Assessing the Impact of Traffic Congestion through Real-time Origin-Destination Routing Transport Simulation

by

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ABSTRACT

The research presents a spatial transport simulation based on the spatial network and the Bureau of Public Roads (BPR) congestion function as an implementation of transport modelling and quantifies the impact of changes in particular road attributes through blockages and widening. Severe traffic congestion profoundly impacts city operations and the daily lives of its residents, gradually evolving into a prominent problem in urban society. This paper focuses on the traffic network within a 10000-meter diameter around the City of London. It employs stochastic algorithms to construct Origin-Destination Metrics and utilises computation to capture traffic behaviour, road preferences, and congestion effects. Then it establishes a real-time traffic system dynamic simulation and congestion effect analysis model that incorporates congestion variables and subsequently conducts traffic simulation and analysis. By introducing the concept of topological betweenness centrality, the relationship between the model and spatial network attributes is further explored to uncover the reciprocal influence law of the real-time transport system. This analysis reveals that congestion notably influences space utilisation patterns, and conversely, changing spatial usage can change congestion to a certain extent. Building upon this, the study delves into pertinent policies and suggestions for mitigating urban congestion, investigating their impact on the transport system. The research reveals that blocking specific roads can significantly impact congestion. While widening policies prove effective for all road widening, they perform even worse for only wide small ratio of roads. This effect varies among different types of spatial roads.

KEYWORDS

Urban transport systems, Real-time Dynamic transport simulations, Congestion variable, Origin-Destination routing, Space Syntax, Traffic changes impact.

CONTENT

1. INTRODUCTION

As an important part of urban development, urban transport plays a significant role in the economic growth of cities. However, with the development of cities, traffic congestion has gradually become a prominent problem in urban transport systems. Traffic congestion occurs when the traffic volume passing through a road section or intersection exceeds its capacity. This overload is typically caused by increased traffic demand within a specific timeframe such as commuting, leading to disruptions in the traffic and leaving vehicles stranded on the road, at intersections, or within particular road sections.

FIGURE 1 GPX DATA

Figure 1 shows the GPX Data for the City of London, revealing the spatial distribution of people travelling and the aggregation of traffic. Traffic congestion is appearing. Addressing traffic congestion is essential for enhancing the quality of life for urban residents and promoting economic development.

Scholars like Beesley have argued that the value of road investment is influenced by the value of time. Financial savings can be achieved by reducing congestion, and the UK Road Pricing Group argues that different modes of transport in various road conditions have a significant impact on urban transport investment (Beesley 1965).

Richard Arnott and Kenneth Small argue that changes in traffic capacity throughout the day create challenges in forecasting and assessing capacity requirements. Vehicle travelling routings are also influenced by travel times, which are affected by congestion. They also emphasise that solving congestion problems requires the application of economic pricing tools and a thorough comprehension of individual travel decisions and interactions (Arnott and Small 1994). Terence C. Lam and Kenneth A. Small explore the complexity of traffic behaviour, offering valuable insights into the factors influencing route choices and the effects of human behaviour on the transport system (Lam and Small 2001). Mark Wardman contributes to the public transport debate, arguing that it is possible to reduce congestion and enhance the overall transport experience by considering different modes of transport and exploring strategies to encourage more efficient vehicle choices (Wardman 2004).

Due to the complexity of urban road systems, traffic congestion does exhibit unique spatial and temporal patterns and dynamic characteristics (Kazerani and Winter 2009). Edward John Manley argues that urban congestion is the result of the actions and interactions of millions of people within a city, where many individuals select the same road sections simultaneously. He contends that it is overly simplistic to only consider the route with the shortest travel time and that spatial layouts should be considered. Furthermore, he suggests that human spatial cognition has been studied by integrating it into a driving framework (Manley 2014).

For that reason, solving congestion requires a wider context of traffic strategies, through which can be alleviated such as guiding and intelligently managing traffic flows, consciously altering the spatial and temporal situation within the road network, and dynamically adjusting the balance of traffic movements. This research will focus on the City of London's transport network and explore urban congestion strategies effects by modelling real-time urban traffic simulation. The Bureau of Public Roads (BPR) function, which quantifies travel times, can be used to calculate congestion utility in travel models. An advantage of the BPR function is its adaptability. The parameters of the curve can be calibrated to reflect locally observed volume-delay relationships, which may vary depending on factors such as road classification and driver behaviour. The equation of this function is as follows:

$$t = t_0 \times \left(1 + \alpha \left(\frac{count}{capacity}\right)^{\beta}\right)$$

where α denotes the ratio of travelling time per unit distance at actual capacity to the travelling time under free-flow conditions, and the parameter β denotes the rate at which the curve deviates from the free-flow travelling time baseline (Anwar, Fujiwara, and Zhang 2011). London was chosen concerning the parameters of the methodology described by Ninad Gore in his study, which was considered applicable to London's roads as well (Gore et al. 2023).

On the other hand, changes in the road's carrying *capacity* can also vary and provide feedback within this function. The variable *capacity* is determined by the characteristics of the road itself, influenced by factors such as road length, the number of lanes, and safe traffic spacing. Adjusting the values of the test criteria proportionally can accurately reflect the impact of transport congestion system attributes, resulting from policies such as road widening.

In this paper, the factors contributing to urban traffic congestion will be examined, including route choices and traffic system capacity. Real-time traffic simulations will be conducted within the road network of the City of London to uncover the relationship between the model and spatial network attributes, ultimately revealing the mechanisms behind congestion generation in dynamic traffic scenarios.

The two research questions of this study can be formulated as follows:

Research question A.

What is the influence of human origin-destination route choices on the usage patterns of urban roads in the context of real-time transport systems that incorporate congestion variables?

The question contains three sub-points as follows:

- Establishment of origin-destination matrices (ODMs) for various time periods, reflecting the spatial and temporal characteristics of the transport network.

- Evaluate the traffic carrying capacity and develop a simulation model with congestion variables.

- Conduct a comparative analysis of weighted and unweighted model simulations for traffic simulation to simulate congestion-weighted movements.

Research question B.

How does the urban transport system reflect the impact of factors like road closures and congestion reduction strategies such as road widening?

The question contains three sub-points as follows:

- Considering simulation studies of specific roads in unweighted scenarios.

- Employing space syntax perspective, primarily Betweenness Centrality, and conducting a situation analysis of specific roads.

- Considering the simulation of situations where roads with high integration and choice value are affected.

2. LITERATURE REVIEW

2.1 URBAN TRANSPORT SYSTEMS MODELLING

In the pursuit of dynamic modelling, Luc Anselin utilises time slices of spatial observations collected from one or more regional transects. These observations can be structured into grid cells through a digitised base map within a Geographic Information System (GIS). In a broader context, any dataset containing location or distance metrics can be regarded as spatial units of observation (Anselin 1988). Timo Teräsvirta introduces a smooth transition autoregressive model, utilising transport simulations from an economic standpoint. This non-linear time series modelling approach is designed to explore the connection between population concentration and transport models. It reveals intricate interactions between demographic factors and transport modelling (Teräsvirta 1994).

Timo's model has similarities with Luc Anselin's concept of "Spatial econometric classification of spatial linear regression models for cross-sectional and spatio-temporal data". Both researchers explored spatial relationships and applied regression models to analyse spatial data. Matthew O. Jackson incorporated network analysis into the study of spatial systems by constructing networks of economic systems and analysing the interactions and relationships within these networks. Jackson's research provides a valuable perspective on the interactions between space and the economy, revealing the underlying mechanisms that shape spatial patterns and processes (Jackson 2008).

The Origin-Destination Weighted Choice Model holds the potential to be a valuable instrument to gauge the demand for vehicular traffic within urban centres, especially in the context of significant urban development (Karimi et al. 2013). Many scholars have explored the regeneration of origin-destination matrices (ODMs) concerning vehicle speeds and vehicle entry into the transport system. Before the introduction of origin-destination matrices (ODMs), James P. LeSage and R. Kelley Pace proposed a gravity model based on spatial autoregressive dependence. However, it's worth noting that the model still heavily relies on the assumption of independence between origin-destination (OD) flows. The OD flows describe the traffic between zones. The data in this matrix reflects the movement of traffic from one area to another, providing insight into the level of congestion on roads (LeSage and Pace 2008). Sharminda Bera and K. V. Krishna Rao explore how traffic count data can be used as a tool for ODM estimation, arguing that the use of traffic counts to estimate ODM introduces complexity, and that it is important to use existing data to estimate updated ODM based on outdated trip information (Bera and Rao 2011).

In the context of implementing Origin-Destination Matrices (ODMs) in real spatial environments, the necessity of conducting all-to-all analyses should be assessed. One approach is stochastic utility theory, such as the logit-based Stochastic User Equilibrium (SUE) concept introduced by H. Yang, Q. Meng, and Michael G. H. Bell in the evaluation process of ODMs. This concept considers the congestion effect when estimating the ODMs (Yang, Meng, and Bell 2001).

2.2 TRAFFIC SYSTEM ANALYSIS FROM A SPACE SYNTAX PERSPECTIVE

Aisan Kazerani and Stephan Winter explore the potential correlation between centrality and traffic flow, arguing that traffic flows exhibit unique characteristics related to the spatial and temporal distribution of traffic demand and emphasising that these dynamic features should not be ignored (Kazerani and Winter 2009). Space Syntax Laboratory at UCL introduced many methods such as angular betweenness centrality, to advance the study of space syntax through the use of Depthmap X (Varoudis et al. 2013). Betweenness centrality measures the extent to which a node is positioned along a path between other nodes. It relates to the global significance and its influence on total network flows. To quantify the degree to which a node lies on a path between other nodes, a space syntax perspective is adopted, integrating spatial attributes like depth, integration, or choice. This integration establishes topological connectivity, resulting in a comprehensive 'all-to-all' metric known as topological betweenness centrality (Al-Sayed et al. 2014).

The study of the spatial structure of vehicular traffic encompasses more than just road analysis. It also delves into broader transport concepts, emphasising how changing traffic conditions influence the spatial layout of cities. Researchers in this field commonly utilise space syntax methods to explore various locations worldwide. One popular approach involves analysing spatial integration before and after a transition occurs. For instance, Ayşe Sema Kubat evaluated the planned construction of bridges in Istanbul, employing both original bridge usage data and space syntax analyses to assess spatial transitions (Kubat et al. 2007). Similarly, Edja Bezerra Faria Trigueiro employs a spatial comparative approach to investigate the decline of centrality in Natal, Brazil (Trigueiro and Medeiros 2007). Lars

Marcus explores the integration of spatial morphology and resilience science to analyse disturbances and repairs from a space syntax perspective (Marcus and Colding 2014). These studies offer a space syntax analysis of traffic, with a central focus on the spatial layouts. Specifically, they provide valuable insights into the broader impact of bridges, a critical road type, on the urban fabric.

In recent years, the dynamic activities and changes induced by bridges have gained significant attention in urban transport discussions. Unlike previous research, Weijia Wang concentrated on footbridges in Hong Kong, conducting morphological analyses of various footbridge types and microscopic studies through in situ methods, including observational counting (Wang, Siu, and Wong 2016). Karl Kropf replicates spatial structure using overlapping methods of morphological and urban organisational analysis (Kropf 2017). Daeyoung Jeong's study of a bridge in Ganghwa County, South Korea, adopts a method involving prospect networks as a research module, leading to clear conclusions about spatial centrality (Jeong et al. 2019). Valerio Cutini tested a computational analysis of street network resilience based on the theory of space syntax to examine bridge collapses, of which those of the Genoa and Bologna bridges serve as case studies, to construct resilient transport systems that can be analysed from a sustainability perspective (Cutini and Pezzica 2020). Space syntax has significant advantages in characterising the spatial pattern of traffic and provides new perspectives for solving urban traffic problems.

3. METHODOLOGY

3.1 RESEARCH FRAMEWORKS

The entire framework of the study is shown in Figure 2, with Chapter 4 of the article aiming to answer Question A and Chapters 5-6 aiming to answer Question B.

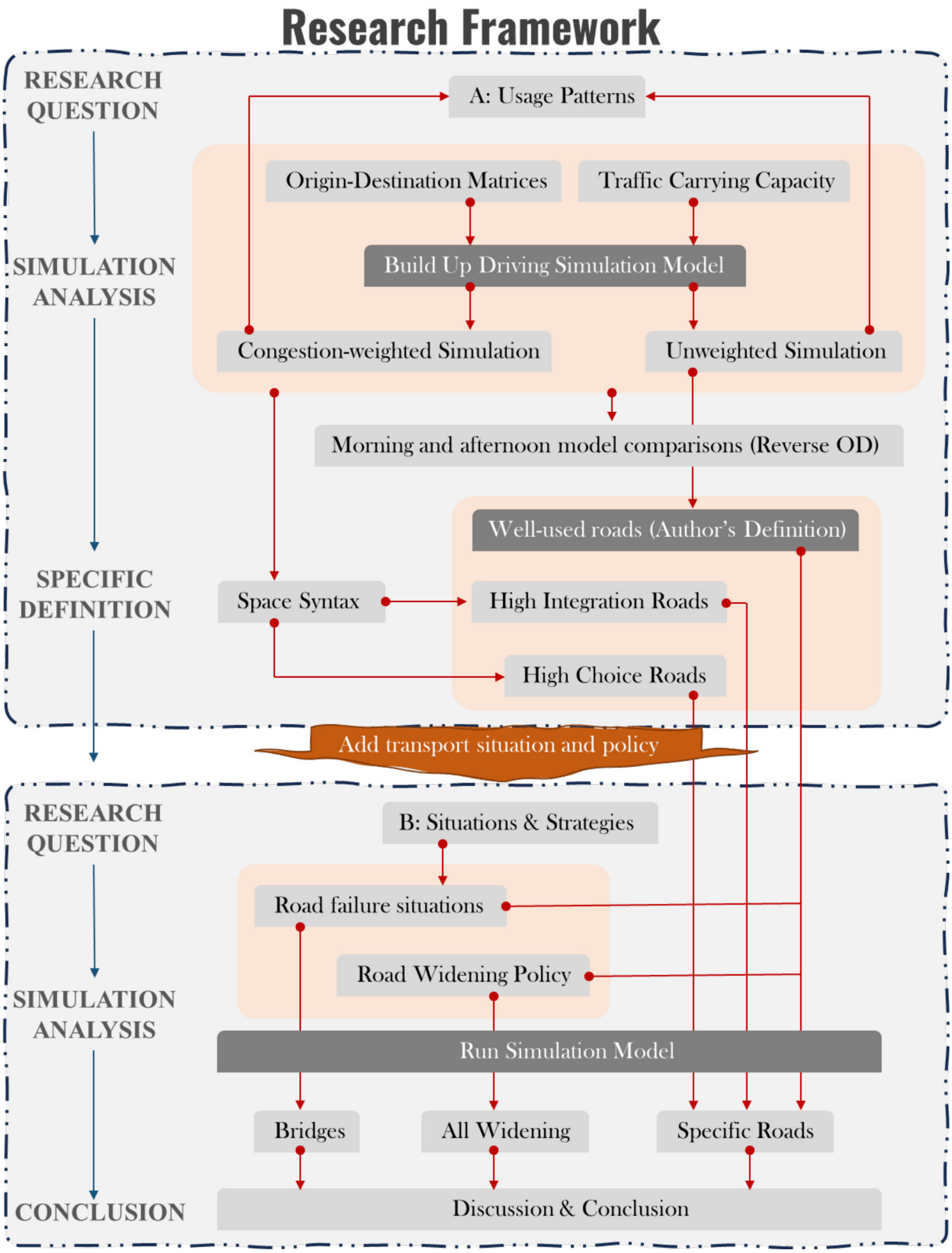


FIGURE 2 RESEARCH FRAMEWORK

Initially, interconnected segment maps were generated within a 5km radius of the City of London using QGIS with OpenStreetMap data. Residential areas from OpenStreetMap's land use data served as the departure points (Origin) for commuting time traffic. Probability estimations for the number of departing vehicles were based on London borough boundary data, sub-district population data, and the London M25 segment map. In addition, the traffic network was examined using Point of Interest (POI) data for commercial services distribution and density to select destinations for commute-time traffic and determine their probabilities. Origin-destination (OD) pairs for each vehicle were constructed using the *random.choice* function from Python's *NumPy* library, thus forming the Origin-Destination Matrices (ODMs) for the system.

The hourly vehicle carrying capacity is determined using data from Transport for London's daily traffic count and the City of London's daily traffic count distribution. This information is then used to create a road choice simulation for Origin-Destination Matrices (ODMs) in Python, with vehicles travelling every 5 seconds.

Subsequently, the Bureau of Public Roads (BPR) function is applied to assess congestion utility in traffic distribution analysis. This aids in the development of a dynamic simulation model for real-time traffic systems and a congestion effect analysis model. Travel simulations are performed, considering changes in speed due to congestion and simulations without accounting for speed changes. Subsequently, the description and comparative analysis of two sets of morning and afternoon simulation data, involving exchanged origin and destination distributions, and results from both weighted and unweighted models, aim to address question A. The analysis also explores the spatial characteristics of the road network model from a space syntax perspective.

Using this simulation model, the impact of traffic standstill scenarios in specific spatial locations can be investigated by modifying congestion coefficients on certain roads within the system. This can be achieved by controlling vehicle speeds or altering the number of bridges on the map. Meanwhile, the effects of widening roads can be examined by adjusting capacity parameters for all or specific roads. These two aspects of the study are intended to be linked to address problem B.

3.2 DATASETS

Readily available data in the UK are used in the study that enable the application of the chosen methods to different city contexts.

The transport variables of the research are as follows: Each variable is constructed from the datasets in Table 1, which is a geographic data vector or raster.

TABLE 1 DATASETS

	Variables			
	Traffic Flow	**Road Networks**	**Residential Distribution & Density**	**Commercial Services Distribution & Density**
Datasets	OpenStreetMap Land Use Data Road Centreline Map GPX Data; Traffic Count https://roadtraffic.dft.gov.uk/downloads; Vehicle Speed Detection https://www.tomtom.com/traffic-index/london-traffic.	London M25 Segment Map.	Census; OpenStreetMap Land Use Data Road Centreline Map GPX Data.	Digimap Point of Interest (POI).

4. MODELLING OF TRAFFIC SIMULATION

The traffic model constructed in Sections 1 and 2 of this chapter serves as the foundation for the simulation in Section 3. Then it is examined from various angles, including with and without congestion weighting, as well as the reversal of OD in the morning and afternoon with different vehicle capacities.

4.1 A REAL PORTRAIT OF URBAN TRANSPORT

In real life, roads serve as carriers for vehicular traffic behaviours every day. Commuting behaviour is a significant topic, as Glenn Lyons and Kiron Chatterjee describe in their report "The average UK worker commutes 139 hours a year, equivalent to 19 standard working days". One in two commuters travels more than 100km to work (in both directions), and one in ten endures a daily commute of over 2 hours (Lyons and Chatterjee 2008). Traffic models can realistically simulate the movement of vehicles. The urban commuting system can be simplified and understood as vehicles journeying from origin to destination. Before setting off, individuals choose their routes based on mapping software and then proceed directly to their destination. Naturally, the vehicles departing at different times influence the road attributes in route selection, giving rise to phenomena like congestion.

This model aims to facilitate the representation of actual urban traffic. Previous research on constructing such models typically revolves around vehicle speed, exemplified by Sharminda Bera and K. V. Krishna Rao's estimation of genuine flow for various ODMs through observations of real link flows (Bera and Rao 2011). In the pursuit of continuous dynamic modelling, Luc Anselin adeptly employs one or more time slices of regional cross-sectional spatial observations (Anselin 1988).

4.2 MODELLING OF TRAFFIC SYSTEM

The traffic model is constructed through 4 steps:

4.2.1 Mapping the Traffic Network

Charting the transport network (segment by segment) based on the London M25 segment map, study radius 5km, total buffer radius 6.5km. As illustrated in Figure 3, the transport system configuration surrounding the City of London is displayed. The data stems from the London M25 segment map and has been tested as a unified traffic system without isolated segments.

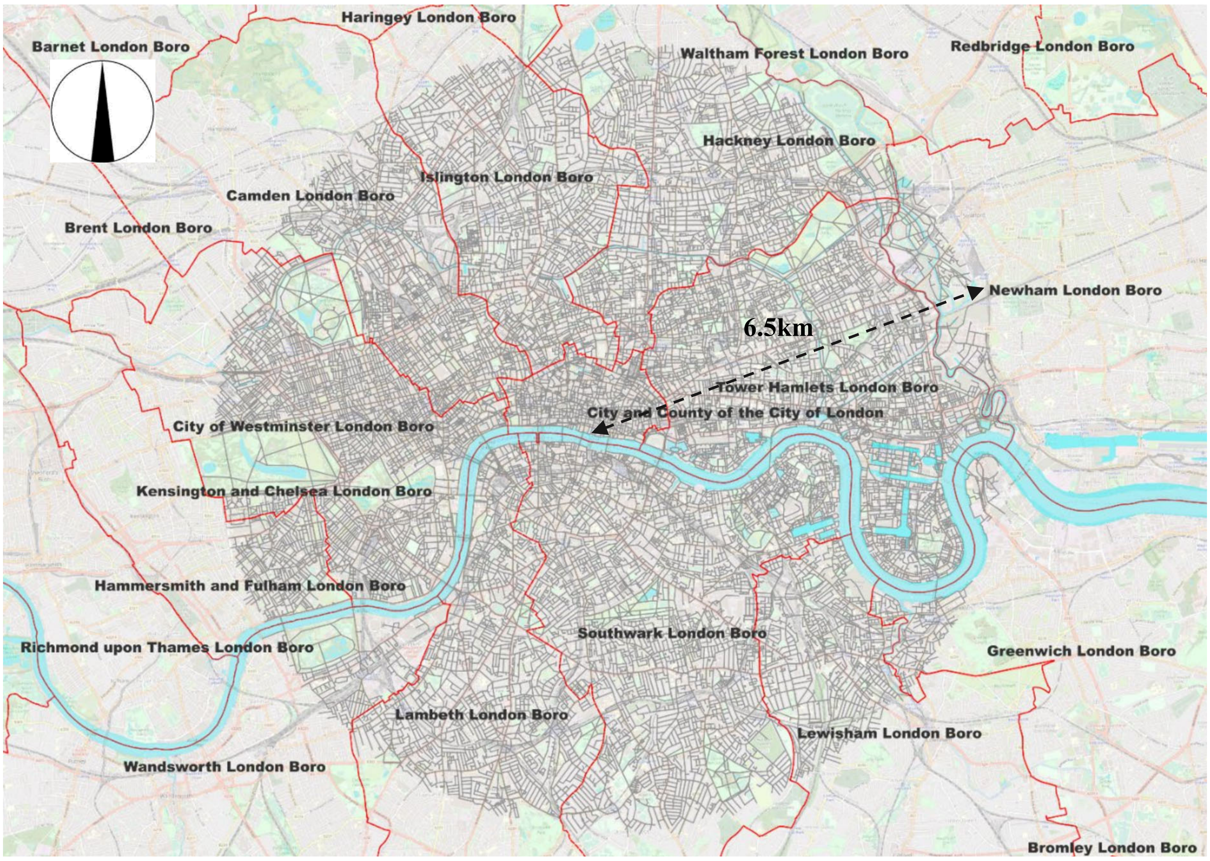


FIGURE 3 MODEL BASE MAP

This selection of this foundational map constitutes a different feature between this traffic model and the preceding ones. The adoption of the Segment map permits the articulation of spatial dynamics. In this context, it can represent the traversal of a small car, with each segment of the journey modelled individually, rather than only considering the commute's entire length.

4.2.2 Identifying Behavioural Activities

The study analysed the spatial attributes to determine the activity generated by the commuting behaviour. Glenn Lyons and Kiron Chatterjee classified them as transport routes from the place of residence to the place of work (Lyons and Chatterjee 2008).

This model utilises OpenStreetMap's residential land use as the departure point (Origin), where the residential location is buffered by 20 metres using GIS to accommodate residents' access to the segments. This is depicted in Figure 4a, with the residential function indicated in yellow and the area's population represented by numbers and colours in the region. The population in the area outside the study zone was adjusted to account for the total population of the region.

(A) ORIGIN: RESIDENTIAL & POPULATION (B) DESTINATION: COMMERCIAL SERVICES

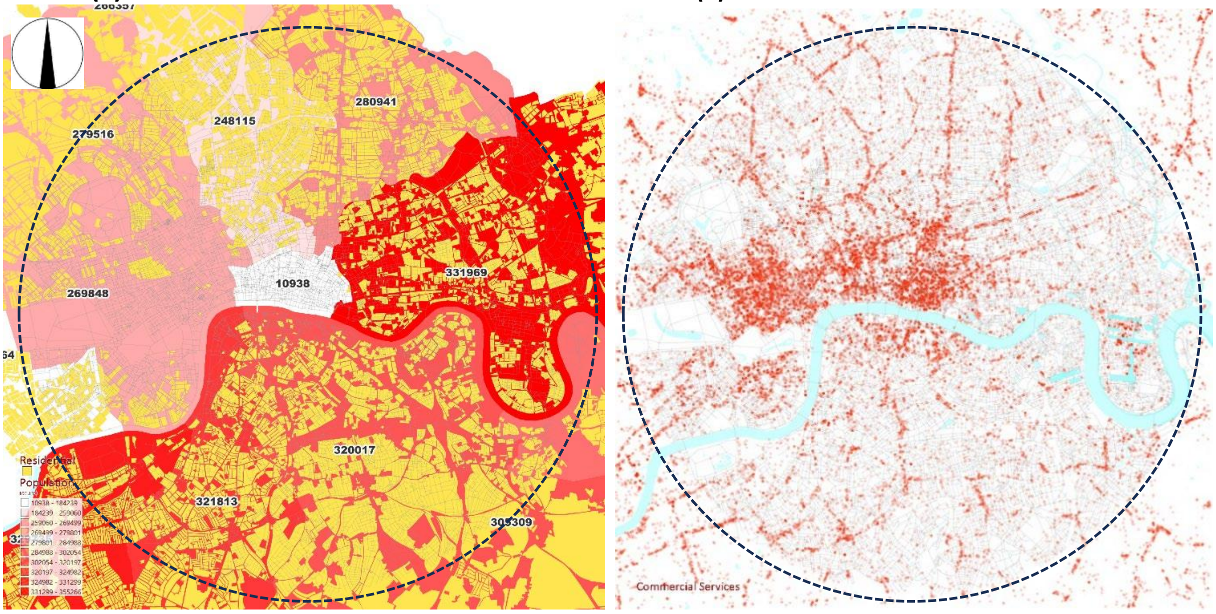


FIGURE 4 ORIGIN & DESTINATION LAYOUT

On the contrary, commercial services were considered workplaces (with buffering applied), employing point of interest (POI) data from Digimap. The spatial distribution of these workplaces is depicted through the arrangement of points, illustrated in Figure 4b.

4.2.3 Creating Origin-Destination Matrices

This functional characteristic, which serves as the origin and destination of activities, is subsequently converted into segments within the system through the allocation of values. For the origin, the assignment relies on population. The formula is as follows:

$$Population = \frac{Segment\ Length}{Total\ Length} \times Total\ population$$

For Destination, assign the count of units touched by each segment.

In this manner, the potential selections for each origin and destination point can be made in a probabilistically random manner, thereby establishing the ODMs for departure and destination points across different periods.

Figure 5 depicts the OD screening sections and the possibilities constructed through the methodology mentioned above. The specific ODMs need to be regenerated as required when vehicles enter the system.

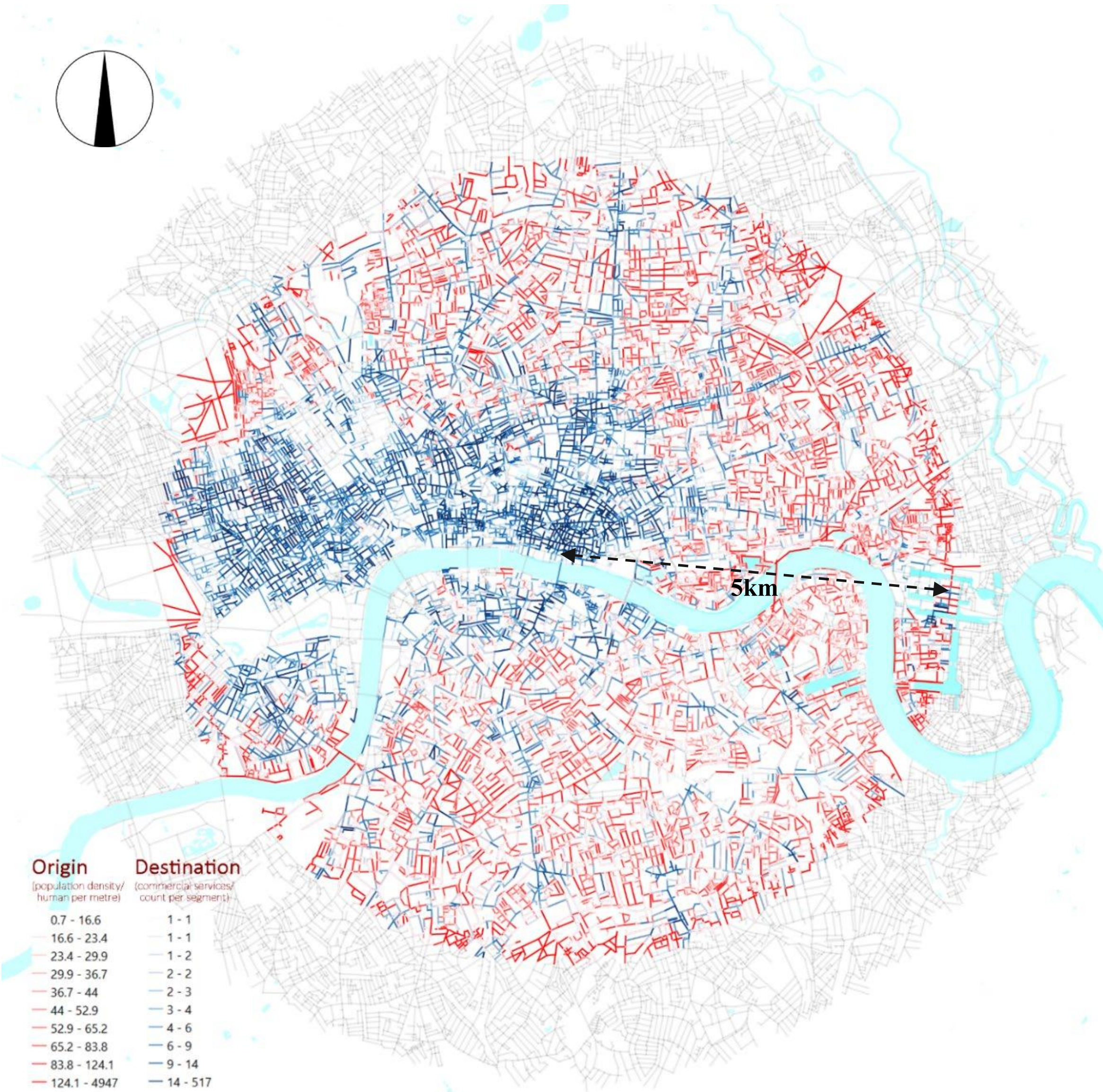


FIGURE 5 ORIGIN AND DESTINATION LAYOUT AND POSSIBILITY (REVERSE ODMS IN THE AFTERNOON)

The exploration of traffic issues through the regulation of OD (origin-destination) link flows is not novel. Although models devised by James P. LeSage and R. Kelley Pace require the exclusion of scenarios with zero flows, they acknowledge that empirical work continues to heavily rely on the assumption of independence between OD flows (LeSage and Pace 2008). Bera and Rao employ presently available information to estimate updated Origin-Destination Matrices based on previous trip data (Bera and Rao 2011). This approach isn't confined to transport modelling alone; it's also prevalent in the examination of urban spatial attributes. For instance, Kayvan Karimi endeavoured to formulate an OD-weighted choice model for predicting real urban spatial utilisation in urban development studies (Karimi et al. 2013).

Regarding the application of ODMs in real spatial contexts, a consideration emerges regarding whether an all-to-all analysis is necessary. Firstly, there are two all-to-all methods exist, the random utility theory, exemplified by Hai Yang, Qiang Meng, and Michael G. H. Bell's Logit-based stochastic user equilibrium, which assigns individuals' choices based on utility, not the most time-efficient option (Yang, Meng, and Bell 2001). This approach suits subsequent analytical discussions employing maximum likelihood estimation, particularly when the dependent variable vector conforms to normal distribution, and when the zero-flow road choices do not exist. Another model incorporates the spatial characteristics of space syntax, wherein concepts like depth, integration, or choice constitute topological connections in graph theory. This results in a balanced all-to-all approach, exemplified in concepts like Tasos Varoudis' angular betweenness centrality algorithms (Varoudis et al. 2013). This method shows the development of stable spatial attributes within the system and carries a high level of credibility.

The rationale for choosing a randomised algorithm (completely different from random utility theory) over an all-to-all approach at this stage can be summarised as follows 3 reasons:

Firstly, the fundamental aspects under comparison in the model include trip counts, travel times, and road selection under different simulation assumptions (congested or uncongested scenarios). The primary objective is to establish uniform criteria for road selection rather than delving into the examination of travel modes or routes within the utility model.

Secondly, the simulation process in the model involves a cyclic iteration wherein the number of vehicles in each segment of a spatial slice at a particular moment influences each other. This interplay alters travellers' road choices in subsequent moments. If the Logit-based all-to-all utility distribution was employed, the temporal dimension's significance would diminish. Additionally, the system's congestion would be represented by a constant coefficient, failing to account for varying congestion effects on road choices (congestion weight remains fixed).

Finally, in the context of actual driving, each vehicle typically follows a single path for a given trip. On the contrary, the generalised all-to-all space syntax calculates relationships between all line segments, lacking the capacity to intuitively depict the driving patterns of individual vehicles. Simultaneously, the study of congestion's impacts necessitates a systematic exploration of the segments' collective vehicle carrying capacity. If the all-to-all approach is employed, the overall carrying capacity constraint may be disregarded.

Considering these factors, the stochastic algorithm is better suited for capturing the dynamics of traffic behaviour, road selection, and congestion effects within the model.

4.2.4 Evaluating Traffic Carrying Capacity

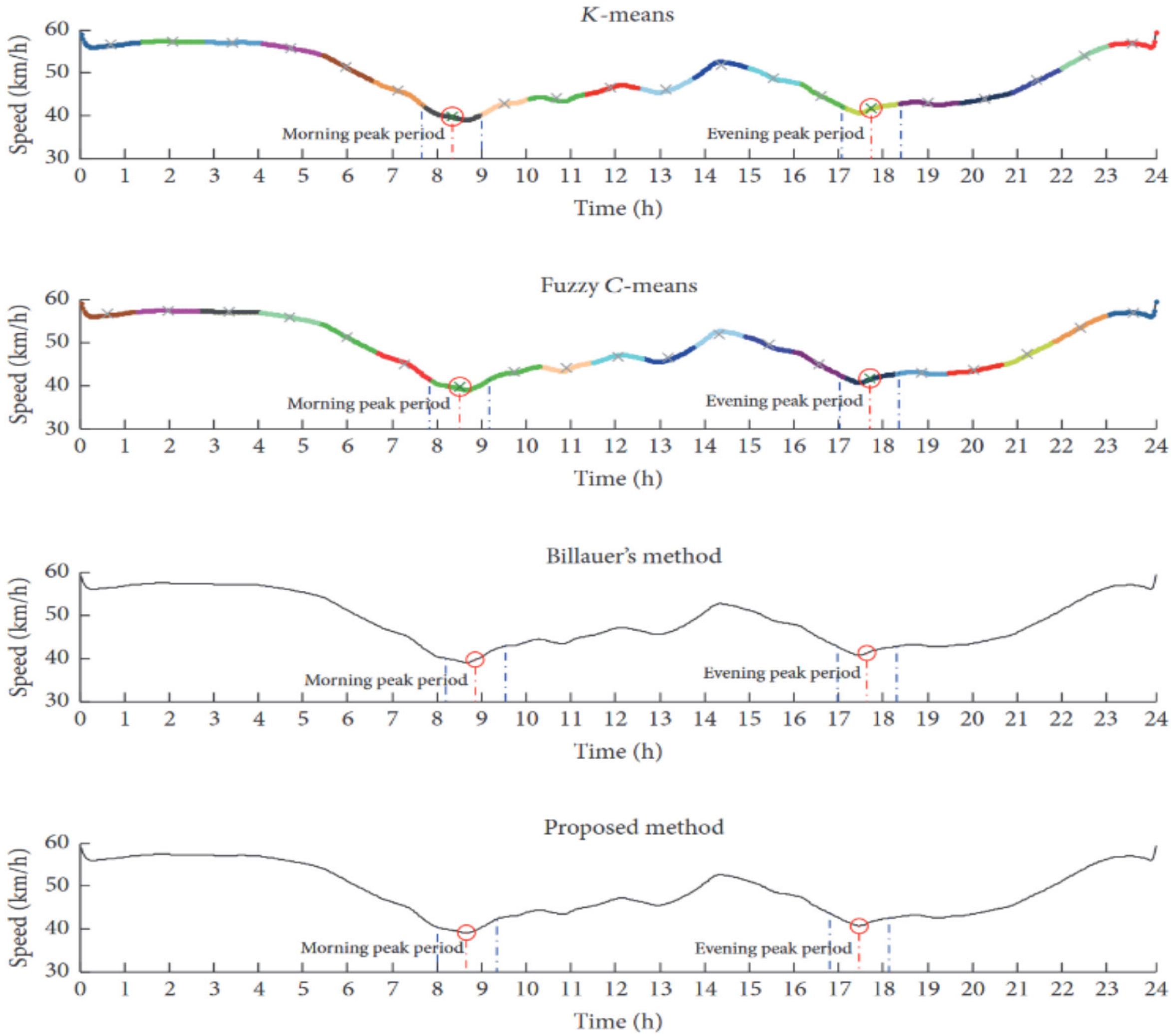
Peak hourly speeds were recorded, and the traffic-carrying capacity of the transport system at a specific time (i.e., the actual number of vehicles during the corresponding period) was analysed using Traffic Count data.

In Andrew P. Tarko's study, he examined peak hour coefficients, which involved observations and fits for vehicle speeds during the AM and PM peak hours (Tarko and Perez-Cartagena 2005). However, the objective of the research is not to explore various modes of transport. Rather, the goal of this model is to predict hourly vehicle volume, enabling an investigation into the most heavily burdened transport system during the morning and afternoon commuting hours of 7:00 AM to 8:00 AM and 4:00 PM to 5:00 PM, respectively.

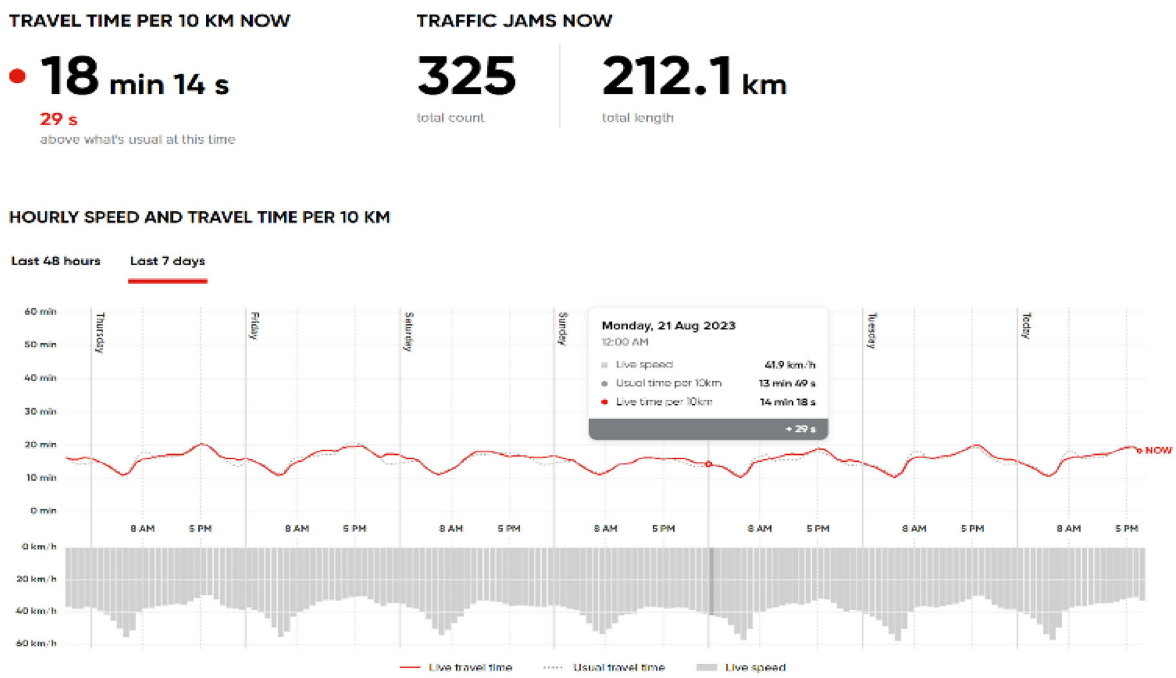
Similar to this approach, Jianli Xiao's 'Traffic Peak Period Detection' also demonstrated comparable performance in terms of the type of speed study. Additionally, the concept of time-space lag is discussed. Figure 6a illustrates peak speeds after smoothing, indicating that congestion is most pronounced from 7:00 AM to 9:00 AM and 4:00 PM to 6:00 PM (Xiao et al. 2018).

Similar results are not limited to this study. Comparable outcomes are evident in Figure 6b, sourced from Tomtom's London Traffic Report website. This depiction utilises data from a weekday, showcasing speed at distinct time intervals calculated using the Usual Time per Kilometer metric.

(A) SPEED OF THE HOURS (XIAO ET AL. 2018)



(B) VEHICLE SPEED DETECTION HTTPS://WWW.TOMTOM.COM/TRAFFIC-INDEX/LONDON-TRAFFIC



(c) Motor Vehicle and People Cycling Counts by Hour Of Day (30 sites) (Vecia 2019)

(d) Real Car Speed and Car Counts

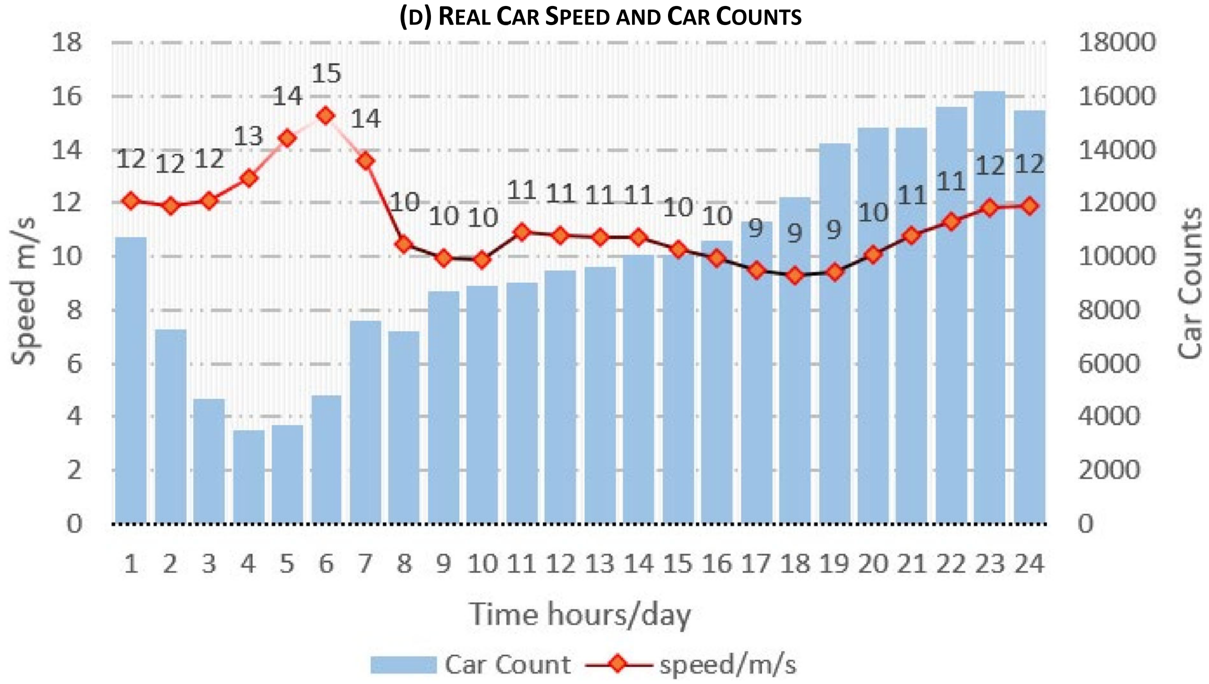


Figure 6 Vehicle Speed & Capacity per Hour

Furthermore, Figure 6c illustrates findings from the 2019 City Traffic Survey (Vecia 2019). This dataset stems from the City of London's link count research and specifically focuses on a subset of transport modes—cars and taxis. The subsequent calculations culminate in the results presented in Figure 6d. Notably, the speeds shown in the figure are integers for ease of visualisation, while all underlying calculations remain accurate.

For assessing the vehicle capacity of the system, the model utilises count data from the Department of Transport of GOV.UK, which is exclusively accessible for the main roads. In this scenario, the calculation approach involves the utilisation of the interpolation method to determine the number of trips across all roads, as illustrated in Figure 7.

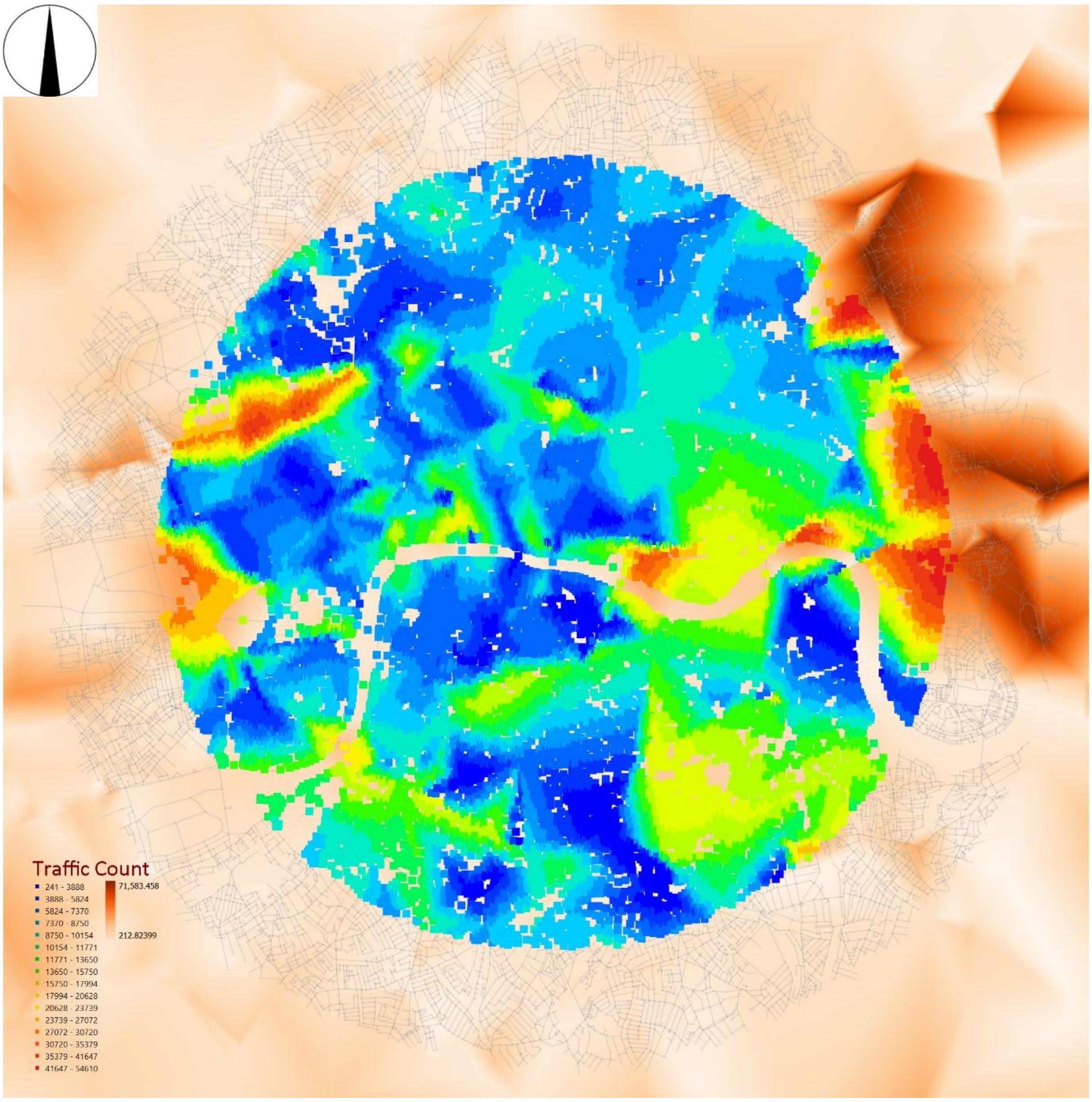


FIGURE 7 INTERPOLATED TRAFFIC COUNT DATA

The formula employed to calculate the vehicle capacity for each period is as follows:

$$Capacity = \frac{total\ count \times average\ segment\ length}{total\ length\ per\ day}$$

The cumulative number of trips is obtained through interpolation, representing the monitoring approach for each segment. By calculating the system's average car capacity with the number of trips, the value for the number of trips can be determined. Subsequently, adhering to the proportions derived from the genuine research relationship, allocation is made to distinct periods.

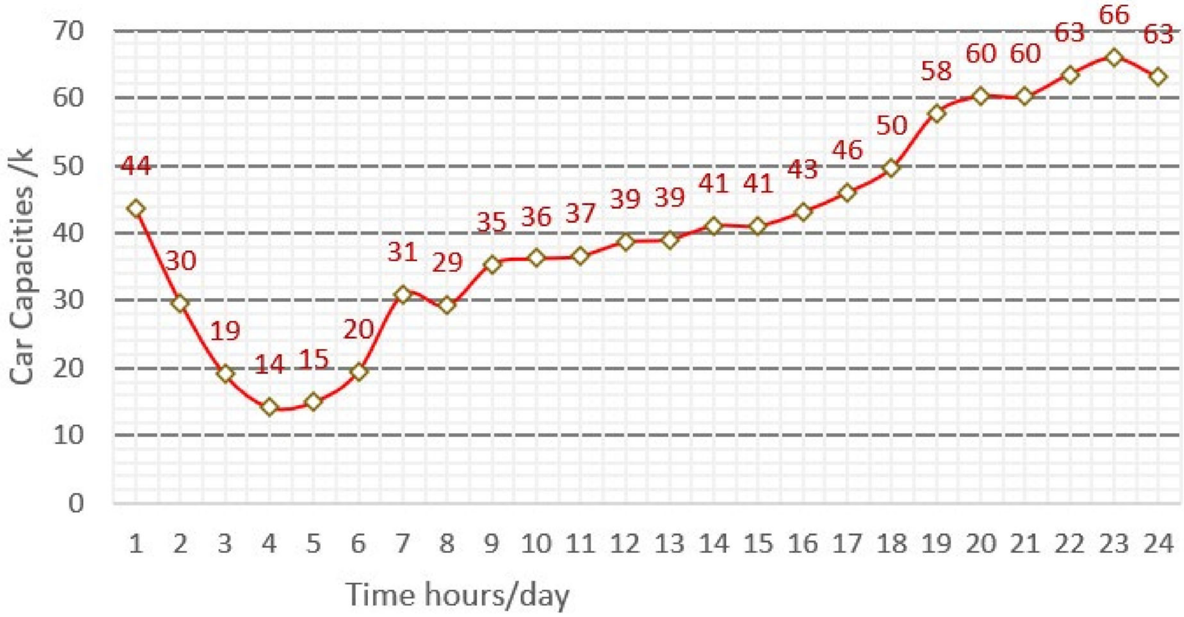


FIGURE 8 CAR CAPACITIES

The illustration of the car system's capacity is presented in Figure 8. Note that the integer representation of speeds within the figure aids visualisation, while the underlying calculations retain their precise accuracy.

Each step of the above analyses contributes to the model's comprehensive representation of urban traffic behaviour and its subsequent analysis.

4.3 TRAFFIC SIMULATION ANALYSIS

4.3.1 Pre-determined Parameters

Based on the traffic system mentioned above, a dynamic traffic simulation was conducted. The traffic system was simulated for 7:00 a.m.-8:00 a.m. and 4:00 p.m.-5:00 p.m., corresponding to the commuting hours under study. When considering peak hour speeds and the operation of real traffic, a crucial point to note is that there should be a sufficient number of vehicles (up to the system's vehicle capacity at that moment) within the system at the beginning of the study period. For this simulation to accurately reflect the actual situation, a preliminary 30-minute simulation of the system from scratch (not factored into the analysis of the results) is necessary to establish the spatial distribution of the traffic system at the start of the hour, specifically identifying the locations of the cars. To clarify, a model for 7:00 a.m. should commence at 6:30 a.m., while a model for 4:00 p.m. should commence at 3:30 p.m.

The BPR function (Bureau of Public Roads) was employed for congestion utility calculation before simulation modelling was conducted on London's road network, using parameters $\alpha = 0.15$ and $\beta = 4$. For enhanced modelling of the BPR function, alternative approaches like Conical Volume-Delay Functions (Spiess 1990) could be explored in future research if they demonstrate value in advancing research in this direction.

4.3.2 Driving Simulation Model Demo for Each Loop

A model of radius 1.5 km, comprising 4152 segments, is chosen for the driving simulation demo, representing the driving calculation small time interval loop. A fixed number of cars is employed to generate the ODMs in Figure 9a.

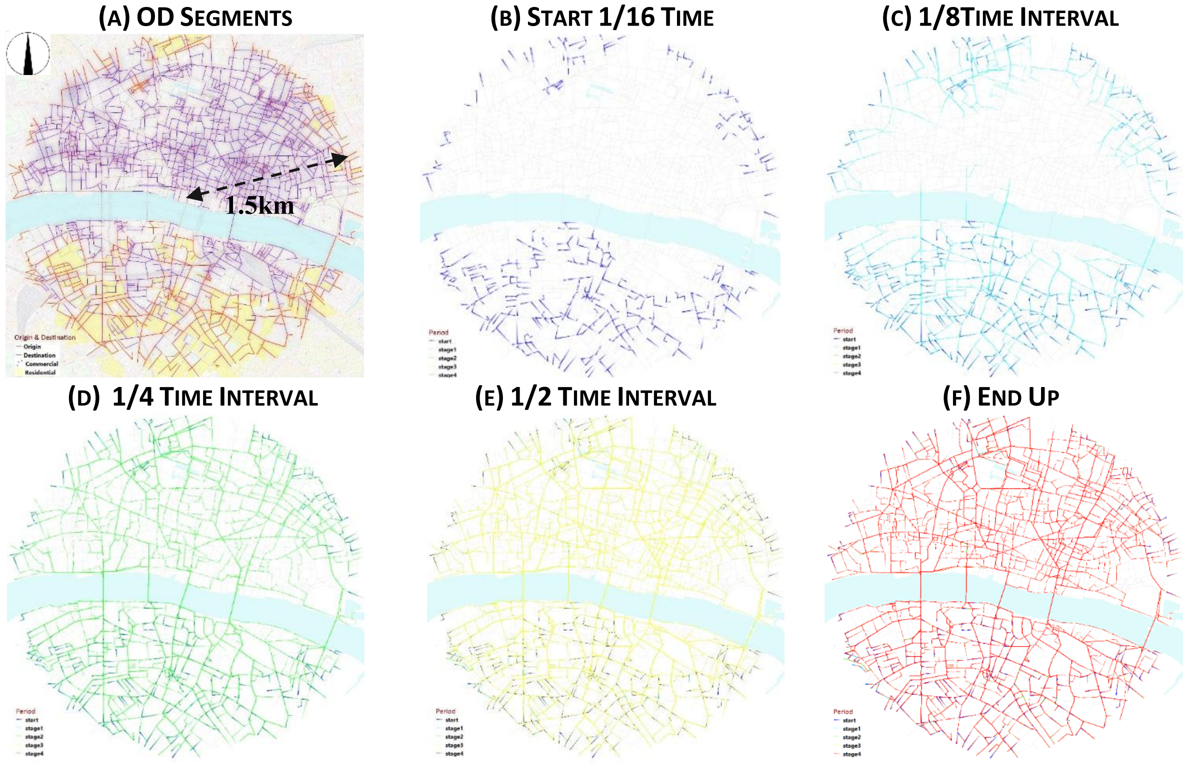


FIGURE 9 ONE CYCLIC PROCESS DEMO OF SIMULATION

In this case, 1000 cars are selected, causing vehicles to depart from the initial point at various intervals. Each second, the speed is calculated based on the number of cars on the current road, leading to congestion. However, its impact on road selection is initially disregarded. This process continues until all vehicles complete their routes.

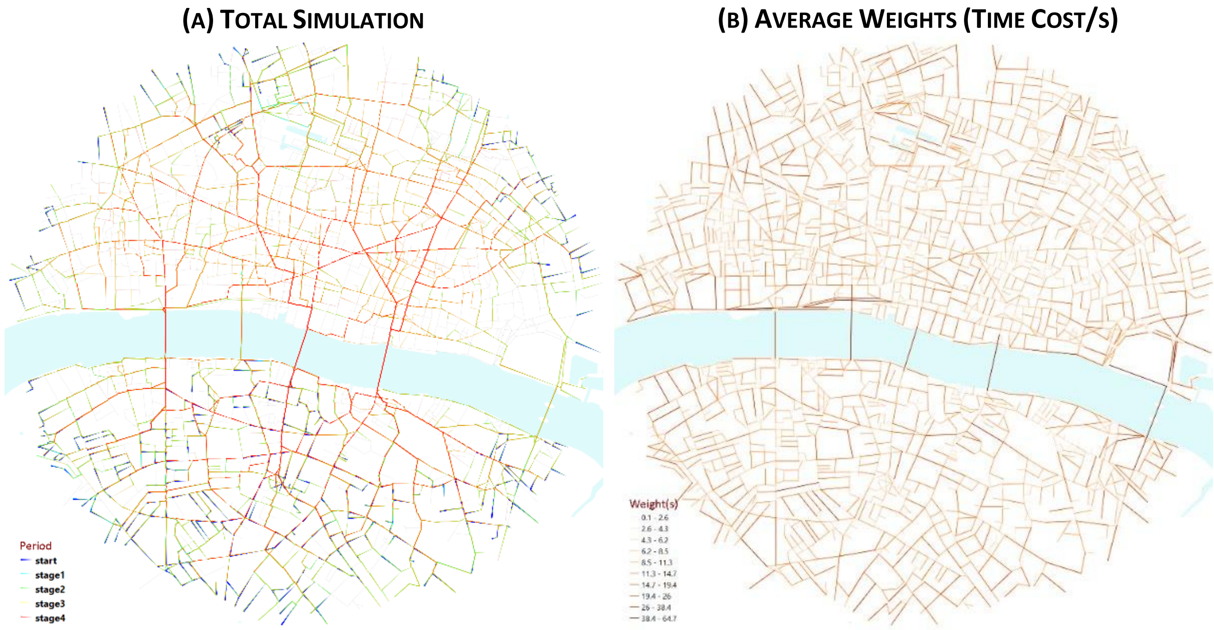


FIGURE 10 TOTAL SIMULATION LAYOUT AND AVERAGE WEIGHTS

With this running pattern, the demonstration can determine the quantity of vehicles in this area and assign corresponding congestion weights to the roads. These weights are based on the average usage frequency, which is the time required for each segment to be traversed, which is shown in Figure 10b.

The model has a notable advantage in its ability to intuitively comprehend vehicle operations and sense the repercussions of vehicle interactions within the system. Nevertheless, it is not without its challenges:

Firstly, the actual model lacks a distinct "starting moment" as the system remains in a perpetual operational state. Furthermore, vehicle interactions persist both before and after the observation period.

Secondly, the frequency of vehicle appearances in the model remains variable, contingent upon the system's capacity to accommodate vehicles, as mentioned in the concept above. The system's scale is limited, resulting in a somewhat one-sided representation.

Thirdly, it is limited to generating fixed weights and lacks the capability to provide continuous time-sliced spatial road choice weights.

The real model is more complex because it requires numerous cycles of the above process. Each cycle generates new weights that affect the next cycle. The following simulation is based on a large model with a radius of 5 km, a total of 29023 segments, an average of 300 vehicles entering the system every 5 seconds, and a total of approximately 300000 vehicles in an hour.

4.3.3 Define the Simulation Steps

The comprehensive model outlined below effectively resolves the aforementioned challenges and calculates fundamental concepts that allow for meaningful comparisons across different systems. Additionally, it serves as the foundation for conducting analogous analyses involving spatial attributes.

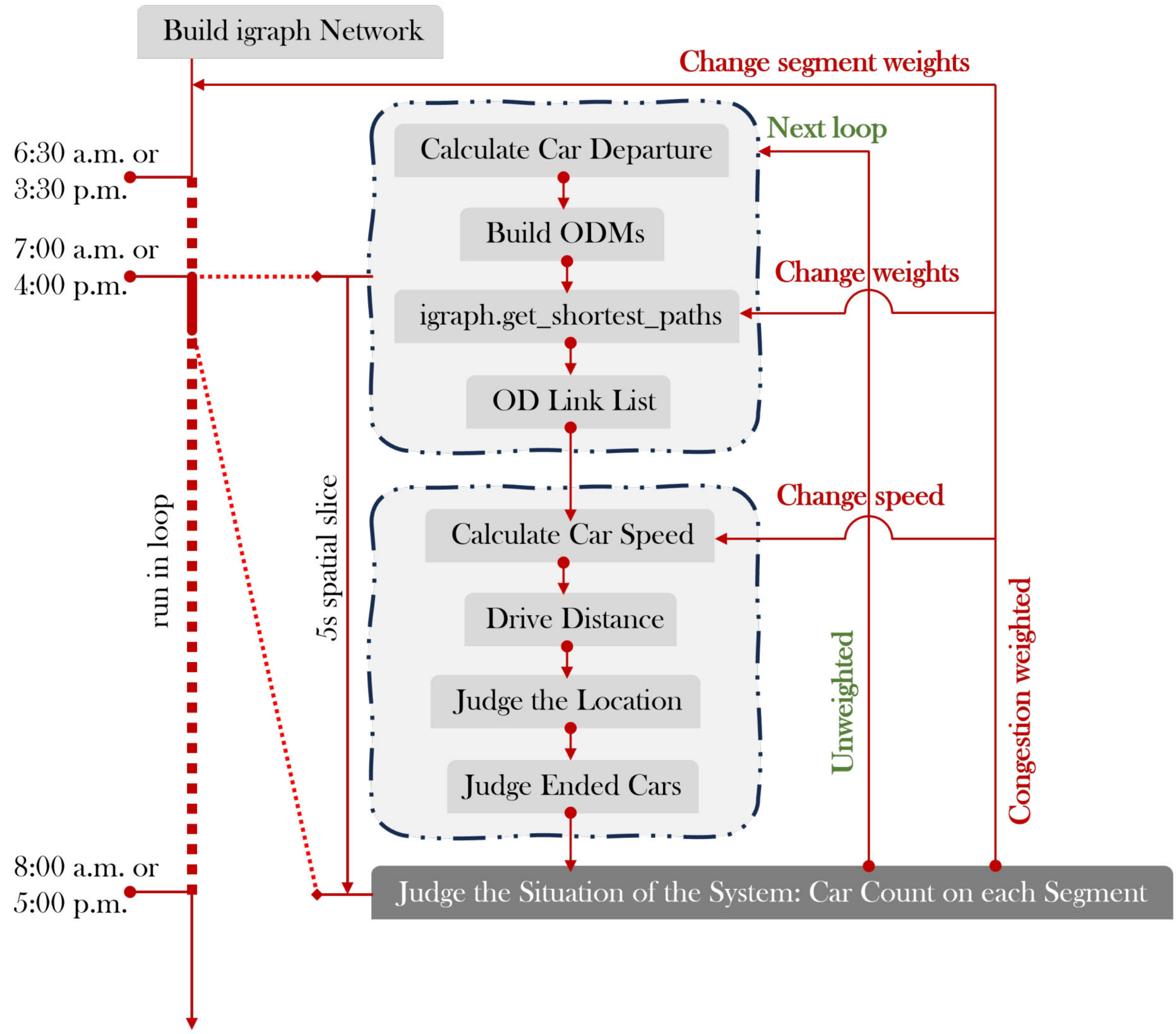


FIGURE 11 MODEL RUN PROCESS PATTERNS

As depicted in Figure 11, the simulation's behaviour involves segmenting the traffic system into a 5-second intervals loop. The 7 activities within each interval encompass:

Firstly, the creation of an *igraph* network to facilitate vehicle movement across segments. Weights corresponding to each segment can be incorporated into this graph-theoretical network. The weighted average value of connected segments is considered for real driving simulation, determining the number of vehicles departing from this slice.

Secondly, the calculation of departing vehicles involves constructing a linear demand function from the hourly vehicle demand in the traffic system. This function is used to subtract the vehicles present in the system, yielding the number of departing vehicles.

Thirdly, integration of population and commercial service distributions with random number control to identify spatial line segments for extra demand vehicles. Corresponding Origin-Destination Matrices (ODMs) are generated for these newly demanded vehicles.

Fourthly, utilising *igraph*'s network shortest path routing function to establish a two-dimensional list of Origin-Destination (OD) links. These links represent the paths vehicles need to travel once they depart.

Fifthly, for the congestion-weighted model, vehicle speeds are calculated using the BPR function. Vehicles are advanced within each 5-second interval based on this function, ensuring their arrival at the slice's designated location. In contrast, the unweighted model maintains a fixed speed.

Sixthly, assessment of the spatial slice's state at the 5-second interval's conclusion, encompassing vehicle positions and segment-specific vehicle counts.

Finally, modification of *igraph* network weights based on the weighted model's slice state. This modification affects road choice and vehicle speeds in subsequent stages. In the weighted model, adjustments to *igraph* network weights are determined by the slice's state, influencing road choice and vehicle speed in the subsequent stage according to the BPR function.

4.3.4 Solutions to Some of The Problems of Modelling

Three issues need to be addressed: Firstly, ODMs are influenced by random numbers, resulting in individualistic and specific model instances. To reduce this, a single model can be executed with various random number seeds using multi-core processing. This approach generates multiple models run, allowing for the averaging of results to produce more representative outcomes.

Secondly, the lack of an all-to-all model results in scenarios with zero flow. Although this poses challenges for certain correlation studies, the fundamental parameters constructed in this model remain valid.

Thirdly, in the model, not all vehicles on a path are equally affected by congestion as per the BPR function. For instance, vehicles at the forefront might not be influenced by vehicles entering from behind. The BPR function averages the impact across all vehicles within the segment, leading to potential issues. This can result in an accumulation of over 10,000 vehicles in a 5-second interval on a road with a capacity for only a few hundred or tens of vehicles, leading to inaccuracies.

The solution to these three problems involves two considerations: Firstly, ensuring that the number of vehicles entering a road remains below its capacity. Secondly, maintaining the number of concurrently affected vehicles within a reasonable range. This can be achieved through iterative testing, adjusting the minimum speed to ensure segment capacity while also guaranteeing the rationality of road weights during the road selection phase for every 5-second interval.

Addressing these issues with the provided solutions will enhance the reliability and accuracy of the model's outcomes.

4.3.5 Results of Simulation Model Analysis

In accordance with the outlined procedure, a total of four distinct sets of models were executed. These sets correspond to two periods, 7:00 - 8:00 a.m. and 4:00 - 5:00 p.m., each encompassing both weighted and unweighted variants. These models were executed repeatedly for a total of five iterations, each time employing distinct random number sequences. The randomness of these numbers was meticulously managed through the utilisation of the *Random Generator* module sourced from the *NumPy* library in the Python programming language.

The Generator provides access to a wide range of distributions and serves as a replacement for Random State. The main difference between the two is that the Generator relies on an additional *BitGenerator* to manage the state and generate the random bits, which are then transformed into random values from useful distributions. The default *BitGenerator* used by the Generator is PCG64. The *BitGenerator* can be changed by passing an instantiated *BitGenerator* to the Generator.

In the initial analysis comparing the congestion-weighted and unweighted model, Figure 12b provides an average representation of vehicle counts across five model runs during 7:00 - 8:00 a.m. as traffic count. This result illustrates the broader distribution of vehicle routing and travel frequency of road use within the models.

(A) FIVE-CORE COMPUTING MODELS

(B) AVERAGE TRAFFIC COUNT (UTILISATION OF ROADS)

FIGURE 12 UNWEIGHTED MODEL TOTAL TRAFFIC COUNT FOR 7-8 AM

In Figure 13, a complete simulation run of the unweighted model is displayed. This illustration presents the final positional records occurring every 5 minutes and captured at each total 60-time slice of 5-second intervals. This visual showcases the spatial distribution of vehicles during the time span. It is important to clarify that colour variations within the graphs signify relative quantitative relationships. They do not stand for the total number of vehicles. Furthermore, the vehicle capacity of the system roads incrementally updates every 5 seconds within this simulation.

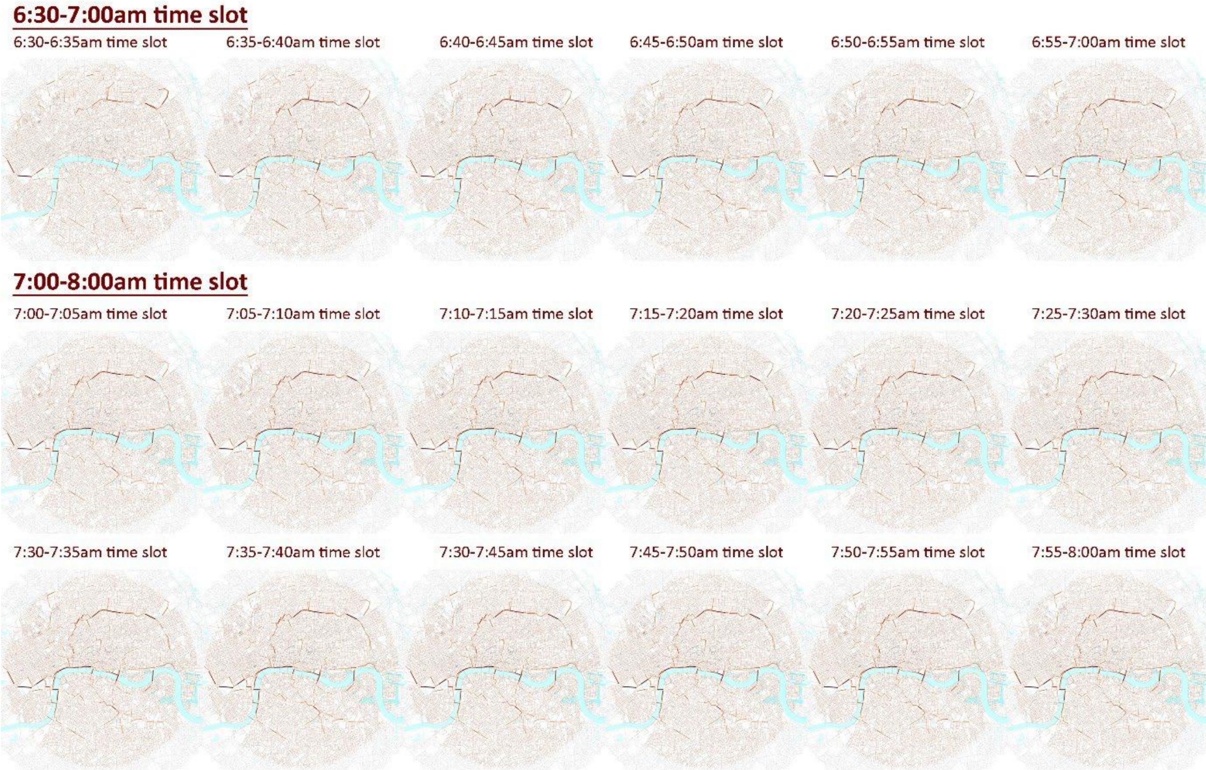


FIGURE 13 COMPLETE SIMULATION PROCESS FOR 6:30-8:00 AM TIME SLOT FOR UNWEIGHTED MODEL

Interestingly, this endeavour uncovered a noteworthy observation: the distinctions among the five sets of models were minimal. This can be attributed to various factors. One aspect is that the controlled probabilities facilitate a more reasoned process in generating ODMs, thereby governing the overarching road choice criteria. Additionally, the criteria governing road choices do not lead to alterations in time intervals, thus not influencing the frequency with which routes are chosen. This holds true even when the total number of cars remains constant.

A marked contrast emerges with the depiction of vehicle distribution incorporating congestion, as illustrated in Figure 14. Similarly, akin to the earlier discussed scenarios, the distinctions among the five model sets are quite minor.

(A) FIVE-CORE COMPUTING MODELS

(B) AVERAGE TRAFFIC COUNT (UTILISATION OF ROADS)

FIGURE 14 WEIGHTED MODEL TOTAL TRAFFIC COUNT FOR 7-8 AM

Nevertheless, a key distinction lies in the fact that the vehicle distribution during the operational phase of the models, showcased in Figure 15, displays noticeable fluctuations from moment to moment.

This variance arises due to the interplay of factors. Despite the uniform probability of generating ODMs for vehicles at each successive 5-second time interval, the perception of congestion—formed by the number of vehicles on each road—and the anticipation of vehicle speeds influence road choice criteria. Consequently, this prompts changes in the vehicle travel path for the ensuing time interval.

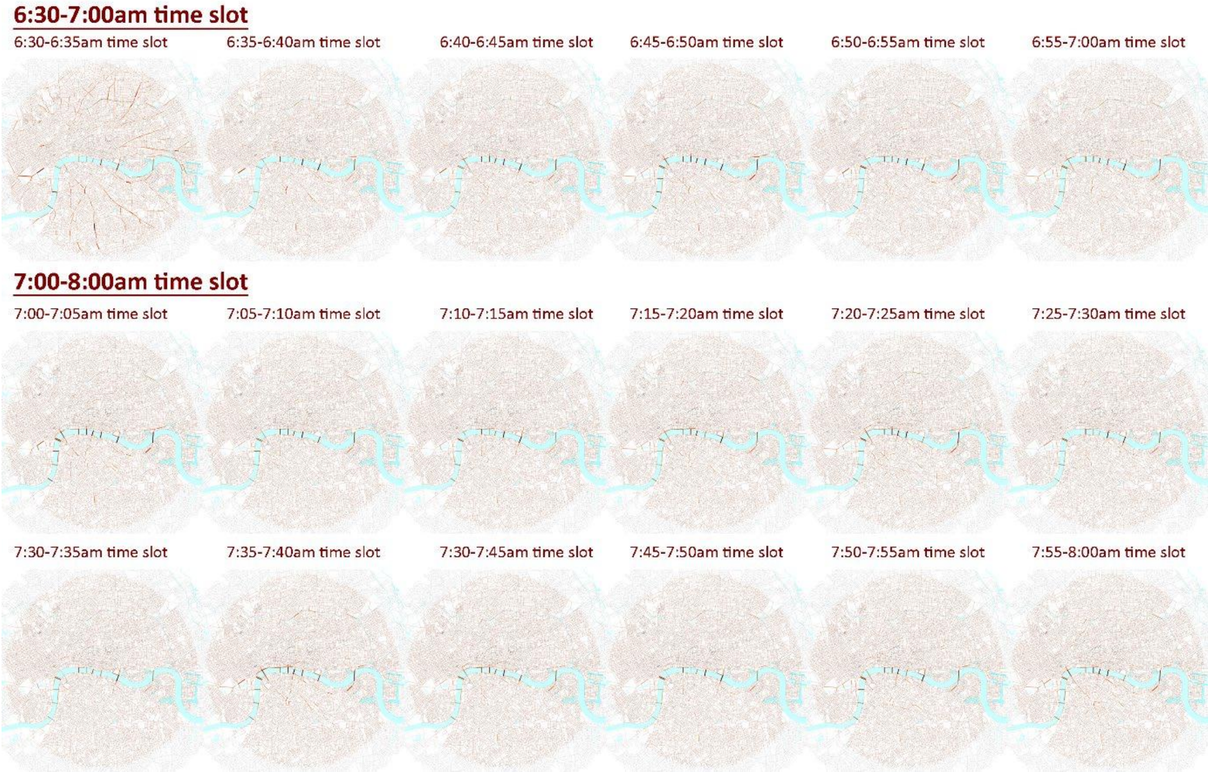


FIGURE 15 COMPLETE SIMULATION PROCESS FOR 6:30-8:00 AM TIME SLOT FOR WEIGHTED MODEL

Comparing Figures 12 and 14, an intuitive insight emerges. In the unweighted model, vehicles demonstrate a propensity to amass on primary roads leading directly to their destinations. These frequently used roads resemble vertical projections of a tree with discernible branches—a phenomenon referred to as "well-used roads" (including 1065 segments) here. Conversely, in the weighted model, the prevalence of vehicles opting for the "well-used roads" often results in substantial speed reduction due to congestion. Consequently, alternative roads around these "well-used roads" become more appealing at that moment, prompting vehicles to select the latter.

The studies mentioned above describe the distribution of vehicles in the 7-8 a.m. time period. Another topic of interest is the distribution of vehicles from 6:30 to 7:00 a.m., i.e., the difference between a model starting from 6:30 a.m. with no vehicles in the system and a simulation from 7:00 a.m. with vehicles already in the system. Specifically, the number of vehicles included in the whole system is shown in Figure 16. The function of the added vehicles may be an influencing factor, but it does not constitute a significant effect if the vehicles grow linearly. The comparison of the distributions between Figure 17a and Figure 13, and the comparison of the distributions between Figure 17b and Figure 15, will be clearer when visualised here.

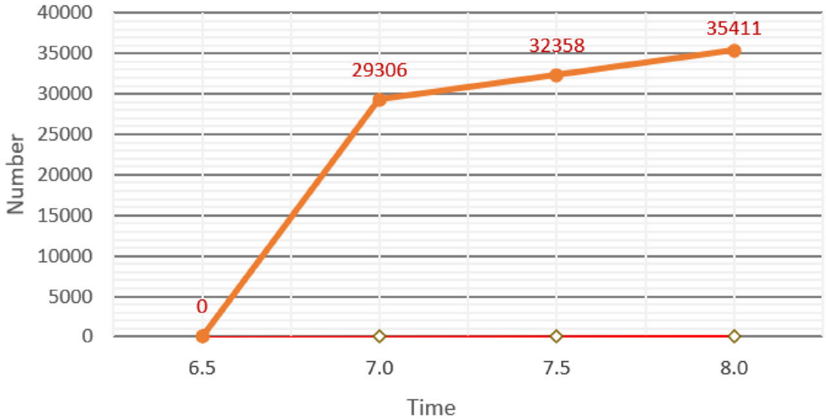


FIGURE 16 NUMBER OF CARS IN THE SIMULATION SYSTEM

(A) UNWEIGHTED MODEL **(B) WEIGHTED MODEL**

FIGURE 17 TOTAL TRAFFIC COUNT FOR 6:30-7:00 AM

On the other hand, the comparison will focus on speed. This average speed is calculated using the length of each segment and the time spent in the system. The time accumulation and calculation occur during the running of the simulation, while the frequency with which a segment is used is derived from the OD (Origin-Destination) lists generated by the ODMs after wayfinding. However, some issues arise in this process. For instance, when the system starts at 7:00 a.m., some vehicles have already covered distances on segments that need to be recorded, and these distances must be excluded. Additionally, certain vehicles may not have completed their full distance by the end of the system's operation; these incomplete paths must be removed from the OD lists. Moreover, there are instances where distances that should not have been travelled are erroneously accounted for. These discrepancies in distances are referred to as "distance" and can sometimes have negative values.

From this, the average speed for each segment is derived using the following equation:

$$Average_{Speed} = \frac{Bincount_{ODlist} \times Length + distance}{Total\ time\ cost}$$

In this manner, the average speeds are allocated to each segment, beginning with the unweighted case as depicted in Figure 18. As anticipated, all the speeds align with the regular speeds determined through calculations in the preceding section. It's important to note that there are instances of 0 flow. These instances arise because these roads have not been chosen within the road selection system. This pattern will persist in all subsequent scenarios and will not be reiterated.

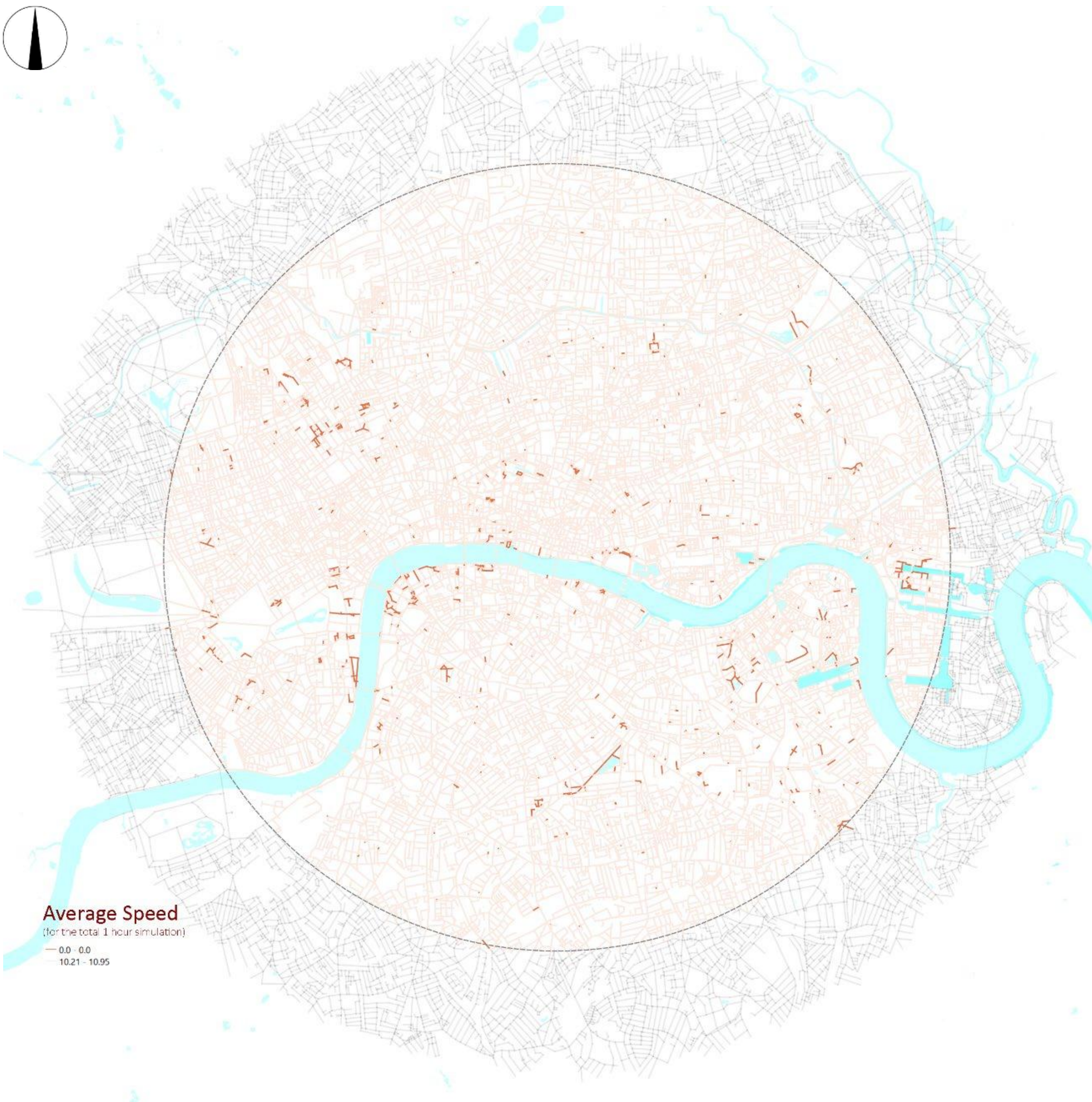


FIGURE 18 UNWEIGHTED MODEL SPEED WITH 0 FLOWS

On the contrary, the weighted model displays the distribution of roads where speeds are compromised due to congestion effects, illustrated in Figure 19 (without 0 flow). In terms of spatial understanding, it becomes more intuitive that the bridges experience the most substantial congestion (3.96 ~ 4.32m/s), resulting in lower-speed roads. The influence of congestion in other urban road segments is more evenly spread, with most roads not undergoing significant speed (10.21 ~ 10.95m/s) reductions. In other congested zones, speeds diminish to approximately half or less.

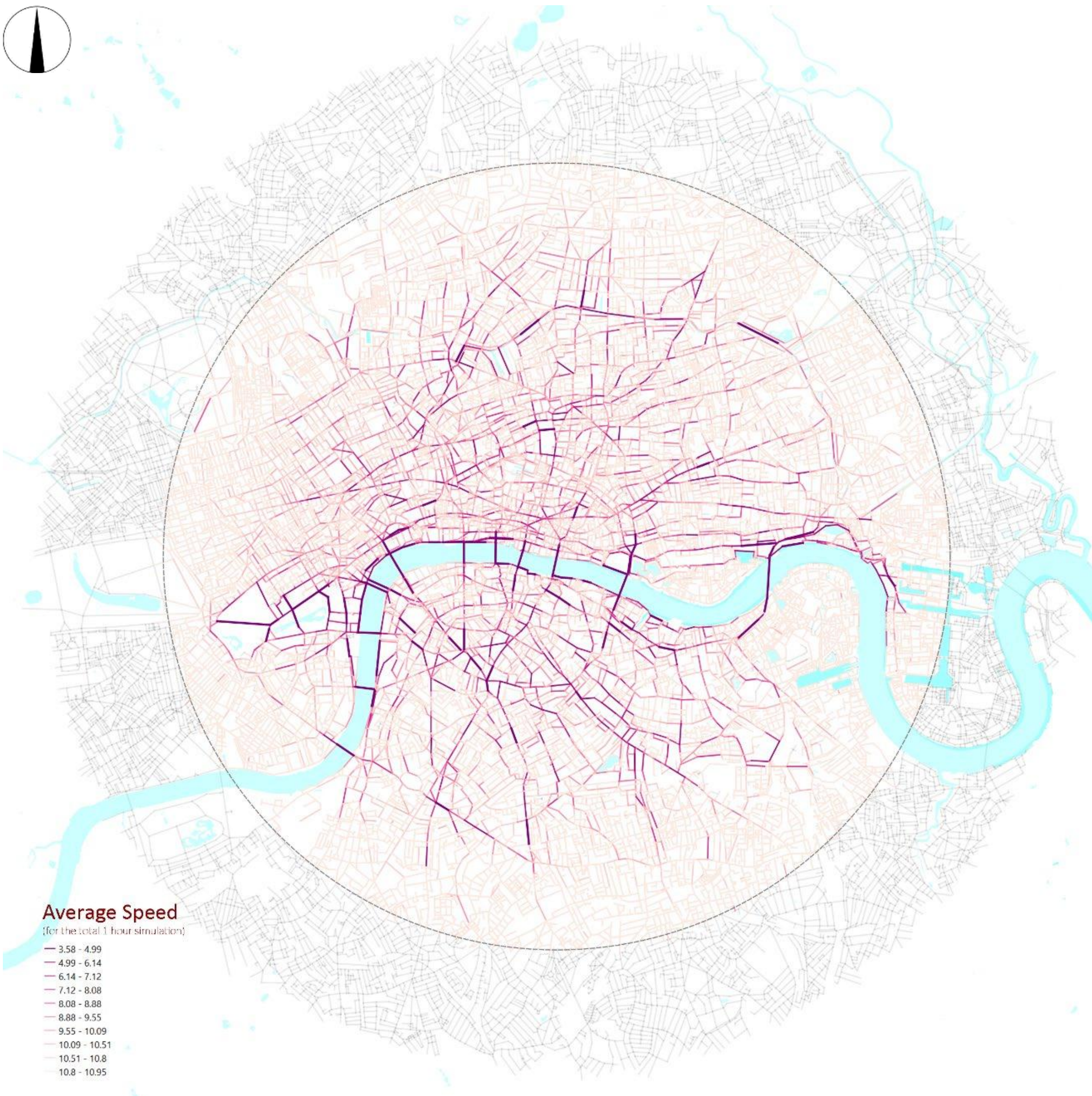


FIGURE 19 WEIGHTED MODEL SPEED FOR 7-8 AM

Notably, the roads running alongside the river are strange, as speeds on this road experience a dramatic drop, nearly matching the extent of slowdown observed on the bridge itself. Conversely, the roads directly along the southern side of the bridge, leading into the city, are among the roads that encounter more pronounced deceleration.

The same analysis was conducted for the 4-5:00 p.m. time frame, as depicted in Figure 20, illustrating the road usage performance during this period, which closely resembles the distribution observed in Figure 12 and Figure 14, although the precise vehicle counts differ.

(A) UNWEIGHTED MODEL **(B) WEIGHTED MODEL**

FIGURE 20 TRAFFIC COUNT FOR 4-5 PM

FIGURE 21 WEIGHTED MODEL SPEED FOR 4-5 PM

This implies that over an extended simulation duration (1 hour), the road usage patterns arising from travel in both positive and negative directions exhibit similarity provided the composition pattern of ODMs remains consistent. However, in real-world road usage, traffic flows in both directions, a facet not fully captured by this simulation. The performance of decreasing speeds differs. However, for the unweighted speeds, there is marginal change as the speeds have remained consistent. Figure 21 displays the weighted model afternoon speed data.

It is evident that there is an increase in the proportion of roads exhibiting reduced speeds. Notably, roads also experience speed reductions compared to the morning conditions.

FIGURE 22 CONGESTION SPEED CHANGES BETWEEN 7-8 AM AND 4-5 PM

Moreover, roads that were already experiencing reduced speeds demonstrate even further reductions. This phenomenon shown in Figure 22 stems from the fact that the afternoon simulation involves approximately one-third more vehicles than in the morning, with the system's capacity depicted in Figure 8. The red colours in Figure 22 represent the sections that have become more congested, while the blue colours represent those that have decreased in congestion.

Similar to the OD distribution in Figure 5, the afternoon commute home pattern leads to increased congestion in residential areas and a more relaxed flow in office areas. Consequently, speeds correlate with the total number of vehicles within the system, ensuring that the vehicles can successfully complete the entire simulation. However, the overall distribution is minimally affected by other components and is predominantly influenced by the presence or absence of congestion-weighted behaviour.

TABLE 2 CONGESTION DEGREE BY TIME COST

Average	Unweighted 7-8:00 am	Unweighted 4-5:00 pm	Weighted 7-8:00 am	Weighted 4-5:00 pm
Car (count)	258055.2	387471.8	232942	326650
Time (s)	128386659.1	192570329.7	128448976.4	192723270.4
Distance (km)	1402600.31	2103553.00	1110415.97	1562483.61
Speed (m/s)	10.925	10.924	8.645	8.107
Time cost per car (s)	497.52	496.99	551.42	590.00

In addition to the spatial distribution of congestion, it's essential to quantify the cost of congestion for a comprehensive assessment of the system's impacts. The level of congestion can be measured in terms of average speed and average vehicle hours.

Respond to question A, as demonstrated in Table 2, firstly, the unweighted system exhibits no impact, experiencing only errors attributable to differences in randomly constructed ODMs. When comparing the afternoon commute to the morning, the system witnesses a substantial increase in congestion due to the greater number of vehicles. This congestion significantly affects the system, leading to nearly a one-fifth reduction in system speed and a considerable increase in the average time vehicles spend in traffic.

When there is no congestion, well-used roads can adequately handle all travelling needs. However, once congestion is taken into account, surrounding roads become filled, leading to congestion.

As the number of vehicles in the system increases, congestion within the system tends to cluster more around origins and less around destinations.

5. ASSESSMENT OF TRAFFIC CHANGES

The first section of this chapter examines the impact of near stopping on congestion in the spatial transport system, utilising roads specified by unweighted simulation and space syntax analysis. The second section shifts focus to the study of bridges.

5.1 "WELL-USED ROADS" BLOCKING ANALYSIS

To depict the spatial distribution of congestion, specifically assessing whether speed impacts exhibit a notably higher magnitude in 'well-used roads' we present in Figure 23, a selection of 1065 lines extracted from the analyses conducted in Session 4.3.5. These segments represent roads that are significantly more frequent than others.

FIGURE 23 WELL-USED ROADS

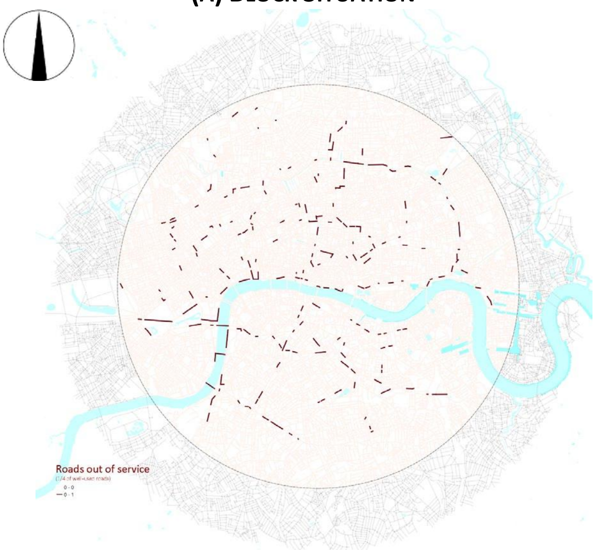
It is a common occurrence for these roads to face various issues, such as illustrated in Figure 24.

(A) TOTAL BLOCKING **(B) PARTLY BLOCKING**

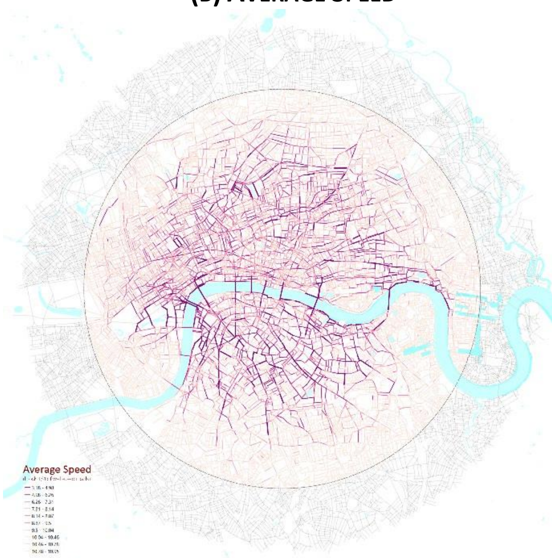
FIGURE 24 ROADS OUT OF SERVICE

To explore the impact of severe problems affecting commuting on these roads, a simulation was conducted in which they are deemed unusable for traffic. In this simulation, 25 per cent of these roads were considered damaged, and the average findings of this analysis are presented in Figure 25 (simulation model 5 as an example).

(A) BLOCK SITUATION



(B) AVERAGE SPEED



(C) TRAFFIC COUNT

(D) CHANGES IN UTILISATION

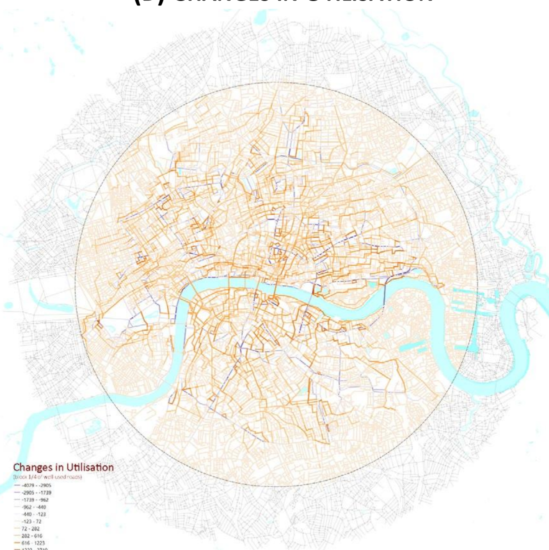


FIGURE 25 RANDOM 25% "WELL-USED ROADS" BLOCKING SIMULATION 7-8 AM (MODEL 5)

While models can significantly differ based on the stochastic algorithm's selection of problematic roads, the figure above displays the average change scenario model 5. In the following sections, more specific models will be compared, including the maximum change (model 3) and minimum change (model 2) scenarios.

Model 3 (Figure 26), which exhibits the most significant change, is characterised by frequent blockages along the mandatory exit routes from the settlement, as confirmed by the OD distribution test. These blockages have a substantial impact on the overall system.

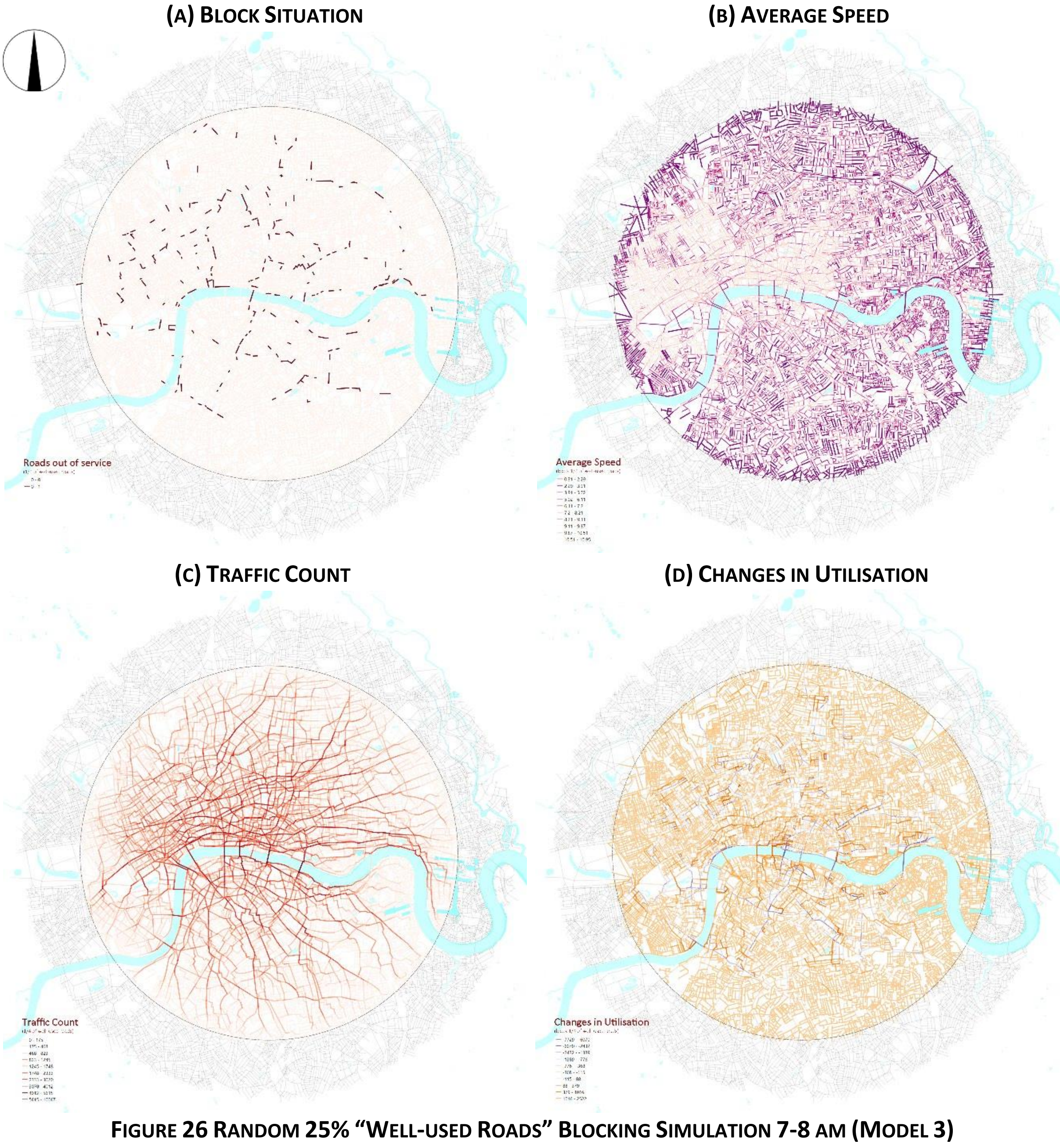


FIGURE 26 RANDOM 25% "WELL-USED ROADS" BLOCKING SIMULATION 7-8 AM (MODEL 3)

Table 3 presents an overview of congestion impacts on the entire system for 7-8:00 am. When comparing the two sets of models, Model 5, and Model 3, we can observe differences. Specifically, Model 2, where road decommissioning is relatively minor, as none of the bridges is selected and does not influence the selection of mandatory OD roads within the model.

TABLE 3 RANDOM 25% "WELL-USED ROADS" BLOCKING SIMULATION 7-8:00 AM

Stuck 25%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	228047	**229727**	**189452**	210651	**210651**	213705.6
Time (s)	128448976.4	128460128.1	**128456235.4**	**128559491.7**	128623602	**128504585.8**	128520808.6
Distance (km)	1110415.97	1115579.54	**1118228.91**	**895013.53**	740529.53	**1017422.10**	977354.72
Speed (m/s)	8.645	8.684	**8.705**	**6.962**	5.757	**7.917**	7.605
Time cost per car (s)	551.42	563.31	**559.17**	**678.59**	610.60	**610.04**	604.34

When the examination of problematic roads is conducted during the 4-5:00 pm timeframe, the system's congestion levels are detailed in Table 4.

TABLE 4 RANDOM 25% "WELL-USED ROADS" BLOCKING SIMULATION 4-5:00 PM

Stuck 25%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	326650	315452	322217	316325	295244	320779	314003.4
Time (s)	192723270.4	192750187.7	192733697.9	192748245.6	192801346.7	192738133.4	192754322.3
Distance (km)	1562483.61	1563080.86	1575139.93	1563207.75	1444710.94	1571127.88	1543453.47
Speed (m/s)	8.107	8.109	8.173	8.110	7.493	8.152	8.007
Time cost per car (s)	590.00	611.03	598.15	609.34	653.02	600.84	614.48

Model 1, representing the average scenario, is visually presented in Figure 27.

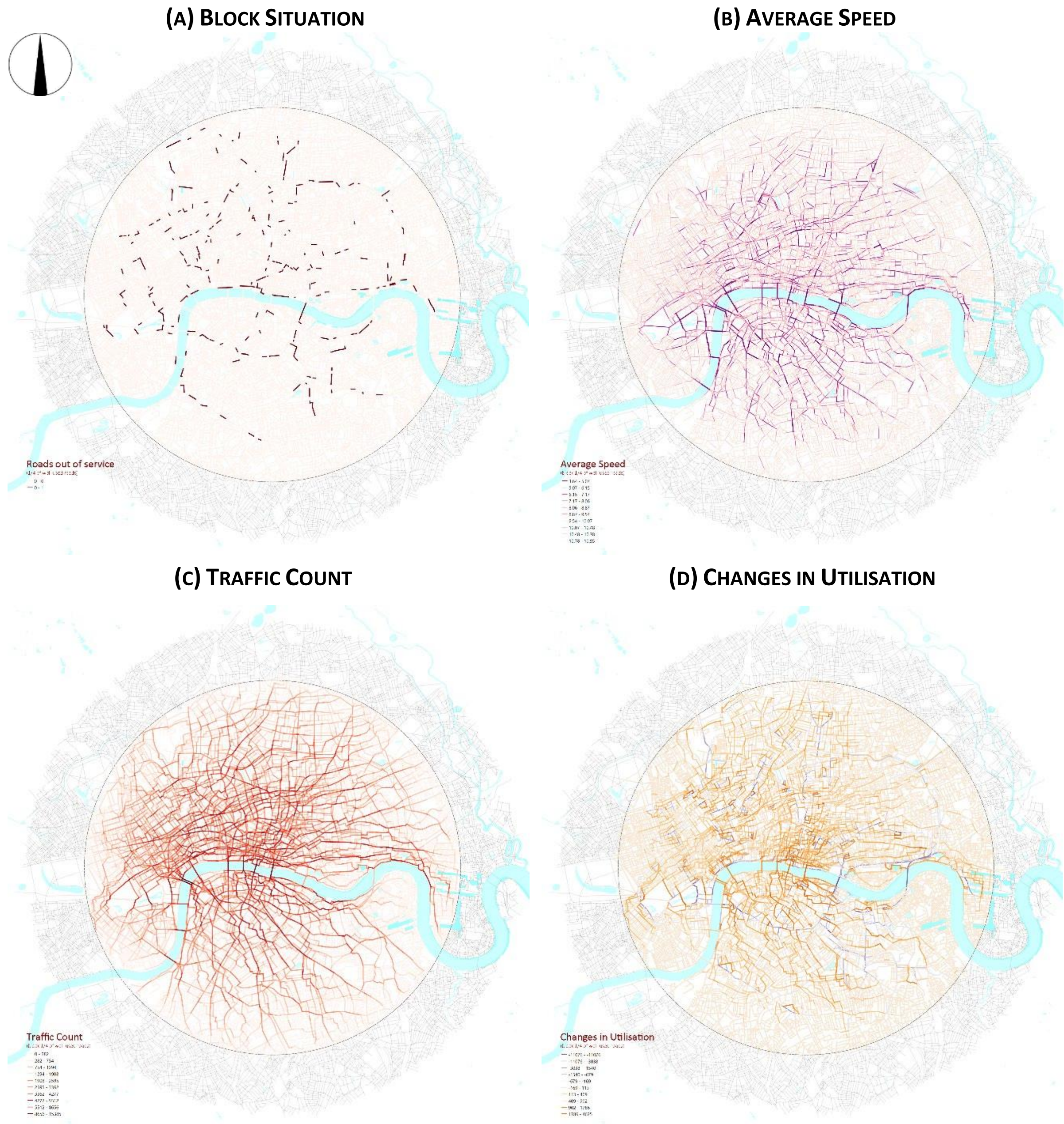


FIGURE 27 RANDOM 25% "WELL-USED ROADS" BLOCKING SIMULATION 4-5:00 PM (MODEL 1)

The statistical comparison of the simulation system with random 50% blocking situation in Tables 5 and 6 reveals that during the morning commute, congestion growth rates, as indicated by the average vehicle time, increase by approximately 9.6 per cent with a 25 per cent road problem and 19.6 per cent with a 50 per cent road problem. In the afternoon, congestion growth rates stand at around 4 per cent for the 25 per cent road problem and spike to 27.5 per cent for the 50 per cent road problem.

TABLE 5 RANDOM 50% "WELL-USED ROADS" BLOCKING SIMULATION 7-8:00 AM

Stuck 50%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	220532	195024	174632	195242	195024	196090.8
Time (s)	128448976.4	128479123.9	128609851.3	128594943.6	128543189.3	128543681.4	128554157.9
Distance (km)	1110415.97	1099922.37	796214.66	833630.28	938030.38	938636.03	921286.74
Speed (m/s)	8.645	8.561	6.191	6.483	7.297	7.302	7.167
Time cost per car (s)	551.42	582.59	659.46	736.38	658.38	659.12	659.18

TABLE 6 RANDOM 50% "WELL-USED ROADS" BLOCKING SIMULATION 4-5:00 PM

Stuck 50%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	326650	246393	316803	229517	256265	248020	259399.6
Time (s)	192723270.4	192924223.4	192746827.9	192966491.2	192899115.9	192919632.5	192891258.2
Distance (km)	1562483.61	1201550.66	1566074.91	1092634.13	1216828.19	1207697.13	1256957.01
Speed (m/s)	8.107	6.228	8.125	5.662	6.308	6.260	6.517
Time cost per car (s)	590.00	782.99	608.41	840.75	752.73	777.84	752.55

While the system-wide impact caused by these roads is expected to be substantial, it's important to note that the randomness in the road damage assignment introduces variability. Consequently, when working with a small sample size, the simulation model may not precisely reflect the rate of change.

5.2 SPACE SYNTAX PERSPECTIVE ANALYSIS

Considering that the model in this study is fundamentally topological in nature, a Segment topological analysis was conducted using a radius of 6500 meters. The betweenness centrality of this spatial network is illustrated in Figure 28.

FIGURE 28 TOPOLOGICAL CHOICE ANALYSIS

A subsequent correlation investigation of the outcomes from the simulation study with the topological betweenness centrality reveals a reversal compared to the prior analysis. In this case, the unweighted model demonstrates an exceedingly high correlation, whereas the weighted model exhibits a significant lack of correlation. The results of this analysis are shown in Table 7 and Table 8. There are plausible explanations for this phenomenon that align well with real-world dynamics. Both the unweighted stochastic simulation model and the all-to-all operations of topological betweenness centrality adhere to the shortest pathfinding principle. In the context of algorithmic approximation, the simulation model's approximation represents a subset of data within this algorithm. The diminished correlation observed in the weighted model is indicative of the contrast between congestion-related factors and spatial choice attributes. In simpler terms, congestion distinctly impacts the utilisation patterns of space.

TABLE 7 CORRELATION BETWEEN UNWEIGHTED MODEL AND CHOICE ANALYSIS

		Unweighted	Choice
Pearson Correlation	Unweighted	1.000	**.863**
	Choice	.863	1.000
Sig.(1-tailed)	Unweighted	.	<.001
	Choice	.000	.
N	Unweighted	29023	29023
	Choice	29023	29023

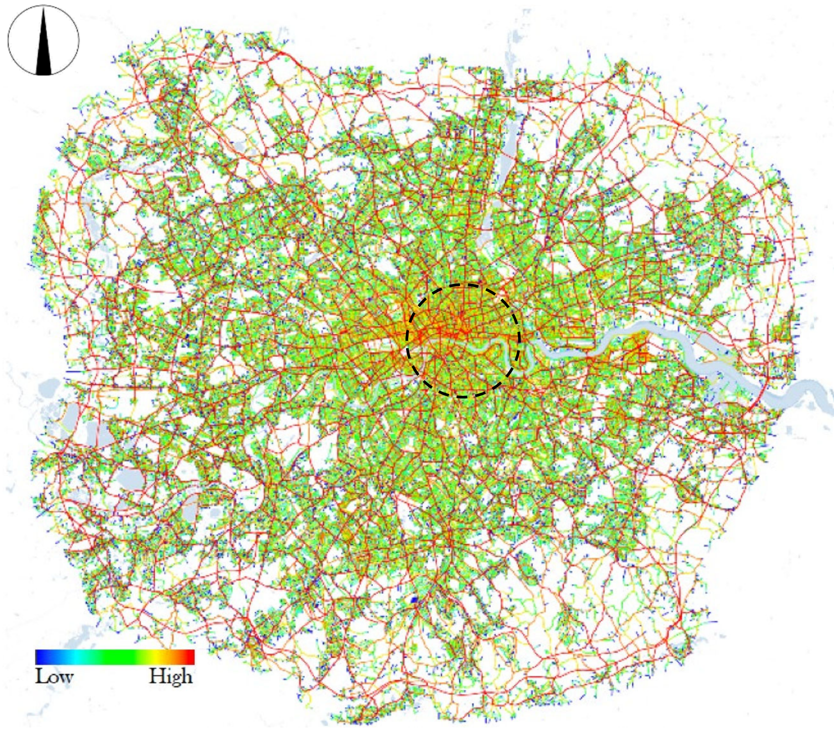
TABLE 8 CORRELATION BETWEEN WEIGHTED MODEL AND CHOICE ANALYSIS

		Weighted	Choice
Pearson Correlation	Weighted	1.000	**.279**
	Choice	.279	1.000
Sig.(1-tailed)	Weighted	.	<.001
	Choice	.000	.
N	Weighted	29023	29023
	Choice	29023	29023

On the one hand, the inclusion of angular betweenness centrality considers tangible parameters that reflect how individuals engage with and utilise space. On the other hand, incorporating congestion as a behavioural factor also acknowledges real-world parameters. In essence, both approaches are oriented towards understanding and harnessing the controlling attributes of actual spatial utilisation.

From this perspective, exploring the attributes provided by space syntax offers a valuable alternative research approach to road studies. An example of a more macro perspective is the identification of 'well-used roads,' which can be investigated not only for failure situations but also for widening. This can be achieved through an angular segment analysis with a radius of 20000 meters for the London M25, selecting the same number of segments as 'well-used roads.' Segments with high integration or choice were then chosen for further examination.

(A) TOTAL LONDON M25

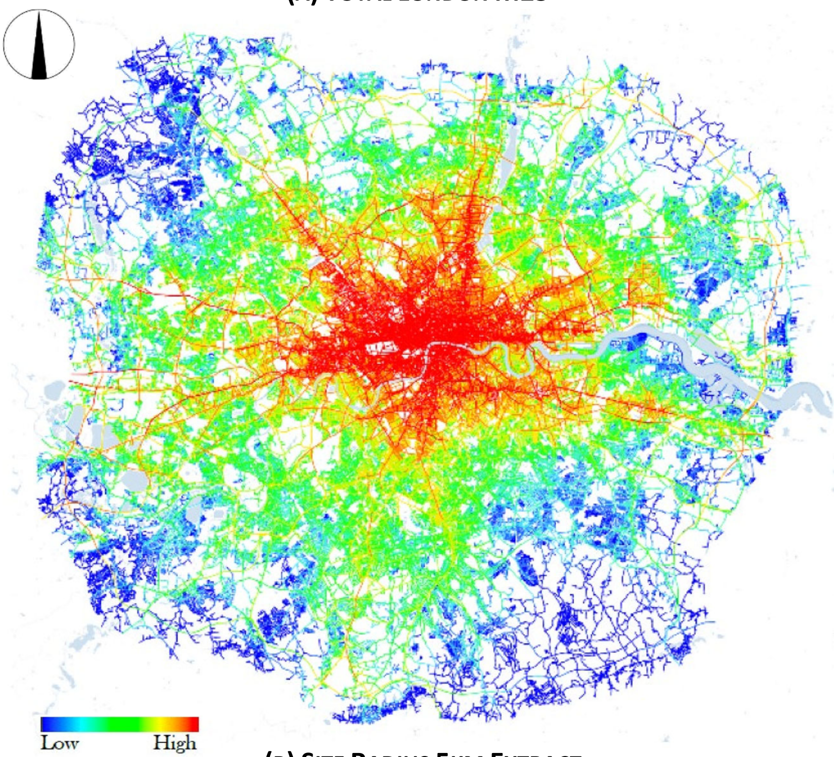


(B) SITE RADIUS 5KM EXTRACT

FIGURE 29 NORMALISED CHOICE R20000M OF M25

For the spatial network level layout, as shown in Figures 29 and 30, graphs of the normalised Choice and Integration analyses are presented for the London-wide M25-scale angular segment analysis with a radius of 20000m.

(A) TOTAL LONDON M25



(B) SITE RADIUS 5KM EXTRACT

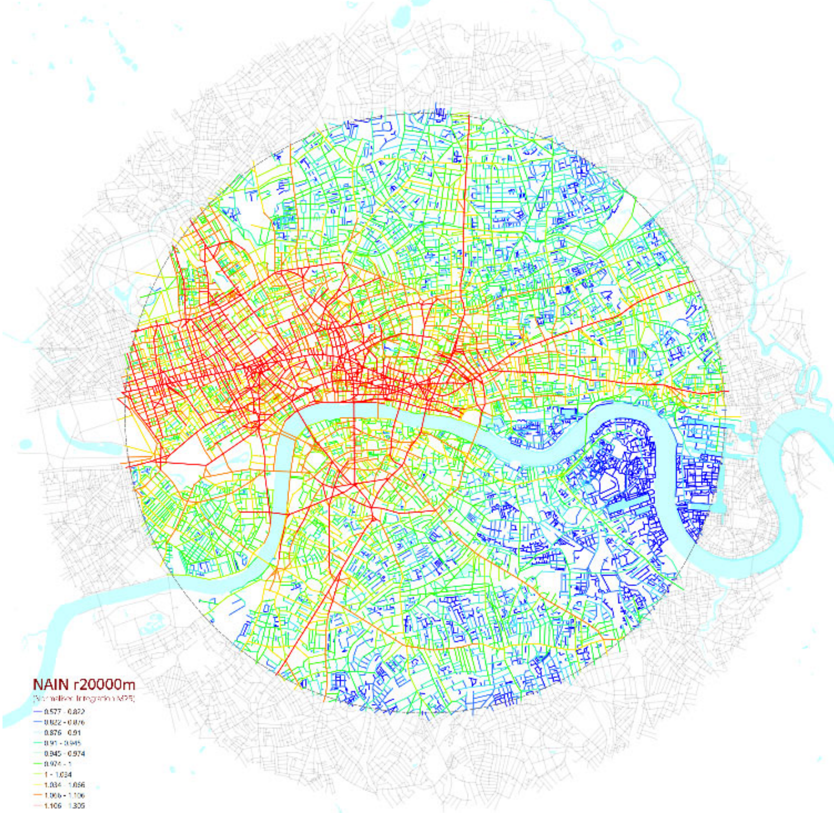


FIGURE 30 NORMALISED INTEGRATION R20000M OF M25

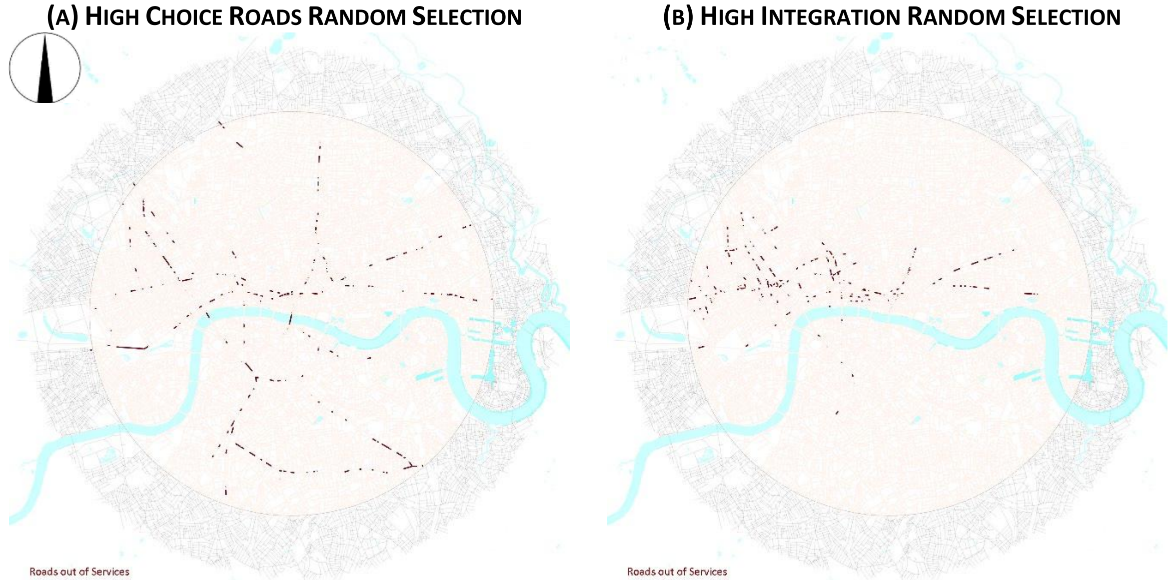
The layout displayed at the study site is depicted in Figures 29b and 30b. In Figure 29a, Choice is visualised as Betweenness Centrality, illustrating the city's distribution primarily through roadways. The angular segment analysis employed here aligns with the centrality representation explored in Varoudis' paper using the new algorithm (Varoudis et al. 2013).

(A) HIGH CHOICE **(B) HIGH INTEGRATION**

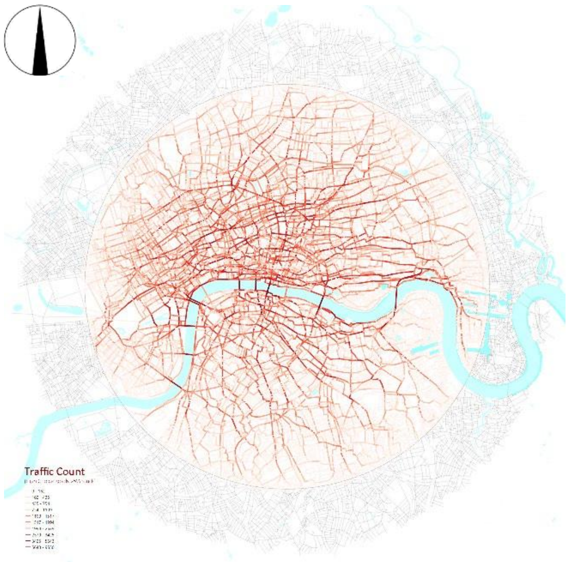
FIGURE 31 HIGH-VALUE ROADS SELECTION (1065 SEGMENTS)

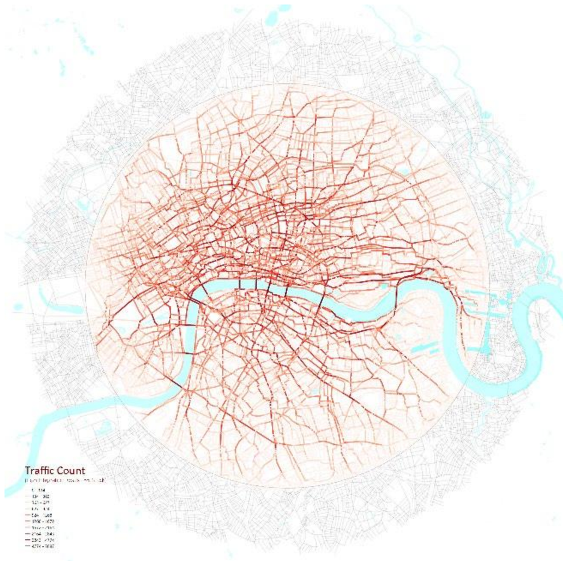
As depicted in Figures 31a and 31b, the top 1065 segments are arranged in descending order of choice, and integration respectively. Such reference models and the study of well-used roads are comparatively informative.

(A) HIGH CHOICE ROADS RANDOM SELECTION **(B) HIGH INTEGRATION RANDOM SELECTION**



(C) HIGH CHOICE MODEL TRAFFIC COUNT **(D) HIGH INTEGRATION MODEL TRAFFIC COUNT**





(E) HIGH CHOICE MODEL SEGMENT SPEED **(F) HIGH INTEGRATION MODEL SEGMENT SPEED**

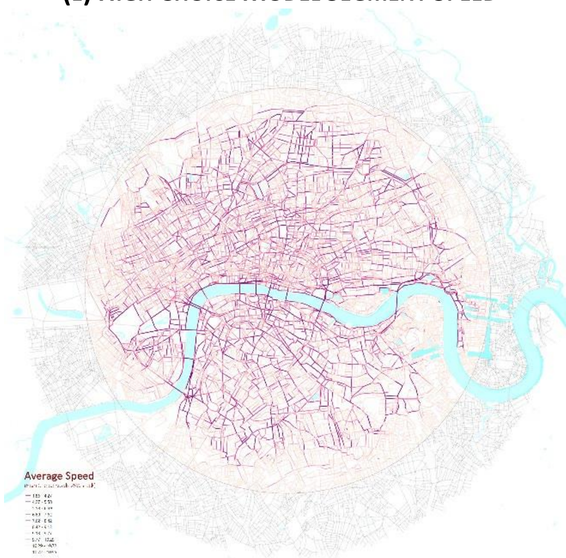


FIGURE 32 BLOCKING SIMULATION RESULT (LEFT FOR HIGH CHOICE; RIGHT FOR HIGH INTEGRATION)

Question B can be addressed here using Figure 32, which models the 25% random interruptions for the 1065 highest-valued integration and choice roads between 7-8 am. It's important to note that this distribution differs significantly from the congestion pattern displayed in Figure 19 and Figure 25b.

However, it's worth mentioning that this distribution can vary considerably when roads are blocked. For a more comprehensive comparison, we can refer to the congestion severity data presented in Tables 9 and 10. In terms of average speed per vehicle and average elapsed time, the situation worsens when highly integrated roads are blocked.

TABLE 9 RANDOM 25% HIGH CHOICE ROADS BLOCKING SIMULATION 7-8:00 AM

Stuck 25%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	201088	212384	188183	208358	195743	201151.2
Time (s)	128448976.4	128527277.1	128501616.1	128561314.1	128510806.6	128542369.5	128528676.7
Distance (km)	1110415.97	955427.97	1018551.34	876215.71	1000832.26	931425.76	956490.61
Speed (m/s)	8.645	7.434	7.926	6.816	7.788	7.246	7.442
Time cost per car (s)	551.42	639.16	605.04	683.17	616.78	656.69	640.17

TABLE 10 RANDOM 25% HIGH INTEGRATION ROADS BLOCKING SIMULATION 7-8:00 AM

Stuck 25%	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	188647	165021	188263	160107	184505	177308.6
Time (s)	128448976.4	128561240.1	128621680.4	128561848.1	128632411.9	128572433.7	128589922.8
Distance (km)	1110415.97	885247.15	753967.39	884050.20	726930.47	856032.30	821245.50
Speed (m/s)	8.645	6.886	5.862	6.876	5.651	6.658	6.387
Time cost per car (s)	551.42	681.49	779.43	682.88	803.42	696.85	728.81

When analysing the afternoon data, it's possible that the gap may widen further. The rate of change for "well-used roads" in the unweighted model could be smaller in scenarios with a higher number of vehicles, while road damage may have a more pronounced effect in the choice and integration models.

TABLE 11 STATISTICAL COMPARISON

Stuck 25% 7-8 am	Weighted	Well-used	High Choice	High Integration
Car (count)	232942	213705.6	201151.2	177308.6
Time (s)	128448976.4	128520808.6	128528676.7	128589922.8
Distance (km)	1110415.97	977354.72	956490.61	821245.50
Speed (m/s)	8.645	7.605	7.442	6.387
Time cost per car (s)	551.42	604.34	640.17	728.81
Congestion Growth	0%	10%	16%	32%
Stuck 25% 4-5 pm	**Weighted**	**Well-used**	**High Choice**	**High Integration**
Car (count)	326650	314003.4	270577.4	229442.4
Time (s)	192723270.4	192754322.3	192864742.5	192967718
Distance (km)	1562483.61	1543453.47	1274793.42	1043955.46
Speed (m/s)	8.107	8.007	6.610	5.410
Time cost per car (s)	590.00	614.48	716.51	844.46
Congestion Growth	0%	4%	21%	43%

5.3 BRIDGE BLOCKING ANALYSIS

In the case of these roads, Figures 10b and 19 in the conclusion of the modelling section consistently highlight the bridges along these high-traffic routes as the most congested elements in the traffic road system. Furthermore, given London's historic bridges, this study took the innovative step of modelling the potential scenario where these bridges cease to function within the traffic system. This assumption aligns with realism and offers a reliable basis for analysis.

In 'Crossing the River', the author classifies the bridges over the Thames in London and traces their history in detail (Cookson 2015). The bridges are also classified in such a way that road bridges are directly involved in the road system and partly provide pedestrian access, while Railway bridges and Footbridges only function in the railway system and pedestrian system respectively.

Like Hammersmith Bridge has faced closure on six occasions throughout its history. Interestingly, it was completely shut from 13 August 2020 to 17 July 2021.

FIGURE 33 BRIDGE BLOCKING

This occurrence is not unique to the Hammersmith Bridge and has been observed with several other bridges in London as well. While Tower Bridge has not experienced as many emergencies, it does have a significant operational pattern. On average, Tower Bridge raises its bascules approximately 800 times per year. This frequency translates to around twice a day, facilitating the passage of ships underneath. However, this operational requirement has occasionally led to traffic disruptions on the bridge.

FIGURE 34 TOWER BRIDGE RAISE ITS BASCULES (GOOGLE)

The simulation with the closure (shown in Figures 33 and 34) of the two well-used bridges illustrated in Figure 23 is presented in Figure 35a, showcasing speed performance in Figure 35b. System congestion during this simulation is detailed in Table 12. Afternoon performance is depicted in Figures 35c and 35d, with system congestion data provided in Table 13.

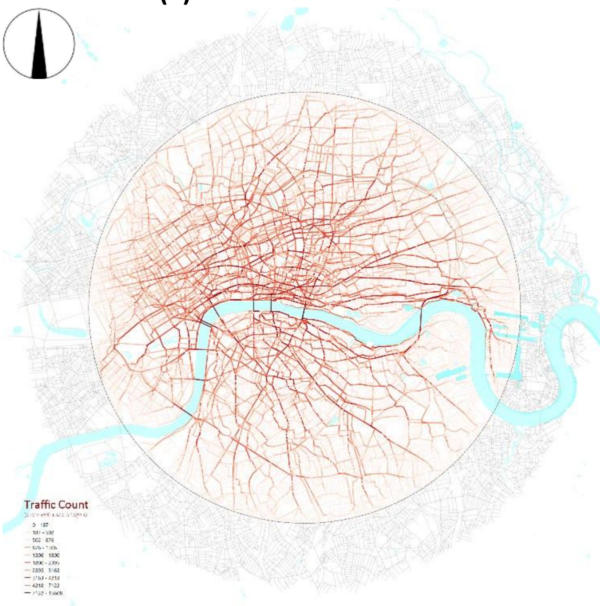
TABLE 12 WELL-USED BRIDGES OUT OF SERVICES SIMULATION 7-8:00 AM

Well-used Bridges	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	227419	227875	227552	227834	227408	227617.6
Time (s)	128448976.4	128463533.6	128461908.1	128462136.8	128461452.1	128462269.1	128462259.9
Distance (km)	1110415.97	1096517.83	1098215.73	1097426.42	1098651.69	1096023.88	1097367.11
Speed (m/s)	8.645	8.536	8.549	8.543	8.552	8.532	8.542
Time cost per car (s)	551.42	564.88	563.74	564.54	563.84	564.90	564.38

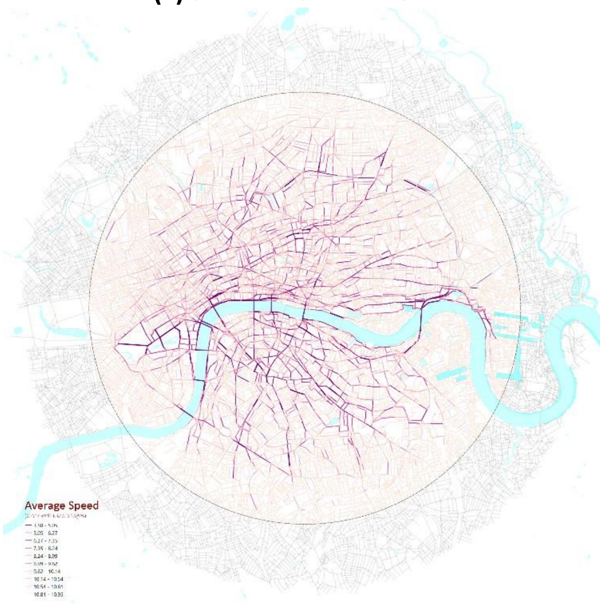
TABLE 13 WELL-USED BRIDGES OUT OF SERVICES SIMULATION 4-5:00 AM

Well-used Bridges	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	326650	317955	317999	317829	316828	317872	317696.6
Time (s)	192723270.4	192744678.5	192746033.2	192744282	192748238.3	192745297.5	192745705.9
Distance (km)	1562483.61	1549259.34	1547740.92	1548521.68	1544067.59	1548280.10	1547573.93
Speed (m/s)	8.107	8.038	8.030	8.034	8.011	8.033	8.029
Time cost per car (s)	590.00	606.20	606.12	606.44	608.37	606.36	606.70

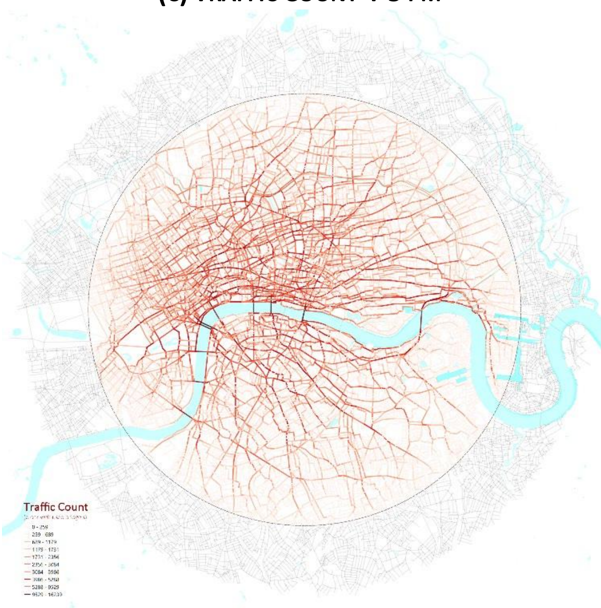
(A) TRAFFIC COUNT 7-8 AM



(B) SEGMENT SPEED 7-8 AM



(C) TRAFFIC COUNT 4-5 PM



(D) SEGMENT SPEED 4-5 PM

FIGURE 35 BLOCKING WELL-USED BRIDGES SITUATION

In the scenario where the two well-used bridges are unavailable, the congestion growth rate for the morning commute is 2.4 per cent, and for the afternoon, it is 2.6 per cent.

Tables 14 and 15 provide an overview of the congestion performance of the system when simulating the closure of two conventional bridges (those not heavily used). The situation is shown in Figure 36.

TABLE 14 NORMAL BRIDGES OUT OF SERVICES SIMULATION 7-8:00 AM

Normal Bridges	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	232942	229411	229722	229722	229457	229540	229570.4
Time (s)	128448976.4	128457481.1	128456662.9	128457054.1	128457821.1	128458190	128457441.9
Distance (km)	1110415.97	1102933.58	1100790.18	1104502.86	1102300.63	1103547.95	1102815.04
Speed (m/s)	8.645	8.586	8.569	8.598	8.581	8.591	8.585
Time cost per car (s)	551.42	559.94	559.18	559.18	559.83	559.63	559.56

TABLE 15 NORMAL BRIDGES OUT OF SERVICES SIMULATION 4-5:00 PM

Normal Bridges	Weighted	Model 1	Model 2	Model 3	Model 4	Model 5	Average
Car (count)	326650	319628	320222	320221	319858	320633	320112.4
Time (s)	192723270.4	192741148	192739160.6	192739516.5	192739982.6	192739409.7	192739843.5
Distance (km)	1562483.61	1551031.51	1550124.64	1549095.87	1549697.96	1551272.58	1550244.51
Speed (m/s)	8.107	8.047	8.043	8.037	8.040	8.049	8.043
Time cost per car (s)	590.00	603.02	601.89	601.90	602.58	601.12	602.10

(A) TRAFFIC COUNT 7-8 AM

(B) SEGMENT SPEED 7-8 AM

(C) TRAFFIC COUNT 4-5 PM (D) SEGMENT SPEED 4-5 PM

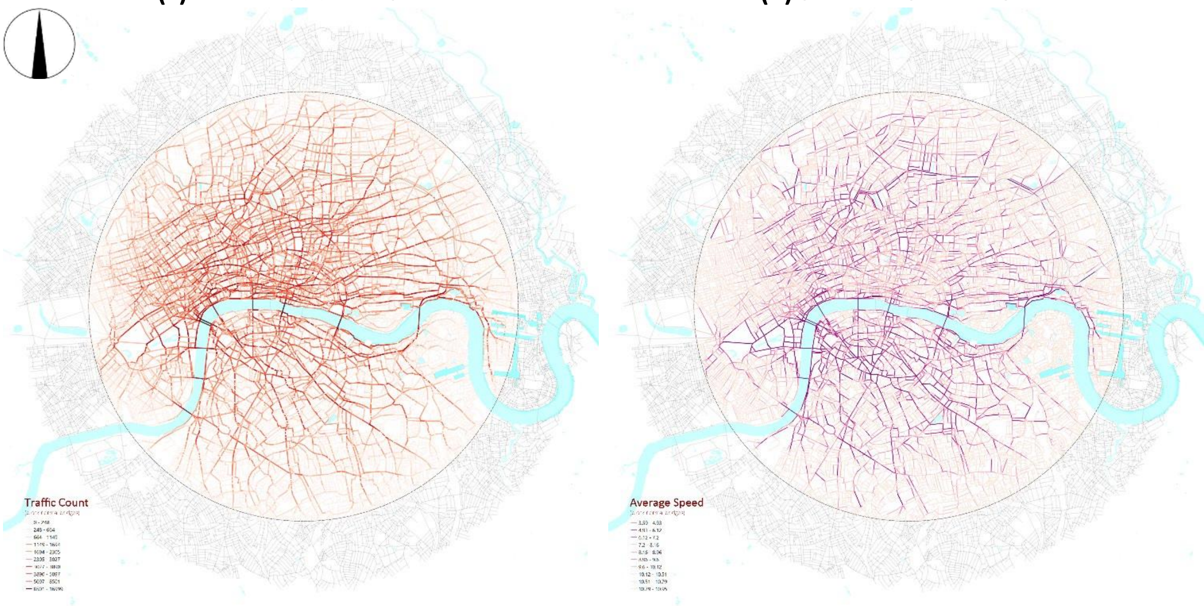


FIGURE 36 BLOCKING NORMAL BRIDGES SITUATION

The congestion growth rate for this scenario is 1.4 per cent in the morning and 2.0 per cent in the afternoon. Respond to Question B, overall, it's evident that the impact of congestion resulting from the closure of the same number of bridges is similar, depending on the original bridge utilisation, but not markedly significant. In terms of spatial distribution, there are no significant differences in the speed reduction distribution between the two groups, except for the bridges that were closed.

6 ROAD WIDENING POLICY ANALYSIS

This chapter examines the impact of road widening policies.

6.1 ALL ROADS WIDENING VS. SELECTED ROADS WIDENING

Beyond addressing congestion from issues like road problems and river bridge closures, cities often implement measures to alleviate traffic congestion by widening roads. In the case of doubling the width of all roads during the 7-8:00 am timeframe, congestion levels are visualised in Figures 37a and 37b. This simulation is done by adjusting the capacity parameters. Similarly, for the 4-5:00 p.m. timeframe, Figures 37c and 37d depict the congestion outcomes.

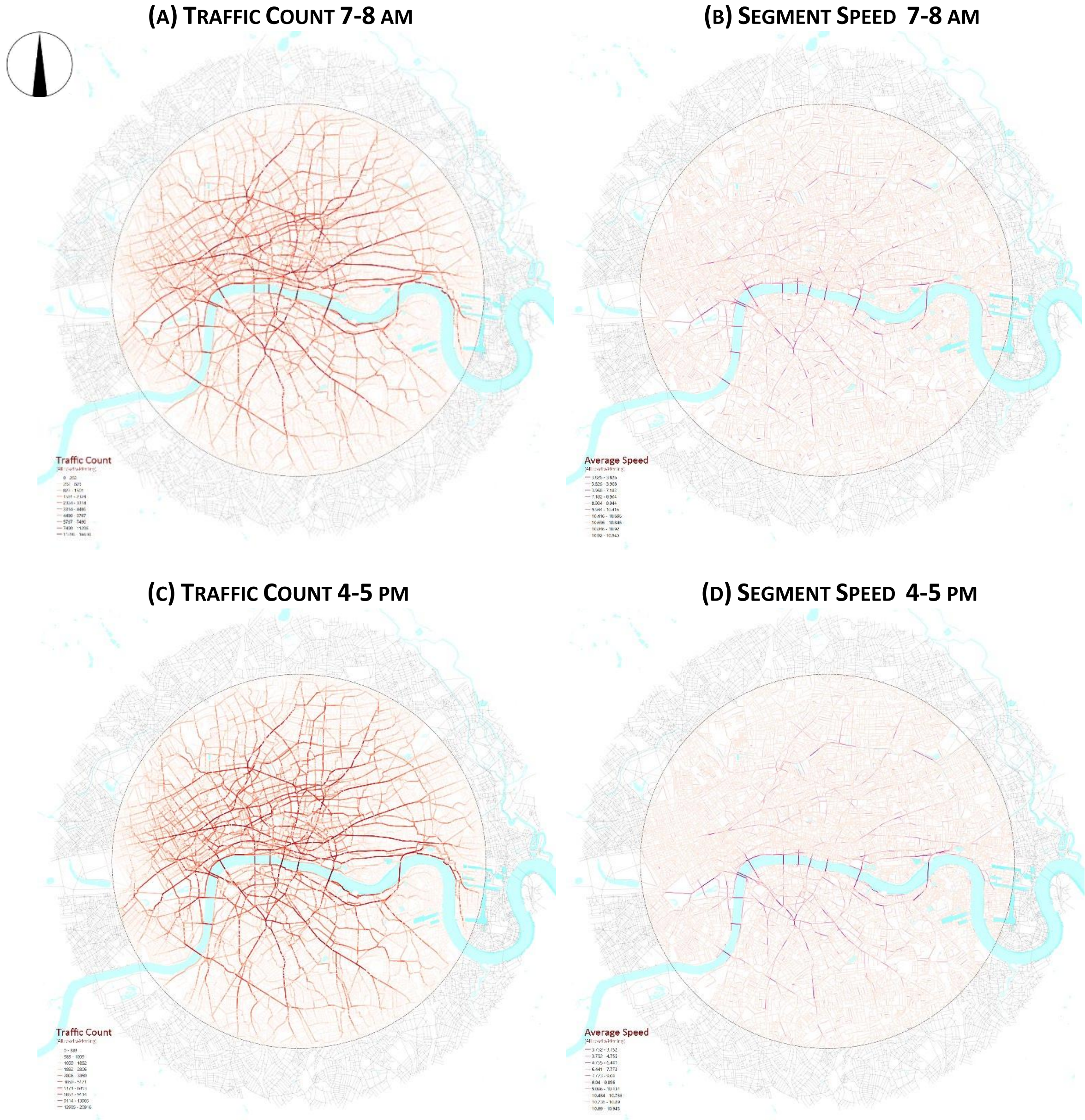


FIGURE 37 ALL ROAD WIDENING

TABLE 16 ALL ROAD WIDENING

All widening 7-8 am	Weighted	Well-used	High Choice	High Integration
Car (count)	232942	258055.2	300583.4	287013
Time (s)	128448976.4	128386659.1	128279882	128314186
Distance (km)	1110415.97	1402600.31	1402356.66	1342248.63
Speed (m/s)	8.645	10.925	10.932	10.461
Time cost per car (s)	551.42	497.52	426.77	447.07
All widening 4-5 pm	**Weighted**	**Well-used**	**High Choice**	**High Integration**
Car (count)	326650	387471.8	451717.4	421820.6
Time (s)	192723270.4	192570329.7	192409957.6	192485111.8
Distance (km)	1562483.61	2103553.00	2103264.37	1969325.95
Speed (m/s)	8.107	10.924	10.931	10.231
Time cost per car (s)	590.00	496.99	425.95	456.32

The congestion performance data is summarised in Table 16. Expanding all roads significantly reduces congestion levels, particularly on non-bridge roads, bringing them to very low levels. This widening strategy proves highly beneficial for the entire system in terms of congestion relief. Notably, even though the speed does not return to the unweighted model levels, the average vehicle travel time is lower than in the unweighted scenario. This is because the unweighted model's choice is topological and unaffected by road attributes. The weighted model looks at the length and ignores congestion should be better.

FIGURE 38 LENGTH WEIGHTED MODEL TRAFFIC COUNT (7-8 AM & 4-5 PM)

As Figure 38 illustrates, the length-weighted simulation represents the road usage pattern, and in this simulation case, it precisely reflects equal proportional changes in both the AM and PM periods.

What happens when only well-used roads (shown in Figure 23) are widened is depicted in the following simulations, Figure 39. This particular policy for congestion relief results in a somewhat larger change than the one mentioned earlier.

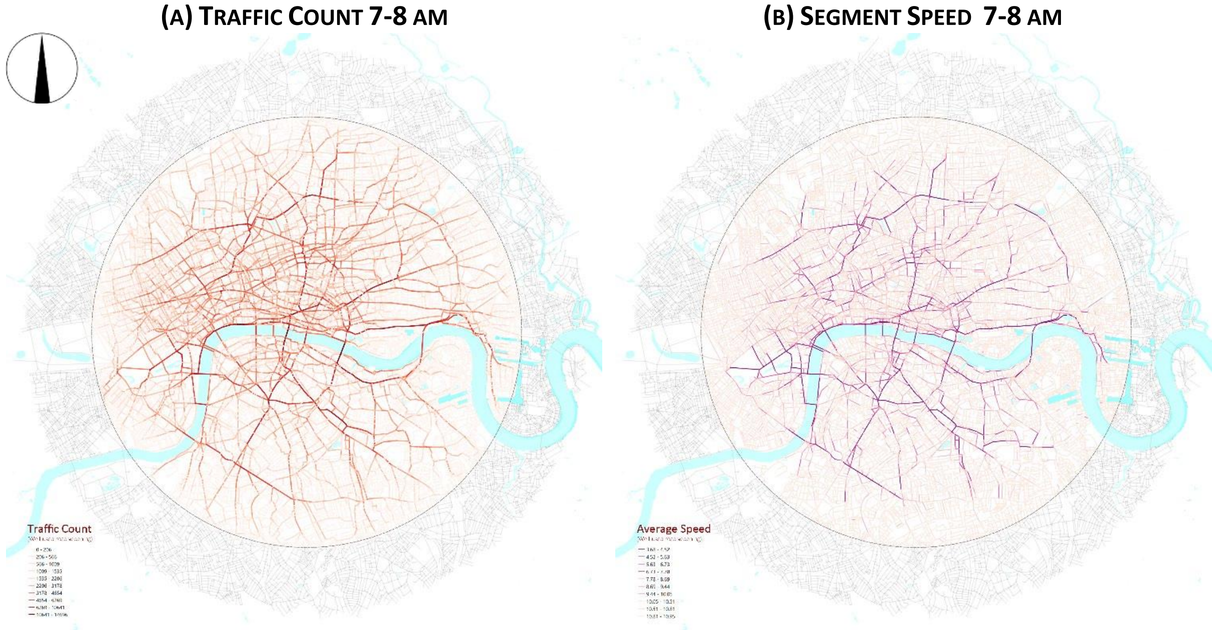


FIGURE 39 WELL-USED ROADS WIDENING

From Figure 39b, these widened roads are, in fact, more affected by congestion, as more people choose that route. Consequently, the number of vehicles experiencing congestion on this route increases. Predictably, due to the time lag, path choices with an average of 500 seconds or more lead to congestion with a delay of 500 seconds. Such a delay must also exist, resulting in an increase in congestion throughout the system, rather than a decrease. Table 17 confirms the impact of this on the overall system.

TABLE 17 WELL-USED ROAD WIDENING

Well-used 7-8 am	Congestion	Unweighted	Length	Average
Car (count)	232942	258055.2	300583.4	209442.8
Time (s)	128448976.4	128386659.1	128279882	128507736.8
Distance (km)	1110415.97	1402600.31	1402356.66	958442.69
Speed (m/s)	8.645	10.925	10.932	7.458
Time cost per car (s)	551.42	497.52	426.77	613.57
Well-used 4-5 pm	**Congestion**	**Unweighted**	**Length**	**Average**
Car (count)	326650	387471.8	451717.4	292046.8
Time (s)	192723270.4	192570329.7	192409957.6	192810134.9
Distance (km)	1562483.61	2103553.00	2103264.37	1326425.97
Speed (m/s)	8.107	10.924	10.931	6.879
Time cost per car (s)	590.00	496.99	425.95	660.20

6.2 HIGH INTEGRATION & CHOICE ROADS WIDENING

This study focuses on 1065 road line segments characterised by high integration and choice for the purpose of road widening. The road segments with high choice chosen for widening are depicted in Figure 31a, while those with high integration are represented in Figure 31b.

The performance after widening is depicted in Figure 40, and these figures exhibit relatively similar distributional performance.

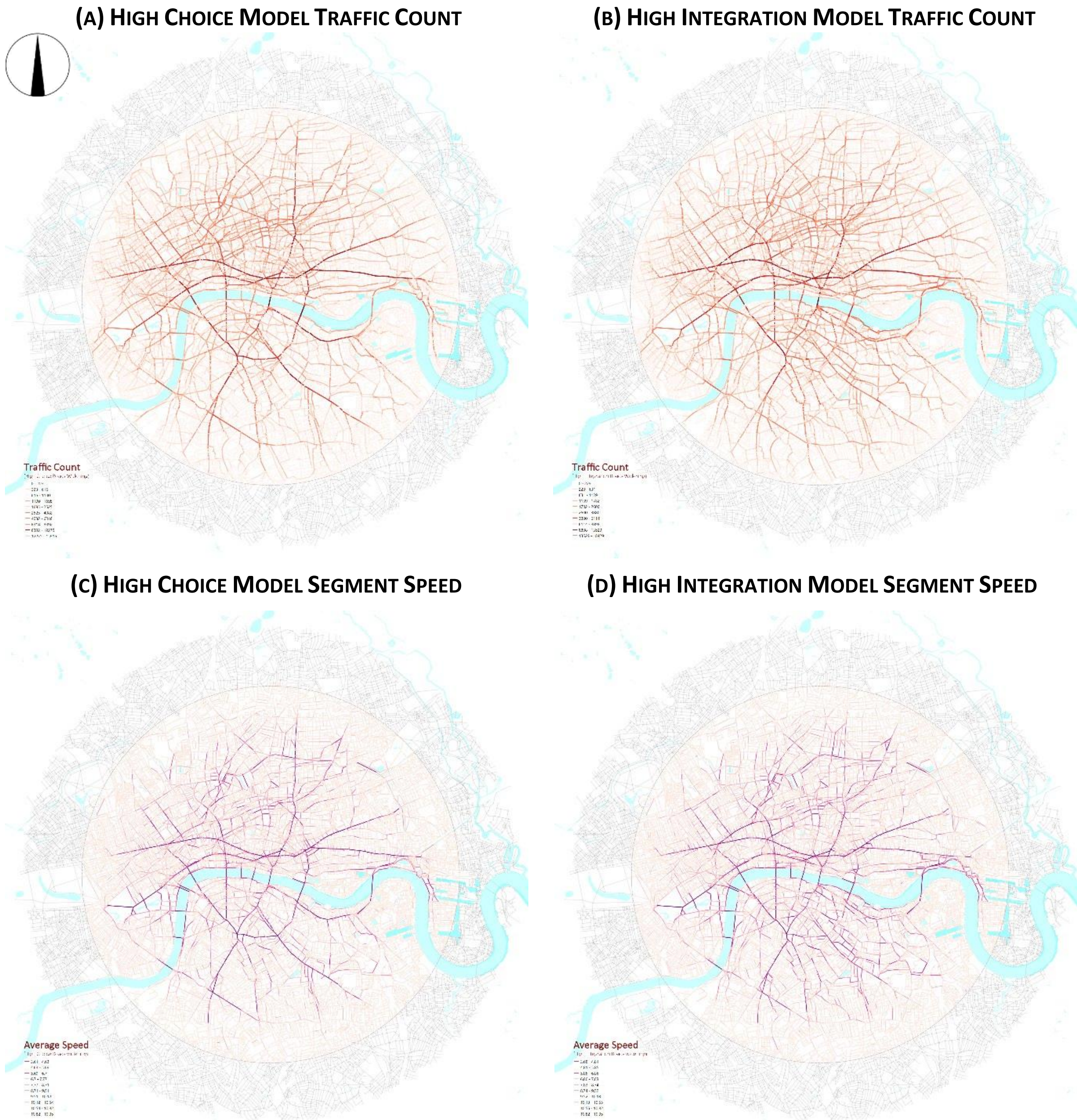


FIGURE 40 WIDENING SIMULATION RESULT (LEFT FOR HIGH CHOICE; RIGHT FOR HIGH INTEGRATION)

To further illustrate the impact of widening, the performance of the new trip distribution minus the pre-widening congested trip distribution is presented below. Additionally, Figure 41 provides insights into the changes in the widened roadways and their usage, zooming in to a 2km radius view. It is evident that the distribution of usage after all widening closely aligns with the length-weighted simulation model. Conversely, the four selective widening models show a higher concentration of people using the widened roads.

FIGURE 41 TRAFFIC COUNT CHANGES AFTER ROADS WIDENING POLICY

6.3 WIDENING POLICY AND CONGESTION

Tables 18 and 19 provide a comprehensive summary of the simulated data from the road widening study. Based on the data presented in these tables, we can conclude that all road widening efforts result in a reduction in congestion.

However, when it comes to widening specific roads, the effect varies, especially when considering the ratio of roads widened to the total number of roads (1065/29023). The unweighted well-used roads experienced the most significant negative impact, followed by the high-selectivity roads, while the high-integration roads fared better in comparison.

It's important to note that these findings do not necessarily imply that widening roads cannot be successful. The percentage of widening and the specific attributes of the roads being widened also play a crucial role in the outcome. However, for roads that already handle a substantial amount of traffic themselves, it's possible that widening them too early might be counterproductive.

TABLE 18 MORNING CONGESTION PERFORMANCE UNDER THE ROAD WIDENING POLICY

Widening 7-8 am	Congestion	Unweighted	Length	
Car (count)	232942	258055.2	300583.4	
Time (s)	128448976.4	128386659.1	128279882	
Distance (km)	1110415.97	1402600.31	1402356.66	
Speed (m/s)	8.645	10.925	10.932	
Time cost per car (s)	551.42	497.52	426.77	
Congestion Growth	0%	-10%	-23%	
Based on Length	29%	17%	0%	
	All Roads	Well-used	High Choice	High Integration
Car (count)	287013	209442.8	211624.4	220618
Time (s)	128314186	128507736.8	128502227.6	128479851.7
Distance (km)	1342248.63	958442.69	964313.98	1020459.52
Speed (m/s)	10.461	7.458	7.504	7.943
Time cost per car (s)	447.07	613.57	607.22	582.36
Congestion Growth	-19%	11%	10%	6%
Based on Length	5%	44%	42%	36%

TABLE 19 AFTERNOON CONGESTION PERFORMANCE UNDER THE ROAD WIDENING POLICY

Widening 4-5 pm	Congestion	Unweighted	Length	
Car (count)	326650	387471.8	451717.4	
Time (s)	192723270.4	192570329.7	192409957.6	
Distance (km)	1562483.61	2103553.00	2103264.37	
Speed (m/s)	8.107	10.924	10.931	
Time cost per car (s)	590.00	496.99	425.95	
Congestion Growth	0%	-10%	-23%	
Based on Length	38%	16%	0%	
	All Roads	Well-used	High Choice	High Integration
Car (count)	421820.6	292046.8	300281.8	313661.6
Time (s)	192485111.8	192810134.9	192789978.5	192756265.1
Distance (km)	1969325.95	1326425.97	1362475.40	1444788.83
Speed (m/s)	10.231	6.879	7.067	7.495
Time cost per car (s)	456.32	660.20	642.03	614.54
Congestion Growth	-17%	20%	16%	11%
Based on Length	7%	55%	50%	44%

7. DISCUSSION

Facing the issue of urban traffic congestion, this dissertation builds a realm of dynamic simulation modelling for real-time traffic systems to respond the Research Question A which was answered by Chapter 4. The core purpose of this method was to find out the relationship between Origin-Destination (OD) route choices and their impact on the real-time traffic system, with a key focus on the spatial network attributes. This study offers an analysis of quantifying congestion costs and their impacts on the transport system. Several findings are presented below:

Firstly, in the unweighted congestion model, vehicles gravitating towards primary routes known as "well-used roads" were observed. However, investigation under the weighted model shows that this preference for "well-used roads" often triggered severe speed reductions due to congestion. Consequently, alternative routes surrounding these congested arteries gained appeal, reshaping vehicle choices.

Secondly, the spatial congestion patterns are shown. Origin-Destination Routing simulations exposed the disproportionate impact of congestion on specific road segments. Notably, bridges traversing rivers emerged as the epicentre of congestion, culminating in reduced road speeds. Conversely, the congestion effect was more evenly distributed across other urban road segments, ensuring relatively stable speeds. When it comes to the influence of commuting patterns, particularly in the afternoon, residential areas experienced heightened congestion while office areas enjoyed smoother traffic flow. Remarkably, this distribution was minimally influenced by other components, primarily contingent upon the presence or absence of congestion weighting.

Thirdly, spatial network analysis revealed the relationship between congestion and spatial utilisation patterns. Perspectives related to the limitations and expansion of transport space demonstrate their evident impact on the transport network system.

Respond to Question B, which was analysed in chapters 5 and 6:

Firstly, congestion in a city is indeed exacerbated by the blockage of roads, and this effect is amplified when congested roadways are located in specific critical areas like exit routes or highly concentrated roads. In the case of bridges, which are susceptible to congestion, the number of bridges that disappear due to blockages is similar regardless of their original purpose, and the additional congestion resulting from their absence is also similar.

Secondly, it's generally beneficial to widen all roads. However, if only a fixed number of roads are widened (in this case, with a ratio of 1065/29023, though higher ratios should be investigated), congestion tends to increase. The severity of the situation is influenced by the widening ratio. The research only considered a small ratio. However, for larger ratios closer to 1, congestion reduction is more likely to occur. Interestingly, widening highly integrated roads results in less additional congestion. This is beneficial for commercial functions that rely on wider roads to maintain traffic-carrying capacity in highly integrated spaces.

8. CONCLUSION

The modelling approach makes some contributions to the field in several ways:

Firstly, it expands the scope of the explicit study on congestion distribution. The model offers a method to explicitly study the distribution and extent of congestion in spatial terms. This allows for a more granular and spatially informed understanding of congestion patterns, which can be crucial for urban planning and transport management.

Secondly, it contributes to studies that predict the impact of various policies on congestion. By simulating the effects of different policies, decision-makers can better understand the potential outcomes and make more informed choices regarding urban development and transport strategies.

Thirdly, the combination of origin-destination modelling, and space syntax enables the incorporation of spatial social-level influences. This means that not only traffic patterns but also the social and behavioural aspects of transport can be considered, providing a more comprehensive view of urban mobility.

Finally, the model's simplification of simulation makes it relatively intuitive to adjust for policy changes or other impacts. This flexibility allows for easier exploration of the effects of different scenarios without the complexity inherent in studying real, dynamic systems.

However, this model has several limitations:

In terms of the study's commuting, it's important to acknowledge that commuting behaviour achieving 100% of traffic, regardless of the proportion of traffic it represents, is unlikely. While the assumption of exclusive commuting in the transport system is rational, it may oversimplify real-world traffic behaviour.

Although the definition of "Origin" compensates for vehicles by adjusting for the population of the outer ring, it's crucial to highlight that London's traffic profile predominantly involves car traffic originating in the outer suburbs, which have limited public transport access (Le Vine and Polak 2019). This factor contributes significantly to the disparity between the simulation model and the real-world situation at this specific scale.

Due to computational constraints, the simulation overlooks the ability of individuals within the system to make changes to their routes over time. For example, switching between roads promptly is commonplace in the current navigation era. Implementing such changes would necessitate substantial computational resources to update the Origin-Destination routing through igraph's algorithm in each iteration. Another issue is that ignoring it results in significant spatio-temporal lag issues, particularly when studying road widening. Addressing this aspect in future research through algorithmic optimisation and other enhancements is a feasible approach.

The future plans are discussed below：

Firstly, implementing algorithms to address lag in the model is a crucial step for real-time applications. Investigating the impact of lag, or the lack thereof, can provide valuable insights into the model's behaviour and its potential enhancements.

Secondly, assessing the effectiveness of real-time regulation through mapping software or traffic broadcasting is an important avenue to explore. This can contribute to more efficient congestion management strategies.

Thirdly, expanding the study's size and complexity by constructing more intricate Origin-Destination Models (ODMs) can help determine whether the scale limitation observed in the model reflects real-world conditions or is due to the model's scale.

Besides, investigating the interplay between multiple policies and their effects on congestion is essential. Understanding how different policies interact can lead to more comprehensive urban planning strategies.

In addition, fine-tuning congestion parameters with more accurate and realistic data is vital. This can lead to a more precise representation of congestion and improve the model's predictive capabilities.

Moreover, including bus and subway transport in the model can offer insights into the impact of public transit policies on congestion and urban mobility.

Finally, defining the logic and proportion of ODM construction based on different behavioural time periods and distributions can provide a more nuanced understanding of how human behaviour influences transport patterns.

These future directions show a holistic approach to improving the model's accuracy, adaptability, and utility in addressing real-world urban transport challenges.

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REFERENCE

Al-Sayed, Kinda, Alasdair Turner, Bill Hillier, Shinichi Iida, and Alan Penn. 2014. 'Space Syntax Methodology'. *Bartlett School of Architecture, UCL: London, UK*.

Anselin, Luc. 1988. *Spatial Econometrics: Methods and Models*. Vol. 4. Springer Science & Business Media.

Anwar, AHMM, Akimasa Fujiwara, and Junyi Zhang. 2011. 'Newly Developed Link Performance Functions Incorporating the Influence of On-Street Occupancy for Developing Cities: Study on Dhaka City of Bangladesh'. In , 23–27.

Arnott, Richard, and Kenneth Small. 1994. 'The Economics of Traffic Congestion'. *American Scientist* 82 (5): 446–55.

Beesley, Michael E. 1965. 'The Value of Time Spent in Travelling: Some New Evidence'. *Economica* 32 (126): 174–85.

Bera, Sharminda, and KV Rao. 2011. 'Estimation of Origin-Destination Matrix from Traffic Counts: The State of the Art'.

Cookson, Brian. 2015. *Crossing the River: The History of London's Thames River Bridges from Richmond to the Tower*. Random House.

Cutini, Valerio, and Camilla Pezzica. 2020. 'Street Network Resilience Put to the Test: The Dramatic Crash of Genoa and Bologna Bridges'. *Sustainability* 12 (11): 4706.

Gore, Ninad, Shriniwas Arkatkar, Gaurang Joshi, and Constantinos Antoniou. 2023. 'Modified Bureau of Public Roads Link Function'. *Transportation Research Record* 2677 (5): 966–90.

Jackson, Matthew O. 2008. *Social and Economic Networks*. Vol. 3. Princeton university press Princeton.

Jeong, Daeyoung, Yun Eui Choi, Lilan Jin, and Jinhyung Chon. 2019. 'Impact of Spatial Change on Tourism by Bridge Connections between Islands: A Case Study of Ganghwa County in South Korea'. *Sustainability* 11 (22): 6516.

Karimi, K, E Parham, E Friedrich, and P Ferguson. 2013. 'Origin-Destination Weighted Choice Model as a New Tool for Assessing the Impact of New Urban Developments'. In .

Kazerani, Aisan, and Stephan Winter. 2009. 'Can Betweenness Centrality Explain Traffic Flow'. In , 1–9. Germany: Leibniz Universität Hannover.

Kropf, Karl. 2017. 'Bridging Configurational and Urban Tissue Analysis'. In , 165–1.

Kubat, Ayşe Sema, H Serdar Kaya, F Sari, Ö Özer, and G Güler. 2007. 'The Effects of Proposed Bridges on Urban Macroform of Istanbul'. In .

Lam, Terence C, and Kenneth A Small. 2001. 'The Value of Time and Reliability: Measurement from a Value Pricing Experiment'. *Transportation Research Part E: Logistics and Transportation Review* 37 (2–3): 231–51.

Le Vine, Scott, and John Polak. 2019. 'The Impact of Free-Floating Carsharing on Car Ownership:

Early-Stage Findings from London'. *Transport Policy* 75: 119–27.

LeSage, James P, and R Kelley Pace. 2008. 'Spatial Econometric Modeling of Origin-destination Flows'. *Journal of Regional Science* 48 (5): 941–67.

Lyons, Glenn, and Kiron Chatterjee. 2008. 'A Human Perspective on the Daily Commute: Costs, Benefits and Trade-offs'. *Transport Reviews* 28 (2): 181–98.

Manley, E. 2014. 'Modelling Driver Behaviour to Predict Urban Road Traffic Dynamics'.

Marcus, Lars, and Johan Colding. 2014. 'Toward an Integrated Theory of Spatial Morphology and Resilient Urban Systems'. *Ecology and Society* 19 (4).

Spiess, Heinz. 1990. 'Conical Volume-Delay Functions'. *Transportation Science* 24 (2): 153–58.

Tarko, Andrew P, and Rafael I Perez-Cartagena. 2005. 'Variability of Peak Hour Factor at Intersections'. *Transportation Research Record* 1920 (1): 125–30.

Teräsvirta, Timo. 1994. 'Specification, Estimation, and Evaluation of Smooth Transition Autoregressive Models'. *Journal of the American Statistical Association* 89 (425): 208–18.

Trigueiro, Edja Bezerra Faria, and V Medeiros. 2007. 'The Bridge, the Market, a Centrality Forever Lost and Some Hope'. In , 036–01.

Varoudis, Tasos, Stephen Law, Kayvan Karimi, Bill Hillier, and Alan Penn. 2013. 'Space Syntax Angular Betweenness Centrality Revisited'. In .

Vecia, Giacomo. 2019. 'CITY STREETS TRAFFIC SURVEY 2019'.

Wang, Weijia, Kin Wai Michael Siu, and Kwok Choi Kacey Wong. 2016. 'The Pedestrian Bridge as Everyday Place in High-Density Cities: An Urban Reference for Necessity and Sufficiency of Placemaking'. *Urban Design International* 21: 236–53.

Wardman, Mark. 2004. 'Public Transport Values of Time'. *Transport Policy* 11 (4): 363–77.

Xiao, Jianli, Hang Li, Xiang Wang, and Shangcao Yuan. 2018. 'Traffic Peak Period Detection from an Image Processing View'. *Journal of Advanced Transportation* 2018: 1–9.

Yang, Hai, Qiang Meng, and Michael GH Bell. 2001. 'Simultaneous Estimation of the Origin-Destination Matrices and Travel-Cost Coefficient for Congested Networks in a Stochastic User Equilibrium'. *Transportation Science* 35 (2): 107–23.

APPENDIX

Simulation Model Code (Congestion Weighted 7-8 AM Model as Example)

The code for studying the corresponding problem can be generated from this set of codes, depending on whether variants of weights and congestion factors are changed or not.

```
import numpy as np
import igraph as ig
# import cProfile
from multiprocessing import Pool
import time


def fix_p(p):  # normalize probability
    if p.sum() != 1.0:
        p = p * (1. / p.sum())
    return p


def congestion(number=0):  # total model

    start_time = time.time()  # record simulation time
    rng1 = np.random.default_rng(seed=number)  # build up random number

    # import files: network [Segment1, Segment2] (from depth map), SiteMap [SegmentID, Length] (from
QGIS)
    network = np.loadtxt(r'D:\demo\_segment_connections.csv', delimiter=',', skiprows=1, dtype='int32',
                         quotechar='"', usecols=(0, 1))
    sitemap = np.loadtxt(r'D:\demo\WayFinding.csv', delimiter=',', skiprows=1, dtype='float',
quotechar='"',
                         usecols=(1, 2))
    # origin destination [id, random] count [hour count]
    origin = np.loadtxt(r'D:\demo\origin.csv', delimiter=',', skiprows=1, dtype='float', quotechar='"',
                        encoding='utf-8-sig', usecols=(1, 6))
    destination = np.loadtxt(r'D:\demo\destination.csv', delimiter=',', skiprows=1, dtype='float',
quotechar='"',
                             encoding='utf-8-sig', usecols=(1, 7))
    count = np.loadtxt(r'D:\demo\TrafficCount.csv', delimiter=',', skiprows=1, dtype='float',
quotechar='"',
                       encoding='utf-8-sig', usecols=(0, 1))

    # fix the probability
    ori_pro = fix_p(origin[:, 1])
```

```
    des_pro = fix_p(destination[:, 1])

    # build up Map & weight and changing weight
    _map = ig.Graph(n=sitemap.shape[0], edges=network)
    _map.es['weight'] = (sitemap[network[:, 0], 1] + sitemap[network[:, 1], 1]) / 2
    site_weight = np.empty(sitemap.shape[0])

    # spt(distance(m))=speed*time; time interval = 5s;
    spt = 5 * 10.94493896

    car = np.empty((0, 2), dtype='int32')  # car[:, 0] location; car[:, 1] steps judge
    dis = np.empty(0, dtype='float')  # travel distance
    # record = np.empty((0, sitemap.shape[0]), dtype='int32')  # record layout
    # period = np.empty((0, sitemap.shape[0]), dtype='int32')

    # run 0.5h and reach 7:00am; 0.5h = 1800s; time interval = 60s; simulation before 7:00am(6:30am
start)
    OD = []
    betweenness = [0] * sitemap.shape[0]

    for t in range(0, 1800, 5):
        num = count[7, 1] * t / 600 - car.shape[0]  # count cars need to add
        print('pre model #{}, t = {}s, add car = {}'.format(number, t, int(num)))  # monitoring

        car = np.append(car, np.zeros((int(num), 2), dtype='int32'), axis=0)  # add cars
        dis = np.append(dis, np.zeros(int(num), dtype='float'), axis=0)  # add distance
        pair = np.empty((int(num), 2), dtype='int32')  # pair origin & destination
        pair[:, 0] = rng1.choice(origin[:, 0], int(num), p=ori_pro)  # random choose origin
        pair[:, 1] = rng1.choice(destination[:, 0], int(num), p=des_pro)  # random choose destination

        for i in range(sitemap.shape[0]):  # find route for the same i = times of repeat
            des = pair[pair[:, 0] == i, 1].tolist()  # the destination of the repeat origin
            if len(des) != 0:
                a = _map.get_shortest_paths(v=i, to=des, weights='weight', output='vpath')
                OD += a
                for m in range(len(a)):
                    for n in range(len(a[m])):
                        betweenness[a[m][n]] += 1

        _del = np.empty(0, dtype='int32')  # clear dead cars
        for j in range(car.shape[0]):  # put cars into OD list j = each car

            if t == 0:
                dis[j] += spt
            elif (1 + (0.15 * (temp[0, [OD[j][car[j, 1]]]][0] * 5 / sitemap[car[j, 1], 1]) ** 4)) < 3:
```

```
                dis[j] += (spt / (1 + (0.15 * (temp[0, [OD[j][car[j, 1]]]][0] * 5 / sitemap[car[j, 1],
1]) ** 4)))
            else:
                dis[j] += (spt / 3)
            while dis[j] >= sitemap[OD[j][car[j, 1]], 1]:  # if it gets onto the next step or next of
next
                dis[j] -= sitemap[OD[j][car[j, 1]], 1]  # step up
                car[j, 1] += 1  # step up
                if car[j, 1] == len(OD[j]):  # judge whether dead
                    car[j, 1] -= 1
                    dis[j] += sitemap[OD[j][car[j, 1]], 1]
                    _del = np.append(_del, [j], axis=0)  # dead cars
                    break
            car[j, 0] = OD[j][car[j, 1]]  # update location

        # delete dead cars
        car = np.delete(car, _del, axis=0)
        # change count
        temp = np.bincount(car[:, 0], minlength=sitemap.shape[0]).astype('int32').reshape(1,
sitemap.shape[0])
        # count
        # record = np.append(record, temp, axis=0)
        # renew distance
        dis = np.delete(dis, _del, axis=0)
        # OD = np.delete(OD, _del, axis=0)
        # renew OD
        for k in range(len(OD)-1, -1, -1):
            if k in _del:
                OD.pop(k)

        # change weight
        site_weight[:] = (sitemap[:, 1] * (1 + 0.15 * (temp[:] * 5 / sitemap[:, 1])) ** 4)
        _map.es['weight'] = (site_weight[network[:, 0]] + site_weight[network[:, 1]]) / 2

    # for o in range(0, len(record), 60):
    #     a = np.array([np.sum(record[o: o + 60], axis=0)])
    #     period = np.append(period, a, axis=0)

    # np.savetxt(r'D:\demo\simulate\weight\start{}.txt'.format(number), period.T, delimiter=',',
fmt='%d')
    # np.savetxt(r'D:\demo\simulate\weight\pre{}.txt'.format(number), betweenness, delimiter=',',
fmt='%d')

    for i in range(len(OD)):
        OD[i] = OD[i][car[i, 1]:]
```

```
    car[:, 1] = 0
    dis[:] = 0
    total = car.shape[0]
    betweenness = [0] * sitemap.shape[0]
    for m in range(len(OD)):
        for n in range(len(OD[m])):
            betweenness[OD[m][n]] += 1
    # record = np.empty((0, sitemap.shape[0]), dtype='int32')
    # period = np.empty((0, sitemap.shape[0]), dtype='int32')
    cost = np.zeros(sitemap.shape[0], dtype='float')

    # spt(distance(m))=speed*time; time interval = 5s;
    end = 8
    for t in range(0, (end - 7) * 3600, 5):
        num = ((count[end, 1] - count[end - 1, 1]) * (t - (end - 8) * 3600) / 3600 + count[end - 1, 1])
- car.shape[0]
        print('real model #{}, t = {}s, add car = {}'.format(number, t, int(num)))

        if num > 0:
            total += int(num)
            car = np.append(car, np.zeros((int(num), 2), dtype='int32'), axis=0)
            dis = np.append(dis, np.zeros(int(num), dtype='float'), axis=0)
            pair = np.empty((int(num), 2), dtype='int32')  # pair origin & destination
            pair[:, 0] = rng1.choice(origin[:, 0], int(num), p=ori_pro)  # random choose origin
            pair[:, 1] = rng1.choice(destination[:, 0], int(num), p=des_pro)  # random choose
destination

            for i in range(sitemap.shape[0]):
                des = pair[pair[:, 0] == i][:, 1].tolist()
                if len(des) != 0:
                    a = _map.get_shortest_paths(v=i, to=des, weights='weight', output='vpath')
                    OD += a
                    for m in range(len(a)):
                        for n in range(len(a[m])):
                            betweenness[a[m][n]] += 1

        _del = np.empty(0, dtype='int32')
        for j in range(car.shape[0]):
            a = car[j, 1]
            c = dis[j]

            if (1 + (0.15 * (temp[0, [OD[j][car[j, 1]]]][0] * 5 / sitemap[car[j, 1], 1]) ** 4)) < 3:
                d = (spt / (1 + (0.15 * (temp[0, [OD[j][car[j, 1]]]][0] * 5 / sitemap[car[j, 1], 1]) **
4)))
            else:
```

```
                d = (spt / 3)

            dis[j] += d
            while dis[j] >= sitemap[OD[j][car[j, 1]], 1]:
                dis[j] -= sitemap[OD[j][car[j, 1]], 1]
                car[j, 1] += 1
                if car[j, 1] == len(OD[j]):
                    car[j, 1] -= 1
                    dis[j] += sitemap[OD[j][car[j, 1]], 1]
                    _del = np.append(_del, [j], axis=0)
                    break
            car[j, 0] = OD[j][car[j, 1]]

            b = car[j, 1]
            if a == b:
                cost[OD[j][a]] += min(d, sitemap[OD[j][a], 1] - c) * 5 / d
            else:
                cost[OD[j][a]] += (sitemap[OD[j][a], 1] - c) * 5 / d
                for k in range(a + 1, b):
                    cost[OD[j][k]] += sitemap[OD[j][k], 1] * 5 / d
                cost[OD[j][b]] += min(dis[j], sitemap[OD[j][b], 1]) * 5 / d

        # delete dead cars
        car = np.delete(car, _del, axis=0)
        dis = np.delete(dis, _del, axis=0)
        temp = np.bincount(car[:, 0], minlength=sitemap.shape[0]).astype('int32').reshape(1,
sitemap.shape[0])
        # record = np.append(record, temp, axis=0)
        # OD = np.delete(OD, _del, axis=0)
        for k in range(len(OD) - 1, -1, -1):
            if k in _del:
                OD.pop(k)

        # change weight
        site_weight[:] = (sitemap[:, 1] * (1 + 0.15 * (temp[:] * 5 / sitemap[:, 1])) ** 4)
        _map.es['weight'] = (site_weight[network[:, 0]] + site_weight[network[:, 1]]) / 2

    # for o in range(0, len(record), 60):
    #     a = np.sum(record[o: o + 60], axis=0)
    #     period = np.append(period, [a], axis=0)

    for i in range(len(OD)):
        OD[i] = OD[i][car[i, 1]:]
    betweenness1 = [0] * sitemap.shape[0]
    for m in range(len(OD)):
```

```
        for n in range(len(OD[m])):
            betweenness1[OD[m][n]] += 1

    result = np.zeros((sitemap.shape[0], 5), dtype='float')
    result[:, 0] = list(range(0, sitemap.shape[0]))  # ID
    result[:, 1] = np.array(betweenness) - np.array(betweenness1)  # real OD = all - future
    result[:, 2] = result[:, 1] * sitemap[:, 1]  # distance = real OD * Length
    result[:, 3] = cost[:]  # time
    result[:, 4] = result[:, 2] / result[:, 3]  # speed = distance / time

    np.savetxt(r'D:\demo\simulate\weight78\total{}.txt'.format(number), [total], delimiter=',', fmt='%d')
    np.savetxt(r'D:\demo\simulate\weight78\result{}.txt'.format(number), result, delimiter=',', fmt='%f')
    # np.savetxt(r'D:\demo\simulate\weight78\location{}.txt'.format(number), period.T, delimiter=',', fmt='%d')
    # np.savetxt(r'D:\demo\simulate\weight78\betweenness{}.txt'.format(number), betweenness, delimiter=',', fmt='%d')
    # np.savetxt(r'D:\demo\simulate\weight78\between_del{}.txt'.format(number), betweenness1, delimiter=',', fmt='%d')

    end_time = time.time()
    print(end_time - start_time)


if __name__ == '__main__':  # below is the main, start at this line
    # congestion()  # run once
    # cProfile.run('congestion()')  # run once with cProfile

    core = 5
    with Pool(core) as pool:
        pool.map(congestion, range(core))
```