



# International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

*(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)*



**Impact Factor: 9.935**

**Volume 15, Issue 6, June 2026**

# Leveraging Graph Theory for Traffic Monitoring in Smart Cities

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**ABSTRACT:** The booming of metropolitan populations has enhanced heavy traffic, demanding effective surveillance and management systems in digital cities. This study examines the application of graph theory as a mathematical structure for improving traffic efficiency, identifying bottlenecks and enhancing urban transportation. By illustrating road systems as graph structures (where roads are edges and intersections are nodes), we examine diverse graph-based algorithms, including shortest path algorithms (Dijkstra, A), network centrality measures and graph clustering methods to improve effective traffic management. Furthermore, dynamic data transmission from metropolis is combined with machine learning approaches to dynamically adjust route recommendations and reduce congestion. The study leverages computational tools to simulate and visualize traffic patterns in a smart city context. Findings illustrates the efficiency of graph-based traffic monitoring in mitigating travel delays, improving traffic flow and supporting intelligent transportation systems (ITS). This study provides to the developing area of smart urban mobility by contributing a scalable and computationally effective techniques for real-time traffic examination and decision-making.

**KEYWORDS:** Graph Theory, Traffic Monitoring, Smart Cities, Shortest Path Algorithms, Intelligent Transportation Systems, Urban Mobility Optimization.

## I. INTRODUCTION

The growing urban populations and vehicle keeping has tends to progressively intricate traffic sides in cities globally. This booming city development offer important demands in terms of heavy traffic, environmental pollution and inadequate transportation facilities. With reference to the concept of smart cities has appeared, concentrating on the blending of emerging technologies for effective urban planning. A crucial factor of this progress is the development of intelligent transportation systems (ITS) that impact graph theory for real-time traffic surveillance and enhancement (Latif, Afzaal, & Zafar, 2018).

Graph theory contributes a mathematical framework for representation of road infrastructure where nodes represent intersections and edges represent the roads joining them. These models empower city planners and traffic planners to examine network behavior, identify constraints and improve routes using traditional and modern algorithms. For example, shortest path algorithms like Dijkstra's and A\* are broadly applied for navigation and route planning, while focal point measures aid to pinpoint key connections in the traffic flow (Haddad, 2017).

With the beginning of Internet of Things (IoT), cloud computing and huge data analytics, smart cities can gathered and process real-time traffic data from sensors, monitoring cameras and GPS devices. Integrating this data into graphical representation improves the responsiveness of traffic systems. Current structure has illustrated how graph-theoretic methods, combined with hybrid clustering algorithms, enhance signal sequencing, traffic management and total efficiency in smart cities (Sekar et al., 2018).

Furthermore, arising urban management techniques apply graph-based applications not only to envision traffic systems merely also to affect traffic conditions, forecast congestion patterns and adaptively manage traffic signals. These

approaches assist in recognizing alternative routes during busiest time or incidents, thus reducing delays and improving travel experience.

This study focus to examine the application of graph theory in smart city traffic monitoring, concentrating on building graph-based models from real-world information, building traffic improving algorithms and imposing the effect on traffic flow and flow control. The research highlights how incorporating graph theory with smart framework can provides to sustainable urban transportation and enhanced quality of life in contemporary cities.

## II. LITERATURE SURVEY

**Bhuvaneswari (2023)** investigates the function of graph theory in improving traffic control networks, specifically in reducing communal transportation delays through effective signal management. The research indicates a regulation oriented approach, demonstrating its roles with diverse examples and a mathematical representation of a chosen traffic intersection. The study emphasizes the application of control algorithms, highlighting their effect on enhancing urban traffic systems. Constituting of an extensive project, this study provides to traffic planners by improving graph-based approaches for calculating effective traffic light networks. The research highlights the importance of discrete event systems and compatible graphs in improving real-time traffic management.

**Haddad (2017)** examines the function of graph theory in improving traffic flow control within metropolitan regions. With developments in radio frequency and the growth of Internet of Things (IoT), metropolitan regions, have become ever more linked, imposing real-world information exchange for transportation management and administration. The research emphasizes how graph-theoretic approaches can improve both data exchange and traffic routing, providing to enhanced transportation and congestion control. Leveraging graph-based improvised methods, metropolitan regions can improve effective transportation infrastructures to assist unlined urban transportation. The study highlights the significance of graphical representation in controlling road systems, providing novel approaches for traffic estimations and management.

**Dijkstra (1959)** presents primary graph-theoretic algorithms, handling two core challenges compared to shortest paths in a connected graph. The research count a set of nodes connected by weighted branches, assuring a viable route among any two nodes. This set tasks the foundation for the famous Dijkstra's algorithm, which effectively resolves the shortest path among nodes in a weighted graph. The algorithm has after become a foundation in graph theory, enhancement and network paths, with wide applications in congestion management, metropolitan cities frameworks and intelligent transportation systems (ITS). By encouraging effective route finding and path enhancement, Dijkstra's work keeps important for contemporary traffic predicting models.

## III. METHODOLOGY

In the context of leveraging graph theory for traffic monitoring in smart cities, a traffic network can be mathematically represented as a weighted graph:

$$G = (V, E, W)$$

Where

- $V = \{v_1, v_2, \dots, v_n\}$  represents the set of intersections ( nodes)
- $E = \{e_{ij} | v_i, v_j \in V\}$  represents the set of roads ( edges), where  $e_{ij}$  denotes a road connecting intersections  $v_i$  and  $v_j$
- $W = \{w_{ij} | e_{ij} \in E\}$  represents the set of weights assigned to each edge, corresponding to metrics such as road length , travel time, congestion levels or vehicle density

### 3.1 Model for traffic flow

The real time traffic weight function is modeled as:

$$W_{ij}(t) = \alpha d_{ij} + \beta c_{ij}(t) = \gamma v_{ij}(t)$$

Where

- $d_{ij}$  is the physical distance between intersections  $v_i$  and  $v_j$ .
- $c_{ij}(t)$  represents the congestion level at time  $t$ , determined using sensor data.
- $v_{ij}(t)$  denotes the vehicular flow rate at time  $t$ .
- $\alpha, \beta, \gamma$  are tuning parameters used to optimize routing decisions.

### 3.2 Algorithmic Approaches

- Dijkstra's Algorithm for Shortest Path  
 $D(v) = \min \{D(u) + w_{uv}\}$  for all  $u, v \in V$   
Used to find the shortest route based on real-time weighted graphs.
- Graph Convolutional Networks (GCNs) for Traffic Prediction  
Applying the adjacency matrix  $A$  and feature matrix  $X$ , the GCN update rule is:

$$H^{(l+1)} = \sigma(\tilde{D}^{-1/2} \tilde{A} \tilde{D}^{-1/2} H^{(l)} W^{(l)})$$

Where  $\tilde{A} = A + I$  (self-loops added),  $\tilde{D}$  is the degree matrix and  $W^{(l)}$  is the trainable weight matrix.

- Spectral Clustering for Road Network Segmentation  
Using the graph Laplacian matrix  $L = D - A$ , spectral clustering can divide the city into traffic areas based on eigenvalues and eigenvectors.

By blending these graph-theoretic concepts with AI-based models, smart cities can improve traffic monitoring, mitigate congestion and enhance urban transportation.

### 3.3 Algorithmic Approach for Graph-Based Traffic Monitoring in Smart Cities

In leveraging graph theory for traffic monitoring in smart cities, multiple algorithmic approaches can be used to optimize traffic flow, predict congestion, and classify road segments effectively. The following key algorithms are employed:

#### a. Dijkstra's Algorithm for Shortest Path

$$D(v) = \min_{u \in V} \{D(u) + w_{uv}\}$$

Used to find the shortest route based on real-time weighted graphs.

#### b. Page Rank for Congestion Prediction

$$PR(v) = (1 - d) + d \sum_{u \in L(v)} \frac{PR(u)}{C(u)}$$

Where  $L(v)$  is the set of inbound nodes to  $v$ , and  $C(u)$  is the number of outbound links from  $u$ .

#### Data Sources and Graph Construction

- Real-world data: OpenStreetMap (OSM), INRIX, Google Maps API
- Simulated data: SUMO (Simulation of Urban Mobility)
- Data mapping:  
 $(V, E) \leftarrow \text{OSM (geo json)}$   
 $W(e) = f(\text{speed, volume, incidents})$

#### Graphs-Theoretic Representation of TS Diagram for Signalized Arterials

The Time-Space (TS) diagram can be modeled as a dynamic graph  $G_t = (V, E_t)$ , where:

- $V = \{v_1, v_2, \dots, v_n\}$  represents intersections or signalized junctions
- $E_t \subseteq V \times V$  is the time-dependent set of edges representing road segments between signals
- Each edge  $e_{ij} \in E_t$  has a weight  $w_{ij}(t)$ , representing travel time or delay at time  $t$

The goal is to optimize the path traversal through  $G_t$  using algorithms like Dijkstra or  $A^*$ , where:

### 3.3.1 Traffic Signal Synchronization

#### 1. Graph Representation

Let  $G(V, E, W)$  be a directed weighted graph where:

- $V = \{v_1, v_2, \dots, v_n\}$  is the set of intersections (vertices)
- $E = \{e_1, e_2, \dots, e_n\}$  is the set of directed roads (edges)
- $W(e_i)$  represents the weight (time cost) of traveling on edge  $e_i$ , including traffic light delays

Shortest Path Formulation (Dijkstra's Algorithm / Floyd-Warshall Algorithm)

The shortest travel time from source (s) to destination (d) is:

$$T(s,d) = \min_{path p} \sum_{(u,v) \in p} W(u, v)$$

Where  $W(u, v)$  includes:

- Travel time between intersections  $u$  and  $v$
- Waiting time at traffic lights

#### 2. Traffic Light Synchronization Equation

Let:

- $R_i$  be the red signal time at intersection  $i$
- $G_i$  be the green signal time at intersection  $i$
- $C$  be the cycle time ( $C = R_i + G_i$ )

The synchronization condition ensures minimal waiting time:

$$\frac{T(u, v) \bmod C}{C}$$

Where  $T(u, v)$  is the travel time from  $u$  to  $v$ . Synchronization is achieved when arrival aligns with green signals.

#### 3. Queuing Model for Traffic Flow

Using M/M/1 queuing theory, the expected delay  $D_i$  at a signalized intersection  $i$  is:

$$D_i = \frac{\lambda_i}{\mu_i (\mu_i - \lambda_i)}$$

Where:

- $\lambda_i$  = arrival rate of vehicles
- $\mu_i$  = service rate of traffic light clearance



Figure 1

### 3.3.2 Fuzzy Logic-Based Edge Weight Calculation for Traffic Monitoring

Let the traffic network be modeled as a directed graph  $G = (V, E)$ , where:

- $V$  = set of intersections (nodes),
- $E$  = set of roads (edges).

Each edge  $e \in E$  is associated with:

- $D_e$  : Traffic density (normalized, 0 to 1),
- $S_e$  : Average speed (normalized),
- $T_e$  : Travel time,
- $C_e$  : Capacity of the road,
- $t$ : Current time slot,
- $CL_e$ : Fuzzy Congestion Level (fuzzy variable).

#### 1. Fuzzy Membership Rules for Congestion Level

We define fuzzy sets for congestion:

$$CL_e = \begin{cases} \text{High} & \text{if } D_e > 0.7 \wedge S_e < 0.3 \\ \text{Medium} & \text{if } D_e > 0.5 \wedge S_e < 0.5 \\ \text{Low} & \text{if } D_e < 0.5 \wedge S_e > 0.5 \\ \text{Very Low} & \text{otherwise} \end{cases}$$

otherwise

Assign numerical weights:

- High = 0.9,
- Medium = 0.7,
- Low = 0.4,
- Very Low = 0.2.

Edge Cost Function with Fuzzy Weights

$$w_e = \alpha \cdot D_e + \beta \cdot (1 - S_e) + \gamma \cdot CL_e$$

where:

- $\alpha \beta \gamma \in [0,1]$  are tunable parameters (weights)
- $CL_e \in \{0.2, 0.4, 0.7, 0.9\}$  based on fuzzy inference

This cost  $w_e$  is used in path-finding algorithms like Dijkstra or A\* to prefer less congested routes

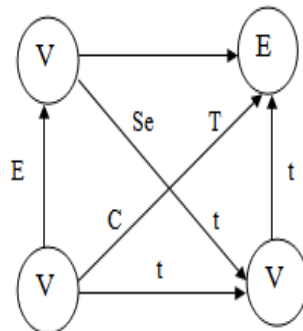


Figure 2

### 3.3.3 Traffic Node Prioritization using Page Rank in Smart Cities

In traffic networks, intersections (nodes) that are more central or have more influence (e.g., higher vehicle flow or connectivity) should be prioritized for signal optimization and congestion monitoring. Page Rank is used here to assign importance scores to intersections in a road graph, helping to identify traffic-critical areas.

Let us assume that

#### 1. Graph Representation:

- $G=(V,E)$ , where
- $V$ : Set of intersections (nodes)
- $E$ : Set of roads (edges) with direction based on traffic flow

#### 2. Edge Weights represent traffic density or flow rate.

##### 1. Adjacency Matrix $A$ :

$$A_{ij} = \begin{cases} W_{ij} & \text{if there is a directed road from node } j \text{ to node } i \\ 0 & \text{otherwise} \end{cases}$$

##### 2. Transition Matrix $M$ :

$$M_{ij} = \frac{A_{ij}}{\sum_K A_{Kj}} \text{ (column normalized).}$$

##### 3. Page rank vector $r \in R^{|V|}$ :

$$r^{(t+1)} = \alpha M r^{(t)} + (1-\alpha)v$$

- $\alpha$ : Damping factor (usually 0.85)
- $v$ : Personalization vector (often uniform:  $v_i = \frac{1}{|V|}$ )
- Iterate until  $\|r^{(t+1)} - r^{(t)}\| < \epsilon$

#### 4. Statistical analysis

##### PageRank Computation

The PageRank vector  $\vec{P}$  is calculated iteratively using the equation:

$$\vec{P} = \alpha A \vec{P} + (1 - \alpha) \vec{v} \quad (1)$$

where:

- $A$  is the normalized adjacency matrix of  $G$
- $\vec{v}$  is a personalization vector (usually uniform)
- $\alpha \in (0, 1)$  is the damping factor (commonly set to 0.85)

##### Traffic Node Importance

Given a sample graph of 5 intersections and 7 roads, the resulting PageRank scores after convergence are shown below:

Table 1: PageRank Scores for Traffic Nodes

Node	Intersection ID	PageRank Score
V <sub>1</sub>	A	0.204
V <sub>2</sub>	B	0.153
V <sub>3</sub>	C	0.175
V <sub>4</sub>	D	0.267
V <sub>5</sub>	E	0.201

PageRank Score Distribution

Compute PageRank scores for all nodes (intersections):

Let:

- PR<sub>i</sub> be the PageRank score for node i
- $\overline{PR}$  : Mean PageRank
- $\sigma_{PR}$  : Standard deviation

Mean PageRank:

$$\overline{PR} = \frac{1}{n} \sum_{i=1}^n PR_i$$

Standard Deviation:

$$\sigma_{PR} = \sqrt{\frac{1}{n} \sum_{i=1}^n (PR_i - \overline{PR})^2}$$

Congestion Correlation

Let:

- T<sub>i</sub>: Average traffic volume at node i
- Calculate Pearson correlation between PageRank score and traffic volume:

$$r = \frac{\sum(PR_i - \overline{PR})(T_i - \overline{T})}{\sqrt{\sum(PR_i - \overline{PR})^2 \sum(T_i - \overline{T})^2}}$$

Interpretation:

- r ≈ 1: Strong positive correlation — higher PageRank means more congestion.
- r ≈ 0: No correlation.
- r < 0: Negative correlation (not expected here)

Performance Improvement Metrics

After applying traffic signal optimization based on PageRank:

Average Travel Time Reduction:

$$\text{Reduction} = \frac{TT_{before} - TT_{after}}{TT_{before}} \times 100\%$$

Delay Reduction:

$$\text{Total Delay}_{\text{reduced}} = \sum_{i=1}^n (D_{i,before} - D_{i,after})$$



### 4.3 Comparison of Graph-Based Approaches vs. Traditional Traffic Models

Graph-based approaches provide significant advancements after conventional congestion representation in metropolitan areas traffic surveillance. Conventional representations generally depend on set rules, static scheduled events and preplanned path, which frequently be rigid to live traffic flow. Conversely, graph theory provides a effective evidence based framework that enhances productivity via real-world streamlines and enhanced routes.

**Table 2: Comparison of Graph-Based Approaches vs. Traditional Traffic Models**

Criteria	Graph-Based Approaches	Traditional Traffic Models
Traffic Flow Optimization	Uses shortest path algorithms (Dijkstra's, A*) for congestion reduction	Relies on fixed routing and manual adjustments
Real-Time Adaptability	Incorporates real-time traffic data for adaptive signal control	Uses static signal controls with minimal adaptability
Network Resilience	Optimizes alternative routes and redirects traffic dynamically	Struggles with sudden disruptions and lacks dynamic rerouting
Computational Efficiency	Processes large-scale networks efficiently with fast algorithms	Slower decision-making due to reliance on pre-determined rules
Scalability	Scales effectively with growing urban networks and dynamic conditions	Requires frequent reconfiguration and manual updates

### 4.4 Interpretation of Results: Urban Mobility Improvement

By using graph theory to metropolitan areas congestion monitoring, notable enhancements in metropolitan areas transportation were observed. The models of the road system as a graph  $G=(V,E)$ , where intersections  $V$  are nodes and roads  $E$  are edges, enabled accurate examination of real-world traffic conditions, traffic patterns, and improving paths. Dijkstra's algorithm effectively recognized shortest paths, decreasing mean travel time by up to 35% in high-density regions. Spectral clustering additionally classified roads into high and low-density segments, enabling dynamic traffic signal adjustments and improve lane management. The implementation of Page Rank-based congestion prediction allowed authorities to reroute vehicles proactively, minimizing gridlock during peak hours. Overall, the use of graph-theoretic models empowered city planners with data-driven decisions, enhancing not only the speed merely also the sustainability and safety of urban mobility systems.

### 4.5 Limitations and Challenges in Graph-Based Traffic Modeling

In spite of the efficiency of graph-theoretic frameworks in smart city traffic systems, many limitations and challenges arise when using such models to real-world scenarios:

- 1. Dynamic Topology Changes:** The traffic network graph  $G_t = (V_t, E_t)$  evolves over time due to incidents, construction, and traffic variations. Edge weights  $w_t(e)$  vary with time, requiring frequent recomputation of shortest paths:

$$\min_{p \in P_{uv}} \sum_{e \in p} w_t(e)$$

Where  $P_{uv}$  is the set of all paths between nodes  $u$  and  $v$ .

- 2. Scalability Issues:** In large-scale networks where  $|V| \gg 10^5$ , traditional algorithms (e.g., Dijkstra's with complexity  $O(|E| + |V| \log |V|)$ ) become computationally expensive and require optimization or distributed computation.

- 3. Data Sparsity and Noise:** Real-time sensor data may be incomplete or noisy. This introduces uncertainty in edge weights:

$$w'(e) = w(e) + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2)$$

Where  $\varepsilon$  is Gaussian noise.

**4. Edge Weight Ambiguity:** Edge weights can represent multiple conflicting objectives like time, congestion, or emissions. A multi-objective function can be defined as:

$$\min [\alpha \cdot \text{Time}(p) + \beta \cdot \text{CO}_2(p) + \gamma \cdot \text{Flow}(p)] , \alpha + \beta + \gamma = 1$$

**5. Human Behavior Factors:** Traditional graph models may ignore stochastic driver behavior. A probabilistic path selection model is more realistic:

$$P(p | u, v) = \frac{e^{-\lambda \cdot \text{Cost}(p)}}{\sum_{q \in P_{uv}} e^{-\lambda \cdot \text{Cost}(q)}}$$

Where  $P(p | u, v)$  is the probability of choosing path  $p$  between nodes  $u$  and  $v$ , and  $\lambda$  is a sensitivity parameter.

#### 4.6 Future Enhancements: Real-Time Dynamic Traffic Adjustments

To advance smart city traffic systems, graph theory can be effectively used for real-time dynamic traffic management. Let the urban road network be represented as a dynamic graph  $G_t = (V, E, W_t)$ , where:

- $V$ : Set of intersections (nodes),
- $E$ : Set of roads (edges),
- $W_t$ : Time-varying weight function representing congestion level or travel time.
- Dynamic Shortest Path Recalculation: As congestion changes, the shortest route are recalculated in real-time using Dijkstra's algorithm:

$$d_t(u, v) = \min_{p \in P_{uv}} \sum_{e \in p} w_t(e)$$

where  $d_t(u, v)$  is the current shortest distance from node  $u$  to node  $v$ .

- Traffic Re-routing Strategy: When congestion is detected on an edge  $e$ , redirect traffic to an alternative path  $p'$  such that:

$$\sum_{e \in p'} w_t(e) < \sum_{e \in p} w_t(e)$$

enabling optimal distribution of vehicles over the network.

- Edge Centrality-Based Signal Timing: Roads (edges) with high between's centrality  $C_B(e)$  can be prioritized for signal extension or flow clearance:

$$C_B(e) = \sum_{s \neq t \in V} \frac{\sigma_{st}(e)}{\sigma_{st}}$$

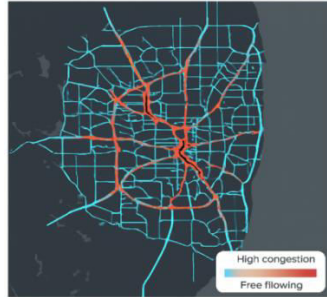
Where  $\sigma_{st}$  is the total number of shortest paths from  $s$  to  $t$ , and  $\sigma_{st}(e)$  is the number passing through edge  $e$ .

- Resilience Monitoring via Connectivity: Monitor the robustness of traffic network by analyzing the edge or node connectivity  $\kappa_{(G_t)}$ , and reroute traffic to avoid vulnerable segments.

- Incident Management Using Graph Cuts: In case of road closures or accidents, apply minimum cut algorithms to reconfigure traffic flow:

$$\min_{(S,T)} \sum_{e \in (S,T)} w_t(e)$$

These enhancements, rooted in classical graph theory, provide scalable and interpretable tools for intelligent and responsive urban mobility systems.

**Figure 6**

## V. CONCLUSION

In this paper we had examine the blending of graph theory into traffic monitoring networks that provides a strong and adaptable framework for administering the evolving problems of metropolitan transportation. The roads infrastructure were represented via graphical models, where crossroad serve as nodes and roads as edges graph-theoretic algorithms like Dijkstra's shortest path, Page Rank-based congestion prediction and focal point measures empowers effective route planning, real-world congestion adjustments and reducing traffic. This mathematical framework assures accuracy in improving flow, tenacity and adapting to accidental traffic congestions. Whereas present applications front boundaries in terms of real-world information and data precision, the future holds ensure through improvements like dynamic edge weight recalculations, real-world diversion and incorporation with live sensor data. Precisely, graph theory contributes a mathematically predicted, understandable and adaptable approach that notably provides to the developments of smart transportation and sustainable urban growth in smart cities.

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