

OPTIMIZED RESOURCE ANALYSIS IN VANET CLOUD USING FOG ENABLED REAL-TIME TRAFFIC CONTROL SYSTEM

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ABSTRACT

The rapid rise in vehicular traffic has led to a significant demand for efficient work and economically feasible intelligent traffic management systems. This research work introduces a novel solution that integrates fog computing (FC) with Internet of Things (IoT) to manage real-time traffic congestion. Utilizing a two-tiered architecture consisting of data gathering mechanisms, real-time processing fog computing nodes, the system offers predictive insights into traffic behavior. Through real-time traffic data processing, selective routing for emergency vehicles, and event-based traffic management, it aims to alleviate urban traffic congestion. The system's edge computing capabilities enable faster response times and lower latency. This intelligent system not only prioritizes emergency vehicles but also predicts traffic flows for special events, enhancing urban mobility. Cloud Computing (CC) supports system scalability, while FC optimizes energy efficiency. Furthermore, the proposed system presents commercial potential for municipalities and private sectors, as it can be monetized through licensing or Software as a Service (SaaS) models. Results from simulations demonstrate efficient resource utilization and reduced traffic congestion, positioning this solution as a cutting-edge tool for smart city initiatives.



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1. INTRODUCTION

The fast growth in the use of vehicles worldwide gives rise to the need for an efficient traffic alleviation system. The last decades saw a rise in significant concern about traffic congestion among road users. Traffic congestion can be defined as a blocked road system created by a long queue of vehicles (Vergis et al., 2020). While not posing imminent threats, it costs urban communities significant

money and time. Road expansions to alleviate vehicle congestion cost almost every country billions of dollars. Traffic congestion can be recurring, such as during rush hours, or non-recurring, caused by unexpected events like accidents or roadblocks. Thus, monitoring road network traffic density is essential. Inter-connected vehicles play a vital role in smart cities, where the vehicles connect over a wireless connection to bring about mobile computation and communication abilities.

Fog computing (FC) plays an intermediate role by residing between vehicles (Tiwari V & Chaurasia B.K., 2017) and the cloud provides vehicles with the power to process, store, and network with other devices in a smart city through Vehicular Ad-hoc networks (VANET) (Chaurasia B.K. et al., 2011). VANET is time-sensitive network. The time needed to process a request from a vehicle in a VANET requires less time. Delay and latency are important performance metrics for VANET and FC. A FC model based on priority can be deployed in vehicle transportation systems in smart cities to deal with such metrics. The findings show a 20% reduction in data latency and a reduction in processing delay by 35% when compared to using CC architecture, hence encouraging effective communication (Farooqi A.M. et al., 2022).



Figure 1. Traffic at a road intersection

VANET is a subset of mobile ad hoc networks (MANET). On-board units (OBUs) in mobile vehicles and roadside units (RSUs) are present in a VANET. With increased computational prowess and communication abilities, peripheral or incremental changes in VANETs revolutionize. A solution used to fulfill the resource requirements (such as computing, storage, and networking) of vehicles in VANET is CC (Chaurasia B.K. & Sharma K, 2019). Due to the specific mobility requirements, location awareness, and low latency, the role of FC in VANET recently emerged as an area of interest for researchers. The collaboration of FC and VANET gives rise to immense possibilities for providing applications and services on the edge of CC. In FC, virtual computing is deployed at scale, and the communication provisions in VANET are made available near mobile vehicles. Mobile devices in VANET may demand low-latency services and short distance local connections via FC (Kai K. et al., 2016). We have included the acronyms used in this paper in Table 1 for convenient reading.

Table 1. Abbreviations used in the paper.

Sr. No	Acronyms	Full Form
1	CC	Cloud Computing
2	FC	Fog Computing
3	EC	Edge Computing
4	SaaS	Software as a Service
5	VANET	Vehicle Ad-hoc Network
6	RSU	Road Side Unit

7	OBU	On Board Unit
8	IoT	Internet of Things
9	AI	Artificial Intelligence
10	CV	Computer Vision
11	FSRCM	Fuzzy-based System for Resource Coordination and Management
12	V2X	Vehicle to Everything
13	TMC	Transport Management Centres
14	RL	Reinforcement Learning
15	DNN	Deep Neural Network
16	CASE	Collaborative and Adaptive Signaling on the Edge
17	SPaT	Signal Phase and Timing
18	V2V	Vehicle To Vehicle
19	V2I	Vehicle To Infrastructure
20	ML	Machine Learning
21	IoV	Internet of Vehicles
22	I/O	Input/Output
23	DSRC	Dedicated Short Range Communications
24	V2P	Vehicle To Pedestrian

Today's urban traffic scenario is marked by severe congestion, especially in metropolitan areas where vehicle numbers are growing rapidly. This increase in traffic leads to frequent bottlenecks, longer commute times, and higher fuel consumption. Additionally, conventional traffic control systems, with their fixed signal timings, lack the flexibility to adapt to various traffic requirements in real time, leading to inefficient traffic management (Chaurasia B.K. et al., 2020) (Figure 1). Compounding the issue, expanding road infrastructure is often impractical due to limited space and high costs. These challenges highlight the need for intelligent, adaptive traffic management solutions to improve mobility, reduce delays, and support sustainable urban development. With IoT, EC, and AI integration to monitor and manage traffic flow effectively, we present a smart and dynamic traffic control system (Figure 2).

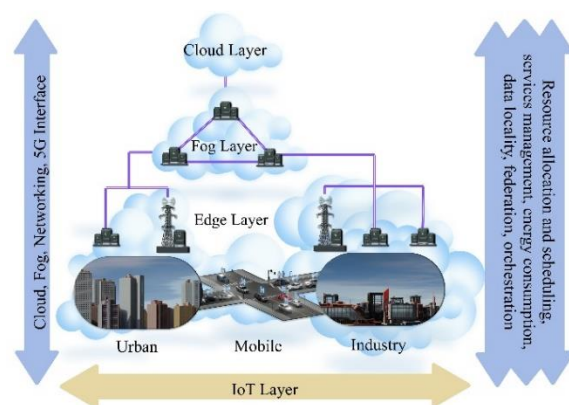


Figure 2. Overview of working of proposed system

Using localized data processing and predictive algorithms allows the system to reduce congestion, optimize traffic signal timing, and enhance urban mobility with minimal delay and energy consumption.

1.1 MOTIVATION

The escalating challenges posed by traffic congestion in urban areas and its impact on economic and environmental aspects motivated this research. With the rapid increase in vehicle numbers, urban areas face significant traffic congestion issues, leading to fuel wastage, increased pollution, and substantial commute delays. Traditional solutions, such as expanding road infrastructure and manual or semi-automated traffic management systems are not only costly but also impractical in densely populated cities, where space is limited and road expansions may not sufficiently alleviate dynamic traffic bottlenecks.

The research addresses these limitations by leveraging advanced technologies, specifically IoT with EC and integrating AI, to enable real-time traffic control. Sensors, cameras, and RSUs allow the system to collect real-time traffic data. The edge nodes process the collected data to lower latency. This decentralized approach to data processing enables rapid responses to traffic conditions, such as adjusting signal timings, resulting in optimized traffic flow and reduced congestion. Incorporating AI allows for adaptive learning and prediction capabilities, enhancing the system's efficiency in managing dynamic traffic conditions. This research aims to contribute to smart city initiatives by providing a scalable, energy-efficient, and adaptable solution for urban traffic challenges, improving urban mobility and supporting sustainable development.

1.2 RESEARCH NOVELTY

This research provides a novel approach for IoT integration with edge computing (EC) and AI technologies to address urban traffic management challenges with optimized resource analysis. Unlike conventional centralized traffic control systems, this research introduces a decentralized framework that utilizes EC for real-time traffic manipulation. CV and EC is used to monitor traffic and significantly reducing latency in decision-making (Liu G. et al., 2022).

The deployment flexibility of IoT in traffic systems can be leveraged for localized data collection. Thus, making the system highly scalable, enabling real-time traffic adjustments with minimal delay (Guerrero-Ibanez J.A. et al., 2018). The deployment of RSUs enhances VANET communication, allowing the system to dynamically adapt to traffic patterns by interacting with connected vehicles, an innovative feature that distinguishes this system from existing models (Guerrero-Ibanez J.A. et al., 2018). The integration of AI-based algorithms for

predictive analysis and traffic flow optimization adds an adaptive component, making it more efficient through continuous learning (Ning Z. et al., 2019).

Moreover, the system addresses critical security concerns by employing secure transmission protocols and encryption at the FC layer, ensuring data integrity throughout the process from edge nodes to the CC servers (Mukherjee M. et al., 2019). This multi-layered architecture offers a robust, secure, and scalable solution for urban traffic management, with real-time data processing by EC, dynamic decision-making with AI, and long-term data storage and analysis with CC (Elsayed A. et al., 2024). This positions the system to address growing urbanization and increasing traffic density more efficiently than traditional models.

1.3 RESEARCH CONTRIBUTION

The contributions of this paper focus on the optimized resource analysis in VANET:

1. Cloud using fog-enabled real-time traffic control for smart city transportation systems.
2. Deployment of IoT devices for live collection of traffic data and edge devices for low-latency processing, thus enhancing scalability of the system.
3. Dynamic traffic signal control for optimizing flow of vehicles and reducing congestion.
4. Use of AI algorithms for continuous adjustment of traffic signals based on live data, which improves responsiveness and flow management.
5. Combining edge processing for real-time decisions with cloud infrastructure for long-term data analytics and scalability.
6. Designed for aligning with smart city development goals.

1.4 PAPER ORGANIZATION

The research work is divided into sections to assist in the exploration of fog-enabled real-time traffic control for smart city transportation systems in conjunction with optimized resource analysis in VANET Cloud. (Figure 3) This paper is organized as follows. In Section 1, the background of VANET Cloud using Fog Enabled Traffic Control Systems is introduced. Followed by Motivation, Novelty, and Research Contribution. Related works are summarized in Section 2, which reviews the recent researches in similar domain. Section 3 discusses methodology used in the proposed system highlighting the convergence of various technologies for a common solution. Section 4 presents the simulation setup used for analyzing the various performance metrics of the proposed system. Section 5 discusses the results of the simulation in detail. While the work is concluded in Section 6, Section 7 presents areas of improvements in the proposed system.

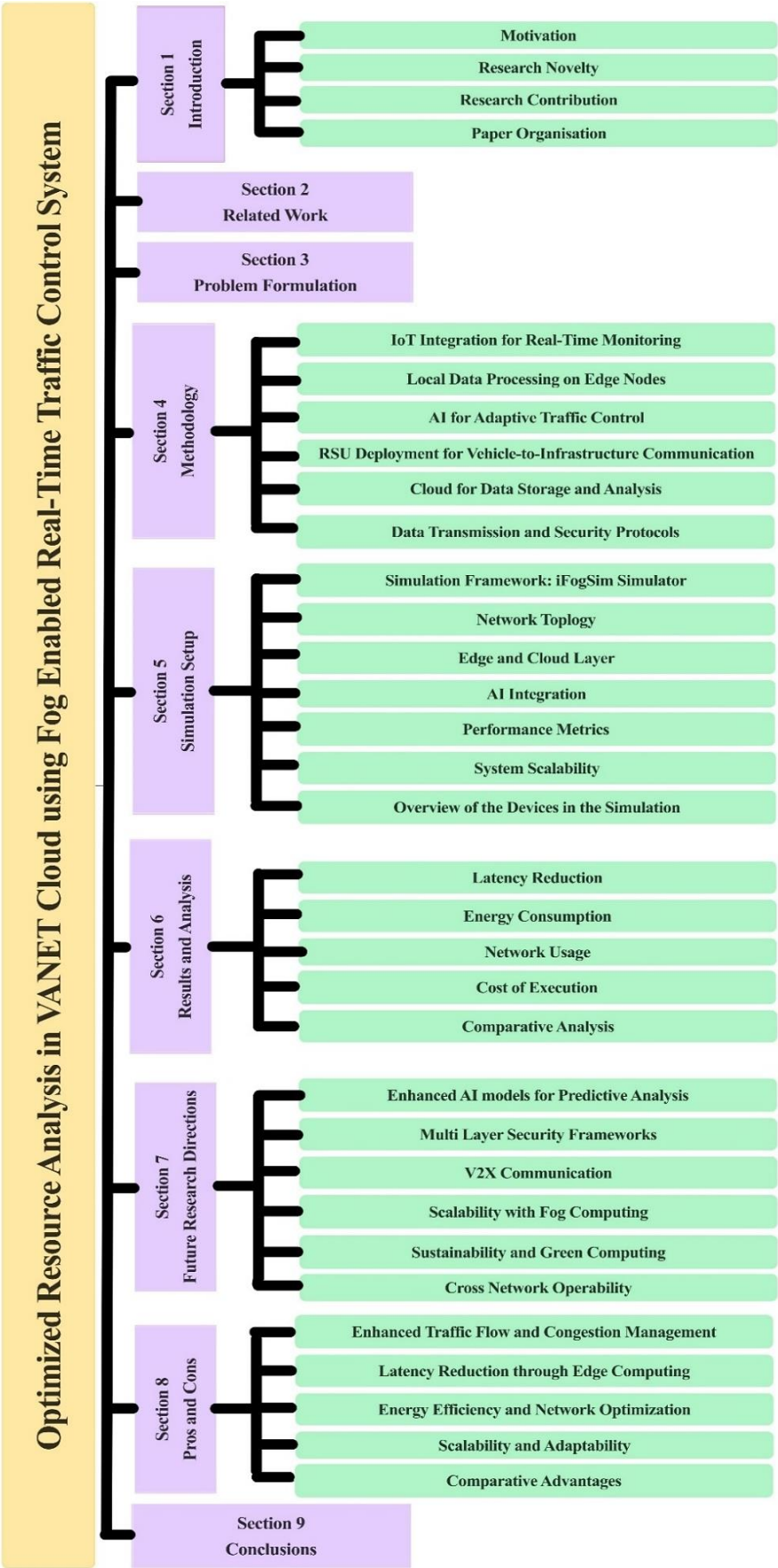


Figure 3. Overview of the content flow used in the paper

Table 2. Comparative Analysis of Existing Techniques.

Sr. No.	Authors, Year, Citation	Work	Issues and Challenges
1	Liu, G. and Shi, H. and Kiani, A. and Khreishah, A. and Lee, J. Y. and Ansari, N. and Liu, C. and Yousef, M., 2022 (Liu G. et al., 2022)	Smart traffic monitoring system using computer vision and edge computing	Limited, real-time capabilities and scalability issues.
2	Ning, Z., Huang, J., Wang, X., Hu, X., Zhang, Z., and Obaidat, M. S., 2019 (Ning Z. et al., 2019)	A cooperative fog computing framework for real-time traffic management in smart cities	High computational overhead in fog nodes.
3	M. Elsayed, K. Mohamed, and H. M. Harb, 2024 (Elsayed A. et al., 2024)	Enhanced traffic congestion management with fog computing: A simulation-based investigation using ifog-simulator	Lack of real-world deployment validation.
4	K. Bylykbashi, Y. Liu, K. Matsuo, M. Ikeda, L. Barolli, and M. Takizawa, 2019 (Bylykbashi K. et al., 2019)	A fuzzy-based system for cloud-fog-edge selection in VANETs, in Advances in Internet, Data and Web Technologies	Ambiguity in fuzzy selection criteria for optimal resource allocation.
5	J. Barthélemy, N. Verstaëvel, H. I. Forehead, and P. Perez, 2019 (Barthelemy J. et al., 2019)	Edge-computing video analytics for real-time traffic monitoring in a smart city	Limited by edge device processing power.
6	A. Ur-Rehman and T. Mahmood, 2020 (Ur-Rehman A. & Mahmood T., 2020)	Reducing congestion in an intelligent traffic system with collaborative and adaptive signaling on the edge	Complexity in adaptive signal tuning algorithms.

2. RELATED WORK

The current technological evolution trend raises the expectations of a massive deployment of VANETs' upcoming vehicles. Due to bandwidth constraints, high latency, variable capacity of wireless links, and dynamic topology, wireless networks such as VANETs face some technical challenges in deployment and management. CC, FC, and EC are possible solutions to these communication challenges. It is suggested to use a Fuzzy-based System for Resource Coordination and Management (FSRCM) in VANETs, which chooses the processing layer of the VANET application data by taking into account factors like data size, time sensitivity, vehicle movement, and remaining storage capacity (Bylykbashi K. et al., 2019).

Tremendous amounts of video data is being captured by traffic management systems that use advancements in video processing for detection and monitoring of traffic

anomalies. Conventionally, the data collected are sent to Traffic Management Centres (TMC) for comprehensive analysis, which may obstruct network paths to the TMC by creating bottlenecks. At the edge of the network, cameras are placed so that the TMC operates as a centralized server deep inside the network. This arrangement leads to two significant challenges:

- Real-time processing and analysis of video data becomes nearly impossible, especially when network conditions deteriorate;
- The continuous capture and transfer of video data may obstruct network paths leading to the TMC by the creation of bottlenecks.

For the alleviation of these bottlenecks, use of edge computing, by placing edge nodes near cameras with computing resources, such as cloudlets is proposed. Though they are constrained by limited resources as

compared to TMC, cloudlets provide localized video processing capabilities (Liu G. et al., 2022). The storage and processing capabilities provided by CC environments alleviate the burden on local systems. However, there are a few drawbacks, such as the increased needs for wider network bandwidth and increase in latency. These drawbacks pose a serious threat to applications like security systems. IoT equipment's need accurate computation of latency for live data processing over the cloud infrastructure. Researchers recommend FC and EC for addressing these problems. FC minimizes latency, conserves bandwidth, addresses security concerns, and ensures reliable data collection across large geographic areas. The transportation of data to the precise processing location distinguishes it from EC. EC means the prowess to process, communicate, and store data in end devices. Use of fog node also lowers arrival time, alleviates concerns about data transmission security and privacy while allowing for faster responses to traffic conditions, making it a more optimal solution than cloud (Elsayed A. et al., 2024), (Barthelemy J. et al., 2019).

Reinforcement learning (RL) is used extensively to alleviate traffic management bottlenecks. However, many previous works leverage cloud-based centralized RL because of the complex computations involved in the underlying deep neural networks (DNN). Developing a Multi-Agent learning with simplified agents and localized states is necessary. Comparable performance to centralized RL is still a challenge. Previous works include Collaborative and Adaptive Signaling on the Edge (CASE). It is a multi-agent RL approach to manipulate the traffic signals' phase and timing. When integrated with a general-purpose GPU-based platform, the improvements in computational times are more than eight times over the computational times achieved by conventional systems. Adaptive traffic signaling based on live data monitoring can be implemented. For managing congestion at signalized intersections, efficient optimization of the Signal Phase and Timing (SPaT) in a dynamic manner can be beneficial economically (Ur-Rehman A. & Mahmood T., 2020).

Traditional solutions, like constructing new roads or expanding existing infrastructure, are often impractical in densely populated urban areas. Limited available land makes it challenging to build new highways or roads, while the construction of overpasses or tunnels is costly and time-consuming. Even when infrastructure improvements occur, they frequently lag behind the rapid increase in traffic. Current approaches, such as V2V communication, often fall short in accurately estimating traffic density. Additionally, traditional traffic signaling systems operate on predetermined timings and fail to respond optimally to fluctuating traffic volumes thus resulting in lengthy queues at intersections (Ning Z. et al., 2019).

In the contemporary digital era, when cloud computing and the Internet of Things (IoT) are important facets of daily life, effective network communication is crucial. The goal of cloud computing is to speed up and reduce the latency of data transfers to the cloud for processing, analysis, and storage. Due to the wide variety and large number of IoT devices, the two most difficult problems in the multi-cloud computing environment are IoT integration and task scheduling. Reducing the overall time required to finish all input operations, identifying the resources needed for the Message Queuing Telemetry Transport (MQTT), and other essential protocols used in this work to display delay and assess the performance of various jobs at various IoT nodes are the main goals of cloud computing-based IoT optimization (Atre A. et al., 2025).

Therefore, optimized resources based real-time traffic control system is proposed to address traffic congestion at intersections in heavy populated cities using CV, EC and IoT integrated with AI. This analysis of live data enables the system to dynamically adjust traffic signal timings which in turn results in optimized flow and reduced congestion. This innovative approach aims at the improvement of the efficiency and effectiveness of transportation systems in smart cities while also improving overall public safety and convenience. The research gap with issues and challenges of existing techniques are comparatively analyzed and summarized (Table 2).

3. PROBLEM FORMULATION

The exponential increase in the number of vehicles due to rapid urbanization have led to severe traffic congestion in modern cities. Today's urban traffic scenario is marked by severe congestion, especially in urban areas where vehicle numbers are growing rapidly. This increase in traffic leads to frequent bottlenecks, longer commute times, and higher fuel consumption. The last decades saw a rise in significant concern about traffic congestion among road users. Efficient traffic management systems require data collection, processing, and decision-making in real-time or near real-time to dynamically adapt traffic signal timings based on the prevailing traffic density. Traditional traffic control systems leveraging CC for centralized data processing face several challenges in terms of high latency, bandwidth overhead and energy inefficiency (Ravish R. & Swamy S., 2021).

4. METHODOLOGY

This research focuses on exploring a smart traffic control system that uses IoT and AU technologies, and EC for efficient management of urban traffic. (Figure 4) shows that the methodology involves the following components:

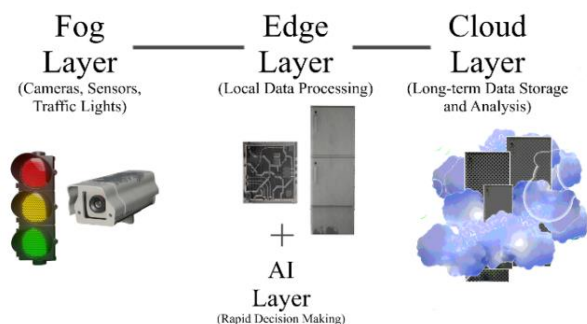


Figure 4. Various layers in the proposed system

4.1 IoT Integration for Real-Time Traffic Monitoring

IoT like cameras, sensors, and RSUs, are placed across the city's traffic network to collect real-time data. These devices, which are connected to edge nodes, process data locally which reduces the latency in the transmission of large data volumes to a centralized server (Bonomi F. et al., 2012), (Guerrero-Ibanez J.A. et al., 2018). The IoT help in achieving a highly scalable solution, as more sensors can be connected to increase system precision without the requirement of any significant alterations to the system.

4.2 Local Data Processing Using EC

IoT generate massive amounts of data. It can be handled by employing EC at the local level. By positioning edge nodes closer to the data sources and processing live data, decisions about traffic light adjustments and congestion alerts can be made rapidly. This setup decreases data transmission latency and reduces the computational burden on centralized cloud servers by minimizing the need for cloud-based processing (Bonomi F. et al., 2012), (Ning Z. et al., 2019). This component is critical in ensuring that the system can adapt to traffic fluctuations with minimal delays.

4.3 AI for Adaptive Traffic Control

AI-based algorithms are embedded into edge devices for real-time traffic analysis and pattern recognition. For the prediction of upcoming traffic congestions based on previously stored and live data, the ML models are trained for adjusting traffic signals accordingly to optimize flow and reduce waiting times. The AI models analyze various parameters such as vehicle density, speed, and congestion levels (Ning Z. et al., 2019). Over time, these models improve their predictions and enhance system efficiency by learning from previous data.

4.4 RSU Deployment for V2I Communication

The deployment of RSUs plays a crucial role in enabling communication between vehicles and the traffic management system. These units collect data from connected vehicles, including speed, location, and route preferences, which is then analyzed to make real-time

traffic adjustments (Ning Z. et al., 2019). RSUs help create a more intelligent system where individual vehicles can influence traffic patterns, leading to more dynamic management of congested areas.

4.5 Cloud for Data Storage and Analysis of Stored Data

For reliable data storage and robust analysis of recorded data, the cloud provides a platform for storing large datasets which can evaluate the performance of the system over time, detect patterns, and plan for future upgrades. Data from multiple edge nodes and IoT are aggregated in the cloud, allowing for holistic traffic system management. Security measures, such as encryption and authentication, are also in place to protect data integrity (Mukherjee M. et al., 2019).

4.6 Data Transmission and Security Protocols

Secure transmission protocols are critical to ensuring that data communicated among IoT, various edge nodes, RSUs, and centralized servers remain protected. Encryption and secure channels are used to prevent unauthorized access or tampering with sensitive traffic information. FC layers are also implemented to manage security at the edge nodes, where data encryption occurs before transmitting information to the cloud (Mukherjee M. et al., 2019).

This methodology creates a highly efficient and scalable traffic management system, combines the benefits of live data processing with AI-driven decision-making and the use of cloud for long-term data storage and analysis.

5. SIMULATION SETUP

The simulation environment was configured using iFogSim, an open-source fog computing environment simulating framework (Gupta H. et al., 2017). The iFogSim enables the creation of an extensive simulation of IoT-based systems, including FC and EC infrastructure, to measure key parameters like latency, energy consumption, and cost (Gupta H. et al., 2017). This section outlines the configuration of the systems used in the simulation.

5.1 Simulation Framework: iFogSim Configuration

The iFogSim was used to simulate the entire traffic management system. It provided a flexible environment to create a layered architecture for integrating IoT, edge devices and CC. The proposed system architecture for the real-time traffic control system (Figure 5). The simulation was set up with predefined traffic scenarios, incorporating various traffic densities, road layouts, and congestion levels (Gupta H. et al., 2017). The platform was used for the simulation of live processing of data on the edge, with virtual IoT.

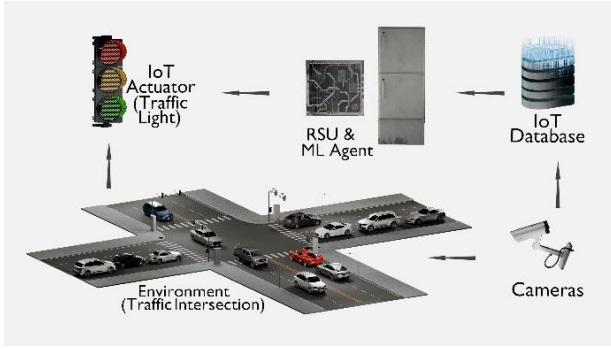


Figure 5. System Architecture for Real-Time Traffic Control System

5.2 Network Topology

The network topology was designed to reflect the real-world urban traffic system. Multiple IoT devices were deployed at intersections, and RSUs were strategically placed throughout the network to monitor traffic flow and vehicle density. The devices generated continuous streams of data, which were processed by the edge nodes. The edge layer was responsible for handling data locally to reduce latency, while the cloud was responsible for persistent data safety and additional computation (Chiang M. & Zhang T., 2016). A number of IoT devices, edge nodes, and RSUs were adjusted during the simulation to understand their impact on system performance, latency, and energy consumption.

5.3 Edge and Cloud Layers

The edge layer consisted of multiple servers positioned near the RSUs. These servers were responsible for processing local traffic data and making decisions on real-time traffic signal adjustments. The cloud layer, simulated as a remote centralized server, stored large datasets for future analysis and conducted high-level computations such as traffic pattern predictions (Chiang M. & Zhang T., 2016), (Li S. et al., 2018). The simulation allowed for the comparison of different configurations of EC and CC layers for the identification of the most efficient structure relating to latency and resource utilization.

5.4 AI Integration

ML models were implemented within the simulation to predict traffic flow and coordinate timings of the traffic signals based on live and historical data. These models were trained using datasets from previous traffic simulations and real-world data from public sources. To ensure that decisions regarding traffic management were made as fast as possible with reduced cost, the AI models were integrated at edge layer which reduces the need for cloud processing (Li S. et al., 2018). The training and inference of these models were simulated, with the results compared to standard non-AI-based traffic management systems.

5.5 Performance Metrics

Several key metrics were taken into account for the evaluation of the performance of the system, given as follows:

Latency was measured as the time elapsed between data generation at the source devices and response generation at the edge nodes. It is the delay between data collection and decision-making, was another critical metric measured during the simulation. The system achieved lower latency by locally processing the data. This latency reduction was especially important in making quick decisions for preventing congestion. The results showed a substantial decrease in latency when EC was integrated into the system, as opposed to a traditional cloud-only architecture (Chiang M. & Zhang T., 2016). The average latency reduction demonstrated the effectiveness of local processing in time-sensitive applications. Latency can be calculated as equation (1):

$$L = M/v_i \quad (1)$$

Here, M is the length of the message (in execution), and v_i is the number of vehicles at the fog layer.

Energy Consumption is a significant focus of the simulation, given the importance of deploying energy-efficient IoV in smart cities. In this work, IoT is equivalent to IoV for smart cities. However, IoT may also have cameras, traffic lights, etc. The fog layer server is deployed for computation and storage to streamline traffic or reduce congestion in smart cities (Chen X. et al., 2019). Minimization in the data volume transmitted to the cloud helped the system in conserving energy by reducing communication overhead and decreasing the need for long-range data transmission. A fog node's processing, communication, and idle activities all affect how much energy it uses.

The equation (2) for fog energy consumption is:

$$E_{Fog} = E_{CPU} + E_{Transmission} + E_{Idle} \quad (2)$$

The equation (3) for CPU energy calculation is:

$$E_{CPU} = P_{CPU} \times T_{Execu} \quad (3)$$

The equation (4) for transmission energy calculation is:

$$E_{Trans} = P_{Trans} \times T_{Trans} \quad (4)$$

The equation (5) for idle energy consumption calculation is:

$$E_{Idle} = P_{Idle} \times T_{Idle} \quad (5)$$

Here, P_{CPU} , and P_{Idle} are the power consumed during transmission by fog node, and power consumed in idle state by the CPU respectively. T_{Execu} , T_{Trans} and T_{Idle} are the time taken to execute the tasks, time taken for data transmission, and time the node spends in idle state, at EC, FC, and CC layer, respectively. Final energy of FC is equation (6):

$$E_{total} = \sum_{i=1}^{N_{fog}} E_{fog,i} \quad (6)$$

where i is the node used in the simulation.

Network Usage in VANET Cloud, uses a FC-enabled real-time traffic control system, and is the number of network resources used for computation and communication between entities like CC servers, fog nodes, and vehicles (Rahmani A.M. et al., 2017). The network usage is equation (7):

$$Net_{Usage} = \sum_{i=1}^{N_{Links}} D_{Size} / N_{Bandwidth} \quad (7)$$

Here N_{Links} is the number of communication between V2V and V2I or I2V within vicinity. D_{Size} is the size of the data being transmitted in VANET Cloud and $N_{Bandwidth}$ is the available network bandwidth for users.

The total cost of the proposed system in terms of processing cost, storage cost and network usage cost.

$C_{processing}$ expresses the processing cost of computational workload as number of instructions executed based on a task's demand on the available MIPS. I and M represent total instructions (in millions) and MIPS of the device respectively in equation (8):

$$C_{processing} = I / M \quad (8)$$

$C_{storage}$ expresses the storage cost as workload processing. D_v and P represent data volume (in MB) and I/O processing (in MIPS) respectively in equation (9):

$$C_{storage} = D_v \times P \quad (9)$$

$C_{network}$ expresses network usage cost as data transmission latency, which is linked to the number of instructions processed by the network interface. D_s and B represent data sent (in MB) and bandwidth (in MB/s). M is the MIPS for transmission respectively in equation (10):

$$C_{network} = \left(\frac{D_s}{B} \right) \times M \quad (10)$$

The total cost is calculated as equation (11):

$$C_{total} = C_{processing} + C_{storage} + C_{network} \quad (11)$$

Here C_{total} , $C_{processing}$, $C_{storage}$, $C_{network}$ are the total cost associated with executing a task, cost of processing a task, cost of storing a task and the cost associated with network usage respectively. Here, C_{total} is represented in terms of MIPS, representing the total number of million instructions required to process, store, and transmit a task.

These metrics were crucial for determining the system's efficiency and feasibility for real-world deployment.

5.6 System Scalability

The scalability is tested by gradually incrementing the number IoT in the simulation. By simulating a small traffic network and then scaling up the simulated traffic network, the system's capacity to handle large networks was evaluated. The results indicated that the system was scalable, with a manageable increase in latency and energy consumption as more devices were added (Gupta H. et al., 2017) ,(Rahmani A.M. et al., 2017).

The simulation setup provided valuable insights into how various system components interact with each other, and how the system would behave under different traffic conditions. By using the iFogSim, a realistic urban traffic scenario was created, allowing the testing and validation of this smart traffic management solution.

5.7 Overview of Devices in the Simulation

The simulation comprises a range of devices, each serving a specific role within the smart traffic management framework. These include fog devices, cameras, sensors, actuators, cloud server and proxy servers. The CC infrastructure (Table 3) serves as the central processing and storage unit, providing high computational power and long-term data storage. The proxy server (Table 4) acts as an intermediary, managing communication between the CC and local FC devices to streamline data transmission.

Table 3. Cloud Devices Specifications and Parameters.

Sr. No	Attribute	Value
1	MIPS	44800
2	RAM	40000 MB
3	Uplink Bandwidth	100 MBps
4	Downlink Bandwidth	10000 MBps
5	Level	-1 (root level)
6	Uplink Latency	0.0 ms
7	Rate per MIPS	0.01 ms
8	Busy Power	$16 \times 103 \text{ mW}$
9	Idle Power	$16 \times 83.25 \text{ mW}$

Table 4. Proxy Server Specifications and Parameters.

Sr. No	Attribute	Value
1	MIPS	2800
2	RAM	40000 MB
3	Uplink Bandwidth	10000 MBps
4	Downlink Bandwidth	10000 MBps
5	Level	1
6	Uplink Latency	100.0 ms
7	Rate per MIPS	0.0 ms
8	Busy Power	107.339 mW
9	Idle Power	83.4333 mW

At the intersection level, fog devices (Table 5) are deployed to process real-time data locally, reducing latency and enabling quicker decision-making for traffic control. These are complemented by cameras (Table 6), strategically placed to monitor traffic conditions and gather visual data for analysis. Additionally, vehicle sensors (Table 7) collect critical metrics such as congestion levels from individual vehicles, enriching the data ecosystem of the simulation.

Table 5. Intersection Fog Devices Specifications and Parameters.

Sr. No	Attribute	Value
1	MIPS	2000
2	RAM	40000 MB
3	Uplink Bandwidth	10000 MBps
4	Downlink Bandwidth	10000 MBps
5	Level	2
6	Uplink Latency	50.0 ms
7	Rate per MIPS	0.01 ms
8	Busy Power	100.0 mW
9	Idle Power	90.0 mW

Table 6. Cameras Specifications and Parameters.

Sr. No	Attribute	Value
1	Transmission Time	10 ms

Table 7. Vehicle Sensors Specifications and Parameters.

Sr. No	Attribute	Value
1	Transmission Time	10 ms

Finally, actuators, such as traffic lights, are used to implement decisions derived from processed data. These devices play a crucial role in dynamically managing traffic flow and minimizing congestion. Each of these components is meticulously detailed in respective tables, outlining their specifications and parameters to provide a comprehensive understanding of their roles in the simulation.

6. RESULTS AND ANALYSIS

In this section, we discuss the key visualizations of our analysis, including a comparative study, traffic congestion reduction, latency reduction, energy consumption, network usage, and system scalability when the number of vehicles in simulation were in the range 5 to 100. The experiments were conducted on a system equipped with an AMD Ryzen 5 4600H processor, 8GB of RAM, and a 512GB SSD. The constant valued parameters used in the evaluation are given below (Table 8).

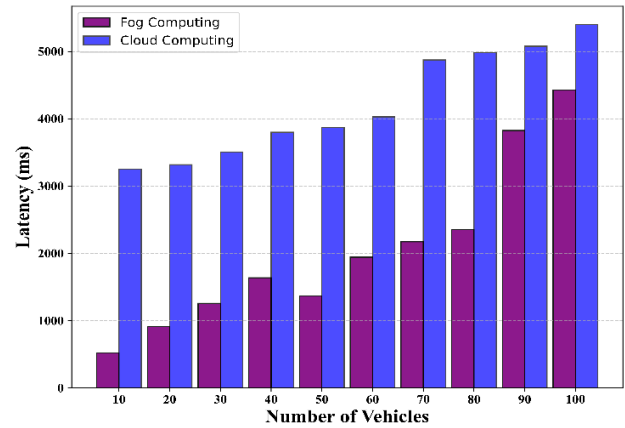
Table 8. Constants used for the evaluation of various performance metrics.

Sr. No	Attribute	Value
1	No. of Intersections	2
2	No. of RSUs	5
3	No. of Cameras per Intersection	4
4	Sensor Transmission Time	10 ms

6.1 Latency

This experiment used five RSUs, two junctions, four cameras installed at intersections, and ten sensors (Figure 6). The latency was analyzed by comparing

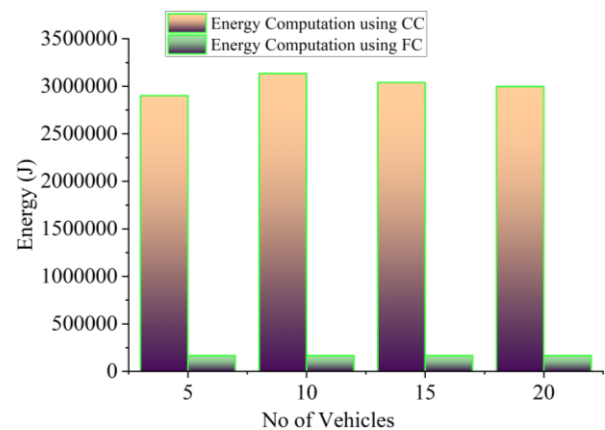
communication between vehicles using fog computing and traditional cloud computing. The results demonstrated that processing data locally via fog computing significantly reduces latency compared to cloud-based processing, demonstrating decreased execution times (Ravish R. & Swamy S., 2021).

**Figure 6.** Execution Times in FC and CC

The system maintains optimal performance up to 50 vehicles communicating within a single RSU. However, as vehicle numbers exceed this, latency begins to increase due to higher data loads. Interestingly, a latency dip is observed around 50–56 vehicles, likely due to efficient load balancing in fog-enabled RSUs. These results confirm that the proposed VANET Cloud system achieves latency optimization by leveraging fog computing, especially in dense vehicle networks, outperforming the 40-vehicle threshold traditionally considered dense in VANETs per DSRC standards (Chaurasia B.K. & Verma S., 2010).

6.2 Energy Consumption

The results indicated that the IoT and other layers of devices consume relatively low energy due to using FC. Minimization in the data volume transmitted to the cloud helped the system conserve energy by reducing communication overhead and decreasing the need for long-range data transmission. The energy used by FC is highly reduced compared to the energy used by traditional CC (Figure 7).

**Figure 7.** Energy Consumption in CC and FC

In addition, when FC is utilised, the energy consumption is at a constant rate, which helps align traffic lights on the basis of data available at the FC layer.

The comparison of CC and FC energy consumption in traffic management, showing a significant advantage in using FC. While CC energy usage steadily increases as the number of cars per RSU grows, FC energy consumption remains constant, regardless of the number of cars. This suggests that FC is far more efficient in handling data processing at the edge, especially in large-scale deployments where car volume increases. CC, on the other hand, demands substantially higher energy, as the need for centralized processing grows with more vehicles. This supports the case for utilizing FC for sustainable and scalable traffic systems.

6.3 Network Usage

Network usage is another crucial metric in evaluating the system's efficiency. The simulation revealed that network traffic was reduced significantly by local data processing. Reduced data transmission between the two layers led to decreased network congestion and lower bandwidth usage. The system effectively handled data processing locally, sending only useful data to the cloud (Satyanarayanan M. et al., 2009). A significant reduction is indicated by the results in the network usage, highlighting the benefits of EC in overhead reduction.

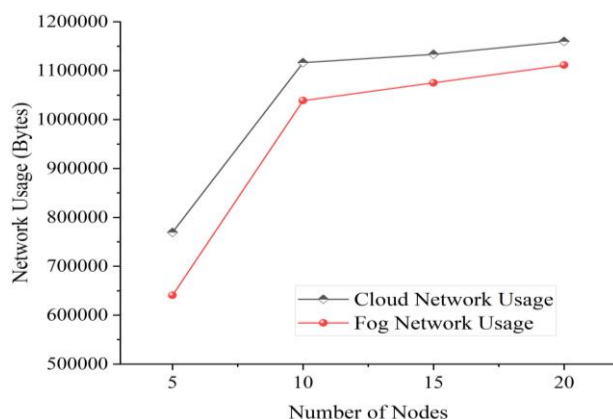


Figure 8. Network Usage Chart

It can be inferred (Figure 8) that the total network usage increases consistently as the number of cars per RSU rises, indicating a direct correlation between traffic density and network load. The increase in cars per RSU places a progressively larger demand on the network. However, after a certain point, the total network usage stabilizes, suggesting the system reaches a bandwidth saturation limit. This observation can guide the design of smart traffic management systems, ensuring they are scaled optimally to handle increasing traffic while maintaining network efficiency and preventing congestion (Ning Z. et al., 2019), (Elsayed A. et al., 2024).

6.4 Cost of Execution

Scalability is a significant factor in determining the ability of the system to handle large traffic networks. Execution costs play a critical role in measuring scalability of the system. The AI models adapted well to the larger traffic datasets, and the edge nodes continued to process data in real-time without significant delays (Satyanarayanan M. et al., 2009). The results indicate that CC performs better as it can be scaled according to the requirements.

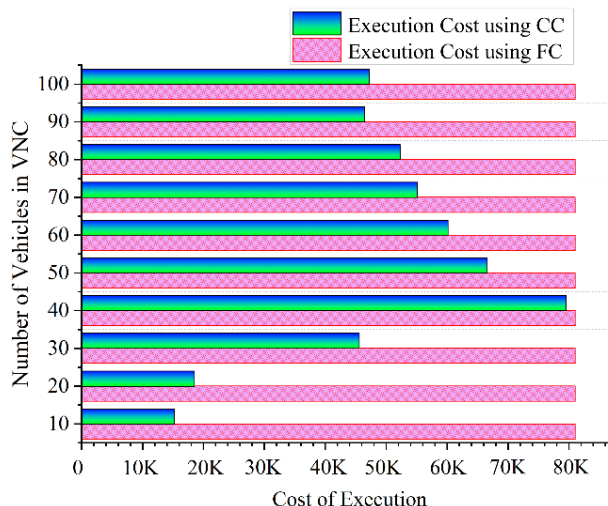


Figure 9. Cost of Execution Chart in CC and FC

The results indicate that the execution costs in FC were stable while highly fluctuating in case of CC (Figure 9). The stability of FC makes it highly predictable and reliable for consistent performance. While CC may be cost efficient, but highly unpredictable. Real-time systems must process high volumes of data with low latency and faster response times (Gomes E. et al., 2021), which is only possible when the possible results can be predicted. This highlights the FC environment's advantage in reducing network latency and processing overheads by leveraging proximity to data sources. Additionally, adoption of a hybrid FC-CC approach could balance the strengths of both systems, utilizing FC for latency-sensitive tasks and CC for compute-intensive operations. This hybrid strategy optimizes the resource utilization and performance in real-time systems.

6.5 Comparative Analysis

A comparative analysis is conducted between the proposed system and traditional methods. The results clearly indicated that the traditional system is outperformed by the proposed system in all key fields, including latency, energy consumption, network usage, and traffic congestion reduction (Cardellini V. et al., 2016). This comparison highlights the benefits of leveraging IoT, EC, and AI in real-time traffic management, providing a strong case for the deployment of such systems in practical context.

There were also strong evidence of the system's effectiveness in managing urban traffic. The combination of EC, IoT, and AI enabled live traffic control while reducing energy consumption, latency, and network usage. These results support the feasibility of implementing this smart traffic solution in smart city environments, where efficient traffic management is a top priority.

7. FUTURE RESEARCH DIRECTION

There are several key areas where the proposed system can be extended in the future. Integration of enhanced AI models, advancement of traffic data analytics, AI-driven robust security protocols, and cross network operability are promising directions. Enhancing the performance, better decision-making and optimization of key performance metrics will improve its applicability in enabling a more interconnected smart city ecosystem. The following are the future aspects of the proposed system:

7.1 Enhanced AI Model for Predictive Analytics

Enhancements such as deep reinforcement learning, can amplify the system's ability to predict traffic congestion and recommend optimal routes more accurately. Incorporating more diverse datasets could improve model generalization and adaptability to different traffic environments (Ning Z. et al., 2019).

7.2 Multi-Layer Security Frameworks

There will always be a room to improve the security architecture. Future researches could focus on multi-layered, AI-driven security protocols that may dynamically adjust to threats in real time, ensuring greater protection across IoT, EC, and CC layers (Mukherjee M. et al., 2019).

7.3 V2X Communication

The extension of the vehicle-to-infrastructure communication to broader V2X, allowing vehicle-to-vehicle (V2V) and vehicle-to-pedestrian (V2P) interactions also, could further optimize traffic flow, reduce accidents, and accommodate more dynamic real-time responses (Ning Z. et al., 2019).

7.4 Scalability with FC

The proposed system can be expanded to a larger scale, like entire cities or regions, by further optimization of FC layers. Investigation of more efficient load-balancing algorithms for fog nodes to handle higher volumes of data can be conducted (Bonomi F. et al., 2012).

7.5 Sustainability and Green Computing

A future focus on reducing energy consumption at edge nodes and cloud servers through green computing techniques could contribute to the environmental

sustainability of large-scale deployments, aligning with global smart city initiatives (Guerrero-Ibanez J.A. et al., 2018).

7.6 Cross-Network Interoperability:

Seamless integration between various components of smart city networks (e.g., smart grids) and the traffic management system could open new pathways for holistic urban management thus, enabling a more interconnected smart city ecosystem.

8. PROS AND CONS

The simulation results provide strong evidence that the combination of these technologies can provide significant improvements in traffic management, energy efficiency, and dynamic decision-making capabilities, making the system an ideal solution for deployment in smart cities.

8.1 Enhanced Traffic Flow and Congestion Management

By leveraging live data collection from various IoT devices, the system dynamically controls traffic light timings using AI algorithms, which led to a substantial decrease in congestion during the simulation (Cardellini V. et al., 2016).

The ability to identify traffic patterns and optimize signal control proved effective in managing traffic flow at critical intersections, thereby reducing travel time for vehicles and minimizing traffic jams. This demonstrates the potential of the system to address the growing traffic challenges in urban areas.

8.2 Latency Reduction Through EC

Local processing of traffic data at the edge rather than relying solely on the centralized server, significantly reduced the latency involved in decision-making. The results indicate a significant decline in response time when compared to traditional CC-based systems (Bhavsar H. & Thakkar D., 2020). Latency reduction is crucial in real-time traffic control system, as it allows the system to react to dynamic road conditions and make decisions in practical context to alleviate congestion.

8.3 Energy Efficiency and Network Optimization

The system demonstrated superior energy efficiency by near-elimination of the need for constant connection with the cloud and optimized processing of data at the edge nodes. The reduction in data transportation not only decreased energy consumption but also alleviated network congestion (Shi W. et al., 2016). The results suggest that the system can be deployed at scale in urban environments without overloading existing infrastructure, which is critical for the sustainability of smart city technologies.

8.4 Scalability and Adaptability

The system maintained its performance efficiently even when with the growth of connected devices, such as cameras and sensors. The edge nodes continued to process data effectively, and the AI algorithms adapted well to the growing dataset without significantly increasing latency or energy consumption (Li S. et al., 2018). This scalability makes the system a robust solution for large urban environments, ensuring that it can handle future increases in traffic volume and network size without compromising performance.

8.5 Comparative Advantages

In comparison with traditional traffic control methods, with predefined traffic light schedules, the proposed system showed remarkable improvements in responsiveness, energy efficiency, and network usage (Gubbi J. et al., 2013). The real time adaptability provided by AI, coupled with the decentralized data processing of EC, highlights the system's competitive advantage in addressing the limitations of conventional systems.

Thus, the proposed smart traffic management system offers a promising solution for the complex challenges posed by urban traffic. Its integration of IoT, EC, and AI provides real-time monitoring and optimization, which not only reduces congestion but also enhances energy efficiency and system scalability. As urbanization continues to grow, the deployment of such intelligent and real-time traffic control systems could revolutionize the way traffic is managed, leading to smarter, more sustainable cities.

CONCLUSION

Our proposed system used the transformative potential of FC and optimized resource utilization and reduced latency in VANET-enabled intelligent traffic control system. The computational resources were placed closer to data source for this approach. This approach establishes a foundation for future advancements in intelligent transportation systems (Gubbi J. et al., 2013). and addresses some key challenges.

One of the standout contributions of the proposed system is the reduction achieved in service latency. This was a vital improvement in VANETs, where real-time decision making directly affected performance, efficiency and cost. By processing time-sensitive traffic applications at proximate Fog nodes, the system minimized delays caused by long-distance data transmission to centralized Clouds. The model leverages dynamic resource allocation and priority-based service placement policies (Ning Z. et al., 2019), ensuring optimal utilization of FC and CC resources. This dual-layered approach not only avoids under-utilization but also alleviates bottlenecks in high-traffic scenarios. The proposed system dynamically adapts to the rapidly changing topology of vehicular networks. The system's ability to maintain consistent performance despite increasing load highlights its potential for future expansion. By balancing computational loads between FC and CC layers, the system can achieve a more cost effective and energy-efficient solution for traffic management. The results have significant implications for smart city development. Real-world implementation of this framework can facilitate seamless traffic flow, reduce congestion, and improve overall urban mobility.

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