The Potential of Integrating Cloud and AI in Autonomous Systems

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***Abstract*—As cloud computing delivers a robust infrastructure for real-time data processing, scalable storage possibilities, and effective AI model training, it is transforming the design and operations of autonomous cars. It is essential for supporting vital services including remote diagnostics, Vehicle-to-Everything (V2X) communication, remote accessing the infrastructure as well as self-governed devices and fleet management optimization for productivity and sustainability. This study illustrates cloud platforms potential based on vehicle performance and safety. Autonomous systems can analyze large amounts of data from sensors, traffic signals, and other vehicles with ease by utilizing cloud resources. This allows for real-time decision-making and improves safety features through data feed collaboration. Through leading industrial examples, we tried integrating the principles and features of cloud computing with autonomous systems to show how this collaboration is influencing the direction of smart mobility. The study also emphasizes how cloud-based technologies open the door for more effective, scalable, and sustainable solutions in the quickly changing automotive sector, in addition to enhance vehicle autonomy. In the end, the cloud will push the transition to a transportation environment that is safer and more intelligent.**

***Index Terms*—Cloud Computing, V-2-X communication, Autonomous Vehicle, MQTT**

I. Introduction

The development of autonomous vehicles marks a tremendous shift in transportation technology, driven by significant advancements in artificial intelligence (AI) and cloud computing. High-resolution sensors, sophisticated data, and continuous connectivity are all necessary for these autonomous vehicle systems to do complex driving tasks with minimal input from humans. The need for real-time data processing and computational resources has increased significantly as cars become more complex and connected to the environment they travel through. Giving Cloud computing a unique opportunity to meet and fulfill these demands[4]. For fleets that are spread across geographies, cloud computing offers high-performance, scalable infrastructure that enables data collection, storage, model training, and analysis. Cloud solutions offer the flexibility to process large datasets centrally, enabling continuous learning and AI model optimization, in contrast to traditional computing systems installed in individual vehicles. Tesla's fleet learning strategy, for instance, entails gathering actual driving data from millions of vehicles, transferring it to cloud servers, and then utilizing the data to facilitate continuous learning and AI model improvement [18][23]. After that, these updates are sent back to the cars via the air, generating a feedback loop that quickly boosts all of the cars' performance. Further, cloud-based platforms have become essential for large-scale simulations, behavioural prediction, modelling, and the building of high-resolution maps for organizations like Volkswagen Group, BWM Group, Toyota and others [19]. These highly computational methods take advantage of platforms like Amazon Web Services, Google Cloud, and Microsoft Azure's elasticity and parallel processing capabilities. Additionally, the cloud enables collaborative development, enabling teams worldwide to concurrently work on AI improvements, test scenarios, and roll out upgrades. This paper explores the framework, emphasizing the potential features of cloud computing that are critical for the growth of autonomous systems. Big data processing, promoting vehicle-to-vehicle and vehicle-to-infrastructure (V2X) communication, AI model training, fleet management, sustainability advancement, and edge computing integration for real-time responsiveness are some of its primary areas of interest. Our goal is to give a thorough overview of how cloud technology is influencing the future of mobility and speeding up the adoption of autonomous driving solutions by looking at real-world examples and new trends.

II. Related Works

The research work for the proposed framework can be classified into the following categories:

A. Cloud and Autonomous Systems

1. The research proposes a cloud-based safety platform for electric vehicles (EVs) that integrates with existing battery management systems (BMS) and provides tailored services. It uses the IoD framework linking

EVs, charging points, and smartphones to the cloud to collect and transmit information. The platform uses historical data and assesses battery health and safety to deliver early alerts and defect diagnostics. The entropy algorithm is used to assess and establish feasibility. 2. The research proposes an effective way to allocate federated cloud resources for autonomous driving using a one-sided matching reverse auction in a vehicle-road-cloud system (OSFC). The use of OSFC preserves cloud efficiency while enhancing computational efficiency by adaptively altering connectivity resources based on the real-time location of vehicles. The OSFC performed better compared to existing methods based on the simulations. 3. A new design framework for in-vehicle information systems (IVIS) as part of a sensor-cloud system (SCS), which integrates networks, sensors, and the cloud to support smarter transportation, is described in this paper. The user experience is enhanced, thus attenuating user concerns regarding sensor-cloud platforms (SCP). The main contributions are identifying new IVIS capabilities linking to user needs, proposing an experiential-based IVIS design framework (inclusively) with the SCS scenario in mind. 4. A comprehensive study of resource management in the context of vehicular cloud computing is provided in this study, a computing paradigm where intelligent cars provide computing, sensing, and storage capabilities. Under the vehicular cloud environment, vehicular systems can now enable delay-sensitive applications, but with high mobility and unstable networks pose some difficulty. This study considers solutions to each of the three resource management phases: pre-assignment, assignment, and post-assignment. The study has determined future research direction, as well as new frameworks for much needed resource monitoring and brokering.

B. Cloud-Edge-Cluster Framework

5. This paper introduces a collaborative cloud-edge cluster framework for vehicle edge computing that combines resources from multiple edge service providers (ESPs) and the cloud to facilitate an increase in demand caused by computational intensive applications such as autonomous driving and augmented reality. The framework offers a dynamic pricing system for ESPs and resource allocation management using software-defined networking (SDN) to handle the progressive demand placed on available resources. To improve resource allocation and task offloading, deep doubly Q-learning (DDQN) and a clustering algorithm are used to manage requests, or possibly using the both. The results showed significant reductions in latency with higher ESP profits than previous methods. 6. This study highlights the MQTT protocol to propose a cloud-based communications architecture that accommodates IoT devices in low bandwidth networks. The communication architecture facilitates the one-to-one or one-to-many with the publish-subscribe pattern for MQTT, and is based on AWS. Protocols used for securely authenticate the client-server communications were accomplished by PuTTY with SSH for public key encryption. The extensibility of this framework allows for a automated internet communications spanning across multiple ubiquitous IoT devices, making it scalable across various devices. 7. The paper explores the intersection of cloud computing and the Internet of Things, specifically how cloud computing platforms can assist in IoT storage and processing limitations. It compares the IoT services of AWS, Google Cloud, and Microsoft Azure to a common IoT architecture. It also conducts a cost study under different loads, as well as a performance study of MQTT middleware across the platforms. The goal is to help developers choose the most appropriate platform for their specific use case.

C. DataFlow and Protocol

8. This paper focuses on the accelerated rise of M2M protocols in the Internet of Things, particularly MQTT because of its widespread implementation. To demonstrate the significance of MQTT, a longitudinal 20-year systematic review and literature review are utilized from various application domains. While identifying the advantages and shortcomings of MQTT, the paper benchmarks and compares it to similar protocols like AMQP and CoAP, and provides a heuristic for evaluating possible MQTT brokers and libraries. It concludes with research questions identified for future development. 9. This study also addresses cybersecurity issues within the growing ecosystem of connected vehicles (CVs), focused on the '(vehicle)-edge' and '(in-vehicle)' platforms. It cites three relevant studies (Android Automotive; MQTT; and ROS) to express major security risks (malware, modification of data, and DDoS) as well as difficulties with trust and privacy. Overall, the authors proposed several means for mitigating risk, including trust based systems and multi-factor authentication, and they pull heavily from the area of IoT security. They further urge additional research on adaptive, cross-domain security solutions. 10. This paper offers a light weight device authentication mechanism to address the vulnerabilities in MQTT protocol in smart home Internet of Things applications. The approach employs light weight cryptographic mechanisms like one-time keys and tokens, to successfully register and authenticate these devices. This not only reduces computational and transmission costs, but it can also protect from impersonation and replay attacks. A formal analysis and prototype implementation demonstrates the extent

to which the proposed mechanism can provide device anonymity and authentication. 11. In this contribution, the authors describe the Mixed Cloud Control Testbed (MCCT), a small-scale experimental testbed based on the Mixed Digital Twin (mixedDT) idea which integrates Digital Twin technology with Mixed Reality, thereby facilitating interaction between their digital counterparts. The mixedDT framework connects the real and virtual domains together. As the MCCT has a real, virtual, and mixed environments, it provides crossover to peripherals like driving simulators and human-machine interfaces. With MCCT, real-time cross-platform connectivity is achieved by being able to operate (synchronously) between virtual, physical, and human vehicles. Using vehicle platooning, this study demonstrated the scalability of the MCCT when investigating vehicle-road-cloud integrations and cooperative activities across vehicles.

D. Federated learning

12. Learning an enabling environment perception in Cooperative Intelligent Transportation Systems (C-ITS) requires deep learning, however training these models typically suffers from a limited number of data, due to the limits of the test vehicle fleet and typically privacy means that data is not shared. This work addressed this problem through a federated learning system called H2-Fed, that allows infrastructure and connected vehicles to collectively learn and improve deep learning models without sharing raw data. H2-Fed employs a hierarchical aggregation method to consistently and accurately learn, while taking into account variation in data distribution, computation, and communication between vehicles and roadside devices. In real-world scenarios where connectivity is low, the framework is able to improve model performance from 68

E. Use of Cloud based Ai technology

13. While the technologies that are driving the rapid growth in data centers - such as 5G, cloud, and AI - present serious concerns surrounding energy use and carbon emissions. AI is being applied in operational enhancements in data centers, unfortunately the training methods used today are often complex and slow. The authors purposed automated AI training and deployment platform, a cloud-edge architectural approach. The automated technology will build unique models for specific room conditions, essentially simplifying the data where data is processed, labeled, trained, and model deployment takes place. Findings from experiments have demonstrated it can support concurrent workloads and decreases training time by 76.214. With advances in artificial intelligence and big data, data privacy is becoming a major concern in smart cities. This paper presents a federated learning training approach based on edge-cloud cooperative collaborative training, which addresses this concern. In this framework, model training occurs locally at the edge or on user's devices rather than uploading unprocessed data to the cloud. This work demonstrates the potential of leveraging local data while still upholding user data privacy. The experimental results of testing the framework on a traffic scenario for vehicle identification showed that it improved data privacy and reduced latency time for detection, which is promising for future applications in smart cities.

III. Methodology

This method describes the design and deployment of a V2X (vehicle-to-everything) environment that is cloud-integrated to improve safety measures, traffic flow, and intelligent communication between vehicles. With AWS services such as IoT Core, Lambda, S3, SageMaker, and CloudWatch to provide real-time communication with vehicles, roadside units, and cloud infrastructure. The designed cloud environment has the ability to include AI/ML for predictive decision-making and real-time analytics. This method represents a scalable, secure, and intelligent approach to develop future-ready transportation networks in smart cities.

A. Fundamental concepts

1. Cloud Computing With cloud computing, we can obtain software, processing power, storage and other resources when we need to access it, but only pay for useful resource through the internet. Cost-effectiveness, scalability, and flexibility are three key attributes of cloud computing that support software development models (SaaS, PaaS, and IaaS). Oracle, Azure, and AWS are important service providers.

2. Vehicle-to-Everything (V2X) V2X allows cars to communicate with networks, humans, infrastructure, and other cars to improve safety and traffic flow. An example would be when an RSU uses edge computing to quickly prioritize an ambulance at an intersection. Edge Computing By processing data close to its source (such as sensors or automobiles), edge computing minimizes latency and bandwidth consumption. It's ideal for making snap decisions in autonomous driving, smart cities, and traffic systems.

3. Edge Computing Edge computing signifies data processing close to its source, such as sensors or cars, and thereby minimizes latency and bandwidth usage. This is valuable for situations requiring purchase decisions, such as in autonomous driving, smart cities, and traffic management systems.

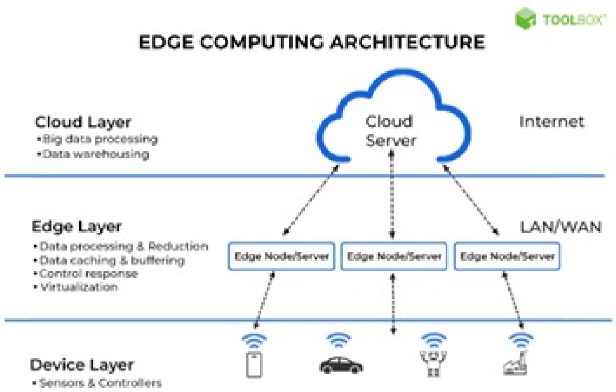

Fig. 1: Edge computing Architecture https://www.spiceworks.com/tech/edge-computing/articles/what-is-edge-computing

4. MQTT is a lightweight messaging protocol ideal for real-time messaging, ideally suited to the Internet of Things. Others subscribe to listen to the communications sent to subjects published from devices. It is frequently used with smart transportation and monitoring systems but has proven to be reliable and scalable.

5. Mesh Topology Data can take various paths in mesh networks since each node connects to multiple other nodes. This allows for great reliability, perfect for IoT, V2X, and smart infrastructure cases where dependable communication must be fast and reliable. In the mesh topology, the number of links can be calculated from the number of nodes in the topology, i.e., if N nodes exist, the links will be N(N-1)/2. This helps to calculate the attached nodes in the system environment at the time of dynamically scaling the resources and creating network configurations.

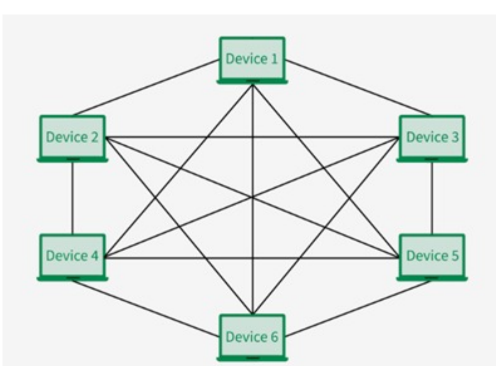

Fig. 2: Mesh topology https://www.geeksforgeeks.org/advantage-and-disadvantage-of-mesh-topology

The framework proposes a novel and unique combination of integrating the Cloud services with the vehicle to X systems, consisting of V-2-V, V-2-I, V-2-P, V-2-X. The entire framework is divided into 3 major layers depending on the technology and the tech-stack being used inside the environment. These 3 layers are connected with the WLAN wifi connectivity technologies like Wi-Fi 6 (IEEE 802.11ax) or IEEE 802.11p [26][28]. They are classified as End Device layer, primarily consisting of the end nodes and software devices that are the last point of contact for receiving and transmitting back the data. This includes Autonomous vehicles, media dashboards, Traffic and signalling infrastructures, Road Side Units, mobile devices, and applications, etc [1][20]. In other words, these can be classified as the clients in broader way. Following is the Edge layer, which includes the Road Side Units (RSU), On Board Units (OBU). OBUs are generally the devices installed on the end node that facilitate seamless and synchronous transfer of data to the computational edge, provided the data is limited to the size of 20-1500 bytes in single window frame. Meanwhile, the RSU is more tend to work towards the request computing, network management using the Software Defined Network (SDN) Policies, providing communication and data exchange conditions between the End devices and the Cloud layer. The third layer is the Cloud layer, which comprises the utilization of the cloud-based infrastructure, platforms, Software, and Computing services categorized with respect to Infrastructure as a Service (Iaas),Platform as Service (Paas) and Software as service (Saas). In the framework Aws is taken into consideration as a Cloud Service Provider (CSP), accordingly Microsoft Azure or any other compatible CSP can be brought under implementations[11].

B. Below is the list of services and tech stack used in the framework:

1. Information Transfer: Message Queuing Telemetry Transport (MQTT), Virtual Private Cloud (VPC), IOT Core, Application Load Balance (ALB), Network Gateway. 2. Server/Computing Service: Lambda(serverless), EC2 instance. 3. Data Storage: S3 bucket. 4. Data Analysis: Kinesis, Redshift, Quicksight, Glue and Athena. 5. AI and ML training: SageMaker, Bedrock. 6. Others: Simple Notification Service, CloudWatch.

C. Grid

The proposed framework utilizes a Mesh grid. As all nodes are highly connected to each other, data is easily shared, and all neighbouring nodes shall fully understand their characteristics and the action state of them. The aims of federated learning can also be met with this topology. The grid guarantees a fault-tolerant system, as there is no single point of failure, guaranteeing 100 percent data delivery.

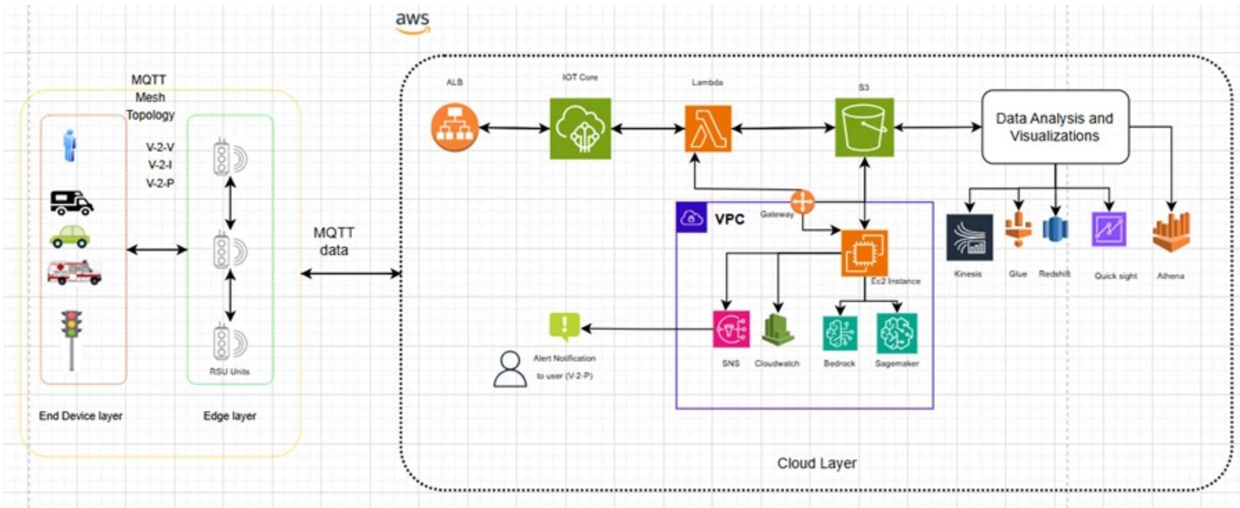

Fig. 3: Cloud based V-2-X framework with data flow.

D. Working

1. The unmanned vehicles interfaces with the RSU, where there is a unique id the Edge layer and Cloud layer are already connected. As a result, a Mesh topology develops, which prominently enables it to spread the latest data to the environment. MQTT is an essential part of data transmission between the cloud and end device nodes[21][24]. Data is collected in JavaScript Object Notation (JSON), which is the most transferable, lightweight for transmission, and easier to compute at edge layer, comprehend and train over the cloud. The main storage format of this information is a key-value format, where the data can be arbitrary and of various types. [4].

2. Now that the connection is successfully established, MQTT starts the data transmission from the unmanned vehicle to the cloud. The RSU is a mediator for this transmission process[15]. AWS IoT Core acts as the broker for the MQTT movement. There is an Application Load Balancer set at cloud infrastructure entry point that oversees incoming request and evenly distributes them across the IOT Core and leverages of services so that the request do not overwhelm the requests, causing failure of service[12].

3. Now the data in Json format once received at IOT Core, the filtering of the JSON file is done with respect to the necessity. Jointly is a lambda function, a server-less computing service that facilitates the triggering of functions automatically based on the rules and thresholds given. This results in data moving into the S3 storage service[14]. The data in JSon format consists of various real-time parameters as mentioned in the below sample code snippet.


```
{
  "time": "2025-05-22T14:30:00Z",
  "rsu_connection_id": "RSU-98765",
  "location": "THI, Ingolstadt",
  "vehicle": {
    "type": "SEDAN",
    "model": "BMW",
    "car_number": "IN AA 777"
  },
  "weather": "16°C",
  "alerts": "N/A",
  "warning": "N/A",
  "speed": "35 kmph",
  "connection_id": "MYCAR123",
  "connected_with": [
    "AAA111",
    "BBB22",
    "CCC133"
  ]
}
```


4. The S3 categorizes the data depending on how frequently the data needs to be fetched. Hence, it stores it into S3-Express one zone for highly fetched data like cookies on websites, S3 Standard for normal, S3 Standard infrequent for less accessed, and S3 Glacier and Deep Archive for least accessed data[13].

5. The data once stored is ready for the next batch of operations, i.e, Data Analysis and Ai model training. In Data analysis, the data is fetched from S3 storage and passed into the different analysis services like :

A. Kinesis: It is used for real-time data ingestion and streaming the analysis. For example, the 1000+ telemetry coming from the RSU is streamlined and collected, which later can be used in monitoring traffic patterns and incident detections.

B. Redshift: Used for large-scale data warehousing and analysis in a structured manner. Example: Track the speed limits in city intersections for over a month.

C. Athena: Used to query SQL data on serverless without storing in the databases. Example: Ad-hoc query resolving without database involvement, emergency cases can be tracked immediately for the prediction factors.

D. Glue: This is typically used to normalize the data in ETL (Extract, Transform, and Load) for Kinesis, Athena, and Redshift. Example: reduce the data duplication, delete unwanted parameters etc.

E. Quicksight: It is a visualization tool used to create informative dashboards and can playa crucial role in operational centres.

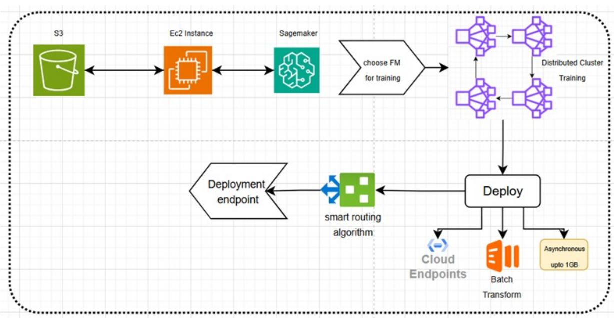

Fig. 4: On cloud data training with AI/ML Models.

6. Secondly, the data in S3 is utilized by the EC2 instance of a decent computation capacity to train the AI models like Neural Networks, Deep Neural Networks, and Large Language Models, Generative AI by using AWS Sagemaker and Bedrock respectively [22]. This fully managed infrastructure service provides us variety of machine learning and Deep learning models to build, train, and deploy the model on cloud premises using the S3 data. For faster training, the model is trained in a distributed fashion in a cluster topology. This takes the help of built-in libraries like TensorFlow, Pytorch, Scikit-learn learn and others. Once the training is completed, Sagemaker provides us with the option to deploy the ready-to-serve data in 3 major ways[16]. First direct storage and deployment to cloud endpoints, which will forward it to the edge layer, followed by the end device layer. Secondly, Batch transform also exists for further offline preprocessing. Lastly, trained data can be sent asynchronously using the Asynchronous Interference at lower latency.

7. Additionally, the EC2 server also sends the recorded insights from S3 and another service to CloudWatch to track the metrics for security, health, and audit checks of the entire system present on the cloud premises. Parallelly, metrics with specific values are created in SNS, and once the values exceed the preset threshold limits or any warning is detected, an alert notification is automatically sent across the end device layer to ensure everybody is made aware of the incident [8][10]. With enhancement by cloud connectivity in V-2-X, the vehicles can take instant decisions as the shared learning and data, such as vehicle on the road, person in vicinity, obstructions, road condition, traffic scenario, broken down vehicle, are made available in real-time[17].

This key information brought into analysis can help the automotive sector make decisions with tremendous potential. These tools work together to create a thorough pipeline for insights into smart transportation systems based on both historical and real-time data. Using this paradigm, vehicles share their route and state of statistics using the reference grid system and can do this without the assistance of a digital road map. Each vehicle can combine the new vehicle data with its plan to better form its understanding of the environment around it. The vehicle data includes movement parameters (which communicate the vehicle's movement direction and speed) that are time-stamped and thus based on the local context. This distributed approach adds to cooperation awareness without any reliance on external infrastructure.

E. Deployment Considerations

The entire framework should be well-connected with high-speed WLAN wifi connectivity to avoid network-based issues and latency problems. Uses of the services and the parameters of the services should be well considered so as to meet both performance excellence as well as cost-optimized solutions.

IV. Results and Evaluations

In order to investigate the performance of the proposed intelligent transportation system concept, a simulated environment was considered through AWS cloud services and other locally developed edge components. The set up successfully showcased real-time communication between simulated vehicles, RSUs.

A. Cost Estimations

The following are the approximate cost estimations for the above-mentioned framework using the AWS Frankfurt region (eu-central-1)[25].

The table provides a monthly cost estimate broken down by major functional category for the implementation of a cloud-based architecture to support V2X communication systems. This includes: device-to-cloud communication, edge-level event processing, scalable object storage, real-time data stream intake and transformations, machine learning model training and inference, and system-level monitoring and alerting. The architecture accommodates high-volume data transfers, low-latency processing, and virtually limitless resource

Function	Service	Cost Estimation	Others
IoT Connectivity	AWS IoT Core	560	100 million messages/month
Edge & Compute	AWS Lambda	103	10 million lambda requests
Data Storage	AWS S3	74	
Data stream & analysis	Kinesis, Glue, Athena etc	162	10 TB data Ingestion/month
AI/ML Training	AWS SageMaker + Inference	356	300 hrs Training
Notifications & Alerts	AWS SNS	5	10 Million alerts
Monitoring and Alarms	CloudWatch	51	Customized Alerts
Data Transfer	Inbound-Outbound	990	10TB Outbound Data
Geospatial	N/A	-	
	Total	**2168**	

TABLE I: AWS Service Cost Estimation for IoT-based Architecture

scaling for operational settings that rely on obtaining data provisioned from vehicular sensors, nuanced behaviors, and messaging actions. The estimates are long-term anticipated usage characteristics - that is, message transfer volumes, function executions, model training compute hours, and outbound data transfers. Overall, the operational costs of the V2X architecture suite are estimated to average €2168 per month, reflecting a high resilience and elasticity in cost that suits the requirement of an intelligent transport type framework for dynamic V-2-X.

B. *Uses cases*

1. Digital twinning.
2. Accident analysis.
3. Risk and fault evaluations.
4. Shared learning.
5. Geo fencing and vehicle monitoring.
6. Tracking the CO2 emissions.
7. Adaptive route optimizations.
8. Enhanced data-driven city planning.

V. Conclusion and Future Work

The proposed framework is a concept that will be a pioneer in the Cloud and automotive field with a vast landscape in regards to V2X-based autonomous vehicles that rely on cloud computing platforms, for example, AWS, for city developers such as Ingolstadt. In the not-so-distant future, vehicles will be communicating in real-time, whether they are communicating with infrastructure or communicating with other vehicles. Additionally, with the better technologies available, including 5G and edge computing,g we will improve traffic flow and road safety. Emergency vehicles will be prioritized, we will predict collisions or ”near misses”, and the vehicle will adjust the driver’s route based on the real-time conditions through deep learning technology. A host of diverse and rich insights that data generates will be used for urban planning in such cities. The impact on logistics and public transport may be surprising. In the near future, we may see systems which will detect cyclists and pedestrians to prevent cyclist and vehicle crashes, as well as smart parking that routes vehicles to available areas. The proposed framework links edge-based artificial intelligence and cloud-scale analytics, and through cooperative learning, machine learning between vehicles that are capturing data. This means the learning continues for our model without sacrificing scalability and privacy[27]. In addition, it is a potent framework for sustainability and predictive maintenance of infrastructure, as well as unprecedented growth towards smarter cities while improving enjoyment and safety for citizens

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