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Article

A real-time traffic data analytics framework for intelligent mobility management during the Hajj season

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Abstract: Traffic surveillance during Hajj season is a crucial consideration in making decisions and ultimately helping to run the business effectively. Usually, large numbers of people need to be handled for transportation and traffic control, such as thousands of buses and vehicles. Yet there is no reliable, real-time information on the Hajj movements needed for measurement, benchmarking, and continual improvement but it is a huge obstacle to efficient management. Such a challenge is addressed in this analysis by developing an API-based system of collecting and analyzing traffic information for real-time use. The system generates hajj route files which contain longitude and latitude-coding geospatial points. These files are then deposited on a web page that displays traffic statistics from the API for each station on each route at defined times. The collected data is then deposited into a series of databases to be used for statistical and analytic purposes, such as estimates of delays and congestion-level estimates. The proposed system provides solid and adaptive real-time analytics that enable better transportation decision making, user experience, and more efficient and safer transport management. The collected data could also be used to alert drivers to estimated journey times to holy sites, and the long-term study helps identify bottlenecks and improve road network design. Overall, this approach helps to develop intelligent decision support systems for sustainable, data-driven traffic management during the Hajj season.

Keywords: Hajj traffic management; real-time traffic analytics; intelligent transportation systems (ITS); spatio-temporal data analysis; decision support systems

1. Introduction

The Hajj is a holy festival celebrated by Muslims at Makkah each year and is the fifth element of Islam. All adult Muslims who can physically and financially sustainably undertake the journey [1] are obligated to perform such a religious ritual. Every year, over two million pilgrims from around the world come to the Kingdom of Saudi Arabia to perform the Hajj rituals [2]. This mass, and this size of crowd, makes it one of the biggest and most complex human mobility events in the world. As a result, logistics and operation of transportation and crowd movements during the Hajj are quite difficult. Transparency and historical traffic analysis is the key to ensuring that millions of pilgrims can travel safely, efficiently and on time across the holy sites of Makkah, Mina, Arafat, and Muzdalifah [3].

Because of the immense volume of people and vehicles, during Hajj, traffic on major routes and inter- sections is often a problem, such as on citadel road and at intermissions [4]. Because of large numbers of pilgrims, many walking, some using buses or authorized vehicles, movement causes spatially and temporally complex patterns of movement. To counter this, the Saudi Ministry of Hajj and Umrah, as well as the transport agencies, have implemented modern methods of transportation management, such as fleet management, electronic ticketing, and mobile tracking of workers via wireless, GSM, and RFID systems. Many existing systems are designed for pre-defined traffic flows and manual monitoring and, often, fail to capture the real-time traffic movement during peak h [5]. Therefore, the decision-makers do not have a coherent, data-driven platform for assessing congestion levels and optimizing route allocation in real time [6].

Recent research has increasingly recognized the value of data analysis and smart technologies to support large-scale event management [7]. Most of the existing research on crowd and traffic control has been done in urban mobility systems or general transportation systems, but not in the context of pilgrimage mobility [8]. This group of studies addresses safety and logistics but largely relies on static, incomplete data sets that cannot follow dynamic crowd behavior and changing traffic.

Modern research has examined mobility trends using satellite imagery, mobile cellular data, and geolocated social media feeds. There is also an interest in introducing IoT sensors, drones and traffic cameras into data collection and event surveillance systems. These diverse data streams typically undergo preprocessing, including cleaning, blending, and aggregating, before analysis is performed using real-time algorithms. These approaches are complementary to Saudi Arabia Vision2030, which targets the digital revolution and smart cities [9]. Despite these advances, there are still many challenges. For example, with regards to Hajj, surveillance of vehicles entering and leaving Makkah is a manual process that can be slow and error prone. The lack of coordination and sharing of data among different authorities complicates the process of establishing a single real-time picture. Systems are not built to capture continuous data from multiple sources and are not set up to anticipate traffic and congestion. To address these limitations, this paper proposes the development of a smart, API-driven, real time traffic monitoring system that collects, displays and analyses congestion information across the major Hajj routes automatically. The system uses file-named geo-referenced routes with sequential coordinates (latitude and longitude) that are stored in a web browser. This interface gets live traffic statistics from an external data platform via an application programming interface (API) which is used to provide peak congestion statistics for each lane at a given period. Also, the units of data are held in a sequenced database that provides statistical and analytical tools such as calculating delay ratios, congestion patterns, and average performance per route.

The proposed solution is a robust, flexible and flexible vehicle traffic analysis protocol that is an extension of other current technologies such as on-board sensors, surveillance cameras, and IoT devices. It can detect congestion early using machine learning controlled control algorithms. It can also forecast traffic automatically by using API data acquisition and a dynamic visualization, making it more efficient, safer, and convenient for travelers, thus improving mobility system design and operation ahead of the Hajj seasons.

The rest of this article is divided into the following sections. Section II reviews the literature and discusses some examples of possible approaches to managing traffic and crowds at large scale events and the Hajj. Section III describes the proposed approach which consists of the system architecture, the use of an API, the analysis of data, and the analysis of instantaneous traffic data. Section IV covers the set-up of the experiment and the analysis of traffic data: route-wise congestion assessment, performance assessment, and traffic patterns visualization. Section V provides a summary of the results, a discussion of implications in practice, and recommendations for future research aiming to improve the safety and efficiency of managing mobility during Hajj.

2. Literature review

Urban mobility and other mass events, such as the Hajj pilgrimage have led to a rapid evolution of intelligent traffic management systems using Big Data, Internet of Things, and Real-Time Analytics. New research in these fields demonstrates new technologies, architecture, and analysis models that support the current development of traffic monitoring models.

New technologies based on the IoT have transformed traditional modes of transportation into data driven and adaptive environments. For urban congestion through real time sensors and predictive analytics, Mutambik [10] proposed a multiagent approach to IoT-based adaptive traffic management. Simulations with multiple agents that characterize vehicles and infrastructure as self-contrasting, behaviorally dynamic entities were found to be effective in reducing travel time by 30% and reducing intersection congestion by 50 %. Similarly, Berres et al. [11], who developed the Chattanooga Digital Twin, provides an end-to-end cyber-physical control system for urban traffic optimization. CT win architecture combines IoT information, environmental sensors, and decision-making analytics to provide real-time situational awareness and adaptive signal control through a web interface. These studies show that IoT sensors and cyber-physical systems can greatly improve adaptive control, scalability, and sustainability, both of which are important requirements for Hajj-scale mobility systems as well.

Informational transportation research has also sought to employ Big Data analytics for decision making in real-time. Recent works such as [3,12,13] also proposed distributed architectures that generate heterogeneous traffic data through machine learning and deep learning algorithms. These models combine historical and streaming data to develop predictive models and enable proactive rerouting, congestion forecasting, and adaptive signal control. Likewise, Nahri et al. [14] proposed an Internet of Vehicles (IoV) architecture featuring fog and cloud computing for real-time event processing in Moroccan urban networks. The system was able to show the utility of localized fog analysis for reducing data processing latency. On top of that, Babar [15] implemented a three-phase big data processing system using Spark to control traffic in real-time IoT, showing the scale of distributed computing

in smart transportation environments. Across these studies, the combination of IoT, fog computing, and Big Data analytics can provide near-instantaneous identification and response to congestion patterns that can be tailored to the spatiotemporal scale of Hajj traffic flows.

For understanding and managing complex traffic data, visualization has become a fundamental component in the quest for traffic congestion alleviation and road safety, as shown in [16] introduction of the Trafair Traffic Dashboard that fuses traffic sensor data and air quality models to expose congestion patterns and environmental influences across European cities. Similarly, the TA-Dash system presented by [17]

Prioritizes interactive spatial-temporal visualization of predicted urban mobility, a feature that enhances the usability of non-expert operators. In the context of pre-emptive safety control, Abdel-Aty et al. [18] Created a web-based real-time traffic safety management and crash prediction system that assimilates CCTV feeds, weather information, and motor vehicle telemetry, whereas a recent 2019 submission from [19]. Presented an end-to-end, cloud-based traffic management service. Traffic Management as a Service TMaaS, that is driven by city-level visualization and permits the interlinking of diverse modes of transport and sharing of data between stakeholders. These systems show the massive capability of intuitive displays and geospatial visualization in transforming raw data into actionable knowledge for decision-makers. Besides traffic streamlining, recent studies are now applying predictive analytics to prevent crashes and forecast future trends, including a UK traffic crash analysis system proposed by [20], which makes use of clustering and deep learning to zero in on places that are prone to accidents, and forecast future crash frequencies. While these predictions are directed towards urban streets, they may provide a wealth of new ideas for modeling factual risks and clogs during mass pilgrimage travel. IoT integration, Big Data analytics, and visualizations could all be cited as the three pillars of the next generation traffic management. There are several areas of gaping research. Current systems are designed for cities and do not respond to high-density event scenarios such as the Hajj pilgrimage. Often, these systems rely on static data models without considering the time-synchronization challenges associated with masses of people performing religious rituals.

In addition, there are few studies focusing on multi-route coordination or real-time congestion analysis of events of brief but large-volume events. Those needs were filled by the present paper's proposal to provide real-time API traffic analytics that are tailored to the unique spatiotemporal patterns of Hajj transportation. Combining APIs, time-series data storage, and logistic congestion modeling, it combines the notion of IoT-enabled adaptive management and Big Data visualization to a large-scale, event-specific scenario. The study highlights the progress made in IoT, Big Data, and visualization of data for transportation systems in urban or simulation-based scenarios and only covers adaptive control of signals, environmental monitoring, or safety prediction, rather than big-scale event-specific mobility. Few other systems address these weaknesses with a comprehensive real-time analysis of API data, spatial databases, and traffic predictions. The proposed system is uniquely positioned to address these shortcomings with a seamless real-time analytics pipeline addressing the unique needs of Hajj traffic. It bridges the gap between data acquisition and decision support, offering scalable insights for proactive traffic management in high-density pilgrimage environments.

Beyond generic distributed data platforms and foundational Internet of Things (IoT) architectures, the critical frontier of intelligent mobility management—particularly under extreme demand variations—increasingly relies on high-precision, deep-learning-based predictive capabilities. This paradigm shift is vital for environments such as the Hajj, where pilgrim and vehicular traffic exhibit highly non-linear, complex spatiotemporal dependencies that cannot be adequately characterized by static or linear analytical systems.

To effectively address these intricate spatiotemporal correlations, recent breakthroughs have introduced hybrid and advanced structural designs. For instance, Yu et al. [21] proposed a Quantum-Inspired Dynamic Spatiotemporal Matching Transformer for Traffic Flow Forecasting. Their framework leverages dynamic matching mechanisms to capture volatile, high-dimensional data dependencies across shifting network topologies, offering a robust blueprint for modeling sudden structural gridlocks. Concurrently, navigating scenarios marked by severe, unprecedented variations in data distribution remains a cornerstone challenge for model generalization. To mitigate this data-scarcity and volatile-shift problem, Lin et al. [22] developed a Cross City Pre-Training Transfer Learning Model for Traffic Flow Prediction. Their methodology demonstrates how transferring localized, pre-trained weights from data-rich environments can fundamentally enhance a predictive framework's robustness and adaptive responsiveness when deployed in completely discrete urban or event-specific scales. Incorporating these high-precision spatiotemporal and transfer-learning prediction modules highlights the academic necessity of augmenting our proposed framework to transition from a localized real-time tracking pipeline into a proactive, frontier-relevant intelligent transportation platform.

The recent literature in **Table 1** shows that IoT, Big Data, and visualization are increasingly being used to integrate information technology in transportation, most of the reviews are from urban or simulation settings, focusing on adaptive signal control, environmental monitoring, or safety prediction, rather than large-scale mobility events. Few frameworks include a single platform to incorporate real-time API data processing, spatio-temporal database management, and predictive congestion modelling. The proposed framework tries to overcome these limitations with a fully integrated, real-time analytics pipeline built for Hajj, blending data acquisition and decision making, providing valuable insights for preventing traffic congestion during big numbers of pilgrimage environments.

Table 1. Compares the related approaches in IoT-enabled and big data-based traffic management.

Study / reference	Technology / framework	Main contribution	Limitation / gap
Mutambik et al. (2025) [10]	IoT, Multiagent Simulation	Developed adaptive traffic management integrating real-time sensor data and predictive analytics; achieved 30% lower travel time and 50% congestion reduction.	Urban context only; lacks application to large-scale event-based mobility (e.g., Hajj).
Xu et al. (2023) [11]	Digital Twin, IoT, Cloud Platform	Proposed CTwin platform for real-time situational awareness and cyber-physical control in urban traffic systems.	Focused on single-city deployment (Chattanooga); limited scalability analysis.
Amini et al. (2017) [13]	Big Data Analytics, ML-based Optimization	Integrated historical and streaming data to optimize traffic flow using adaptive routing and congestion forecasting.	Does not address data latency or edge processing issues.
Nahri et al. (2018) [14]	IoV, Fog & Cloud Computing	Introduced IoV architecture for real-time data collection and visualization in Moroccan road networks.	Early-stage implementation; lacks full-scale deployment results.
Babar et al. (2019) [15]	IoT, Spark, Big Data Processing	Proposed three-phase big data processing scheme for IoT-based smart transportation.	Limited performance benchmarking; no visualization or decision-support layer.

Table 1. (*Continued*).

Study / reference	Technology / framework	Main contribution	Limitation / gap
Rahmani et al. (2022) [16]	Visualization, IoT Sensor Networks	Developed Trafair Dashboard for visualizing traffic data and air quality impact in European cities.	Focuses on environmental metrics rather than real-time traffic prediction.
Tempelmeier et al. (2020) [17]	Interactive Visualization, ML Models	Created TA-Dash dashboard for spatial-temporal traffic analytics and non-expert accessibility.	Lacks predictive control or adaptive decision-making capabilities.
Abdel-Aty et al. (2023) [18]	Big Data, Real-Time Visualization	Designed proactive traffic safety management system using crash prediction and CCTV data integration.	Limited scalability to multi-city or large-event contexts.
Van den Bossche et al. (2020) [19]	Cloud Computing, TMaaS Platform	Developed multimodal cloud-based traffic management as a service integrating various data sources.	Emphasis on urban multimodality; no congestion modeling module.
Feng et al. (2020) [20]	Big Data, ML & Deep Learning	Created accident analysis and prediction platforms using clustering and time-series models.	Focuses on safety prediction rather than real-time traffic flow analysis.
Yu et al. (2025) [21]	Quantum-Inspired Spatiotemporal Transformer	Captures highly non-linear spatiotemporal correlations through a dynamic matching mechanism to forecast traffic flow.	High computational complexity for training; requires intensive server architecture less suitable for real-time edge processing.
Lin et al. (2026) [22]	Cross City Pre-Training & Transfer Learning	Enhances model generalization under drastic variations in data distribution by transferring pre-trained spatial weights.	Requires a massive and rich source-domain dataset for initial pre-training before transferring knowledge to the target domain.
Proposed Framework (This Study)	API-based Real-Time Data Analytics, Time-Series DB, Logistic Modeling	Develops a real-time system for monitoring and analyzing Hajj traffic via API integration, spatiotemporal database, and congestion classification models.	Addresses previous gaps by enabling scalable, event-specific, real-time analytics for high-density pilgrimage mobility while building the mathematical baseline for downstream integration of advanced predictive modules [21,22].

3. Proposed methodology

To enhance the clarity and readability of the mathematical formulations used throughout this study, **Table 2** summarizes the primary symbols, variables, and parameters employed across the real-time analytics framework.

Table 2. Nomenclature and mathematical notations for congestion estimation models.

Notation / symbol	Variable / parameter name	Operational context	Functional scope
d	Route distance	Given Parameter	Physical length of the route segment in kilometers (km)
t	Free-flow travel time	Given Parameter / Baseline	Ideal travel duration in min (min) under non-congested conditions
p	Congestion percentage	Given Parameter / Metric	Real-time traffic congestion scale measured as a percentage (%)
R_c	Congestion ratio	Calculated Variable	Fractional conversion of congestion (p/100) used in Equation 1 and Equation 5
v_f	Free-flow speed	Calculated Variable	Theoretical legal speed threshold of the route segment in km/h
v_a	Actual speed under congestion	Calculated Variable	Reduced vehicular velocity calculated under linear degradation states ($p < 75\%$)

Table 2. (*Continued*).

Notation / symbol	Variable / parameter name	Operational context	Functional scope
x	Logistic base variable	Intermediate Variable	Mathematical input value mapped directly from R_c for the exponential function
M	Logistic multiplier function	Calculated Operator	Non-linear amplification scaling factor capturing severe network saturation ($p >$ 75%)
T_{actual}	Expected / Estimated travel time	Final Output	Ultimate calculated travel time outcome in min (min) across both model regimes

The proposed approach provides a robust and adaptable framework for real-time monitoring, analysis, and visualization of traffic flow during the Hajj season. The system also uses the API to collect data, processing data in spatio-temporal fashion, and analyses to develop informational strategies to assist in transportation planning and decision making. It consists of five main components; Data Acquisition, Data Processing, Database and Storage, Analytics and Modeling, Visualization and Decision Support (Show **Figure 1**).

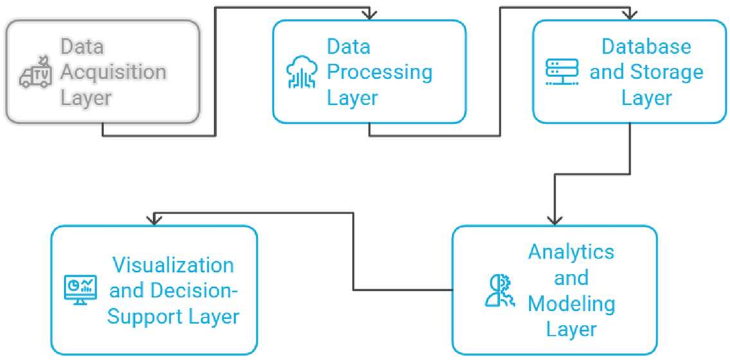

Figure 1. Overall workflow of the proposed Hajj traffic analytics framework.

The architecture of the proposed real-time Hajj traffic analytics framework can be seen in **Figure 1**. The system provides traffic data to collect, process, analyze and visualize the pilgrimage, providing in-real-time information on the level of congestion and enabling informed decision making [23]. The framework is made up of five different layers, each with its own function as discussed below.

1. **Data acquisition layer:** This layer collects real-time traffic data from the Mapbox API that is used to provide dynamic information about traffic conditions in the Hajj region. This data stream contains several essential components:

- Route identifiers: Unique codes for each road segment or route used to follow specific traffic paths.
- Geographic coordinates: The latitude and longitude values represent the precise locations of vehicles and congestion points.
- Timestamps: Time markers for time-series analysis and tracking of chronological events.

- Traffic flow values: Quantitative measurements of traffic flow such as average speed or density that relate to actual congestion intensity.

The API provides feedback to the live traffic conditions, providing the data base for later processing and analysis.

2. **Data processing layer:** The Data Processing Layer provides an abstract, generic, and generalisable format for raw data [24]. It does the following operations :

- Filtering: Emphasizing irrelevant, duplicate, or incomplete entries to improve data quality.
- Normalization: Normalizes the traffic values to the same range in order to compensate for route length and capacity differences.
- Transformation: Recombines raw traffic points into time intervals, for example 5 or 15 min and converts JSON/CSV data in to structured data.
- Route file parsing: Reads route geometry files that contain spatial data about Hajj paths.
- Data merging: This unit of data merges route geometry with live API data into a single spatio- temporal data set that can be used to store and analyse.

3. **Database and storage layer:** Processed traffic data are stored in a sequential relational database optimized for time-series operations. This database architecture supports :

- Time-series analysis: Enables tracking of traffic evolution, peak detection, and temporal corre- lation.
- Historical comparison: Facilitates evaluation of year-to-year or day-to-day variations in mobility patterns.
- Congestion labeling: Stores automatically generated congestion states (low, moderate, high) for model evaluation and long-term learning.
- This layer provides a scalable and reliable backbone for continuous and historical traffic analysis.

4. **Analytic and modeling layer**: This is the layer of analysis that identifies congestion and predicts travel delays. It consists of two modules : Analytical Modeling (AML) and Analytical Modeling (ADM):

- Congestion detection module: Calculates the delay ratios by comparing the actual travel time to the theoretical free flow time. Traffic conditions are classified as low, moderate, high.
- Travel time and severity prediction module: Implements two analytical models :
- Proportional model : Estimates travel time as a function of route length and current traffic flow [25].
- Logistic model: The log model is an non-linear model that uses historical traffic data to predict congestion severity based on time of day, route type, and traffic density.
- The logistic model offers superior accuracy in high-traffic conditions, improving the prediction capability and facilitating proactive traffic management.

5. **Visualization and decision support layer:** The last layer provides interactive visualization and decision support tools to authorities to monitor and manage traffic [26]. The most important functions include :

- Interactive route maps: Real-time maps displaying congestion intensity using color-coded routes.
- Dynamic congestion monitoring: Continuous updates of delay and traffic flow statistics for each monitored route.
- Analytical dashboards: Configurable dashboards presenting performance indicators such as travel time, congestion ratio, and route utilization.
- This layer enhances situational awareness and supports timely decision-making, ensuring the safety and efficiency of transportation during the Hajj pilgrimage.

In the case of Hajj, the proposed system increases operational efficiency and decision-making, as well as service, safety, and user experience. Further, it demonstrates the possibilities of implementing advanced data infrastructures, analytics, and decision-support systems in non-profit and public sector organizations [27] that must continually strive for improved transparency and sustainability that allow them to move toward adaptive, evidence-based, and citizen-centric transportation management strategies [28].

3.1. System overview

It has a hybrid architecture, where clients view the data collected from the server and data analysis is done on the client. Initial data collection starts by obtaining real-time traffic data through Mapbox Tilequery API [29]. Data is cleaned up and transformed before being stored in a spatial database. The data are analyzed using a hybrid congestion model to estimate travel times and bottlenecks.

Mapbox (mapbox.com) is the foundation for visualization and spatial interaction. Mapbox is one of the leading commercial vendors of high-performance maps and navigation tools. It provides a full-featured interface for location-based data visualization, geocoding, and navigation. Mapbox's rich library architecture allows developers to create custom, dynamic, and interactive applications far beyond a simple map. It is especially well-suited to use as a participatory or decision-support mapping environment where large amounts of data need to be visualized, when collected and an engaging presentation layer is needed, or where expert GIS knowledge is not available [30].

3.2. Data acquisition and preprocessing

Traffic data for Hajj season was collected using geo JSON route files, representing the main roads of mobility between Makkah, Mina, Arafat and Muzdalifah. Routes were segmented with 100m between points in each direction to provide spatial precision and API query limit.

The Mapbox Tilequery API captured congestion data every 15 min for each coordinate. Dataset includes 23 routes with 1386 traffic records for the peak pilgrimage days (7–10 Dhul Hijjah). While this 15-min sampling frequency provides a reliable baseline for mapping macroscopic macro-phased patterns across days, it introduces an inherent smoothing effect that may omit the precise onset of transient, acute congestion. In a hyper-dynamic mass mobility environment like the Hajj, where millions of pilgrims shift between locations inside narrow operational windows, a 15-min granularity limits the immediacy of 'real-time' early warning systems, potentially delaying reactive routing protocols by several min during sudden flow surges.

3.3. Database architecture

To handle the large amounts of traffic data, a spatial relational database was set up. The schema is composed of three interrelated tables:

- Routes include route identifiers, total distance, base travel time (without congestion), and route codes.
- Traffic points store latitude and longitude of each point sampling data, and the level of congestion at each point.
- Traffic trips: records time-series data on traffic congestion and timestamps for each point.

The structure allows seamless querying and can be used to aggregate time, place and date as well as calculate mean delay or congestion percentage per route.

3.4. Congestion estimation models

So, the author may obtain an accurate estimate of travel time under different congestion conditions, the author constructed (1) a Proportional Model for high levels of congestion ($p < 75$ %) and (2) a Moderate Congestion Model and (2) a Logistic Multiplier Model for heavy congestion ($p \geq 75$ %). Both models are robust to computing overhead and real-world estimates for the full range of traffic conditions during the Hajj season.

3.4.1. Method 1: Proportional model (p < 75 %)

For congestion levels below 75 %, a proportional model grounded in physical traffic flow theory was adopted. This model assumes a linear relationship between traffic density, route length, and travel time, providing sufficient accuracy for moderate congestion scenarios.

Given Parameters.

d: Route distance (km).

t: Free-flow travel time (min).

p: Congestion percentage (%).

Computation steps.

Congestion ration:

$$R_c = \frac{p}{100} \tag{1}$$

Free-flow speed:

$$V_f = \frac{d}{t/60} = \frac{60d}{t} \tag{2}$$

Actual speed under congestion:

$$v_a = v_f \times (1 - R_c) \tag{3}$$

Expected travel time:

$$T_{actual} = \frac{a}{v_a} \times 60 \tag{4}$$

This proportional approach is a good fit for travel time estimates under normal and moderate congestion. But once the congestion rises past 75 %, the linear model no longer applies and the travel time balloons (e.g., over 500 min on long routes). Hence, the model uses a nonlinear logistic model to estimate the increase in travel time during extreme congestion.

3.4.2. Method 2: Logistic multiplier model ($p \geq 75$ %)

The high congestion levels were captured by a Logistic Multiplier Model to account for the nonlinear saturation of traffic flow. Unlike proportional models, this model estimates actual travel time based only on the percentage of congestion and the free-flow duration and is not distance dependent.

Given parameters.

t: Free-flow travel time (min).

p: Congestion percentage (%).

Computation steps.

1. Congestion ration:

$$R_c = \frac{p}{100} \tag{5}$$

2. Logistic base variable:

$$x = R_c \tag{6}$$

3. Logistic multiplier function:

$$M = 4 + \frac{x}{e^x + 1} + 1 \tag{7}$$

where the constant term Equation (4) acts as a calibration factor determined empirically to maintain numerical stability and approximate real-world travel times.

4. Estimated travel time:

$$T_{actual} = t \times M \tag{8}$$

Using this approach, the travel time of an object will not grow as soon as traffic becomes full, resulting in more realistic results for situations that are near perfect.

3.5. Sensitivity analysis of the logistic multiplier

To test the effect of slope on the logistic function, the author tested Equation (1) and (8). **Figure 2** shows that if slope is 1, congestion is very linearly related to the logistic multiplier. This may indicate that congestion may be very sensitive to changes, and such a configuration does not account for the rapid increase in travel time as seen in high-density traffic in real life. **Figure 3** shows that increasing the slope to Equation (8) gives us a strong non-linear response. The logistic multiplier grows stronger with congestion, distinguishing between successive levels of congestion, and thus increasing the realism of the model. Over several tests, the author founds that the optimal slope for our models was Equation (8); this ensures that the model properly reproduces the exponential growth of travel time in severe congestion while remaining numerically stable.

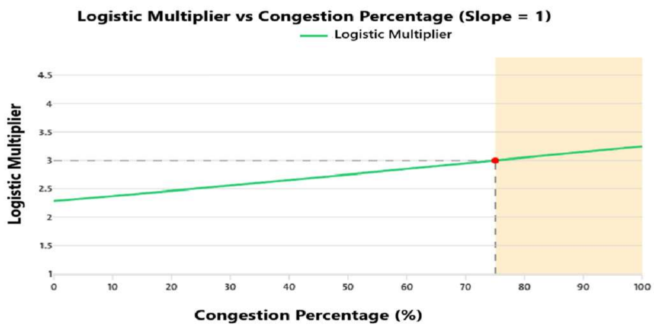

Figure 2. Logistic multiplier behavior for slope = 1 (quasi-linear response).

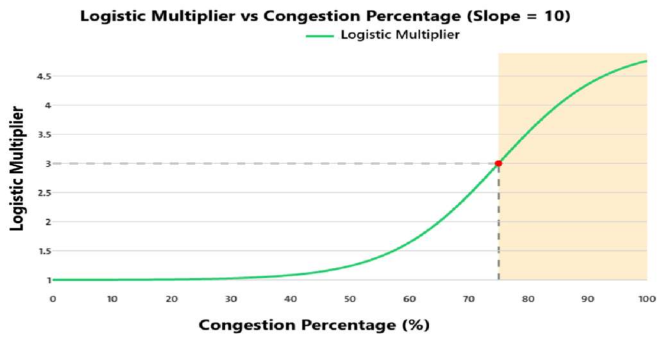

Figure 3. Logistic multiplier behavior for slope = 10 (non-linear response).

4. Experimental results

4.1. Overview of data collection

The proposed real-time traffic analytics framework was tested on data collected during the Hajj season 1446 H (2025 CE) and added 1386 traffic records for 23 roads connecting the major pilgrimage sites (Makkah, Mina, Arafat, Muzdalifah). I sampled all routes every 15 min as described in Section 3, in order to keep track of all pilgrims' movements. The datasets span more than 72 h and cover the entire pilgrimage route between Makkah to Arafat and back to Mina. This rich data set provides an unprecedented insight into the time pattern of congestion and inter-route dependence due to one of the largest annual mass movement events in the world.

4.2. Route-wise traffic summary

To measure the flow of pilgrim traffic, we divided the traffic across these five routes into two primary types of operations linked to the Hajj transport project: Mina, Arafat and Muzdalifah. Each route is a separate part of the Hajj transportation project. **Table 3** lists the number of routes, total traffic, and average travel delay for each category of routes during Hajj 1446 H. The network performance in the corridors is starkly different. The highest average delay was 9.8 min on the Mina Arafat sections, as they were the bottleneck in the transfer of pilgrims to the 9th Dhul Hijjah. It is during this period when convoys from Mina to Arafat are at the start of ritual, which are very full and there is very little redundancy. The Makkah Mina and Muzdalifah Minah segments, for example, could flow without any congestion, with the average delay of less than 2 min, indicating that Hajj authorities were well-established in planning and scheduling buses. The moderate congestion on the Makkah Arafat and Arafat Muzdalifah movements indicates a transitional point in the pilgrimage, giving the network an additional 224 kilometers. **Table 4** contains all 23 tracked routes with the associated routes name and distance.

Table 3. Route-wise traffic summary during Hajj 1446 H.

Route group	No. of routes	Total captures	Avg. Delay (min)
Makkah Mina	11	625	1.5
Makkah Arafat	3	303	6.0
Mina Arafat	5	300	9.0
Arafat Muzdalifah	2	50	5.0
Muzdalifah Mina	2	108	1.0
Total	23	1386	–

Table 4. Detailed route-wise traffic summary during Hajj 1446 H.

Corridor/Stage	Route ID	Route name/Infrastructure segment	Distance (km)
Makkah → Mina	R01	King Abdullah Rd Al-Aziziyah	3.9
	R02	King Fahd Rd Al-Hajj Street	4.8
	R03	King Abdulaziz Road - Majlis Al-Jinn	7.2
	R04	King Khalid Rd Al-Aziziyah	4.1
	R05	King Khalid Rd Al-Ma’asim	5.0
	R06	Al-Jamarat Tunnel Al-Hajj Street	4.5
	R07	King Abdulaziz Rd Daqam Al-Wabr	1.9
	R08	King Faisal Rd Al-Shisha	6.4
	R09	Al-Jamarat Tunnel Al-Jowharah Al-Hajj Street	6.6
	R10	Al-Arab Market Rd Ring Road 4	6.0
	R11	King Abdullah Rd Al-Ma’asim	2.4
Makkah → Arafat	R12	Al-Jamiah Tunnel - Arafat First	12.5
	R13	Route Al Jamiah Bridge - Arafat Second	14.6
	R14	Route Al Hada - Saad Street	19.5
	R15	King Abdullah Road 25	18.7
	R16	Al-Jamarat Tunnels - Al-Jowharah Road	18.6
	R17	King Fahd Road 68	24.6
	R18	Al-Ma’asim Ring Road 4 - Al-Taif Road	20.2
	R19	King Faisal Road 50	15.1
Arafat → Muzdalifah	R20	King Faisal Rd 50	9.6
	R21	Al-Arab Market Rd 62	10.4
Muzdalifah → Mina	R22	King Faisal Road 50	3.5
	R23	Al-Arab Market Road 62	4.1
Cumulative Network		Full network coverage (23 unique routes)	224.2 km

This range of distances reflects the extent of variability in the network. There are short lines running across MakkahMina (27 km) and longer lines running between sites (1525 km) between MinaArafat and MakkahArafat. The difference in delay indicates the heterogeneity of the networks in longer corridors as they run over each other, waiting in tunnels, and on narrow roads, and the less dense cities have more redundancy and lower entry restrictions.

Figures 4–13 complement these quantitative summary presentations by providing map-based visualizations of selected routes extracted from the system's geospatial dashboard. These maps are representations of actual road contours and waypoint contours as extracted from the Mapbox API, which show the physical overlap between corridors and the topological determinants that influence traffic flow behavior such as tunnels, elevation gradients and intersection density. This visualization furthers the theoretical framework, linking temporal measures of congestion to spatial parameters, providing a more holistic view of mobility performance during Hajj.

4.3. Spatial interpretation of route maps

Figures 4–13 also provides a view of the design differences between these corridors. The MakkahMina routes (e.g., R01, R02) are small urban corridors linking Al-Aziziyah and Al-Hajj Street to multiple exit points, which can ease congestion and streamline traffic at the early part of the Hajj. But, the MakkahArafat and MinaArafat corridors (R12 R19), which traverse mountainous terrain and tunnels (e.g., Al-Jamiahand Al-Jamarat), are longer routes with complex topologies and often encounter bottlenecks at intersections or exits from tunnels as **Figures 4**, **5**, **10** and **11**. The ArafatMuzdalifah and MuzdalifahMina corridors (R20, R22) are more straight and open roads and can quickly restore flow during peak congestion. Among the five different routes, the King Faisal 50 Route (R20, R22) is the smoothest route in terms of switching between the dual carriageway layout; though, the Al-Arab Market 62 Route (R21, R23) is one that may be more complicated by the conflicting routes into Mina. This spatial data enhances the ability of the system to combine geospatial intelligence with detailed monitoring and accurate depictions of the route and bottlenecks.

Figure 4. MakkahArafat via Al-Jamiah Tunnel Arafat First (R12).

Figure 5. MakkahArafat via Al-Jamiah Bridge Arafat Second (R13).

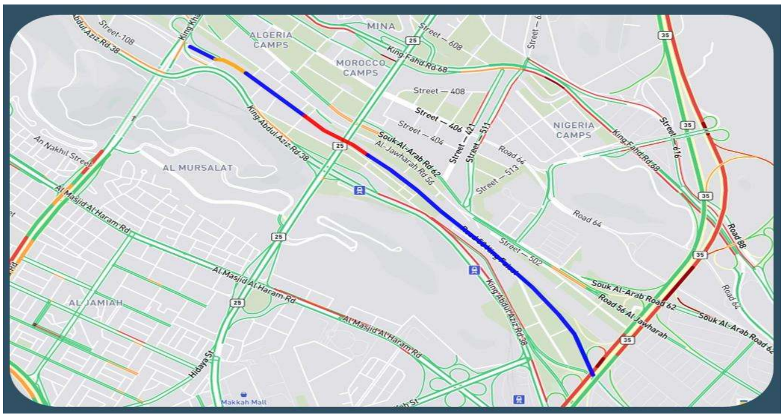

Figure 6. MuzdalifahMina via King Faisal Road 50 (R22).

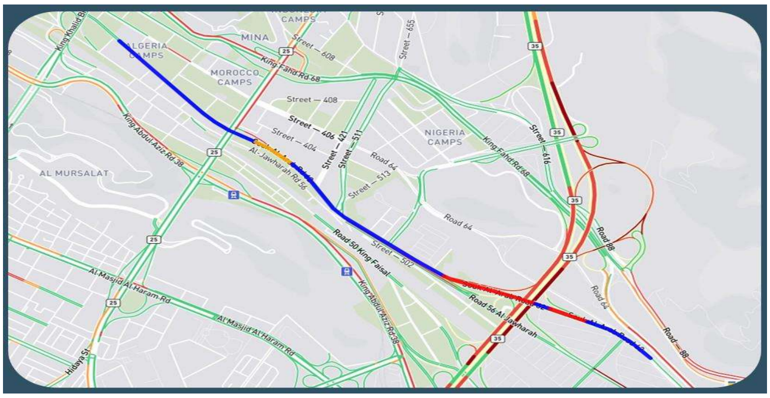

Figure 7. MuzdalifahMina via Al-Arab Market Road 62 (R23).

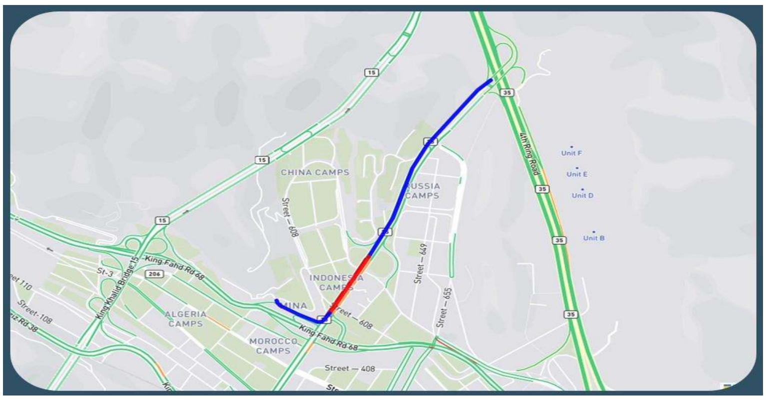

Figure 8. MakkahMina via King Abdullah Rd Al-Aziziyah (R01).

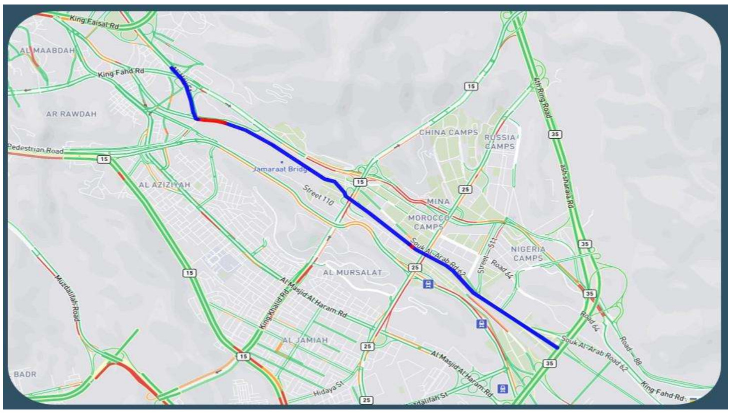

Figure 9. MakkahMina via King Fahd Rd Al-Hajj Street (R02).

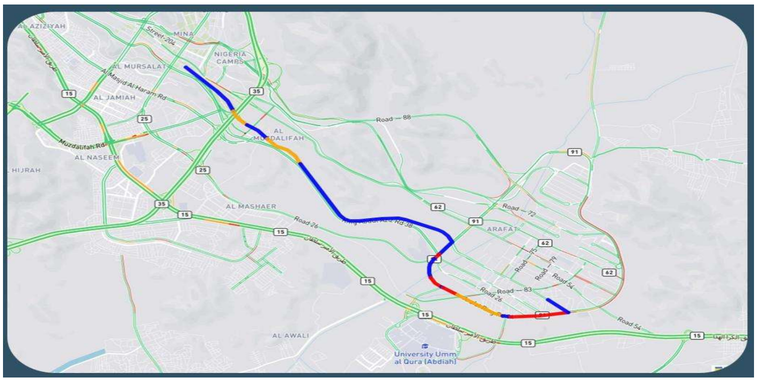

Figure 10. MinaArafat via King Abdullah Road 25 (R15).

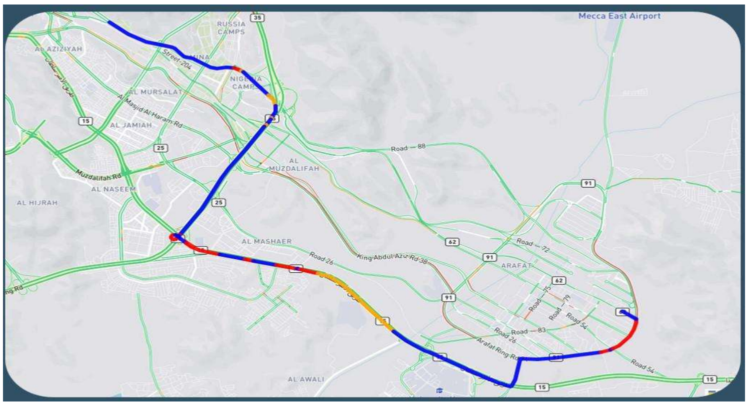

Figure 11. MinaArafat via Al-Jamarat Tunnels Al-Jowharah Road (R16).

Figure 12. ArafatMuzdalifah via King Faisal Road 50 (R20).

Figure 13. ArafatMuzdalifah via Al-Arab Market Road 62 (R21).

4.4. Temporal variation of congestion

Temporal aggregation of the dataset reveals distinct congestion phases corresponding to key ritual activities. **Table 5** summarizes the number of captures and average delays for each day. An analysis of the timing of the data sets reveals distinct congestion phases for specific ritual events. The following table shows the total number of captures and average delays per day, as seen in **Table 5**.

Table 5. Daily congestion variation during Hajj 1446 H.

Day (Hijri)	Captures	Avg. Delay (min)	Remarks
07 Dhul Hijjah	176	1.5	Early departures; low congestion
08 Dhul Hijjah	721	5.0	Peak movement Makkah → Mina (*Tarwiyah*)
09 Dhul Hijjah	405	7.0	High congestion Mina → Arafat (*Arafat Day*)
10 Dhul Hijjah	84	1.5	Return phase; dispersed traffic

4.5. Congestion classification

Each of the data captures was considered a congestion category according to the delay ratio. **Table 6** reports a summary of the classification. While about 15 % of all records were in states of high congestion,

Table 6. Congestion classification based on delay ratios.

Congestion level	Threshold (delay ratio)	Captures	Percentage (%)
Low	< 25%	546	39.4
Moderate	25–75%	75	5.4
High	> 75%	208	15.0

These states accounted for more than 60 % of the total time spent on delay. This distribution demonstrates the frameworks responsiveness to critical periods of congestion that have disproportionate operational impacts.

4.6. Temporal analysis of the Muzdalifahmina corridor

The figure compares two principal routes—Route King Faisal 50 (R22) and Route Al Arab Market 62 (R23)—where solid lines denote actual observed travel times and dashed lines represent their respective no-congestion baseline durations. Specifically, the 'Baseline' values plotted in **Figures 14–18** represent the theoretical free-flow travel time (t) for each route. This value is calculated based on the route distance (d) and the legal speed limits of the road segments, representing the ideal travel duration in the absence of any traffic congestion or operational delays. While historical averages from the Mapbox API were used to validate general trends, the dashed baseline reflects this static, theoretical free-flow speed (v_f) to highlight the exact magnitude of the delay ratio during peak ritual movements.

Figure 14 shows how trip times for the return movement from Muzdalifah to Mina have changed overnight during the 9th 10th Dhul Hijjah. This phase is also related to the post-Arafat dispersal period, when millions of pilgrims travel back to Mina to perform the stoning (Ramy al-Jamarat). The figure compares two principal routes Route King Faisal 50 (R22) and Route Al Arab Market 62 (R23) where solid lines denote actual observed travel times and dashed lines represent their respective no-congestion baseline durations. The results indicate that traffic flow is exceptionally smooth throughout this return period with both R22 (King Faisal 50) and R23 (Al-Arab Market 62) travelling at near baseline throughout the monitoring period.

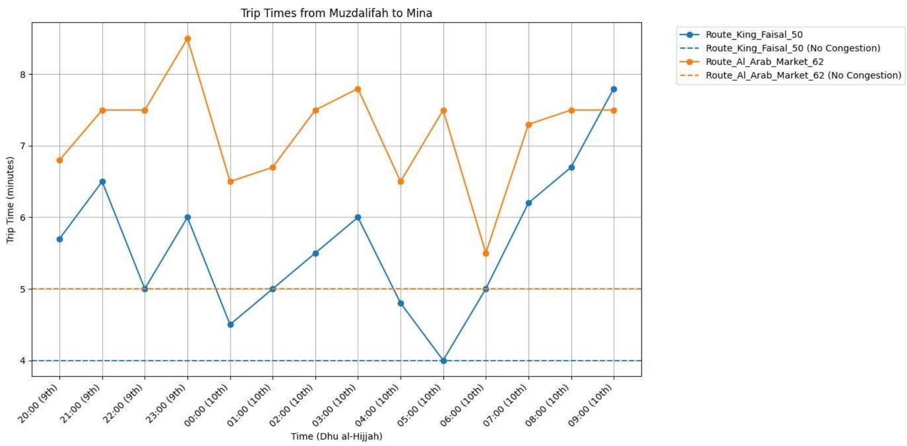

Figure 14. Temporal variation of trip times from Muzdalifah to Mina across the two main routes (night of 9th 10th Dhul Hijjah).

The trip times observed only show small deviations, typically within 23min, during the brief peak period between 02: 00 and 04: 00 (10th Dhul Hijjah), after which congestion levels slowly normalize. The small difference is due to the efficiency of the long movement window and the timely post-Arafat scheduling in comparison to the heavy congestion on MinaArafat and ArafatMuzdalifah corridors. The efficiency of the machine was affected by several factors, including:

- Distribution of time: The return movement was uneven over the night and did not occur at the same time as the peak loading seen at earlier times.
- Shorter distances: Both routes cover less than 4 km (see **Table 3**), which reduces cumulative delays.
- Route redundancy: The multiple parallel tracks between Muzdalifah and Mina prevented congestion and traffic swaying.

This constant proximity of travel times to the base proves the very low average delay of 1.0 min recorded for this corridor group in **Table 2**. This is also consistent with the trends seen in **Table 4**, which indicate that average delays have fallen on the 10th Dhul Hijjah following the completion of the major rituals. Overall, the transfer between MuzdalifahMina suggests that a distributed approach to scheduling, multi-route management and timing planning provides almost optimal flow of traffic during peak pilgrimage season. This can be used as a basis for the subsequent evacuation and redistribution of mass movement.

4.7. Temporal analysis of the Minaarafat corridor

In part, this is due to the coordinated departure of pilgrim convoys from Mina camps and the relatively small number of outbound routes to Arafat. The morning rush of pilgrims having left Arafat at noon and entering the city at midday put added pressure on the road network. As a result, commutes were short but more congestion laden. **Figure 15** shows how the system has determined both the magnitude and persistence of these congestion episodes. The difference between actual and baseline travel time for all routes monitored also supports the classification of this corridor as the most congestion-prone segment of the network. This is consistent with **Table 2**, which indicates the highest average delay (9 min) for the MinaArafat group.

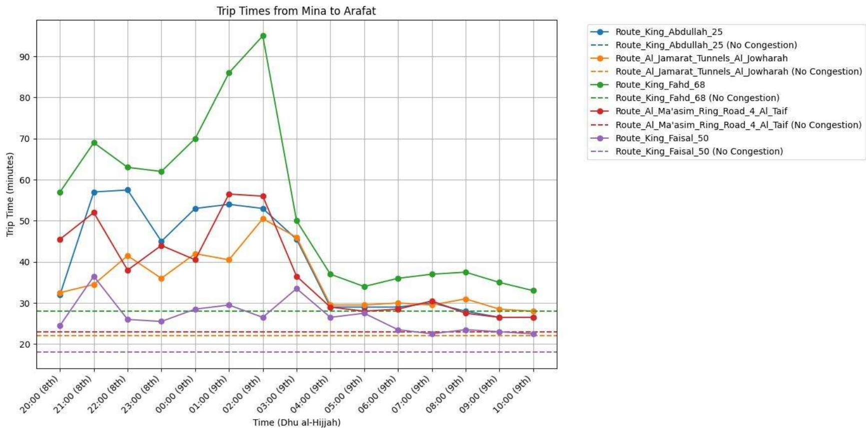

Figure 15. Temporal variation of trip times from Mina to Arafat across multiple routes (9th Dhul Hijjah).

4.8. Temporal analysis of the MakkahMina corridor

Figure 16 displays the chronological trend of travel time on several routes linking Makkah to Mina during the early years of pilgrimage (7th 8th Dhul Hijjah). Each solid line is the actual travel time when congestion is present while the dashed line represents the travel time at baseline - no congestion from the API.

The results indicate a gradual increase in congestion beginning late on the 7th Dhul Hijjah and increasing between 02:00 and 06:00 on the 8th Dhul Hijjah. This is a part of the Tarwiyah period, which occurs as large pilgrim boats begin heading from Makkah to Mina to prepare them for ritual events later in the day. Some routes, such as R02 (King Fahd RoadAl-Hajj Street) and R03 (King Abdulaziz Road Majlis Al Jinn) have strong congestion peaks approaching 15 min, compared to baseline no-congestion duration of less than 9 min. This sharp deviation reflects both the temporal clustering of movement on the road and the model’s sensitivity to route-specific saturation levels. On top of that, oscillatory oscillations between 02:00 and 06:00

indicate frequent convoy release or timing shifts by traffic officials to coordinate flow across parallel corridors. The trip starts to stabilize after 06:00, with major convoy transfers complete and traffic onwards to Mina camps sizing up gradually.

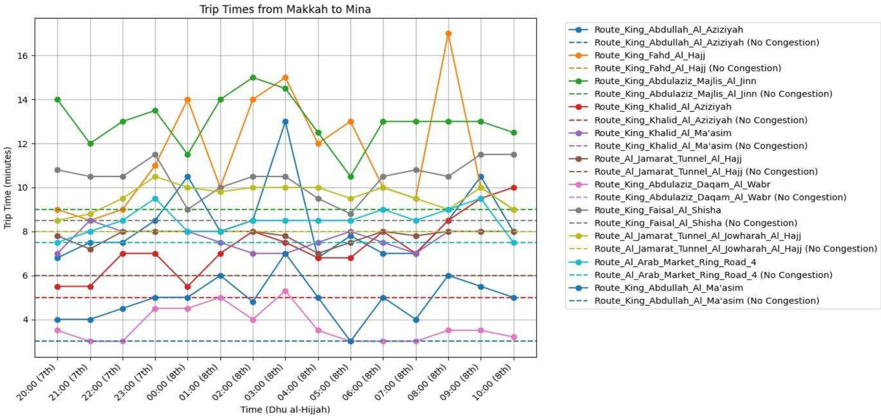

Figure 16. Temporal variation of trip times from Makkah to Mina across multiple routes (7th 8th Dhul Hijjah).

4.9. Temporal analysis of the ArafatMuzdalifah corridor

Figure 17 shows the average time taken to travel from Arafat to Muzdalifah on the evening of the 9th Dhul Hijjah, one of the busiest days of the pilgrimage because of the congested traffic. The two main routes are King Faisal Road 50 and King Road 62. The solid lines represent actual travel time during congestion, while the dashed lines represent the base time (no congestion) travel data from API. This **Figure 17**.

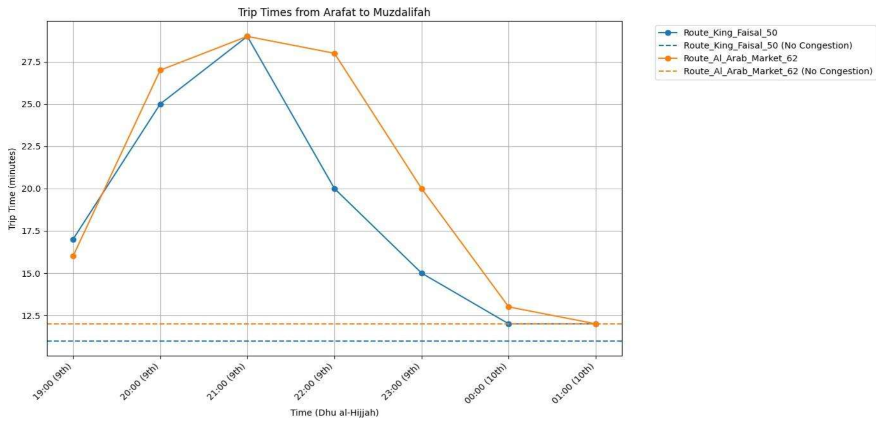

Figure 17. Temporal variation of trip times from Arafat to Muzdalifah during the evening of 9th Dhul Hijjah.

indicates how severe the traffic conditions were in a six-hour period between 19:00 (9) and 01:00 (Dhul Hijjah) Dhul Hijjah. Both routes have significantly longer travel times around 21:00, as pilgrim trains begin their journeys after sunset. R20 (King Faisal 50) is just over 28.5 m long and R21 (Al Arab Market 62) is slightly longer at 28.7 m and more than double the baseline of 11.5 and 12.2 min. This is not free-flow, but it indicates that the bottleneck is more frequent than R20 (King Faisal 50) and can return faster from 20:00–23:00. In this case, indicating that R21 (Al Arab Market 62) is faster than R20 (King Faisal 50) and it is often longer than R20 (R21) and that the bottleneck will persists in the city, and thus will generally return quicker than R20 (King Faisal 50) in the evening of the 9th through night. Again, this shows that the Arafat-Muzdalifah transfer is one of the busiest segments of the pilgrimage route as it is punctually scheduled and takes place on a small corridor. As of 23:00, but, traffic congestion gradually dissipates because of the dispersal and convoy management strategies in place by the government.

Plus, the time course of this phase was like that of daily peak in congestion (**Table 4**), and thus it follows that this model can capture, quantify, and interpret short-term but very high-intensity congestion episodes with fine-tuned temporal resolution.

4.10. Temporal analysis of the MakkahArafat corridor

Figure 18 reports the trajectory of the trip times from Makkah to Arafat from the 8th to the early h of the 9th Dhul Hijjah. Three major routes are compared: R12 (Al Jamiah Tunnel Arafat First) (blue), R13 (Al Jamiah Bridge Arafat Second) (orange), and R14 (Al Hada Saad Street) (green); solid lines are travel times at pilgrimage and dashes indicate baseline (no-congestion) time periods determined from the API.

This **Figure 18** displays a prolonged and acute period of congestion that stretches over almost 24 h, a reflection of the large-scale pilgrimage from Makkah to Arafat. Overnight and through the early morning of the 9th, when traffic is highest due to simultaneous convoy arrival on limited-capacity corridors, trip times continue to increase throughout the day on the 8th Dhul Hijjah. As traffic levels increase, the duration of the journey across all routes gradually increases during the early build-up period (08:00–18: 00, 8th Dhul Hijjah). The green R14 Al Hada Saad Street has the longest and earliest congestion and peaks around 17:00 at a rate of 47-min nearly twice the baseline length of 25-min. The most intense congested time is between 20:00 (8th) and 04:00 (9th), which coincides with the main overnight transfer of pilgrims to Arafat. The longest delay is 67 min, approximately 60 min, or nearly 60 min, at 03:00 (9th). Blue R12 (Al Jamiah Tunnel Arafat First) also exhibits very high congestion, at a peak of about 35 min around 04:00 (9th), compared to a baseline of 15.5 min. Meanwhile, R14 (Al Hada Saad Street) (green) has a secondary congestion peak around 02:00(9th) and maintains a delay of about 42 min until gradually recovery. As dawn approaches, from 15:00–28:00, 9th Dhul Hijjah, congestion gradually eases as most of the most of the vehicular convoys successfully complete their scheduled operational movements across the network segments. Trip times begin to return to baseline in 2030 min, and R12 (Al Jamiah Tunnel Arafat First) provides the fastest rate of return to baseline at 20 min.

Overall, the results show that the MakkahArafat transfer is one of the most delayed parts of the pilgrimage network, mainly due to mass departures parallel within a small window of operation. Peak delays over one hour suggest the combined effects of convoy overlaps, limited infrastructure capacity and strict timing requirements. These results also closely match those seen in **Table 4**: Daily congestion, thus confirming the proposed real-time analytics frameworks capability to capture and characterize extended congestion periods with high temporal accuracy.

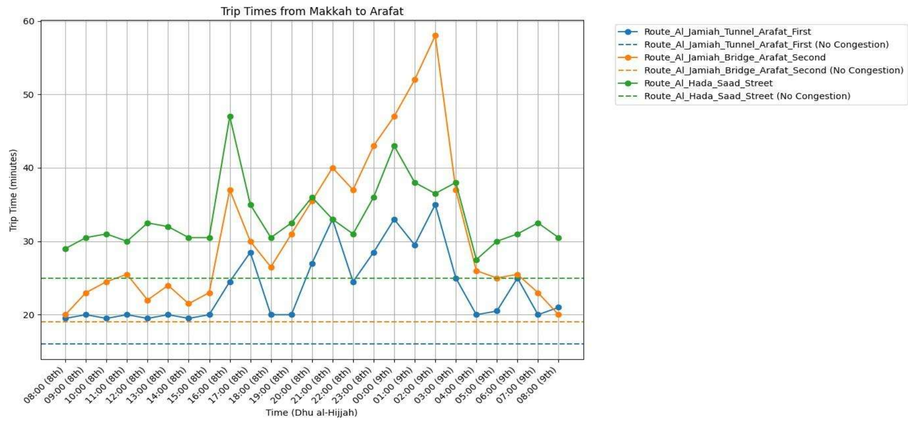

Figure 18. Temporal variation of trip times from Makkah to Arafat across the 8th9th Dhul Hijjah.

4.11. Traffic condition analysis across key intersections

During the Hajj period, an in-depth assessment of traffic conditions across major intersections was con- ducted to quantify congestion levels and identify critical bottlenecks. The analysis, illustrated in **Figure 19**, shows the distribution of traffic states categorized as Congested, Slightly Congested, and Not Congested at representative intersections observed between 7–10 Dhul Hijjah 1446 H. The results reveal that several in- trisections experienced severe congestion, with more than 40 % of observations falling into the Congested category. Specifically, intersections such as Prince Sultan Rd & 4th Ring Rd (R17, R18, R14, R13, R12) reported 52.8 % congestion Rather than a purely volume-driven delay, this acute bottleneck formation is fundamentally tied to the severe topographical constraints of the area, previously introduced in Section 4.3. The intersection serves as a critical convergence node immediately following a major elevation gradient, forcing high-heavy vehicular streams—predominantly high-capacity pilgrim buses—to navigate a prolonged uphill ascent. This deceleration is further compounded by the abrupt transition from open-air road segments into restrictive tunnel entry points nearby. The sudden reduction in lateral clearance and natural illumination causes drivers to instinctively drop speeds, inducing a cascading backpressure wave through the approach lanes. Consequently, the physical topology creates a systemic bottleneck where the combined effects of uphill gradient deceleration and tunnel entry bottlenecks structurally restrict maximum throughput, resulting in the localized 52.8 % accumulation capacity observed during peak operational windows, while Souq Al-Arab Rd 62 (R21, R23) had 47.2 % congestion and King Abdullah Rd 25 & Arafat Ring Rd (R19, R15, R16) recorded 45.0 %. Others, like Prince Sul- tan Rd (University Rd) and Arafat RingRd & Road No.3, were similarly dense, with heavy traffic, often in high numbers, and overwhelmingly over-crowded, which suggests they are system-critical nodes that require attention immediately. Not all major arterials were heavily congested (25–40%), such as the intersection of 4th RingRd & King Fahd Rd 68, R17, R18. The flow at these intersections was intermittently moving and varied from one to another a wave like congestion during convoy coordination. Some intersections were slightly overcrowded, with occasional slowing, varying speeds, likely caused by wave-like traffic surges during convoy coordination. Some intersections appeared slightly congested, with occasional slow down, but no prolonged queuing. Prince Sultan Rd & 4th Ring R18, R17, R19, R15, R16) and Fatima Al-Zahra St (R12, R13) had 18.3 % and 6.93% lightly congested traffic, respectively. These intersections may require micro- time adjustments at traffic signals or lane management. Some intersections were largely free flowing during the observation period. King Abdullah Rd 25 & Souq Al-Arab62 (R10, R01) was 96.5 % traffic in a Not Congested status, while Al-Haj St& Prince Majed Rd Rd (emphR06, R10) and 4th Ring Rd & King Abdullah Rd 25 (R07, R11) were 84.2% and 96.49 % free flow, respectively. These intersections are oftenlocated along secondary or contiguous routes, offering relief routes to the main arterial networks. Overall, the analysis reveals that the primary radial routes and junctions with ring road are most affected when traffic is very busy for Hajj, while most secondary and feeder roads are sufficiently busy. Also, congestion in the cross-lane with a density above 40 % should be addressed to minimize system delay, such as signaling, reallocating temporary lane, and deviating traffic in synchronized convoy traffic.

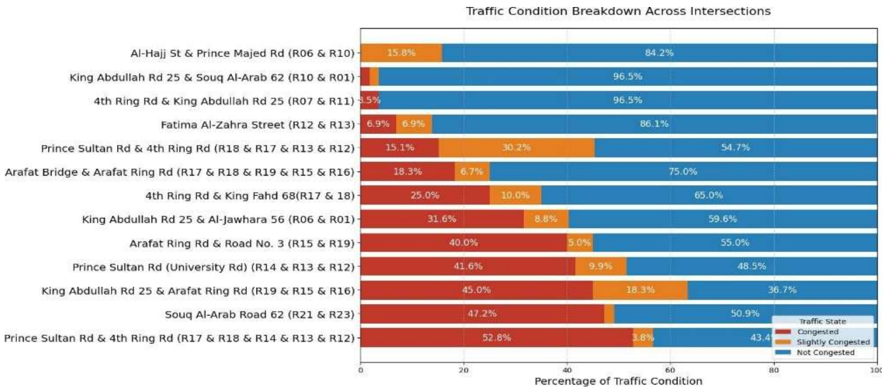

Figure 19. Traffic condition breakdown across major intersections during Hajj 1446 H. The chart shows the percentage distri- bution of Congested, Slightly Congested, and Not Congested states across key network junctions.

4.12. General discussion

This approach successfully combined the processing of real-time data, congestion modeling, and spatiotemporal visualization in the design of Hajj1446 H and will be used to characterize dynamic mobility. This system, which uses the Proportional Model for moderate congestion and the Logistic Multiplier Model for severe congestion, allowed for a robust estimation of travel times in several operating conditions. This combination of methods allowed for realistic quantification of delay in real-time without numerical instability even in extreme congestion situations such as the MinaArafat and ArafatMuzdalifah transitions. The time-series analysis revealed that peak congestion coincided with ritual times, suggesting that the Hajj traffic flow is not only driven by network capacity but also by behavioral and temporal clustering. In some ways, the model provided an ability to capture this and provide a readable, data driven, representation of the network for days. Also, the geospatial map of routes and intersection breakdowns provided useful information on spatial bottlenecks and the implications of ring roads and radial access routes on flow efficiency in general. This time-solved, coarser model provides a more responsive and contextually responsive model that can be seamlessly integrated into operational control centers so that decisions are taken in real time, rather than aggregate models. Voir several directions for future studies based on the promising results of this study:

- **Dynamic model calibration:** Future implementations will likely allow for dynamic parameter tuning of the logistic multiplier based on real-time traffic sensor data and automated updates via the API.
- **Granularity and sensitivity analysis:** Future framework revisions will actively transition from a 15-min sampling interval to a high-resolution 5-min telemetry interval. Conducting a comparative sensitivity analysis using 5-min interval data is necessary to evaluate the model's capacity to intercept fine-grained transient bottleneck formations. This increased temporal resolution will substantively minimize data latency, drastically refining the precision and responsiveness of early warning indicators in operational control environments.
- **Integration with advanced deep learning architectures:** While the combination of the Proportional Model and the non-linear Logistic Multiplier Model offers a computationally lightweight and numerically stable approach for real-time estimation, it exhibits limitations in fully capturing the complex, dynamic evolution of traffic flow over time. To cope with sudden, highly volatile traffic surges during extreme peak periods, future iterations of this framework can supplement these analytical models with more sophisticated deep learning architectures. Specifically, Spatio-Temporal Graph Neural Networks (STGNNs) could be integrated to map the Hajj road network as a dynamic graph, explicitly modeling the spatial dependencies between adjacent corridors and intersections alongside their temporal evolution. Furthermore, Transformer-based models can be deployed to utilize self-attention mechanisms, allowing the system to learn long-range temporal dependencies and anticipate transient congestion onset before it propagates through the network. Incorporating these neural architectures into the existing API-driven pipeline would create a hybrid predictive framework capable of balancing real-time computational efficiency with deep spatiotemporal accuracy.
- **Integration with predictive analytics:** Short-term forecasting methods such as LSTM, or hybrid deep learning/metaheuristic models, could help predict congestion onset and duration more accurately.
- **Multi-modal analysis:** Adding pedestrian, bus, and train data streams will allow for a more holistic assessment of mobility as ritual sites change places.
- **Integration of decision-support:** Such as the model outputs to an interactive dashboard with intelligent module to recommend a route and module to schedule a convoy will allow operators to act.
- **Scalability and transferability:** It will be further studied to check if the proposed framework can be scaled to large datasets and used for other large-scale events such as Umrah seasons or sporting events.

These improvements will render the proposed analysis model as a fully integrated intelligent transportation decision-making system with adaptive and predictive capabilities in response to events.

5. Conclusion

This paper presents a new, fully data-driven method for real-time assessment of traffic and congestion conditions during Hajj 1446 H. By combining proportional and logistic modeling, the model produced realistic and consistent estimates of travel time for 23 routes and several congestion phases. In this paper, we describe the temporal characteristics of main corridors (MakkahMina), MinaArafat, Arafat- Muzdalifah, and MuzdalifahMina. Time-lapse analyses of major corridors (MakkahMinah Mina, MinaArafat, Arafat-Muzdalifah, and MuzdalifahMinahMina) reveal that the MinaArafat transfer is the most heavily prone to operational delays phase while the return route has an almost optimal flow due to the distributed scheduling. At the spatial and intersectional scale, further analysis uncovered key nodes on the network where adaptive management can be useful in improving throughput. In providing a scalable, transparent and empirically validated architecture for monitoring congestion, this work establishes the foundation for next-generation intelligent Hajj management systems and contributes to the wider vision of sustainable, intelligent urban mobility.

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Ethical approval: Not applicaple.

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Conflict of interest: The author declares no conflict of interest.

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