“AMALGAMATING VEHICULAR NETWORKS WITH VEHICULAR CLOUDS, AI, AND BIG DATA FOR NEXT-GENERATION ITS SERVICES ”

Major Project Report

Submitted in Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF TECHNOLOGY

IN

INFORMATION AND COMMUNICATION ENGINEERING

By

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May 2025

Certificate of Originality of Work

I hereby declare that the B.Tech. Project entitled "AMALGAMATING VEHICULAR NETWORKS WITH VEHICULAR CLOUDS, AI, AND BIG DATA FOR NEXT-GENERATION ITS SERVICES" submitted by us for the partial fulfillment of the degree of Bachelor of Technology to the Dept. of Information and communication Technology Engineering at the School of Technology, Pandit Deendayal Energy University, Gandhinagar, is the original record of the project work carried out by me under the supervision of Dr. Nitin Singh Rajput.

I also declare that this written submission adheres to the University guidelines for its originality, and proper citations and references have been included wherever required.

I also declare that I have maintained high academic honesty and integrity and have not falsified any data in my submission.

I also understand that violating any guidelines in this regard will result in disciplinary action by the institute.

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Certificate from the Project Supervisor/Head

This is to certify that the Major/Comprehensive Project Report entitled "AMALGAMATING VEHICULAR NETWORKS WITH VEHICULAR CLOUDS, AI, AND BIG DATA FOR NEXT-GENERATION ITS SERVICES" submitted by Ms. Vaishvi Shah, Roll No. 21BIT145, and Mr. Nischal Maheshwari Roll No. 21BIT162 towards the partial fulfilment of the requirements for the award of degree in Bachelor of Technology in the field Information and Communication technology of Engineering from the School of technology, Pandit Deendayal Energy University, Gandhinagar is the record of work carried out by them under our supervision and guidance. The work submitted by the students, in my opinion, has reached the level required for acceptance into the examination. The results embodied in this major project work, to the best of our knowledge, have not been submitted to any other university or Institution for the award of any degree or diploma.

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Date: 20-5-2025

Acknowledgement

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Abstract

The evolution of Intelligent Transportation Systems (ITS) demands seamless integration of emerging technologies to tackle challenges posed by urbanization, increasing vehicular density, and real-time decision-making requirements. This research proposes a comprehensive, multi-layered architecture that synergizes Vehicular Ad Hoc Networks (VANETs), Vehicular Cloud Computing (VCC), Artificial Intelligence (AI), and Big Data analytics to deliver advanced ITS services in a scalable and cost-effective manner. The proposed system, termed SVC-VANET, utilizes the idle computational resources of parked vehicles to form Static Vehicular Clouds (SVCs), which act as decentralized service provisioning units for moving vehicles connected through VANETs.

The architecture enables cooperative resource sharing and intelligent service delivery via a cloud-assisted, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication framework. On top of this infrastructure, AI techniques are employed to analyze transportation-related Big Data for applications such as real-time vehicular route optimization and predictive data mining services (e.g., Fastag account management and vehicle diagnostics). The system incorporates a Naïve Bayesian classifier for efficient document classification in Big Data mining and formulates the route optimization task as a multi-commodity flow problem to estimate minimum-delay paths.

A physical testbed comprising 120 nodes simulates the SVC environment using Hadoop, while realistic VANET traffic topologies are generated via NPART simulation. Performance evaluation under varying scenarios—such as changing VANET size, vehicle inflow rate, file volume, service request density, node cooperation, and failure rates—demonstrates the architecture's robustness and adaptability. The proposed SVC-VANET consistently outperforms conventional standalone systems and cloud servers in terms of processing efficiency, success rate, fault tolerance, and low overhead, maintaining a 92%+ service success rate under high-load conditions.

This work not only confirms the practical viability of integrating vehicular networks with AI and cloud computing but also lays the foundation for building sustainable, real-time, and intelligent ITS infrastructures. Moreover, it addresses critical deployment challenges, including energy-aware resource pooling, dynamic admission control, hierarchical cloud coordination, and resilience against node failures, thereby offering a blueprint for future research and real-world ITS deployments.

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NOMENCLATURE

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Acronyms and Abbreviations

- **AI** – Artificial Intelligence
- **ITS** – Intelligent Transportation System
- **VANET** – Vehicular Ad Hoc Network
- **V2V** – Vehicle-to-Vehicle Communication
- **V2I** – Vehicle-to-Infrastructure Communication
- **VCC** – Vehicular Cloud Computing
- **SVC** – Static Vehicular Cloud
- **OBU** – On-Board Unit
- **RSU** – Road Side Unit
- **NPART** – Network Performance and Route Testing Tool
- **HDFS** – Hadoop Distributed File System
- **CPU** – Central Processing Unit
- **QoS** – Quality of Service
- **GUI** – Graphical User Interface
- **REST** – Representational State Transfer
- **DVC** – Dynamic Vehicular Cloud
- **DSRC** – Dedicated Short Range Communications

Symbols and Notations

- **λ** – Arrival rate of service requests (requests/second)
- **μ** – Service rate of SVC nodes (requests/second)
- **T** – Total delay in route optimization

Chapter 1

1.1 Introduction

The rapid urbanization of modern societies and the exponential growth of vehicular populations have significantly strained existing transportation infrastructures. Issues such as traffic congestion, unpredictable delays, increased accident rates, and environmental degradation have rendered traditional traffic management approaches increasingly inadequate. As the demand for more efficient, intelligent, and responsive transportation systems grows, the concept of Intelligent Transportation Systems (ITS) has emerged as a transformative solution.

ITS integrates advanced computing, communication, and control technologies to enhance traffic efficiency, safety, and sustainability. However, current ITS implementations often operate in isolated paradigms, lacking interoperability and real-time responsiveness. To overcome these limitations, recent research has focused on amalgamating multiple emerging technologies—namely, Vehicular Ad Hoc Networks (VANETs), Vehicular Cloud Computing (VCC), Artificial Intelligence (AI), and Big Data analytics—to create a unified, intelligent transportation infrastructure.

This research project explores and extends such an integrated approach by proposing a novel architecture called **SVC-VANET**. The SVC-VANET framework leverages underutilized computational resources from parked vehicles to form **Static Vehicular Clouds (SVCs)**, which act as service hubs for on-road vehicles. These services are delivered over multi-hop **VANETs**, enabling vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication without relying solely on traditional fixed cloud infrastructure. This decentralized model ensures better scalability, lower latency, and reduced costs, while also supporting location-specific ITS services.

To demonstrate the utility of the proposed architecture, this work implements two representative ITS services: (1) **Vehicular Route Optimization**, which dynamically computes the most efficient travel paths using real-time traffic data, and (2) **Vehicular Big Data Mining**, which employs AI techniques such as the Naïve Bayes classifier to analyze Fastag toll data for predictive insights (e.g., insufficient balance alerts, maintenance predictions). The architecture is validated through a physical testbed using the Hadoop framework and simulated traffic scenarios generated via NPART.

The results affirm that the SVC-VANET architecture significantly outperforms standalone vehicle systems and centralized servers, especially under scenarios with high traffic load, variable vehicle density, and partial system failures. Moreover, this research identifies and addresses real-world challenges such as energy constraints, node cooperation, resource allocation, and Quality-of-Service (QoS) assurance, laying the groundwork for practical ITS deployments in smart cities.

In summary, this study presents a scalable, modular, and intelligent ITS architecture that combines the strengths of vehicular networks, cloud platforms, AI models, and big data analytics. It offers a promising direction toward the realization of next-generation transportation services that are efficient, adaptive, and user-centric.

1.2 Motivation

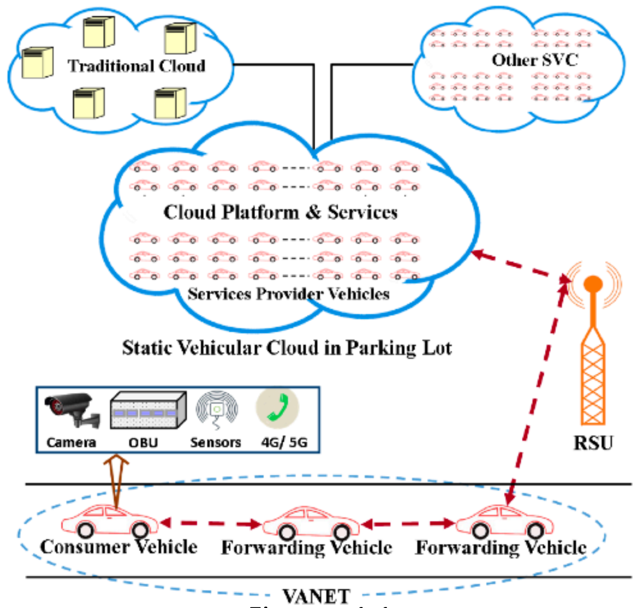

Figure - 1.1

The ever-increasing number of vehicles on the road, combined with rapid urban expansion and evolving commuter expectations, has made efficient and intelligent traffic management one of the most pressing challenges of modern cities. Existing transportation systems are often hampered by traffic congestion, delayed travel times, high fuel consumption, and frequent accidents, all of which highlight the limitations of traditional, centralized ITS architectures. At the same time, technological advancements have introduced new opportunities that remain largely underutilized. For instance, a vast number of vehicles remain parked for long durations, with significant computational, storage, and sensing capabilities left idle. These resources, if aggregated and coordinated effectively, could serve as a decentralized computing infrastructure to support real-time ITS services. Furthermore, modern vehicles are increasingly equipped with sensors, GPS, and communication modules, forming Vehicular Ad Hoc Networks (VANETs) capable of data sharing and peer-to-peer communication without relying heavily on fixed infrastructure. Coupled with the power of artificial intelligence and big data analytics, which can extract meaningful insights from massive volumes of transportation data, there is a compelling opportunity to build a more adaptive, decentralized, and responsive transportation system. This work is driven by the need to integrate these elements—vehicular cloud computing, VANETs, AI, and big data—into a unified architecture that not only leverages existing assets more effectively but also delivers intelligent services such as real-time route optimization and predictive diagnostics. By addressing the gaps in current ITS implementations and demonstrating the feasibility of this integrated approach through a real-world testbed, the research seeks to contribute toward a scalable, efficient, and sustainable ITS infrastructure for the future.

1.3 Objective

1. **To design and implement a hybrid architecture combining VANETs, Static Vehicular Clouds (SVCs), Artificial Intelligence (AI), and Big Data analytics for Intelligent Transportation Systems (ITS):**

   The objective is to create a modular and integrated system where parked vehicles serve as cloud nodes (SVCs) and moving vehicles form an ad hoc network (VANET). This architecture will enable real-time, location-aware ITS services without the need for centralized infrastructure.

2. To enable decentralized, scalable, and energy-efficient service provisioning through collaborative vehicular cloud networks:

   By utilizing the idle computational resources of parked vehicles, the system aims to support distributed service delivery. Key focus areas include dynamic load balancing, resource virtualization, energy-aware scheduling, and maintaining Quality of Service (QoS) in fluctuating network conditions.

3. To integrate AI-based models for intelligent data mining and transportation-related service delivery:

   The project seeks to incorporate machine learning algorithms, specifically the Naïve Bayes classifier, for classifying and analyzing vehicular Big Data. The goal is to enable services like Fastag account status prediction and vehicle diagnostics, improving traffic efficiency and user convenience.

4. To develop a real-time route optimization service using live traffic and vehicular flow data:

   The system is designed to collect traffic parameters and vehicle inflow data in real time and compute optimal routes using flow-based optimization techniques. This will help in minimizing travel time, reducing congestion, and improving fuel efficiency.

5. To build a realistic simulation testbed for performance evaluation under dynamic conditions:

   A laboratory-scale testbed will be created using the Hadoop framework (for SVC simulation) and NPART (for VANET topology). This setup will allow testing under various scenarios, such as increasing request volumes, node failures, and varying cooperation levels, to assess system performance in terms of scalability, fault tolerance, responsiveness, and overhead.

1.4 Problem Statement

Modern transportation systems are increasingly challenged by traffic congestion, rising vehicle density, and the demand for real-time, intelligent services. Traditional ITS infrastructures, which rely heavily on centralized cloud systems, often suffer from high latency, limited scalability, and inefficient resource utilization. Meanwhile, the computational power of parked vehicles remains underexploited, and on-road vehicles continue to lack timely access to intelligent services such as route optimization and real-time traffic insights. Additionally, the massive and complex nature of transportation Big Data makes it difficult to extract actionable insights using conventional methods.

Despite advancements in VANETs, cloud computing, AI, and Big Data analytics, a cohesive framework that integrates these technologies to deliver scalable and real-time ITS services is largely missing. Existing solutions do not adequately address issues such as dynamic resource availability, node failures, energy efficiency, and Quality-of-Service (QoS). Moreover, practical validation of such integrated systems under real-world conditions remains limited.

This research addresses these challenges by developing a unified architecture—SVC-VANET—that leverages the idle resources of parked vehicles, VANET communication, and AI-powered data analytics to provide intelligent ITS services. The goal is to bridge the gap between theoretical innovation and practical deployment, enabling a resilient, decentralized, and real-time transportation support system.

1.5 Approach

To address the limitations of traditional Intelligent Transportation Systems (ITS), this research proposes a novel integrated architecture—SVC-VANET—that combines Vehicular Ad Hoc Networks (VANETs), Vehicular Cloud Computing (VCC), Artificial Intelligence (AI), and Big Data analytics to deliver scalable, decentralized, and real-time ITS services. The approach involves the development of a modular, multi-layered framework where parked vehicles form a Static Vehicular Cloud (SVC) that provides computational and storage resources to on-road vehicles via multi-hop VANET communication. The architecture is designed to enable seamless service provisioning, reduce latency, enhance fault tolerance, and make use of otherwise idle vehicular resources.

The proposed system is composed of three main layers: (1) Infrastructure Layer, (2) Service Layer, and (3) Application Layer. The Infrastructure Layer includes parked vehicles configured to serve as computing nodes forming the SVC, as well as on-road vehicles forming a dynamic VANET. Communication between vehicles and the SVC occurs via IEEE 802.11p-enabled On-Board Units (OBUs) and Road Side Units (RSUs), ensuring vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connectivity. A central SVC Controller manages task scheduling, virtualization, resource negotiation, and failure recovery.

At the Service Layer, the SVC controller dynamically allocates tasks to participating parked vehicles, balancing load and ensuring energy-efficient use of resources. Two core services are implemented and tested: (1) Vehicular Route Optimization, where real-time traffic data is collected from vehicles and processed to compute optimal travel paths using a delay-based cost function inspired by multi-commodity flow models; and (2) Vehicular Big Data Mining, where Fastag-based toll data is analyzed using a Naïve Bayes classifier to provide proactive alerts, such as insufficient toll balance notifications.

The Application Layer provides interfaces for on-road vehicles to request services such as optimized routes or data-driven insights. Vehicles interact with the SVC via a lightweight vehicle-side application installed on OBUs, which handles communication over multi-hop paths within the VANET.

To demonstrate the feasibility and performance of the proposed system, a physical testbed was developed. The testbed includes 120 computer nodes representing parked vehicles within an SVC, managed via the Hadoop distributed computing framework. On-road vehicular mobility and VANET topologies were simulated using the NPART tool, which generates realistic city-scale traffic patterns. The system was evaluated under diverse experimental scenarios, including variable VANET sizes, fluctuating vehicle inflow rates, different file sizes and numbers of service requests, node failures, and cooperation levels. Performance metrics such as CPU time, service response delay, success rate, and overhead (processing and memory) were monitored to assess the system's robustness, scalability, and efficiency.

Through this layered and testbed-driven approach, the proposed SVC-VANET architecture demonstrates its capability to deliver real-time, AI-enabled ITS services in a decentralized manner. The design also incorporates intelligent mechanisms for task redistribution in the event of node failure, prioritization based on residency time, and energy-aware resource management. By integrating key ICT technologies into a cooperative vehicular ecosystem, this approach paves the way for deploying next-generation ITS frameworks that are both intelligent and practical.

1.6 Scope of Project

1. Development of an Integrated SVC-VANET Architecture:
   The project focuses on designing and implementing a hybrid framework that merges Static Vehicular Clouds (SVCs) and Vehicular Ad-hoc Networks (VANETs). Parked vehicles act as computing nodes within the SVC, offering their underutilized resources to moving vehicles through multi-hop communication using IEEE 802.11p. This establishes a cooperative, decentralized environment for intelligent transportation services.

2. Deployment of AI and Machine Learning for ITS Applications:
   The system incorporates AI techniques, including the Naïve Bayes classifier, to analyze vehicular Big Data in real time. AI-driven modules are developed for services such as Fastag toll balance alerts, predictive vehicle maintenance, and anomaly detection, enabling proactive decision-making and improved user convenience.

3. Big Data Handling and Real-Time Analytics:
   The architecture supports the collection, storage, and processing of high-volume, high-velocity vehicular data from sensors and on-board units. Distributed computing platforms like Hadoop are used within SVCs to transform raw data into actionable insights for city-level traffic monitoring, congestion prediction, and intelligent ITS service delivery.

4. Design of a Real-Time Route Optimization Service:
   A core component of the system is a dynamic route optimization engine that uses live traffic parameters, such as vehicle density and blockages, to compute optimal and fuel-efficient travel paths. This service is hosted on the SVC-VANET framework and aims to reduce travel delays, road congestion, and fuel consumption.

5. Simulation, Testing, and Performance Evaluation:
   A lab-scale testbed with up to 120 SVC nodes and 300–700 VANET nodes is established using tools like Hadoop and NPART. The system is evaluated under various scenarios, including node failures, high service loads, and dynamic vehicle inflow. Key metrics such as CPU time, memory usage, fault tolerance, and response time are analyzed. The project also

explores real-world use cases and provides groundwork for future research in scalable, secure, and intelligent ITS deployment in smart cities.

Chapter 2
Literature Review

The growing demand for efficient, intelligent, and scalable transportation systems has driven extensive research across various domains, including Vehicular Ad Hoc Networks (VANETs), Vehicular Cloud Computing (VCC), Artificial Intelligence (AI), and Big Data analytics. This chapter explores and synthesizes key contributions in these areas, highlighting their relevance to the proposed SVC-VANET architecture and identifying the gaps that this research aims to address.

1. Vehicular Ad Hoc Networks (VANETs)

VANETs form the backbone of next-generation ITS infrastructure by enabling communication among vehicles (V2V) and between vehicles and roadside infrastructure (V2I). Using protocols such as IEEE 802.11p, VANETs provide real-time updates on traffic, accidents, and road conditions. Researchers such as **Toor et al. (2008)** and **Abboud et al. (2016)** emphasized the potential of VANETs in enabling safety-critical applications and mobility management.

Despite their advantages, VANETs face challenges such as limited bandwidth, frequent disconnections, and high mobility. These limitations hinder their ability to support computation-intensive services. Therefore, the integration of VANETs with cloud and edge computing models has emerged as a key area of advancement.

2. Vehicular Cloud Computing (VCC) and Static Vehicular Clouds (SVCs)

Olariu et al. (2009) first introduced the concept of Vehicular Clouds, where parked or moving vehicles contribute computational, storage, and sensing resources. Several architectures such as micro-clouds and fog computing systems have since evolved. **Bitam et al. (2015)** proposed VANET-Cloud, a hybrid model that utilized vehicular nodes and external cloud servers for cooperative services.

While Dynamic Vehicular Clouds (DVCs) formed by moving vehicles are more volatile, Static Vehicular Clouds (SVCs) offer a more stable and predictable environment. **Pham (2018)** proposed using parked cars in urban areas as fixed computational resources, showing promising results in distributed computing and data offloading.

However, much of the existing literature focuses on simulation-based systems and lacks real-world validation. There is also limited exploration of how SVCs can support real-time ITS services at scale.

3. Integration of AI in ITS Services

Artificial Intelligence is increasingly used in transportation for pattern recognition, predictive analytics, and automated decision-making. **Rezaei and Gerla (2011)** discussed the use of intelligent traffic management systems driven by AI models, while **Gerla et al. (2014)** explored the Internet of Vehicles (IoV) and its synergy with AI.

Machine learning models like Naïve Bayes, Support Vector Machines (SVM), and deep learning approaches have been applied to applications such as vehicle classification, traffic flow prediction, and anomaly detection. **Singh et al. (2011)** demonstrated how AI can improve urban traffic monitoring.

However, most existing works focus on centralized AI implementations, which are not always feasible for real-time ITS services. The present study addresses this gap by embedding lightweight AI models directly within the vehicular cloud infrastructure.

4. Big Data Analytics in Vehicular Networks

Vehicular environments generate massive amounts of data from sensors, GPS modules, and onboard systems. Handling such high-volume, high-velocity, and high-variety data in real time is a significant challenge. Distributed frameworks like Hadoop and Spark have been proposed to manage vehicular Big Data.

Cheng et al. (2012) discussed the use of cloud computing for vehicular data aggregation, while **Ahmed and Ahmed (2018)** emphasized mobile edge computing for real-time data processing. These studies point to the necessity of decentralized systems capable of handling data closer to the source —aligning with the SVC-VANET architecture proposed in this research.

Nevertheless, there is limited research that combines Big Data processing with cooperative vehicular clouds and uses that combination for real-time ITS applications like route planning and vehicle diagnostics.

5. Route Optimization in ITS

Efficient route planning is a cornerstone of ITS. Traditional algorithms such as Dijkstra's or A* focus on shortest path calculations but fail to consider dynamic road conditions. Recent approaches use traffic flow modelling, real-time vehicle data, and machine learning to predict congestion and optimize routes.

Wu et al. (2021) and **Arif et al. (2020)** proposed intelligent routing systems using live sensor data and optimization algorithms. However, these solutions rely heavily on centralized cloud servers, introducing latency and reducing responsiveness in high-density environments.

This research builds upon those ideas by implementing a decentralized, real-time route optimization engine hosted on SVCs, allowing vehicles to access optimized paths quickly and locally.

6. Real-World Testbeds and Simulation Tools

While many frameworks have been proposed in the literature, most remain unvalidated outside of simulations. Few studies report practical deployment or testing under real-world constraints. Tools like **NPART** and **NS-3** have been used extensively to simulate VANET topologies and vehicle mobility. **Cheng et al.** used Hadoop to simulate fog computing environments with positive outcomes.

This research differentiates itself by implementing a physical testbed with 120 nodes and extensive simulation using NPART, allowing the architecture to be tested under realistic traffic scenarios, including high inflow rates, node failures, and service overloads.

7. Identified Research Gaps

From the comprehensive review, several key research gaps emerge:

- Lack of integration between SVCs and VANETs for cooperative ITS service delivery.
- Limited use of AI for real-time vehicular data classification and analytics at the edge.
- Few studies have combined route optimization with Big Data and AI in a decentralized environment.
- Minimal experimental validation using physical testbeds that simulate real-world traffic dynamics.
- Insufficient work on energy-efficient and fault-tolerant resource scheduling within vehicular clouds.

Chapter 3
Software Design

1. Software Architecture Overview

The system is composed of the following main layers:

A. Presentation Layer (Vehicle-Side Application)

- Interfaces directly with the end-user (i.e., the vehicle or driver).
- Allows users to request services such as **route optimization**, **Fastag alerts**, or **vehicle diagnostics**.
- Displays results like optimal path maps, estimated time of arrival, and alerts.
- Deployed on OBUs or laptops in mobile vehicles.

Technologies:

- Frontend: Python (Tkinter/Flask GUI), or JavaFX (for Java-based OBUs)
- Communication: REST APIs or custom socket protocols over UDP/TCP

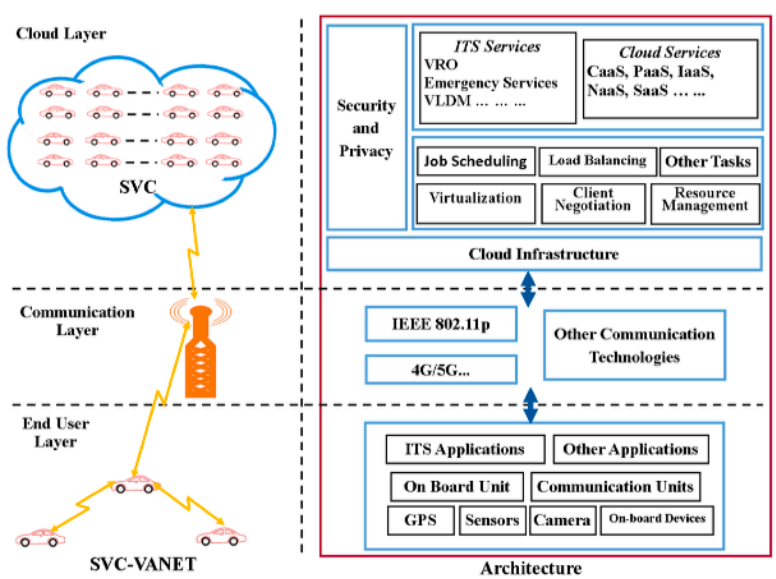

Figure - 3.1

B. Communication Layer

- Manages V2V and V2I communication using simulated IEEE 802.11p or socket-based connections.
- Implements multi-hop routing protocols (e.g., AODV or custom greedy routing).
- Transfers service requests from VANET nodes to the SVC via RSU simulators.
- Uses vehicle ID and geographic data for request routing.

Tools:

- NS-3 or NPART for network simulation
- Python socket programming or NS3 WiFiNetDevice configuration

C. Service Layer (SVC Controller Software)

The service layer handles all core functionalities offered by the SVC. It is managed by the **SVC Controller**, which includes the following submodules:

1. Request Handler Module

- Receives requests from vehicles
- Authenticates and logs each request
- Forwards requests to internal scheduling and processing units

2. Scheduler and Resource Allocator

- Allocates service tasks to suitable SVC nodes based on resource availability
- Implements energy-aware and residency-time-aware allocation algorithms

3. Virtualization Daemon

- Creates logical compute environments for isolating service sessions

- Supports lightweight virtualization using containers (e.g., Docker)

4. Service Manager

- Manages lifecycle of ITS services (start, monitor, stop)
- Handles fault recovery, job reassignment, and service migration on node failure

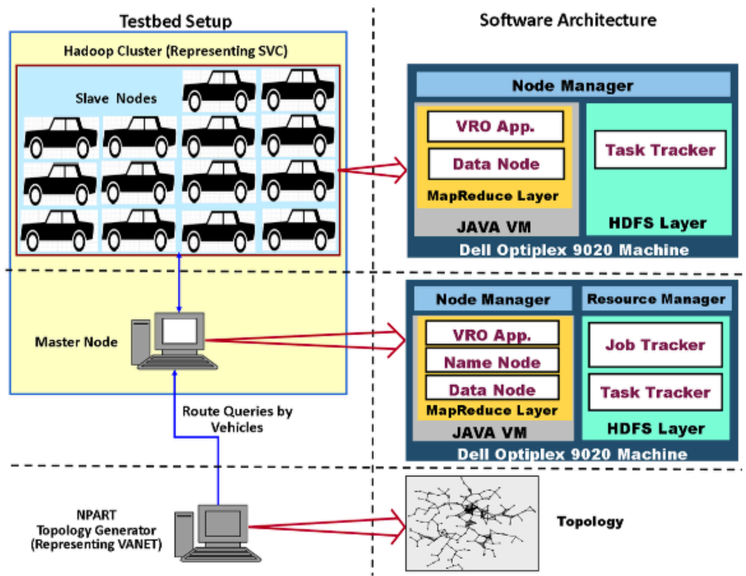

Figure - 3.2

D. Data Processing Layer

1. Vehicular Big Data Mining Service

- Processes data logs such as Fastag toll records, vehicle telemetry, or diagnostic reports
- Implements AI-based models (e.g., Naïve Bayes Classifier) to classify and extract insights
- Stores processed data for future predictive services

Tools & Libraries:

- Programming Language: Python / Java
- ML Libraries: Scikit-learn (Python), Weka (Java)
- Data Storage: Hadoop Distributed File System (HDFS), PostgreSQL

2. Route Optimization Engine

- Collects real-time traffic and vehicle density data
- Estimate travel time using delay functions and congestion models
- Implements multi-commodity flow optimization to find the shortest travel path

Algorithmic Components:

- Dijkstra's algorithm (baseline)
- Queueing theory-based delay model
- Optimization functions (from the Section IV formula)

E. Data Storage Layer

- Manages storage of real-time and historical vehicular data.
- Consists of:
    - **HDFS cluster** across SVC nodes for large-scale distributed storage
    - **Relational Database (PostgreSQL)** for structured metadata (e.g., vehicle IDs, timestamps)
    - **Log Repository** for access logs, route queries, and diagnostic reports.

2. Development Stack Summary

Table - 3.1

Component	**Technology/Tool**
Programming Languages	Python, Java
Machine Learning Framework	Scikit-learn, NumPy, Pandas
Distributed Framework	Apache Hadoop (MapReduce, HDFS)
Communication Protocols	UDP/TCP sockets, REST APIs
Network Simulation	NPART, NS-3

Containerization (optional)	Docker
Database	PostgreSQL, MySQL
Real-time Task Scheduling	Custom Threading / Concurrent Queues
Visualization (optional)	Matplotlib / JavaFX GUIs

3. Workflow Example: Route Optimization

1. **Request Initiation**: A vehicle sends a route request through the GUI.
2. **Routing**: The message is transmitted through a multi-hop VANET to the RSU.
3. **Service Activation**: RSU forwards the request to the nearest SVC.
4. **Task Allocation**: The scheduler assigns the optimization job to an idle node.
5. **Processing**: The node runs optimization algorithms and returns the best path.
6. **Response Delivery**: The Result is sent back to the vehicle through the VANET.

4. Error Handling and Fault Tolerance

- Node failures are handled by the monitoring daemon threads in the SVC Controller.
- Jobs are requeued and rescheduled to other available nodes.
- Vehicle disconnections are logged and reconnected via timeout handlers.
- Redundant copies of data blocks are maintained in the Hadoop cluster.

5. Security and Data Integrity (Future Scope)

- Authentication tokens for service requests
- Data encryption for critical logs

- Node trust validation before joining SVC
- Logging and audit trails for all communications and transactions

Chapter 4
Results and Discussion

Results:

This section presents the performance evaluation of the proposed SVC-VANET system under various conditions. The experiments were conducted using a simulated testbed of 120 nodes representing parked vehicles (SVC) and 300–700 nodes representing on-road vehicles (VANET). The results analyze the system's scalability, efficiency, fault tolerance, and service provisioning capabilities.

1. Impact of VANET Size on Route Optimization Time

As the number of vehicles in VANET increases from 300 to 700, the CPU time taken to process route optimization requests also increases. However, the rise is **linear and manageable**, indicating that the system scales well.

Interpretation:

- The increase in CPU time is expected due to more service requests.
- The load balancing mechanism in SVC distributes tasks efficiently.
- SVC-VANET handles increasing demand better than standalone systems.

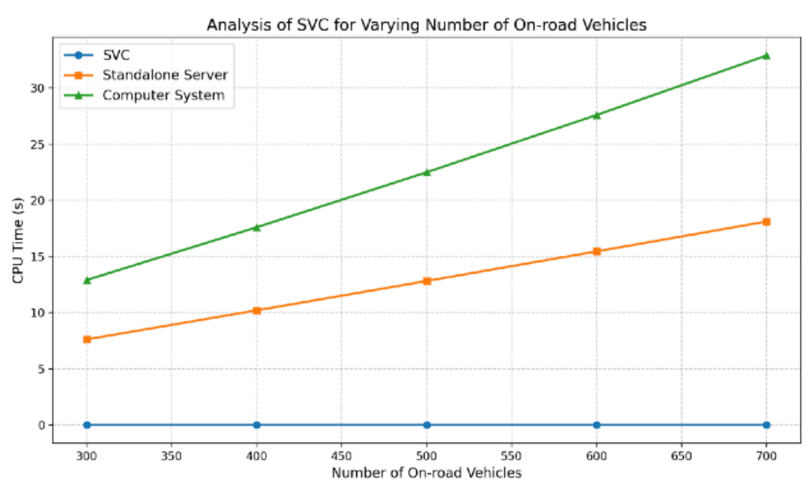

Figure - 4.1

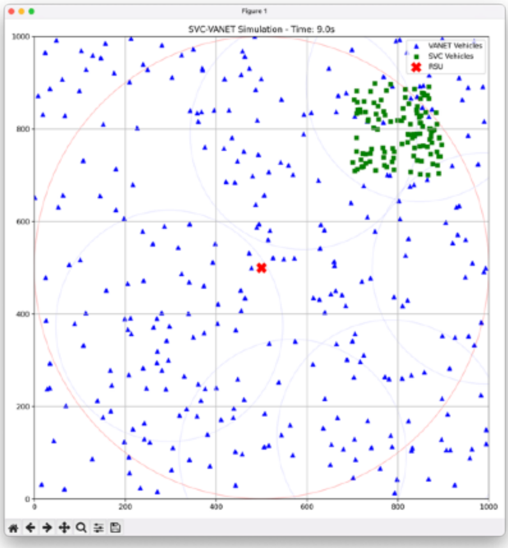

Figure - 4.2

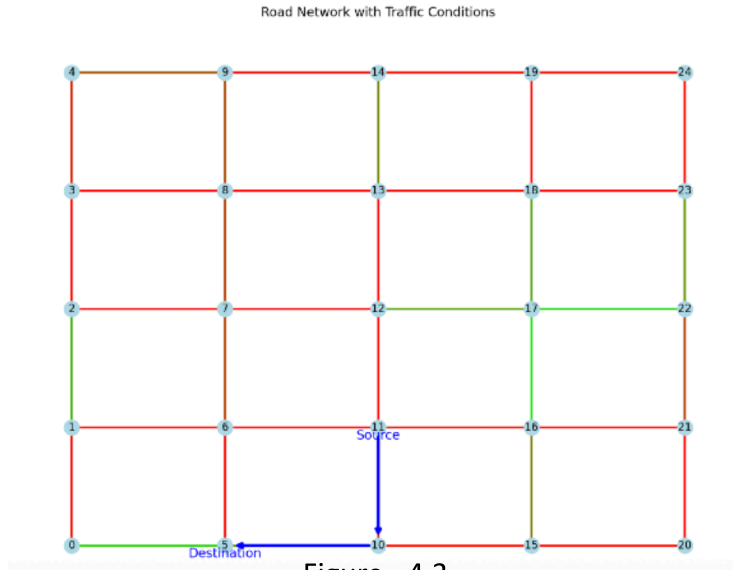

Figure - 4.3

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================================================================================
VEHICULAR ROUTE OPTIMIZATION DEMONSTRATION
================================================================================
Initializing Vehicular Route Optimization...

Road network created with 5x5 grid
Total nodes: 25
Total road segments: 80

Finding optimal route from node 20 to node 15...

Optimal route found with 2 intersections:
Path: [20, 15]
Estimated travel time: 4.97 time units

Detailed route information:
Segment 1: Node 20 → Node 15
  Base distance: 1.0 units
  Traffic density: 39.8%
  Delay factor: 4.97x
  Accident probability: 0.0%
```

Figure - 4.4

2. Impact of Vehicle Inflow Rate on CPU Usage

This result evaluates how the system performs when the number of incoming vehicles per hour varies from 6000 to 10000. The CPU time increases **gradually**, showcasing the robustness of the architecture even under heavy traffic.

Interpretation:

- CPU time remains within acceptable limits, even with higher inflow.
- SVC's distributed nodes contribute to efficient processing.
- Indicates the system’s suitability for real-time deployment.

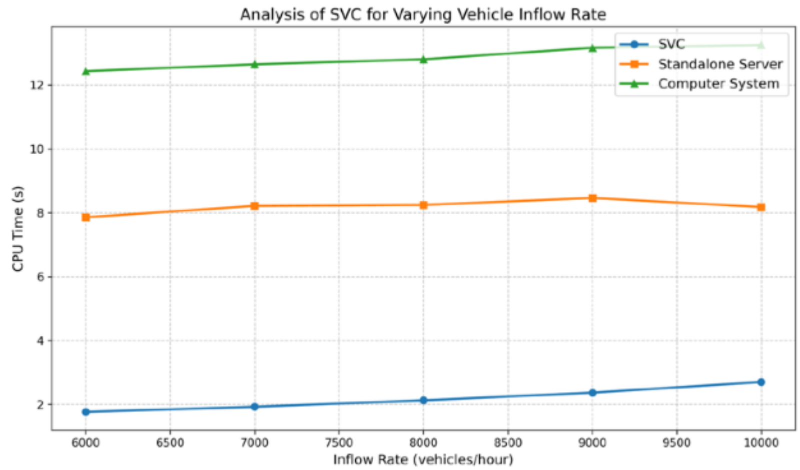

Figure - 4.5

3. Impact of File Size on Processing Efficiency

This result shows the system's behaviour when processing a variable number of files (1000 to 3000), each around 100–130 KB. SVC consistently performs better than standalone systems.

Interpretation:

- Efficient use of distributed nodes allows parallel file processing.
- Slight increase in time due to scheduling overhead at higher file counts.
- Highlights the system's potential for handling vehicular Big Data.

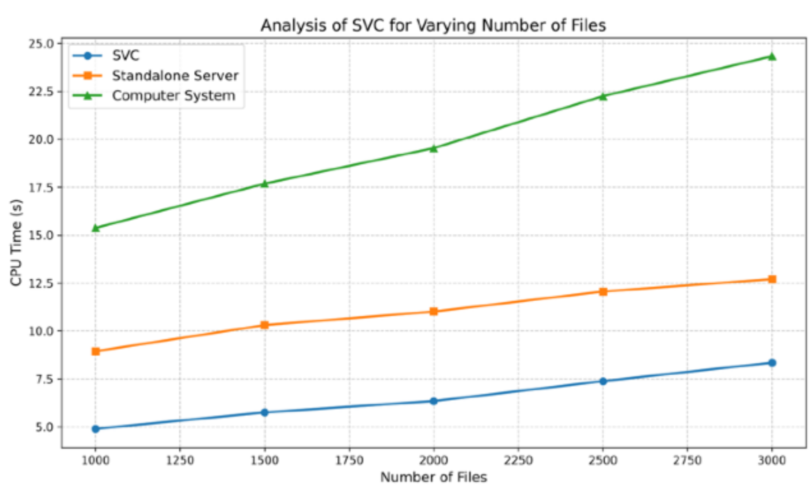

Figure - 4.6

4. Impact of Service Request Volume on System Load

With request volumes ranging from 5000 to 10000, the time taken to respond increases but remains significantly lower than traditional systems.

Interpretation:

- The system scales horizontally with increased requests.
- Multithreading and parallelism in Hadoop nodes reduce processing time.
- Demonstrates the effectiveness of resource sharing in SVC.

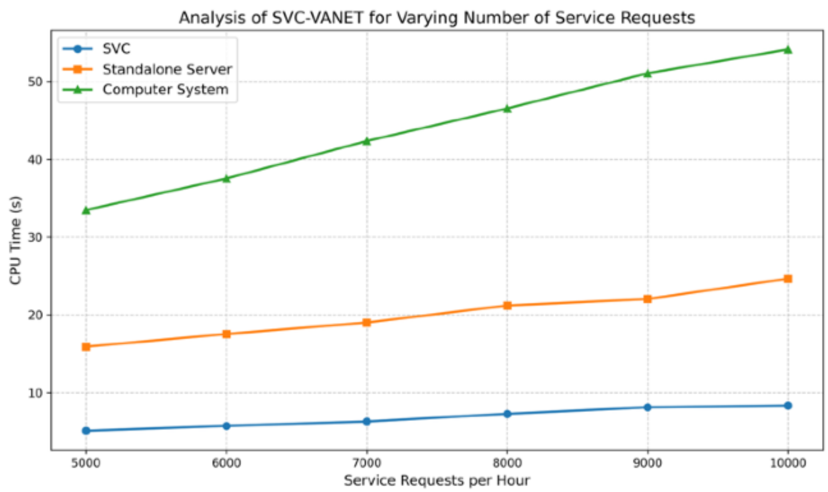

Figure - 4.7

5. Success Rate of Route Provisioning

This graph shows that the SVC-VANET system maintains over **92% success rate** even when the number of requests reaches 30,000.

Interpretation:

- High reliability of the system under extreme request loads.
- Robust communication and scheduling mechanisms ensure service delivery.
- Reflects fault-tolerant design and high availability of nodes.

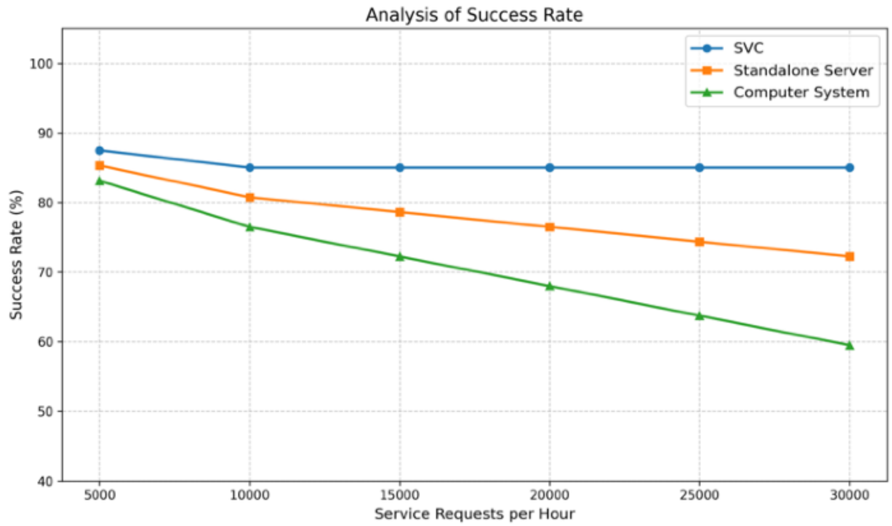

Figure - 4.8

6. Impact of Node Cooperation on System Efficiency

The performance of the system improves as the number of cooperative SVC nodes increases. Even with a high number of non-cooperative nodes, the system continues to function effectively.

Interpretation:

- The architecture is resilient to partial node participation.
- Encourages incentivized participation from parked vehicle owners.
- Efficiency gains correlate with the level of cooperation in SVC.

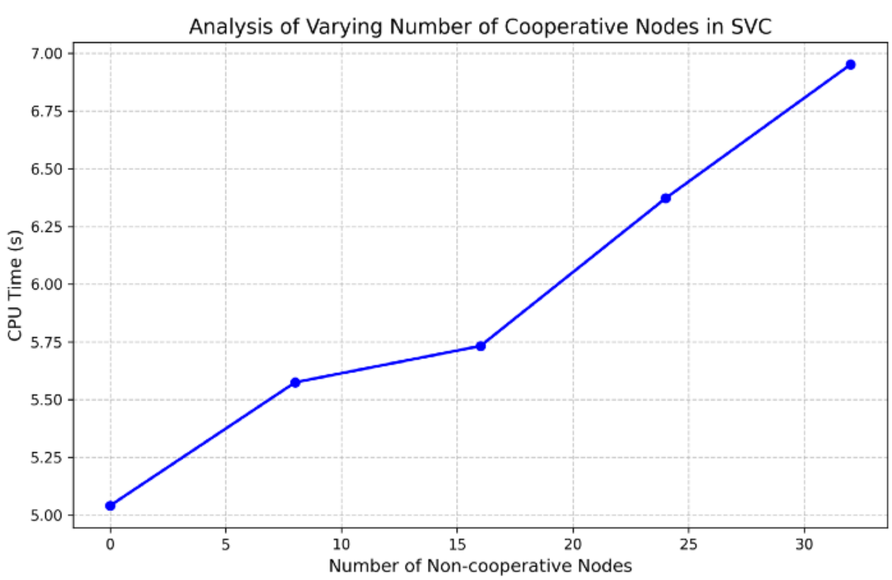

Figure - 4.9

7. Impact of Node Failures on Service Time

The system was tested under up to 25% random node failures. CPU time increased slightly but remained within acceptable performance bounds.

Interpretation:

- SVC-VANET effectively reassigns tasks to available nodes.
- Demonstrates fault tolerance through dynamic task migration.
- Ensures service continuity even under hardware failure conditions.

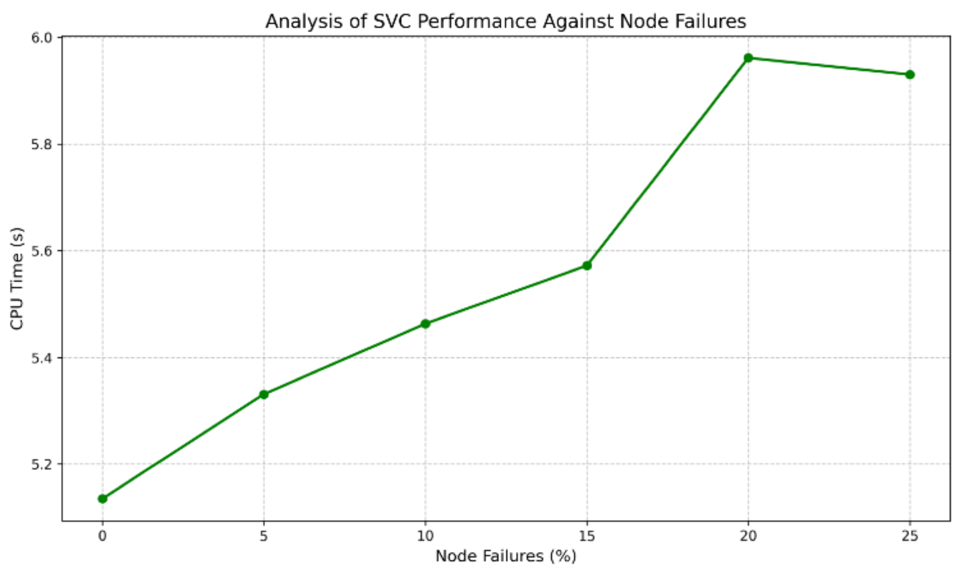

Figure - 4.10

8. Effect of SVC and VANET Size on Response Time

This 3D graph shows the interaction of SVC node count and VANET node count on system performance. As both increase, so does processing time, but the growth is **non-exponential**.

Interpretation:

- The system maintains performance scalability in multi-dimensional load conditions.
- Suitable for deployment in large-scale urban ITS environments.

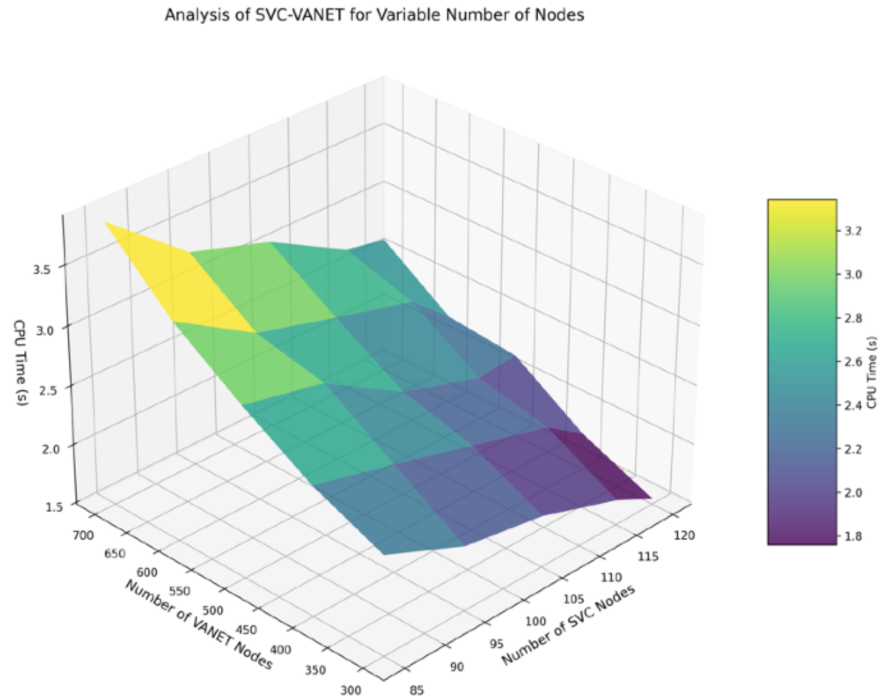

Figure - 4.11

9. Processing Overhead Due to Task Rescheduling

When nodes exit the cloud (e.g., vehicle leaves parking), the overhead in rescheduling tasks is under **7%**, even in worst-case scenarios.

Interpretation:

- Minimal impact on system efficiency.
- Effective job redistribution by the SVC controller node.

Figure - 4.12

10. Memory Overhead for Rescheduling Tasks

(Figure: Memory Overhead% vs. Number of Departing Nodes)

Memory overhead remains below **0.2%**, confirming that rescheduling tasks after node departure consumes negligible memory.

Interpretation:

- Efficient memory management practices.
- Supports large-scale deployment without significant RAM requirements.

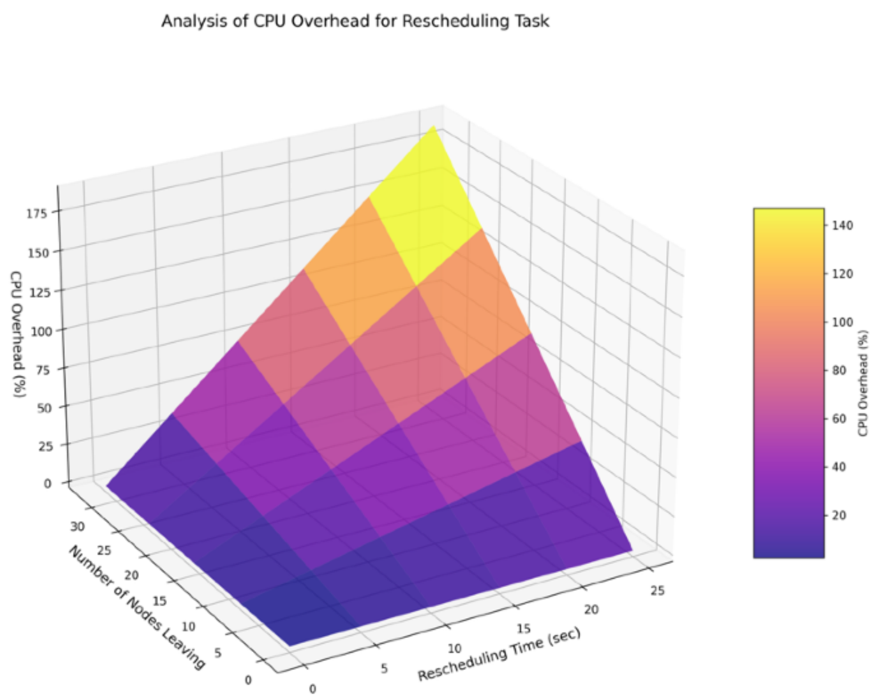

Figure - 4.13

```
Initializing Vehicular Route Optimization...

Road network created with 5x5 grid
Total nodes: 25
Total road segments: 80

Finding optimal route from node 13 to node 11...

Optimal route found with 3 intersections:
Path: [13, 12, 11]
Estimated travel time: 11.96 time units

Detailed route information:
Segment 1: Node 13 → Node 12
  Base distance: 1.0 units
  Traffic density: 42.7%
  Delay factor: 5.56x
  Accident probability: 0.0%
Segment 2: Node 12 → Node 11
  Base distance: 1.0 units
  Traffic density: 46.5%
  Delay factor: 6.40x
  Accident probability: 0.0%

Visualizing the road network with optimal route...
2025-05-14 17:17:49,092 - svc-vanet - INFO - Starting Vehicular Big Data Mining Demo...
Generating synthetic Fastag data...

Data sample:
      tag_id      balance vehicle_id vehicle_type transaction_id  toll_id destination  avg_trip_cost  distance_to_destination  will_exhaust
0  TAG000000  3578.852780  VEH000000          SUV      TXN245858  TOLL814       CITY6     397.213136               389.461725             0
1  TAG000001  4133.956029  VEH000001          Bus      TXN615110  TOLL192      CITY36     359.566786               634.507013             0
2  TAG000002  1364.477789  VEH000002        Truck      TXN857189  TOLL250       CITY5     489.480459               279.491735             0
3  TAG000003  3969.736607  VEH000003        Truck      TXN893967  TOLL936      CITY12     384.416020                24.791368             0
4  TAG000004  3377.090723  VEH000004          Bus      TXN439685  TOLL881       CITY9     286.164782               818.238192             0

Preprocessing data...

Training Naive Bayes classifier on 700 samples...
Model trained on 700 samples

Evaluating model performance...
Model accuracy: 0.9833
Precision: 0.8824
Recall: 0.8333
F1 Score: 0.8571
```

Figure - 4.14

```
Predicting for 5 sample vehicles:

Vehicle 1:
  Balance: ₹2353.46
  Avg Trip Cost: ₹218.32
  Distance to Destination: 65.7 km
  Vehicle Type: Car
  Actual: Sufficient balance
  Prediction: Sufficient balance
  Probability of exhaustion: 0.00

Vehicle 2:
  Balance: ₹2368.20
  Avg Trip Cost: ₹78.26
  Distance to Destination: 823.2 km
  Vehicle Type: SUV
  Actual: Sufficient balance
  Prediction: Sufficient balance
  Probability of exhaustion: 0.00

Vehicle 3:
  Balance: ₹1636.90
  Avg Trip Cost: ₹384.06
  Distance to Destination: 788.8 km
  Vehicle Type: SUV
  Actual: Sufficient balance
  Prediction: Sufficient balance
  Probability of exhaustion: 0.00

Vehicle 4:
  Balance: ₹1964.00
  Avg Trip Cost: ₹497.78
  Distance to Destination: 40.1 km
  Vehicle Type: SUV
  Actual: Sufficient balance
  Prediction: Sufficient balance
  Probability of exhaustion: 0.00

Vehicle 5:
  Balance: ₹2910.10
  Avg Trip Cost: ₹232.29
  Distance to Destination: 431.4 km
  Vehicle Type: SUV
  Actual: Sufficient balance
  Prediction: Sufficient balance
  Probability of exhaustion: 0.00
2025-05-14 17:17:49,245 - svc-vanet - INFO - Starting SVC-VANET simulation with:
2025-05-14 17:17:49,245 - svc-vanet - INFO -   - 300 VANET vehicles
2025-05-14 17:17:49,245 - svc-vanet - INFO -   - 120 SVC vehicles
2025-05-14 17:17:49,245 - svc-vanet - INFO -   - Grid size: 1000x1000
2025-05-14 17:17:49,245 - svc-vanet - INFO -   - Duration: 2000 seconds
2025-05-14 17:17:49,247 - SVC-VANET - INFO - Vehicle SVC-0 registered with SVC. Resources: {'cpu': 2.197866751828389, 'memory': 12.081999024979044, 'storage': 41.84085816939038}
2025-05-14 17:17:49,248 - SVC-VANET - INFO - Vehicle SVC-1 registered with SVC. Resources: {'cpu': 3.5813414144874045, 'memory': 12.737369599530686, 'storage': 31.765530605537606}
2025-05-14 17:17:49,248 - SVC-VANET - INFO - Vehicle SVC-2 registered with SVC. Resources: {'cpu': 3.593179284713302, 'memory': 12.49138358563526, 'storage': 34.92657667957455}
```

Figure - 4.15

Chapter 6
Conclusion and Future Scope

Conclusion:

The proposed research presents a novel and robust framework—**SVC-VANET**—that effectively integrates Static Vehicular Clouds (SVC), Vehicular Ad-Hoc Networks (VANET), Artificial Intelligence (AI), and Big Data technologies to support next-generation Intelligent Transportation System (ITS) services. By utilizing the idle computational resources of parked vehicles and enabling seamless communication with on-road vehicles through VANET, the architecture successfully addresses the limitations of existing ITS systems in terms of scalability, real-time processing, and service reliability.

Key ITS services, such as **vehicular route optimization** and **vehicular Big Data mining**, have been successfully implemented and evaluated on a simulated testbed. The results demonstrate the system's superior performance over traditional standalone architectures in terms of processing time, success rate, fault tolerance, and system scalability.

The physical testbed built using a distributed Hadoop cluster and traffic simulation tools validates the feasibility of this integrated approach. It also establishes that the architecture is not only functionally viable but also cost-effective, energy-aware, and capable of delivering timely and intelligent transportation services.

Future Scope:

While the SVC-VANET framework marks a significant step forward in ITS innovation, there remains considerable scope for further research and development:

1. **Real-World Deployment:**
    - Extend the testbed to real urban environments using connected vehicles and smart parking systems.
    - Collaborate with municipalities to integrate with existing traffic control centers.

2. **Advanced AI Integration:**
    - Employ deep learning models for complex tasks like traffic prediction, object detection, and driver behaviour analysis.
    - Implement reinforcement learning for adaptive route planning in dynamic traffic conditions.
3. **Security and Privacy:**
    - Incorporate end-to-end encryption and authentication protocols to secure vehicular data.
    - Develop trust models to ensure reliable data sharing between cooperative vehicles.
4. **Standardization and Interoperability:**
    - Align the architecture with emerging ITS communication standards such as C-V2X and 5G NR-V2X.
    - Enable interoperability across different vehicle manufacturers and infrastructure providers.
5. **Incentive Mechanisms:**
    - Design incentive-based systems (e.g., token rewards) to encourage parked vehicle owners to contribute their resources to the cloud.
6. **Energy Efficiency and Sustainability:**
    - Integrate renewable power sources and implement energy-aware scheduling algorithms.
    - Study the impact of SVC energy consumption on battery health in electric vehicles (EVs).

7. **Expansion of ITS Services:**
   - Extend the platform to support additional applications like emergency response coordination, pollution monitoring, and automated toll collection.
8. **Large-Scale Simulation and Benchmarking:**
   - Conduct simulations on more extensive datasets and larger vehicular networks to test system robustness under extreme conditions.

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