AI-Driven Vehicular Data Mining and Route Navigation for Advance ITS: Integrating V2X, Cloud Computing and Big Data Analytics

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***Abstract*—The rapid growth of vehicular populations has intensified challenges such as congestion, delays, and inefficiencies in traditional traffic management systems. This work proposes an integrated paradigm that combines cloud computing, vehicle-to-everything communications, Artificial Intelligence, and Big Data analytics to enhance Intelligent Transportation Systems. Two representative ITS services are presented, first, AI-driven FASTag data mining using a Naïve Bayes classifier to identify insufficient toll balances and proactively notify drivers, and second, optimal route navigation, modeled as a multi-commodity flow problem, to minimize end-to-end delays by leveraging vehicular density and stochastic delay factors. Performance evaluations show that the proposed architecture outperforms standalone servers and conventional systems, achieving reduced CPU time, higher success rates, and resilience against up to 15% node failures. Overhead analysis further highlights that CPU cycles are the primary bottleneck, while memory usage remains modest. In general, the integration of cloud, Vehicle-to-everything, Artificial Intelligence, and Big Data provides a scalable, fault-tolerant, and cost-effective platform for next-generation ITS.**

***Index Terms*—Intelligent Transportation System, Naïve Bayes Classifier, Vehicular Cloud, Vehicular Communication.**

I. Introduction

Modern society continues to encounter significant difficulties in everyday transportation. It is because of the rapid urbanization and the exponential growth of vehicular populations that have significantly strained existing transportation infrastructures. According to some studies, there are more than 1.6 billion vehicles on the road by 2025, with an annual growth rate of 1.7% [1]. In such an ever-growing scenario, traditional traffic management approaches become inadequate and lead to issues such as traffic congestion, unpredictable delays, increased accident rates, and environmental degradation. Since the demand for more efficient and responsive transportation systems grows, modern Intelligent Transportation Systems (ITS) have to adapt accordingly. To overcome these limitations, ITS should seamlessly integrate advanced computing, communication, and control technologies to improve traffic efficiency, safety, and sustainability. However, current ITS implementations often operate in isolated paradigms, lacking interoperability and real-time responsiveness. Recent research has focused on amalgamating multiple emerging technologies such as cloud computing, Big data analytics, autonomous vehicles, and vehicular communication technologies [2]. However, not only is integration of these technologies required, but applications that run on these modern systems are also required to be more intelligent and efficient.

The integration of Vehicle-to-Everything (V2X) communication technology, Vehicular Cloud Computing (VCC), Artificial Intelligence (AI), and Big Data analytics can transform traditional transportation systems into advanced ITS. These technologies enable real-time information processing and sharing for traffic monitoring, route planning, and safety management. The cooperative use of resources creates a mutually beneficial ecosystem between on-road and parked vehicles. Parked vehicles, often idle for extended durations, can act as distributed computing nodes within Static Vehicular Clouds (SVCs). By contributing their underutilized computational and storage resources, they support data aggregation, processing, and dissemination. In turn, on-road vehicles benefit from receiving timely traffic insights and optimized routes, compensating parked vehicles with minimal remuneration for their contributions.

Several ITS applications, such as real-time route navigation and optimization, require high-volume traffic and environmental data, as well as intensive computational resources, often beyond the capacity of individual vehicles. In such scenarios, V2X serves as the communication backbone, enabling vehicles to establish connections with the infrastructure. Through this cooperative framework, vehicles can access AI-driven services powered by large-scale Big Data analytics, enhancing accuracy and responsiveness.

The joint operation of SVC, V2X, Big Data, and AI ensures scalable, efficient, and cost-effective service delivery. This synergy not only improves transportation efficiency and safety, but also motivates the deployment of innovative ITS applications. Ultimately, such integration provides a productive and rewarding model for all stakeholders, ensuring optimal use of vehicular resources while driving progress towards next-generation intelligent mobility solutions.

This work proposes two representative ITS services: (i) AI-driven vehicular Big Data mining and (ii) vehicle route navigation, on an ITS infrastructure that includes V2X communications and cloud computing facilities. The effectiveness of these services is evaluated, highlighting the practical potential for next-generation ITS deployments. In this work, a paradigm is considered where Vehicular Cloud Computing (VCC) with V2X establishes an ITS infrastructure. It provides a unified infrastructure and communication backbone for ITS. In addition to this paradigm, AI and Big Data analytics are incorporated to ensure efficient and reliable delivery of ITS services. Within this architecture, the SVC functions as the service provider, while moving vehicles on surrounding road segments act as service consumers, as shown in Fig. 1. This arrangement enables the deployment of both conventional cloud-based services and ITS-specific applications, including traffic management, vehicle navigation assistance, and dissemination of real-time road condition information. These services are made accessible to various stakeholders, such as drivers, safety controllers, and transportation authorities, intelligently and resiliently.

II. Related Works

In this section, a literature review on the modern technologies involved in this work for next-generation ITS is presented.

A. Vehicular Clouds

Vehicular Clouds (VCs) consist of a group of vehicles that interact and coordinate with each other to virtualize and share their computing and communication resources with users, typically following a pay-as-you-go model [3]. This approach offers significant advantages by enabling efficient utilization of otherwise underused resources at reduced costs. Beyond traditional cloud services, VCs support a wide range of ITS-related applications, such as traffic management support and real-time parking assistance [4]. Olariu et al., first introduced the concept of Vehicular Clouds, where vehicles contribute computational, storage, and sensing resources with others [5]. Since then, several architectures have evolved. Bitam et al. proposed VANET-Cloud, a hybrid model that utilized vehicular nodes and external cloud servers for cooperative services [6]. VCs are generally classified according to the mobility of the participating vehicles into two main types. Static Vehicular Clouds (SVCs), which are typically formed in parking areas equipped with cloud computing infrastructure [7]. Dynamic Vehicular Clouds (DVCs), which consist of a group of moving vehicles, often traveling at similar speeds on highways or within urban congestion zones [8]. Although DVCs formed by moving vehicles are more volatile, SVCs offer a more stable and predictable environment. In this work, SVCs are part of the system model.

B. Vehicular Big Data Analytics

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. Cheng et al. discussed the use of cloud computing for the aggregation of vehicular data [9]. In another work, Abas et al. emphasized mobile edge computing for real-time data processing [10]. 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.

C. AI for ITS Services

There are several applications in the ITS domain that benefit from AI techniques. In [2], a detailed review of such applications is presented. In [11], the deep learning approach is used to predict future traffic conditions that help optimize traffic signal timings and manage congestion. AI algorithms are integral to perception, decision making, and path planning in self-driving cars [12]. AI is applied to smart parking solutions to detect available spaces, guide vehicles, and predict parking availability using computer vision and predictive analytics [13]. Travel-time prediction and incident detection require AI algorithms like gradient boosting [14]. However, no ways have been presented to offer a large set of applications running on integrated architectures and common platforms.

III. System Model and Architecture

Figure 1 illustrates the system model adopted in this work. The architecture follows a three-layer structure that consists of vehicles, an intermediate communication layer, and the cloud infrastructure. The cloud layer incorporates a Static Vehicular Cloud (SVC), established in a parking facility, and supported by a traditional cloud backend. This SVC assists in executing various AI-driven applications. The cloud infrastructure is further connected to ITS elements, such as toll booths, via a 5G communication network. Vehicles are equipped with FASTag and Global Positioning System (GPS) modules, enabling them to interact with the ITS through Near Field Communication (NFC) and cellular V2X communication. On-board applications can request services such as route optimization or FASTag-related data retrieval. The cloud infrastructure processes these requests by performing FASTag data mining and computing optimal routes, which are then communicated back to the vehicles to assist in navigation and decision-making. In this system model, vehicles are capable of

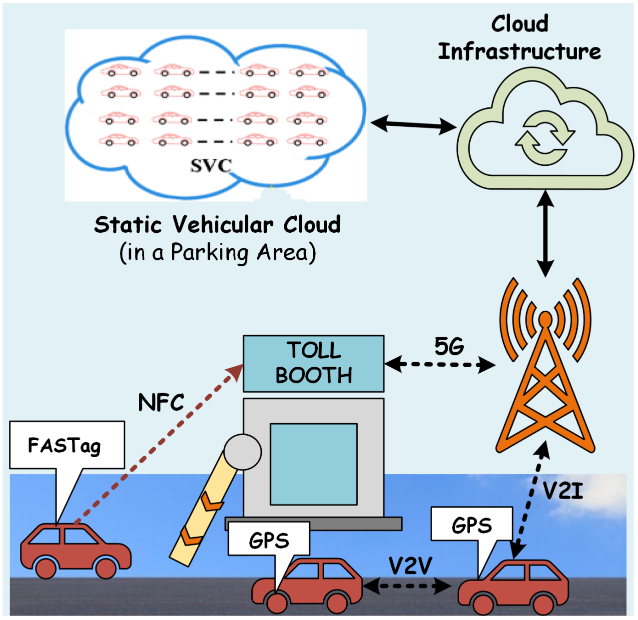


Fig. 1: The system model for vehicular cloud-assisted ITS

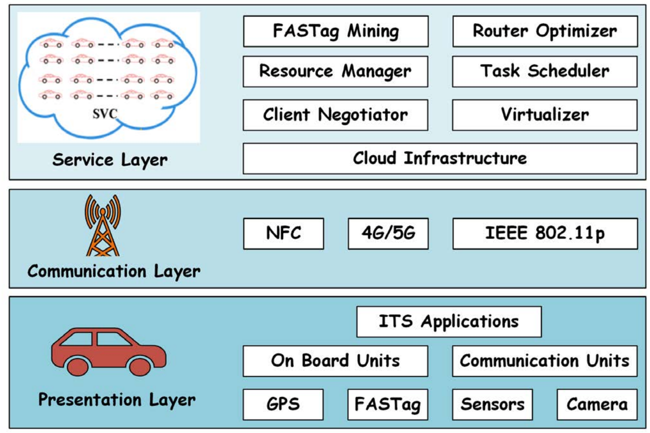


Fig. 2: Architecture of vehicular cloud-assisted ITS

communicating over multiple hops using V2V communication technology using IEEE 802.11p. If the vehicle is away from the roadside unit or cellular base station, then it could send data over multi-hop Vehicular Ad hoc Networks (VANETs).

Figure 2 illustrates the architecture implemented in this work, which is based on our previous work [2]. In this architecture, the system model is organized into three distinct layers: presentation, communication, and service. The presentation layer consists of components located on vehicles, such as sensors, GPS modules, and on-board units (OBUs). Its primary role is to perceive the environment, perceive relevant data, and send service requests to the upper layers to access various ITS services. The communication layer enables seamless interaction between vehicles and cloud infrastructure by employing multiple communication technologies, including Near Field Communication (NFC), IEEE 802.11p, and cellular V2X communications. This layer supports various vehicle-to-everything (V2X) scenarios, ensuring reliable data exchange under dynamic traffic conditions. The service layer is responsible for receiving service requests from vehicles, processing them, and distributing computational tasks to suitable vehicles within a Static Vehicular Cloud (SVC). In addition, it manages essential backend functions such as resource allocation, client negotiation, service orchestration, and virtualization, ensuring optimal use of available vehicular and cloud resources.

IV. AI-driven FASTag Mining and Route Navigation

This section presents two potential ITS applications are proposed, to operate on top of the system model outlined in the previous section.

A. Naïve Bayesian Classifier based FASTag Mining

In India, the national electronic toll collection system mandates the use of FASTag, an RFID-based card affixed on the vehicle windshield for automatic toll payment. Linked accounts can be recharged online through service providers or participating banks. By February 2020, nearly 2 million passenger cars were processed through toll plazas in a single day, generating vast amounts of vehicular data [15]. This FASTag data, if mined in real time, can provide significant value to ITS. Vehicles with insufficient FASTag balance before reaching their destination can be identified and notified, allowing timely top-ups and avoiding delays at tolls. Such data-driven services offer multiple benefits, such as better passenger experience, reduced travel time and fuel consumption, increased business opportunities for service providers, and smoother traffic management due to fewer stops.

To develop a vehicular Big Data mining service in an SVC, it is necessary to design and implement a suitable data mining model. In this work, the focus is on an AI-based learning technique, specifically the Naïve Bayes Classifier. The information collected from each vehicle at a toll booth as a structured document. This document can consist of multiple fields, such as Vehicle ID, FASTag ID, Time stamp, vehicle type, balance in FASTag account, origin, and destination toll plazas. Using these features, the Naïve Bayes Classifier can be trained to classify or predict various outcomes, such as whether a vehicle is likely to face balance exhaustion before reaching the next toll, which can be mathematically represented as $D_n = \{d_1, d_2, d_3, ...d_x\}$.

Consider the document $D = \{D_1, D_2, D_3, ...D_n\}$ and the class $C = \{C_1, C_2, C_3, ..., C_m\}$, there is a need to map $\mathcal{F} : D \to C$. If the fields of a document are not independent of each other, which is true in real-world scenarios, using Naïve Bayes Classifier, a document is classified by [16]:

$$P(c)P(d_1, d_2, d_3, ..., d_x) = \frac{P(c)\prod_{i=1}^{x} P(d_i|c)}{\sum_{\mathfrak{c}}[P(\mathfrak{c})\prod_{i=1}^{x} P(d_i|\mathfrak{c})]} \quad (1)$$

where P represents the probability and, for simplicity, C is used for C_m and D is used for D_i. Now, the decision rule for assigning a document to the best possible class $\hat{C}$, i.e., the class with the maximum posterior probability, is expressed as follows:

$$\hat{C} = \underset{c\in C}{argmax} P(c) \prod_{i=1}^{x} P(d_i|c) \tag{2}$$

The training process of the AI-based agent, using the Naïve Bayes Classifier based mathematical model, is presented in Algorithm 1.

Algorithm 1 Naïve Bayes Classification for FASTag Mining

```
Given: Training set 𝒯 = {D^(j), c^(j)}_{j=1}^N
Goal: Learn mapping F : D → 𝒞 by using eq. 2
procedure TRAINING(Parameter Estimation)
    for k = 1 to m do
        P(C_k) ← j/N : j = count{c^(j) = C_k}
    end for
    for k = 1 to m do
        Compute counts of each field d_i ∈ D labeled C_k
        Apply Laplace function and set P(d_i | C_k)
    end for
end procedure
procedure INFERENCE(Classification of a New Document
  D = {d_1, ..., d_x})
    for k = 1 to m do
        Value(C_k) ← log P(C_k) + Σ_{i=1}^{x} log P(d_i | C_k)
    end for
    Ĉ ← arg max_{c∈𝒞} Value(c)
    Return Ĉ
end procedure
```

B. Optimal Route Navigation System using V2X

Traffic congestion often leads to long delays, accidents, and driver frustration. Real-time traffic information can alleviate this by enabling dynamic route selection with lower congestion levels. Such data can be collected from vehicles on specific road segments through the wireless communication backbone, aggregated, and processed at a centralized facility to compute optimal routes. This functionality can be effectively supported by the SVC-assisted ITS infrastructure. In the proposed ITS application, vehicles are assumed to be equipped with advanced ICT technologies that enable seamless participation in cooperative traffic management. Each geographical partition is supported by an SVC that hosts a route optimization server. Vehicles are assumed to cooperate under a consensus mechanism and continuously share relevant traffic data. On the vehicle side, an onboard application collects information on parameters such as vehicle speed, traffic density, and blockage location using GPS, sensors, and cameras. This information, along with the intended destination, is periodically transmitted to the local SVC using V2X communications. The SVC aggregates traffic data from all participating vehicles. When a vehicle requests the optimal route to a destination, the query is forwarded to the local SVC controller. The controller delegates the route computation task to a subset of SVC nodes, which estimate travel times across candidate paths using a function of vehicular density and expected delay. The recommended path, selected to minimize end-to-end delay, is then returned to the vehicle via V2X communications.

The routing mechanism draws parallels with data communication networks, where intersections act as routers, roads as links, and vehicles as packets. Thus, the vehicular route navigation problem can be modeled as a multi-commodity flow problem, where the objective is to identify optimal paths for multiple concurrent flows while minimizing routing delays, which is expressed as follows:

$$\mathcal{T}_r = min_{r\in R}\left[\sum_{s=1}^{n}\frac{r_s}{\mathcal{A}_f}\left(\frac{1}{\rho_s - r_s}\right) + \mathcal{T}_{delay} \pm P\mathcal{T}_{acc.}\right] \tag{3}$$

where route $r \in R$ is defined as the aggregate of individual road segments s, among all available routes in the set R. For each segment, the vehicle arrival rate is represented by $\mathcal{A}_s$, while ρ denotes the maximum capacity that the road segment can accommodate. The travel delay experienced on a route is denoted as T_{delay}. Stochastic factors, such as accidents or sudden obstructions, are incorporated through a probability term P, which indicates the likelihood that a vehicle will accelerate or decelerate under such conditions. The additional delay caused by this behavior is captured by T_{acc}, quantifying the extra time incurred during acceleration or deceleration.

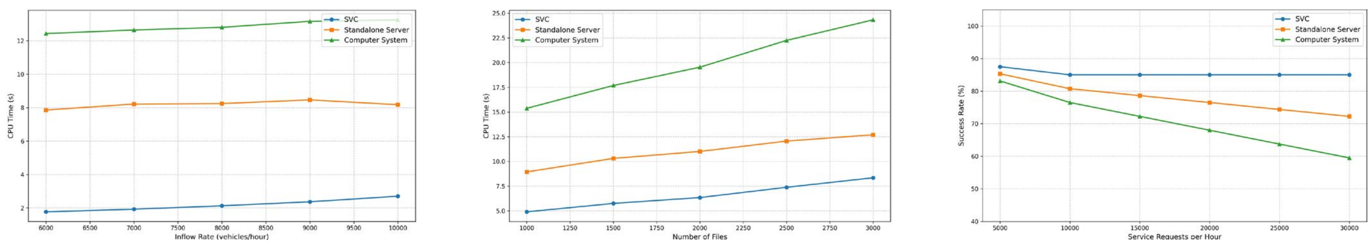
V. Experiment Setup and Result Analysis

A. Experimental Setup for Vehicular Cloud Assisted ITS

To evaluate the proposed framework, the simulation scenario illustrated in fig. 1 is employed. Vehicles equipped with GPS modules and NFC cards execute the two proposed applications while driving across multiple road segments. The SVC functions as the primary service provider, integrated within a three-layer architecture as shown in fig. 2. The simulation testbed consists of 120 parked vehicles acting as static nodes and 300–700 mobile nodes representing on-road vehicles. Vehicular mobility topologies are generated using NPART, where vehicle speeds range between 5–40 km/h, and the minimum inter-vehicle distance is maintained at 3 meters to reflect realistic traffic conditions. For wireless communications, the IEEE 802.11p standard is adopted to support V2X interactions. The SVC infrastructure is established using the distributed Apache Hadoop framework, enabling scalable data aggregation and processing. To implement the AI-based algorithms, the experimental environment leverages Python along with standard data science libraries such as Scikit-learn, NumPy, and Pandas.

B. Discussion on Results

Figure 3 illustrates the performance analysis of the system that runs the AI-driven FASTag mining application compared to a standalone server and a standalone computer.



(a) CPU time vs. vehicle inflow rate

(b) CPU time vs. no. of files

(c) Success rate vs. nu. of service requests

Fig. 3: Performance analysis of the system running AI-driven FASTag mining application.

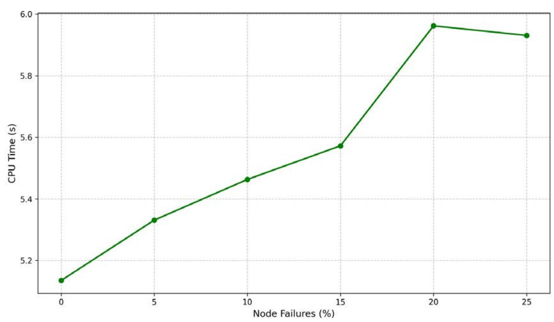


Fig. 4: Performance analysis of the system with route navigation application against node failures.

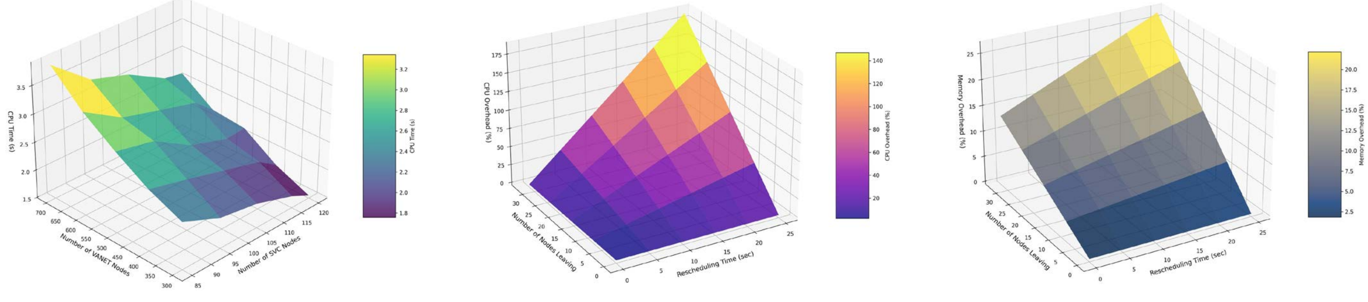
Figure 3a illustrates the CPU time performance of three different architectures, SVC, a standalone server, and a single computer system, as a function of the inflow rate i.e., the number of vehicles crossing a road segment in an hour, ranging from 6000 to 10000 vehicles per hour. The CPU time represents the time required to handle the queries of these vehicles. The SVC shows the lowest CPU time across all inflow rates. CPU time increases gradually from about 1.7 seconds at 6000 vehicles/hour to nearly 2.7 seconds at 10000 vehicles/hour. The SCV performs better than the standalone server and the computer system. This indicates that the SVC scales efficiently with increasing traffic, maintaining very low computational overhead.

Figure 3b shows the variation in CPU time with respect to the number of files processed in the three computing architectures. The SVC architecture outperforms in this scenario by 40% to 60% compared to the standalone server and the computer system. The SVC achieves the lowest CPU times for all file sizes. The CPU time gradually increases from ~ 4.9 seconds at 1000 files to ~ 8.3 seconds at 3000 files. The growth is relatively smooth, highlighting efficient scalability for increasing file volume. Thus, the analysis confirms that SVC is the most efficient and scalable solution, capable of handling growing workloads with minimal CPU overhead.

The graphs shown in fig. 3c illustrate the success rate achieved by all three architectures under varying loads of the number of service requests made by the vehicles per hour, ranging from 5,000 to 30,000. SVC maintains the highest and most stable success rate. In general, it is better for $\sim 3\%$ to $\sim 21\%$ compared to a standalone server and a computer system. This indicates that SVC is the most reliable architecture for managing large service loads in real-time ITS applications.

In SVC, participating vehicles are generally parked in an area, and vehicles may have to leave at any point in time, which could cause node failures in SVC while performing the tasks. Therefore, the next evaluation is to analyze the performance when there are multiple node failures in the system. Here, the route navigation application is considered for evaluation. The graph in fig 4 illustrates the effect of node failures on system processing time. In can be seen that up to $\sim 15\%$ node failures, CPU time increases moderately, suggesting that the system can tolerate limited failures without severe performance impact. However, beyond it, CPU performance deteriorates significantly, but it is in an acceptable range. This insight is crucial for designing robust and fault-tolerant ITS.

Finally, an overhead analysis is performed and presented in fig. 5. Figure 5a shows the 3D surface plot that illustrates the variation in CPU time as a function of the number of SVC nodes and VANET nodes. Higher node density leads to more data and request handling, thereby increasing computational requirements. In contrast, when the number of SVC nodes is larger, CPU time is significantly reduced, demonstrating the system's ability to offload and parallelize tasks efficiently across multiple service nodes. In fig. 5b, CPU overhead as a function of rescheduling time and the number of nodes leaving the system. CPU overhead grows sharply with both parameters. For small-scale failures, the CPU overhead remains moderate, but as failures scale to 30 nodes, the overhead increases rapidly. Longer rescheduling times further amplify the



(a) Performance analysis (CPU time) (b) Overhead analysis (time) (c) Overhead analysis (memory)

Fig. 5: Performance and overhead analysis of the ITS system.

overhead since the system must repeatedly reallocate resources and recompute task mappings. The third plot, i.e., fig. 5c extends the analysis to memory overhead, evaluated under the same parameters. Compared to CPU overhead, memory overhead increases more gradually. With 30 nodes leaving and longer rescheduling times, the memory overhead peaks only around 20–22%, significantly lower than the CPU overhead. This shows that while memory consumption increases with workload instability. However, the primary concern is CPU cycles rather than memory availability.

VI. Conclusion and Future Work

This article explored the integration of cloud computing, V2X communications, AI, and Big Data analytics to improve ITS. In this paradigm, parked vehicles contribute idle resources as SVCs, which provide real-time services to on-road vehicles through V2X communications. Two representative ITS services were demonstrated, namely, FASTag data mining using a Naïve Bayes classifier to predict balance exhaustion and alert drivers in advance, and route optimization modeled as a multi-commodity flow problem to minimize end-to-end delay using vehicular density and delay factors. These services highlight the potential of AI-driven big data solutions for efficient real-time decision-making in ITS. Performance evaluations confirmed that SVC-based solutions outperform standalone servers and nodes, offering reduced CPU time, higher success rates, and resilience to up to 15% node failures. In general, SVC, V2X with AI and Big Data presents a scalable, cost-effective, and fault-tolerant foundation for next-generation ITS, paving the way for robust real-world deployment. In the future, more advanced ITS applications will be developed, and a dedicated testbed can be created for performance evaluation.

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