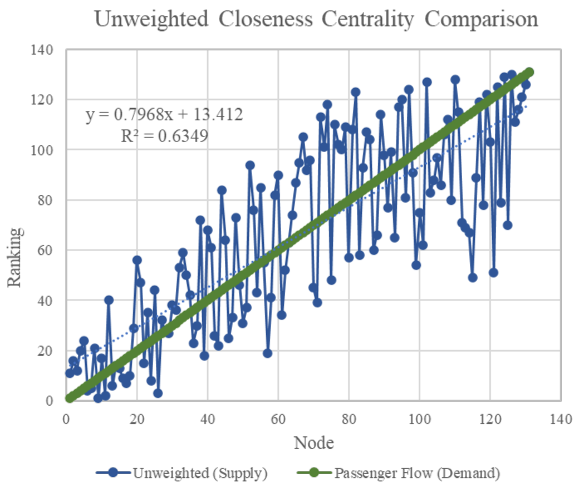


Figure 4.29: Compatibility Comparison of Closeness Centrality of Unweighted Network

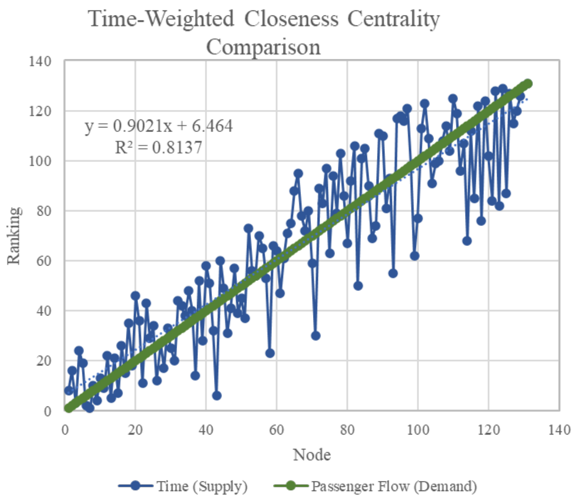


Figure 4.30: Compatibility Comparison of Closeness Centrality of Time-weighted Network

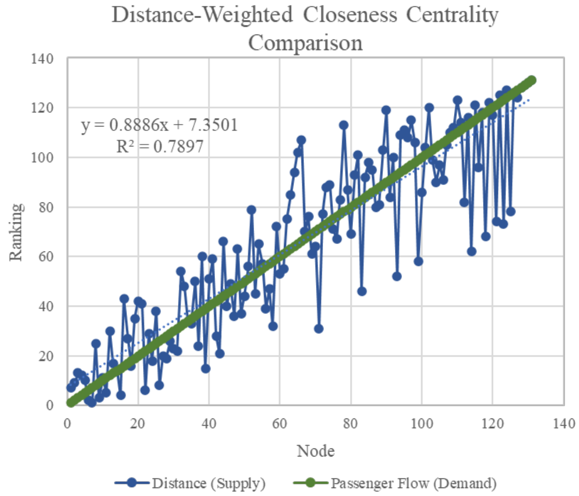


Figure 4.31: Compatibility Comparison of Closeness Centrality of Distance-weighted Network

4.6.4 Summary

The comparison between topological analysis and passenger demand analysis reveals the effectiveness of the network fulfilling the usage pattern. Compatibility graph for average shortest path length and closeness centrality observes a minimal fluctuation for different parameter-weighted networks while betweenness centrality graph shows significant fluctuation with relatively lower regression value. While there is predominantly positive correlation between supply and demand, which indicates partial compatibility of the current network with the passenger flow demand, there remains room for improvement to the network.

4.7 Global Network Overview

This section compares the performance and connectivity of the current and forecasted urban rail transit network of Klang Valley with multiple major cities. Zhang et al (2013) have conducted a comprehensive study in calculating the topological characteristics of 30 urban rail transit networks worldwide. The study analysed the unweighted network with multiple indicators based on graph theory and complex network theory. The results for 5 major countries and their corresponding node numbers, average shortest path length, betweenness centrality, degree centrality, and clustering coefficient values are extracted to facilitate the comparative analysis with the Klang Valley network. Table 4.9 shows the indicator values of urban rail transit network of 5 major cities compared to current and forecasted Klang Valley network. The ranking of the multiple indicator values according to Table 4.14 is shown in Figure 4.32.

Table 4.14: Indicator Values of Major Cities Urban Rail Transit Network

City	Node	Degree Centrality	Betweenness Centrality	Clustering Coefficient	Average Shortest Path Length
Klang Valley	177	2.41	1246.5	0.0143	14.09
Klang Valley (Forecasted Network)	225	2.43	1085.0	0.0116	14.85
Hong Kong*	90	2.09	574.3	0.0241	11.91
Paris*	300	2.37	1945.6	0.0157	12.01
Tokyo*	227	2.42	1270.4	0.0338	10.23
London*	323	2.32	2464.9	0.0387	14.31
New York*	422	2.34	2794	0.0365	12.13

*Source: Zhang et al. (2019)

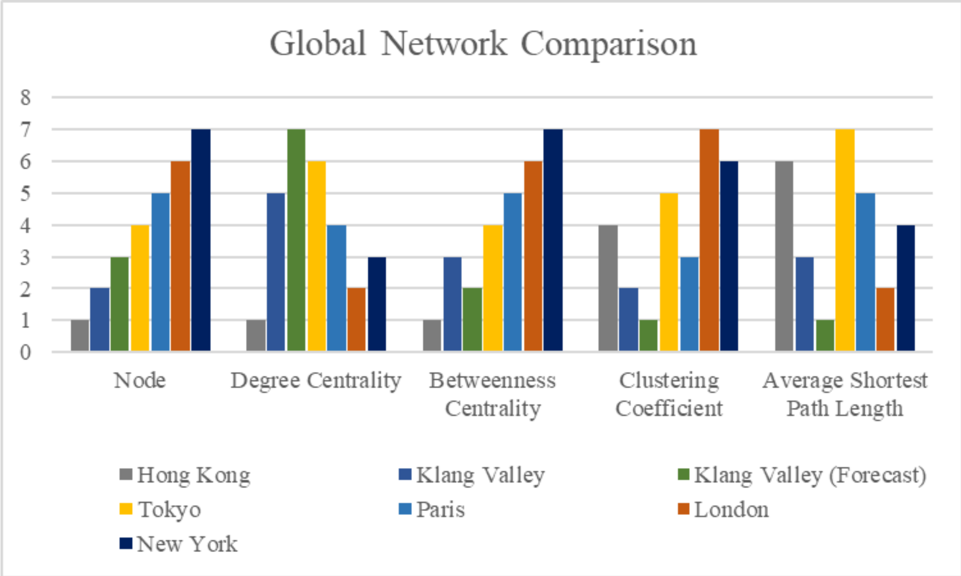


Figure 4.32: Global Network Ranking with Indicators

The Klang Valley network has 177 nodes and increase to 225 nodes in the forecasted network. Although the Klang Valley network has greater number of nodes compared to cities with lower populations like Hong Kong, the network still has lower number of nodes compared to large cities like New York and London network.

The average betweenness centrality values show a linear increment trend compared to the increase of number of nodes (Zhang et al., 2013). The increase in node number can increase the number of node pairs. A higher average betweenness centrality illustrates a more centralised network while a lower value means a decentralised network. The betweenness centrality ranking of current and forecasted network of Klang Valley lies at relatively low position, indicating relatively decentralised network.

High average degree centrality indicates high number of interchange stations and improved connectivity around the network. The current Klang Valley network ranks number 3 and increase to ranking number 1 with the forecasted network due to the increment of number of interchange stations. Tokyo, Paris and New York networks are among those with high degree centrality.

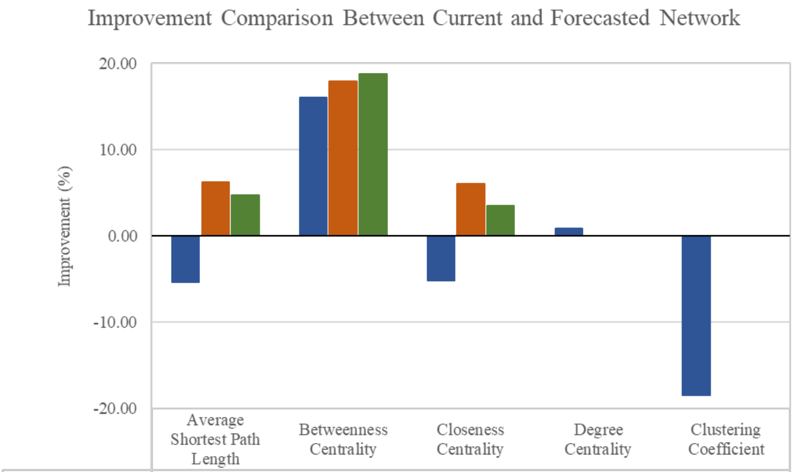
Clustering coefficient ranking also has a similar ranking trend with the node number and betweenness centrality ranking among the networks with slight changes. The current and forecasted Klang Valley networks are among the networks with the lowest clustering coefficient. London has the highest clustering coefficient, indicates highly interconnections among the stations of the network. Hong Kong network with relatively low rankings for node number, degree centrality and betweenness centrality has a high clustering coefficient and average shortest path length ranking, indicating the well-established and well-planned network with great connectivity.

The current and forecasted network of Klang Valley has relatively low ranking among the networks. The Klang Valley network has high degree centrality but low in average shortest path length. The possible reason to the disparity is the lack of optimisation of interchange station location selection which did not provide optimised shortest path between OD. The overall trend of current and forecasted network of Klang Valley is similar when ranked among the networks. New York, London, Tokyo and Paris networks among the networks with consistent high ranking for all 5 indicators.

Acknowledging the limitations of the data extracted from the research paper by Zhang et al. (2013) is important. With the advancement and increasing attention to the urban rail transit network, the results obtained dated back in 2013 may be superseded with results from an improved network. The comparative analysis of the current and forecasted network of the Klang Valley highlights underscore deficiency in terms of multiple indicators when compared to well established networks of major cities, which highlights the need for improvements within the Klang Valley network infrastructure to enhance connectivity and align with global transit standards.

4.8 Summary

The findings in this study mainly focus on the comparative analysis and the percentage improvement of the forecasted network with the inclusion of LRT 3 and MRT Circle Line compared to the current operational Klang Valley urban rail transit network, and the compatibility between the supply and demand of the network is discussed in this chapter. Figure 4.33 shows the percentage improvement of global indicator value of the forecasted network compared to the current network.



	Average Shortest Path Length	Betweenness Centrality	Closeness Centrality	Degree Centrality	Clustering Coefficient
Unweighted	-5.38	16.05	-5.16	0.83	-18.53
Time-weighted	6.23	17.89	6.06		
Distance-weighted	4.71	18.75	3.50		

Figure 4.33: Percentage Improvement Comparison Between Current and Forecasted Network.

Average shortest path length, betweenness centrality and closeness centrality show positive improvement in multiple parameter-weighted network, except for unweighted network analysis due to the unrealistic representation of edge weight. Degree centrality shows minor increment in average number of connections due to the new interchange station with the inclusion of new transit lines. However, clustering coefficient shows drastic decrement due to the increase of network size, indicating the rate of connection increase among nodes cannot keep pace with the increase of network size. New stations from LRT 3 and MRT Circle Line superseding the previous stations as the top-ranking stations indicates the effective alignment of the new stations. Stations concurrently appear on multiple indicators in different parameter-weighted network analysis list have greater influence on the network. Probability distribution graph for all indicators when weighted with different parameters in current and forecasted network shows strong correlation with power law distribution pattern, except for closeness centrality follows normal distribution pattern.

The study also analyses the network supply and demand. Figure 4.34 shows the regression value of the compatibility between available network infrastructure with the passenger flow demand results.

Figure 4.34: Regression Value of Compatibility Between Supply and Demand

The compatibility results show overall positive correlation between the supply and demand of the urban rail transit network of Klang Valley, except for betweenness centrality with relatively lower regression value, indicating improvements to the network infrastructure is required to improve the correlation between supply and demand. Comparison between the topological connection with passenger flow demand helps identify underutilization or overutilization of a station, guiding improvement efforts. The ranking comparison of the current operational and forecasted Klang Valley urban rail transit network with 8 major city networks shows deficiency in multiple indicators, indicating improvement is required to align with global transit network standards.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In conclusion, the study of the Klang Valley urban rail transit network with journey time, distance, and passenger flow data weighted network analysis and computed with 5 quantitative indicators provides comprehensive insight to the performance and connectivity of the network.

The performance of the current and forecasted Klang Valley urban rail transit network was quantitatively compared with 5 indicators including average shortest path length, betweenness centrality, closeness centrality, degree centrality and clustering coefficient in unweighted, time-weighed and distance weighted network. The global average shortest path length value shows 5.38% decrement in unweighted network analysis while an increment of 6.23% and 4.71% were observed in time-weighted and distance-weighted network analysis respectively. A similar pattern was observed in global closeness centrality value with 5.16% decrement in unweighted network analysis while an increment of 6.06% and 3.50% were observed in time-weighted and distance-weighted network analysis respectively. The reduction in average shortest path length and closeness centrality in unweighted network analysis is due to the inaccurate representation of edge weighted compared to time and distance. An overall increase in global betweenness centrality for unweighted, time-weighted and distance-weighted with 16.05%, 17.89% and 18.75% positive improvement respectively. The introduction of new transit lines to the network has enhanced the connectivity and reduction of significance of each individual station, evidenced by the reduction of local and global betweenness centrality, which reduce the possibility of bottleneck congestion. A minimal 0.83% improvement to the global degree centrality was observed in the unweighted network analysis due to the increased interchange stations while a significant decrement of 18.53% to the global clustering coefficient due to the lack of connections among adjacent stations with the increase in network size. The emergence of stations from LRT 3 and MRT

Circle Line on the top-ranking stations shows effective alignment of the new transit lines. The introduction of new transit lines to the network has enhanced the connectivity and reduction of significance of each individual station, evidenced by the reduction of local and global betweenness centrality, which reduces the possibility of bottleneck congestion.

The compatibility of the network’s infrastructure and the passenger flow demand is compared in this study. The regression value of the comparison between supply and demand based on average shortest path length and closeness centrality was relatively high with values ranging from 63.49% to 78.97%, while relatively lower value for betweenness centrality with values ranging from 17.58% to 29.61%. The ranking difference for each station facilitates the identification of underutilisation and overutilization of a station. The partial compatibility between the supply and demand suggests the rooms for improvement to the network.

The performance and connectivity of the current and forecasted network is compared with urban rail transit networks of major cities. The comparison of the Klang Valley network with major cities highlights the strengths and weaknesses of the network, facilitating best practices for future improvements. Both current and forecasted Klang Valley urban rail transit network exhibit high degree centrality but relatively low in betweenness centrality, clustering coefficient and average shortest path length due to the lack of optimisation of interchange stations at planning stage.

5.2 Recommendations for Future Work

There are several recommendations to improve the study of the Klang Valley urban rail transit network. Firstly, passenger flow data for KTM lines is recommended to obtained from the operator to facilitate the comprehensive compatibility analysis between the supply and demand of the overall urban rail transit network. Next, it is recommended to enhance the analysis of the network by incorporating additional indicators to evaluate the optimised train frequency and capacity constraints of trains coaches and station platforms to facilitate the high volume during peak hours. Other than that, it is recommended to reconduct the analysis of the forecasted network by replacing the assumed data of LRT 3 and MRT Circle Line with the actual journey time, distance, and passenger flow data to accurately assess the impact to the overall network. Besides, it is recommended to conduct robustness analysis by simulating the removal of important stations from the network and analyse the ability of the network in handling failure of a station. In addition, the study of the public transportation in Klang Valley is recommended to incorporate bus and other vehicle networks to increase first mile and last mile connectivity.

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APPENDICES

Appendix A: Transfer Time and Distance of Interchange Stations.

	From		To		Transfer	
	Station Name	Transit Line	Station Name	Transit Line	Time (min)	Distance (KM)
1	Kampung Batu	KTM 1	Kampung Batu	MRT 2	4	0.19
2	Bandar Tasik Selatan	KTM 1	Bandar Tasik Selatan	LRT Sri Petaling	3	0.11
3	Kajang	KTM 1	Kajang	MRT 1	3	0.25
4	Sungai Buloh	KTM 2	Sungai Buloh	MRT 2	4	0.27
5	Kepong Sentral	KTM 2	Sri Damansara Timur	MRT 2	3	0.19
6	Abdulah Hukum	KTM 2	Abdulah Hukum	LRT Kelana Jaya	2	0.10
7	Subang Jaya	KTM 2	Subang Jaya	LRT Kelana Jaya	3	0.11
8	Sentul Timur	LRT Ampang	Sentul Timur	LRT Sri Petaling	1	0.10
9	Sentul	LRT Ampang	Sentul	LRT Sri Petaling	1	0.10
10	Pudu	LRT Ampang	Pudu	LRT Sri Petaling	1	0.10
11	Maluri	LRT Ampang	Maluri	MRT 1	5	0.20
12	Sungai Besi	LRT Sri Petaling	Sungai Besi	MRT 2	4	0.10
13	Putra Height	LRT Sri Petaling	Putra Height	LRT Kelana	1	0.10

				Jaya		
14	Ampang Park	LRT Kelana Jaya	Ampang Park	MRT 2	10	0.23
15	Dang Wangi	LRT Kelana Jaya	Bukit Nanas	Monorail	9	0.37
16	Bukit Bintang	Monorail	Bukit Bintang	MRT 1	6	0.18
17	Kwasa Damansara	MRT 1	Kwasa Damansara	MRT 2	1	0.10
18	TRX	MRT 1	TRX	MRT 2	1	0.10
19	Sultan Ismail	LRT Ampang	Sultan Ismail	LRT Sri Petaling	1	0.10
	Sultan Ismail	LRT Ampang	Medan Tuanku	Monorail	10	0.70
	Sultan Ismail	LRT Sri Petaling	Medan Tuanku	Monorail	10	0.70
20	Masjid Jamek	LRT Ampang	Masjid Jamek	LRT Sri Petaling	1	0.10
	Masjid Jamek	LRT Ampang	Masjid Jamek	LRT Kelana Jaya	3	0.10
	Masjid Jamek	LRT Sri Petaling	Masjid Jamek	LRT Kelana Jaya	3	0.10
21	Plaza Rakyat	LRT Ampang	Plaza Rakyat	LRT Sri Petaling	1	0.10
	Plaza Rakyat	LRT Ampang	Merdeka	MRT 1	6	0.30
	Plaza Rakyat	LRT Sri Petaling	Merdeka	MRT 1	6	0.30
22	Hang Tuah	LRT Ampang	Hang Tuah	LRT Sri Petaling	1	0.10

	Hang Tuah	LRT Ampang	Hang Tuah	Monorail	3	0.17
	Hang Tuah	LRT Sri Petaling	Hang Tuah	Monorail	3	0.17
23	Chan Show Lin	LRT Ampang	Chan Show Lin	LRT Sri Petaling	1	0.10
	Chan Show Lin	LRT Ampang	Chan Show Lin	MRT 2	5	0.21
	Chan Show Lin	LRT Sri Petaling	Chan Show Lin	MRT 2	5	0.21
24	Titiwangsa	LRT Ampang	Titiwangsa	LRT Sri Petaling	1	0.10
	Titiwangsa	LRT Ampang	Titiwangsa	Monorail	2	0.16
	Titiwangsa	LRT Ampang	Titiwangsa	MRT 2	4	0.14
	Titiwangsa	LRT Sri Petaling	Titiwangsa	Monorail	2	0.16
	Titiwangsa	LRT Sri Petaling	Titiwangsa	MRT 2	4	0.14
	Titiwangsa	Monorail	Titiwangsa	MRT 2	4	0.16
25	Kuala Lumpur	KTM 1	Kuala Lumpur	KTM 2	1	0.10
	Kuala Lumpur	KTM 1	Pasar Seni	LRT Kelana Jaya	4	0.21
	Kuala Lumpur	KTM 1	Pasar Seni	MRT 1	6	0.30
	Kuala Lumpur	KTM 2	Pasar Seni	LRT Kelana Jaya	4	0.21
	Kuala Lumpur	KTM 2	Pasar Seni	MRT 1	6	0.30
	Pasar Seni	LRT Kelana Jaya	Pasar Seni	MRT 1	4	0.10

26	Putra	KTM 1	Putra	KTM 2	1	0.10
	Putra	KTM 1	PWTC	LRT Ampang	10	0.75
	Putra	KTM 1	PWTC	LRT Sri Petaling	10	0.75
	Putra	KTM 2	PWTC	LRT Ampang	10	0.75
	Putra	KTM 2	PWTC	LRT Sri Petaling	10	0.75
	PWTC	LRT Ampang	PWTC	LRT Sri Petaling	1	0.10
27	Bank Negara	KTM 1	Bank Negara	KTM 2	1	0.10
	Bank Negara	KTM 1	Bandaraya	LRT Ampang	5	0.24
	Bank Negara	KTM 1	Bandaraya	LRT Sri Petaling	5	0.24
	Bank Negara	KTM 2	Bandaraya	LRT Ampang	5	0.24
	Bank Negara	KTM 2	Bandaraya	LRT Sri Petaling	5	0.24
	Bandaraya	LRT Ampang	Bandaraya	LRT Sri Petaling	1	0.10
28	Kl Sentral	KTM 1	Kl Sentral	KTM 2	1	0.10
	Kl Sentral	KTM 1	Kl Sentral	LRT Kelana Jaya	3	0.10
	Kl Sentral	KTM 1	Kl Sentral	Monorail	6	0.29
	Kl Sentral	KTM 1	Muzium Negara	MRT 1	9	0.46
	Kl Sentral	KTM 2	Kl Sentral	LRT Kelana Jaya	3	0.10
	Kl Sentral	KTM 2	Kl Sentral	Monorail	6	0.29

	Kl Sentral	KTM 2	Muzium Negara	MRT 1	9	0.46
	Kl Sentral	LRT Kelana Jaya	Kl Sentral	Monorail	6	0.25
	Kl Sentral	LRT Kelana Jaya	Muzium Negara	MRT 1	9	0.52
	Kl Sentral	Monorail	Muzium Negara	MRT 1	12	0.77