Micro-Safe: Microservices- and Deep Learning-Based Safety-as-a-Service Architecture for 6G-Enabled Intelligent Transportation System

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***Abstract*—In this paper, we propose a microservices and deep learning-based scheme, termed as Micro-Safe, for provisioning Safety-as-a-Service (Safe-aaS) in a 6G environment. A Safe-aaS infrastructure provides customized safety-related decisions dynamically to the registered end-users. As the decisions are time-sensitive in nature, the generation of these decisions should incur minimum latency and high accuracy. Further, scalability and extension of the coverage of the entire Safe-aaS platform are also necessary. We assume road transportation as the application scenario and propose a microservices- and deep learning-based platform for provisioning ultra-low latency safety services to the end-users in a 6G scenario. We design the proposed solution in two stages. In the first stage, we develop the microservices-enabled application layer to improve the scalability and adaptability of the traditional Safe-aaS platform. Moreover, we apply the state space model to represent the decision parameters requested and the decision delivered to the end-users. During the second stage, we use deep learning models to improve the accuracy in the decisions delivered to the end-users. Additionally, we apply an assortment of activation functions to analyze and compare the accuracy of the decisions generated in the proposed scheme. Extensive simulation of our proposed scheme, Micro-Safe, demonstrates that latency is improved by $26.1-31.2\%$, energy consumption is reduced by $22.1-29.9\%$, throughput is increased by $26.1-31.7\%$, compared to the existing schemes.**

Keywords*—6G, Microservices, Deep learning, State space model, Safety-as-a-Service (Safe-aaS), Road transportation, and Decision parameters.

I. Introduction

In the last few decades, the ratio of on-road casualties due to accidents to the number of on-road vehicles has increased significantly. As observed from the report of the WHO [1], traffic accidents are one of the reasons behind the death of approximately 1.35 million people per year. Further, more than half of the traffic deaths comprise pedestrians, cyclists, and motorcyclists. To minimize the rate of on-road causality and improve the traffic conditions, various advanced technologies like Advanced Driver Assistance Systems (ADAS) [2] and Intelligent Transportation System (ITS) [3] are produced. Moreover, intimating safety-related information beforehand to the end-users may minimize the rate of accidents. To address the safety-related issues in road transportation, we propose a microservices- and deep learning-based Safety-as-a-Service (Safe-aaS) architecture for 6G-enabled ITS.

The Safe-aaS infrastructure dynamically provides customized safety services to multiple registered end-users at the same time instant. The device layer of Safe-aaS comprises different types of sensor nodes, which are either present at a specific geographical location or on the automobiles. These deployed sensor nodes after acquiring sensed data transmit it to the edge nodes/cloud, depending upon their time-critical requirement. The end-users from different geographical locations simultaneously register to Safe-aaS, choose certain decision parameters, and pay through the Safe-aaS's Web portal. Therefore, the maintenance of end-user's credentials, generation of decisions, and forecasting the demand of end-users are complex tasks. Finally, providing safety services timely to end-users and maintaining the accuracy of the generated decisions is necessary to ensure their on-road safety. Therefore, provisioning safety services with minimum latency, high throughput, and high data rate are necessary. With the emergence of 6G features [4] in the Safe-aaS platform, energy consumption is minimized, massive connectivity is enabled, therefore, safety services are provided to the increased number of end-users. Considering these aspects, we propose microservices- and deep learning-based Safe-aaS infrastructure for a 6G environment.

Existing research works proposed various schemes such as monitoring and providing real-time feedback to the drivers and centralized controller to avoid collision among vehicles, [2], [3], [5] for the smooth handling of traffic and on-road congestion, and minimize accidents. Safe-aaS [6] is one of the available platforms, that renders customized and virtualized safety services to the registered end-users. Founded on the concept of decision virtualization, these services are dynamically provided to multiple end-users. On the other side, a huge number of end-users simultaneously register to the Safe-aaS platform and request safety services. These end-users provide certain credentials, select decision parameters, and make payments. Therefore, storage, processing, mapping of the generated decisions with the requested decision parameters, is a complicated task. Further, the generated decisions are time-critical, and any delay in delivery of these decisions or providing partially correct/incorrect decisions may lead to a hazardous situation. Considering these facts, we are strongly motivated to propose a microservices- and deep learning-based Safe-aaS platform such that the scalability of the platform and accuracy of the generated decision is improved.

Motivating Scenario: Fig. 2 depicts a 6G network-based infrastructure where different types of stationary and non-stationary sensor nodes are placed at different geographical locations. The edge nodes process the time-critical raw sensed data, while the other non-time-sensitive data are sent to the cloud. We consider U_i as the end-users, who registered to the Safe-aaS platform for receiving on-road safety-related decisions. Considering the decision parameters opted by the end-user U_1, the sensed data is non-time-sensitive and is transferred to the cloud for processing. On the other hand, the end-user U_2 seems to request for decision parameters, where the sensed data is time-sensitive. Hence, the sensed data is transmitted to the edge nodes for processing. As the primary aim of the proposed scheme is to minimize the delay, so we consider a 6G-enabled Safe-aaS infrastructure. Additionally, to improve the accuracy of the generated decisions, we consider that a deep neural network is deployed at the edge nodes and cloud/server. We consider road R_1 to be more congested as demonstrated in Fig. 2. As R_1 connects to several office routes, so it is likely to be congested during the day compared to that at night time/weekends. Therefore, the number of end-users requests is high during office hours. The segregation of various units minimizes the delay incurred in the generation and delivery of the decision. We group the end-users based on the location and design the micro-services depending upon the services required. Hence, the application of microservices significantly minimizes the overall delay and deep learning improves the accuracy of the generated decisions.

In this paper, we propose a microservices- and deep learning-based scheme for provisioning safety services to the end-users in a 6G-enabled ITS environment. The proposed scheme, Micro-Safe, maintains a trade-off between scalability and adaptability of the Safe-aaS platform, and accuracy of the generated decisions. We aim to address the following issues: (a) How do the Safe-aaS platform manages the credentials of end-users, their requested decision parameters, processing of their requests, and generated decisions?, (b) How to avoid processing of similar decision parameters multiple times (c) How to maintain the accuracy of the generated decisions?, and (d) How to render safety services to the end-users with minimal delay? The specific contributions of this work are as follows:

- In this paper, we design a microservices- and deep learning-based Safe-aaS platform for 6G-enabled ITS, such that the generated decisions are delivered with minimum latency, high throughput, and improve the scalability and adaptability of Safe-aaS.
- We represent the decision requested, processed, and generated decision as a state space model. We consider the decision parameters selected by the end-users as the *input matrix*, microservices involved in processing them as the *system matrix*, and generated decisions as the *output matrix*. Further, we group the locations which are frequently selected as a destination by the end-users during the specific time of the week in the form of a matrix. Thereafter, we introduce an additional cost charged from the end-users, depending upon their location and time duration.
- In Safe-aaS, the decisions to be delivered to the end-users are time-critical, therefore, timely delivery and maintaining the accuracy of the decisions is necessary. We apply deep neural network (DNN) to improve the accuracy of the decisions to be delivered to the end-users. We classify the proposed DNN using various activation functions with different learning rates.
- Extensive simulation results demonstrates that the proposed scheme, Micro-Safe helps to improve the performance in terms of energy consumption, latency, throughput, and packet delivery ratio, compared to Safe-Passé [7] and ITS-Cloud [8].

The rest of this paper is organized as stated below – Section II highlights the prior researches done in the domain of Machine learning algorithms and their application on road safety. The Section III depicts the problem scenario, mathematical formulation, and the solution approach that is followed by Section IV that discusses the simulation setup, benchmarks, and results, and finally Section V summarizes the proposed work along with the future scope of work.

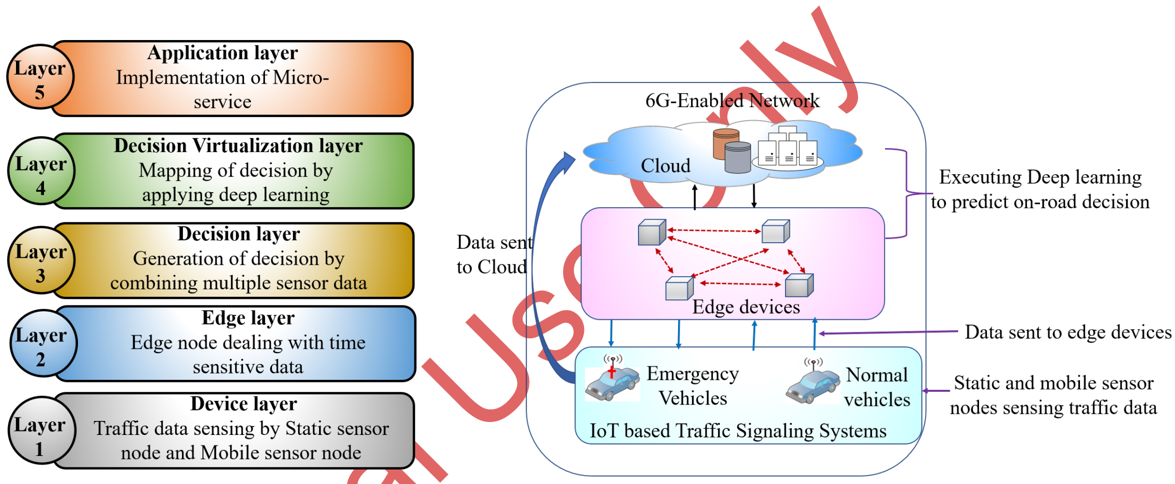
II. Related Work

In this section, we discuss various research problems such as on-road congestion, road safety, and real-time detection system in the field of road transportation [3], [5], [6], [9]. We also discuss some research works undergone in the 6G environment [4], [15], [16] and various deep learning applications [10], [11], [17], [18]. Further, we discuss the existing research works related to microservices [12]–[14], [19], [20].

Jiménez *et al.* [3] proposed a system that emphasizes on advanced perception techniques, vehicle automation, and communication between vehicles (V2V) and with the infrastructure (V2I). The authors discussed two features of road transportation - safety and efficiency. Similarly, Barmpounakis and Vlahogianni [5] used the crowdsourced smartphone data to detect the powered two-wheelers (PTW). The authors evaluated and analyzed the accuracy of the developed model, applying popular machine learning approaches. On the other hand, Roy *et al.* [6], [7], [9] designed a unique platform, Safe-aaS, to provide customized safety-related decisions dynamically to the end-users, on a payment basis. Additionally, the authors coined the term 'decision virtualization', founded on which the same virtualized decision is forwarded to multiple end-users.

On the other hand, various models are proposed for the analysis of communication in heterogeneous networks for 5G environment [21]. Further, device-to-device communication can be improved using mobile crowdsensing (MCS) and C-RAN [22]. With the emergence of 6G wireless communication networks, provisioning services with ultra-low latency, massive reliability, and low latency communications are possible. However, maintaining statistical delay and error-rate-bounded QoS system architecture is a challenging task. Zhang *et al.* [23] proposed a system architecture to overcome these challenges over mmWave-based user-centric networks. Further, with the rapid growth in the heterogeneous, dynamic, and large-scale vehicular network, necessary features such as ultra-low latency, high reliability, and high security, have become necessary. Considering these characteristics of the 6G environment, Zhang et al. [16] discussed the various device-to-device (D2D) communication solutions for mobile edge computing, network slicing, and non-orthogonal multiple access (NOMA) cognitive networking. Similarly, She *et al.* [15] explored the key communication features of 6G networks - ultrareliable and low latency communications (URLLCs). The authors stated that with the advancements in deep neural networks, deep learning has been developed as an enabling technology for URLLCs in future 6G networks. Additionally, deep learning is applicable for anomaly detection in smart grid [11].

Hasselbring and Steinacker [12] proposed the characteristics of microservice architectures in one of the biggest European e-commerce platforms, which enables scalability,



(a) The block diagram (b) The system architecture

Fig. 1: Micro-Safe

TABLE I: Summary of the existing research works on road safety and microservice architecture

Protocol	**IoT**	**Microservice**	**AI/ML**	**6G**	**Fog/cloud**
ADAS [2], [3], [5]	✓	×	✓	×	×
Safe-aaS [6], [7], [9]	✓	×	×	×	✓
Deep learning and 6G [10], [11]	✓	×	✓	✓	×
Microservice Framework [12]	×	✓	×	×	×
Microservices Architecture [13]- [14]	×	✓	×	×	✓
Micro-Safe	✓	✓	✓	✓	✓

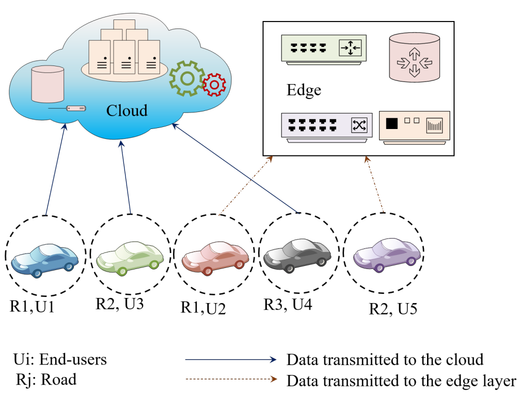


Fig. 2: Motivating Scenario for Micro-Safe

agility, and reliability. They explored vertical decomposition within the self-contained systems and detailed descriptions of the microservices applied in that organization. Similarly, Wen *et al.* [13] proposed a reliable and trustworthy microservice framework, which minimizes the inconsistency between the user security requirements and provides them actual services. They took upon a hybrid approach for the selection and deployment of the microservices. Further, various web companies have adopted microservice architecture for the usage of large-scale applications in the cloud as a set of small services. Villamizar *et al.* [14] put forth the comparisons among these web applications utilizing three different application scenarios - monolithic architecture, a microservice architecture run by the cloud customer, and another microservice architecture run by the cloud service provider.

Synthesis: From the existing research works on road safety, microservices, and deep learning, we observe that there exists a lacuna in the field of microservices-based ITS in a 6G environment research domain. On the other hand, Safe-aaS is a recently introduced unique infrastructure which provides customized safety-related decisions to the end-users. Therefore, any delay in delivery of decisions or delivery of incorrect/partially correct decisions may result in a hazard. Further, the integration of microservices and 6G with the traditional Safe-aaS infrastructure improves the speed, scalability, integrity, and throughput. We present the summary of the available research works on road safety and microservices in Table I.

III. System Model

We assume a ITS scenario where Safe-aaS infrastructure is implemented. The Service Oriented Architecture (SOA)-based Safe-aaS infrastructure provides customized safety-related decisions dynamically to the end-users, on a pay-per-use basis. Typically, a Safe-aaS architecture consist of five layers – device, edge, decision, decision virtualization, and application, as demonstrated in Fig. 1(a). The device layer comprises of heterogeneous types of static and mobile sensor nodes that are placed at various geographical locations and into vehicles, respectively. Depending on the time-critical necessity of the sensed data, the primary processing of these sensed data is undergone either at the edge layer or cloud. Further, these primarily processed data is transmitted to the decision layer

TABLE II: List of symbols used

Parameter	Description
$\mathcal{B}_t$	Input matrix storing decision parameters selected by n end users
$\mathcal{A}_t$	Input matrix storing the micro-services for processing n end-users' request
$X(t)$ and $Y(t)$	The set of state and output equations of Safe-aaS
$x(t)$ and $y(t)$	The state and output variables of the state space representation
$\mathcal{G}_t$	Group of geographical location at various time instants w.r.t. traffic condition
$\mathbb{P}_j$	Price charged from registered end-users
C_q^{dp}	The cost of the q^{th} decision parameter
t_u^{eff}	Time duration of service requirement selected by end user
C_{lt}	Cost incurred w.r.t the location and time selected by end user
$\mathbb{PR}_j$	The profit of SSP

for generation of decision. In this layer, multiple sensor data is combined for generating a decision. The logical mapping of the obtained decisions as per the requirement of end-users are performed at the decision virtualization layer. Further, using the concept of decision virtualization, simultaneous delivery of the same decision to multiple end-users is provisioned. Finally, the application layer provides the interface between the end-users and the Safe-aaS architecture. The end-users register to the Safe-aaS architecture, select some decision parameters as per their requirement, and make payment, through a Web portal. Fig. 1(b) illustrates the schematic representation of the 6G-based Micro-Safe architecture. We consider that the j^{th} end-user requests for k^{th} decision parameter at any time instant t, which is represented as d_{jk}, where $1 \leq j \leq n$ and $1 \leq k \leq y$. $\mathcal{B}_t$ is an input matrix that comprises the decision parameters selected by the n end-users during registration. Therefore,

$$\mathcal{B}_t = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1k} & \cdots & d_{1y} \\ \vdots & \vdots & \ddots & \cdots & \ddots & \vdots \\ d_{j1} & d_{j2} & \cdots & d_{jk} & \cdots & d_{jy} \\ \vdots & \vdots & \ddots & \cdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nk} & \cdots & d_{ny} \end{bmatrix} \tag{1}$$

$\mathcal{B}_t$ is a matrix of order $n \times y$, where n and y are the number of end-users and decision parameters displayed through the Web portal. The rows of the matrix $\mathcal{B}_t$ comprises decision parameters selected by an end-user at the t^{th} time instant. The columns represent the end-users, who are registered for safety services. On the other hand, in the backend of the application layer, various management units such as Service Level Agreement (SLA), Financial, Decision Storage or Inventory, Demand Prediction and Forecast, and Risk management units, are involved in the decision delivery process and decision parameters selected by the end-users. In such a scenario, the scalability, maintenance, and adaptability of each of these units is a complex task. The segregation of these various units is one of the possible solutions to this problem. Considering these facts, we design a microservice-based application layer for the Safe-aaS infrastructure. Suppose, each of these microservice-based management units is represented as M_{ij}, where $1 \leq i \leq m$ and $1 \leq j \leq n$. Further, M_{ij} is the i^{th} type of microservice unit engaged in the generation of decision for the j^{th} end-user. $\mathcal{A}_t$ is the matrix that consists of the list of microservices involved in processing the request of the n end-users and generation of decision, which is represented as,

$$\mathcal{A}_t = \begin{bmatrix} M_{11} & M_{12} & \cdots & M_{1j} & \cdots & M_{1n} \\ \vdots & \vdots & \ddots & \cdots & \ddots & \vdots \\ M_{i1} & M_{i2} & \cdots & M_{ij} & \cdots & M_{in} \\ \vdots & \vdots & \ddots & \cdots & \ddots & \vdots \\ M_{m1} & M_{m2} & \cdots & M_{mj} & \cdots & M_{mn} \end{bmatrix} \tag{2}$$

Each of the rows of the matrix $\mathcal{A}_t$ represents the microservices involved in the generation of a decision of the j^{th} end-user. We denote any M_{ij} as a Boolean function, 1 or 0, depending upon the microservice units participating in the decision generation. Further, the decision delivered to the j^{th} end-user, based on the decision parameters opted by him/er, is denoted as D_j. The decision for n end-users is represented by the matrix $\mathcal{C}_t^T$, as demonstrated in Equation (3).

$$\mathcal{C}_t^T = [D_1 \quad D_2 \quad \cdots \quad D_j \quad \cdots \quad D_n] \tag{3}$$

$\mathcal{C}_t$ is the output matrix that comprises the generated decisions. The input provided by the j^{th} end-user at any time instant t is represented by $\mathbb{B}_t$. Based on the decision parameters selected by the end-users, as represented in $\mathcal{B}_l$, a decision is provided to them. The decisions generated are represented along the columns of the matrix $\mathcal{C}_t$. The transposed form of $\mathcal{C}_t$ is $\mathcal{C}_t^T$, which is of order $1 \times n$. We represent the microservices-based Safe-aaS architecture applicable for the 6G-enabled ITS scenario as a state space model, where $\mathcal{A}_t$ is the system matrix of order $m \times n$, $\mathcal{B}_t$ is the input matrix of order $n \times y$, and $\mathcal{C}_t$ is the output matrix of order $n \times 1$, at any time instant t. The input matrix, $\mathcal{B}_t$, comprises decision parameters selected by the end-users. Further, the type of microservice units involved to generate a decision for each of the end-users is represented by the system matrix, $\mathcal{A}_t$. The output matrix, $\mathcal{C}_t$, consists of the decision to be transferred to the end-users, depending upon the decision parameters selected by them. The state-space representation of the state and output equation of a Safe-aaS infrastructure is mathematically represented as,

$$X(t) = \mathcal{A}_t x(t) + \mathcal{B}_t y(t) \text{ and } Y(t) = \mathcal{C}_t x(t) \tag{4}$$

where $X(t)$ and $Y(t)$ represent the set of state and output equations of Safe-aaS. Further, $x(t)$ and $y(t)$ are the state and output variables of the state space representation.

In another aspect, certain locations may be frequently selected as destination points by the end-users. Further, the time period for which safety services are utlized by them may be similar. For example, any office location and duration of service during the weekdays. One of the possible solutions to this problem is to group these locations with respect to time. We represent this group of location and time duration as set $L = \{L_1, L_2, \cdots, L_g\}$ and $T = \{T_1, T_2, \cdots, T_t\}$ respectively. $\mathcal{G}_t$ is the matrix which represents the group of a geographical location at various time instants with respect to the road traffic condition. Depending upon the services availed by the end-users from a specific geographical location and at a specific time, we group these locations with respect to time for ease in delivery of generated decisions. Therefore,

$$\mathcal{G}_t = \begin{bmatrix} G_{11} & G_{12} & \cdots & G_{1j} & \cdots & G_{1g} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ G_{i1} & G_{i2} & \cdots & G_{ij} & \cdots & G_{ig} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ G_{t1} & G_{t2} & \cdots & G_{tj} & \cdots & G_{tg} \end{bmatrix} \tag{5}$$

Each of the rows of the matrix $\mathcal{G}_t$ represents the different group of locations at a particular time duration, where any G_{ij} denotes the j^{th} group of location at the i^{th} time duration, based on the services requested. Further, these decisions are safety-related in nature, therefore, delivery of inaccurate/partially correct decisions may result in any road incident/accident. On the other hand, a deep neural network (DNN) possess non-linearity characteristics and provides variable interactions, which helps to enhance the accuracy of the generated decisions. We apply DNN at the edge layer and cloud, where the raw sensed data is primarily processed. Based on the DNN, the prediction is done and the decision is generated. The generated decisions are finally transmitted to the end-users. In our proposed scheme, Micro-Safe, we apply rectified linear unit (ReLU), logistic, softmax, and tanx functions to analyze and perform a comparative analysis, in terms of their performance. The activation function of ReLU [24] is defined as $y = max(0, x)$. We adopt Adam [25], an adaptive learning rate optimization algorithm, to solve the weight optimization. In order to apply the learning rate for each of the weights of the neural network, Adam utilizes the estimations of the first and second moments of a gradient.

Motivated by the concept of price charged proposed by Safe-Passé [7], we design the price charged from the end-users in our proposed scheme. In Safe-Passé paper [7], the authors computed the price charged, based on the time period for which safety services are used by them. The delay experienced in delivering the decisions by the Safety Service Provider (SSP) to the end-users is modeled in terms of the penalty cost in the traditional Safe-aaS paper [6]. Further, depending upon the total number of decision parameters selected by the end-user, the delay occured in the delivery of decisions, and the group of the destination location, we model the price charged from end-users as:

$$\mathbb{P}_j = \sum_{q=1}^{z} (C_{dp}^q d^q) t_u^{eff} - C_p t_d^{eff} + C_{lt} \tag{6}$$

where C_{dp}^q represents the cost of the q^{th} decision parameter (DP), d^q, selected by the end-user over a time duration, t_u^{eff}. C_p is the penalty cost incurred by any SSP for a delay incurred of t_d^{eff}. Further, the cost incurred depending on the location and time is represented as C_{lt}. We mathematically define t_u^{eff} as the ratio of the time duration for which the end-user has requested, t_{use}, to the maximum allowable time duration, t_{max}, for which safety services are provided. Mathematically:

$$t_u^{eff} = \frac{t_{use}}{t_{max}}, t_{use} < t_{thres} \text{ or, } t_{use} \geq t_{thres} \tag{7}$$

t_{thres} is the boundary time beyond which the SSP provides discount to the end-users. In case, $t_{use} \geq t_{thres}$, the end-user receives a discount, dis. Further, motivated by the concept of penalty cost incurred by the SSP, we formulate the penalty cost, C_p, if the on-road safety services requested by the end-users are delayed beyond the time duration, t_{allw}. Therefore, t_d^{eff} is mathematically represented as $t_d^{eff} = \frac{(t_{rcv} - t_{allw})}{60}$, where t_{rcv} is the time when safety services are received. Further, C_{lt} comprises the additional cost incurred by the end-users. Based on the group of locations, price is charged by the SSP from the end-users. Mathematically:

$$C_{lt} = \begin{cases} C_{l_1} + C_{t_1}, & \text{for } G_{11} \\ C_{l_2} + C_{t_1}, & \text{for } G_{12} \\ \vdots & \\ C_{l_g} + C_{t_1}, & \text{for } G_{1g} \\ \vdots & \\ C_{l_g} + C_{t_t}, & \text{for } G_{tg} \end{cases} \tag{8}$$

We calculate the profit of each of the SSPs in terms of the price charged from the registered end-users, rent paid by the sensor and vehicle owners, and setup and maintenance costs. Inspired by the profit of the SSPs calculated in Safe-Passé and Safe-aaS, we mathematically represent the profit of SSPs as:

$$PR_j = \sum_{p=1}^{z} P_p - \sum_{k=1}^{s} R_k - C_{mt} \tag{9}$$

where P_p represents the price charged from the p^{th} end user. C_{mt} represents the setup and maintenance cost of the network components. R_k^j is the rent paid to the j^{th} SSP by the k^{th} sensor/vehicle owner and s represents the total number of sensor and vehicle owners.

Algorithm 1 depicts the transmission of decision generated to the j^{th} end-user. Step 1 states the transmission of sensed data by the sensor node. The registered end-user selects the decision parameters for generating the on-road safety-related decisions as discussed in Steps $2-5$. Step 6 describes the selection of the micro-services as per the requirement of the end-user for decision generation. Step 7 discusses the generation of safety-related decisions using DNN. Finally, in Step 8, the generated accurate decision is transmitted to the k^{th} end-user.

Algorithm 1 Safe-aaS prediction using deep learning and micro-service

INPUTS: $\mathbb{S}_t$, $\mathbb{B}_t$, $\mathbb{A}_t$
OUTPUT: Decision predicted by DNN
PROCEDURE:

1: The sensed data is transmitted to the edge nodes/cloud
2: **for** j = 1 to n **do** ▷ n: Number of end-users
3: **for** i = 1 to y **do** ▷ n: Number of decision parameters
4: Decision parameters selected by the end-user, as per Equation (1).
5: **end for**
6: The micro-services are selected by the j^{th} end-user's requirement, as per Equation (2)
7: Compute decision using DNN, as per Equation (3)
8: Accurate decision is transmitted to the j^{th} user
9: **end for**

IV. Performance Evaluation

A. Simulation Design

We evaluate and analyze the performance of the proposed scheme, Micro-Safe, in this section. For simulation, we consider simulation area of $1000 \times 1000m^2$ having a 6G network with $50-250$ registered end-users. The available data packets are 8 kB in size. Further, we execute 100 simulation runs with a confidence interval of about 95%. The simulation parameters used at the time of performance evaluation are listed in Table III. As both static and mobile sensor nodes are present in Safe-aaS, therefore, we use Gauss Markov mobility model [26] for calculating the speed and direction of the mobile nodes, which is mathematically represented as:

$$s_i^t = \alpha s_i^{(t-1)} + (1-\alpha)\bar{s}_i + \sqrt{(1-\alpha^2)} \times s_i^{x(t-1)} \tag{10a}$$

$$d_i^t = \alpha d_i^{(t-1)} + (1-\alpha)\bar{d}_i + \sqrt{(1-\alpha^2)} \times d_i^{x(t-1)} \tag{10b}$$

where α is the tuning parameter. The mean speed and direction of the mobile sensor nodes are represented by $\bar{s}_i$ and $\bar{d}_i$, respectively. Further, the random variable from a Gaussian distribution, $s_i^{x(t-1)}$ and $d_i^{x(t-1)}$, assigns randomness to the speed and direction of the mobile sensor node at the $(t-1)^{th}$ time instant. Fig. 3 represents the path of three mobile nodes generated using the Gauss Markov mobility model, considering the value of α as 1. We observe a randomness behavior in the mobility of these mobile sensor nodes.

TABLE III: Simulation Parameters

Parameter	Value
Number of end-users	$50-250$
Packet size [27]	8KB
Mobility model of ANs	Constant Position
Edge technology	6G Access Node
User's deployment strategy	Uniform-Random

B. Benchmarks

For evaluating and analyzing the proposed scheme, Micro-Safe, we consider two existing schemes as benchmarks - Safe-Passé [7] and ITS-Cloud [8]. Roy and Misra [7] proposed a dynamic handoff mechanism for provisioning safety services in a 5G-based ITS environment. In a practical scenario, the region where the SSP provides services is finite. Therefore, the safety services provided to the end-users may be interrupted, when they cross from one region to another. The authors considered charges due to selection of services for a round trip/one-way, local/intercity, and during peak/off-peak hours to estimate the price charged from end-users and profit of SSP. On the other hand, Bitam and Mellouk [8] proposed a new cloud computing model to upgrade the consequences associated with road transportation. Further, they applied the concept of static and dynamic cloud-based sub-models. However, none of these existing schemes considered the application of microservices and deep learning to improve the throughput, data rate, minimize the delay incurred, and accuracy of the proposed scheme. We represent the benchmark schemes as Safe-Passé [7] and ITS-Cloud [8] respectively. We evaluate the proposed scheme in terms of the delay incurred, the energy consumed, the data rate, the packet delivery ratio, and the throughput.

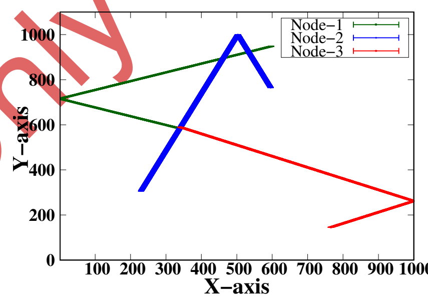


Fig. 3: Path of three mobile nodes using Gauss Markov mobility model

C. Results

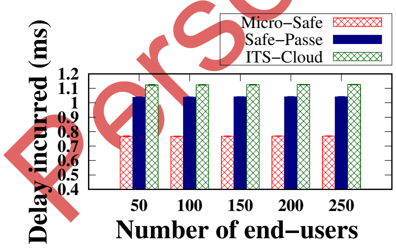
We evaluate *Micro-Safe* using different performance metrics such as accuracy, energy consumed, data rate, throughput, price charged from the registered end-users, and profit of SSP, in this section which are described as follows:

Accuracy in on-road prediction: One of the primary objectives of Micro-Safe is to render customized safety-related decisions to the registered end-users. We apply DNN in our proposed microservices-enabled scheme to evaluate the accuracy of the generated decisions. We used a vehicular sensor data set [28] to perform a comparative study among the different components of DNN and select the best suitable one for Micro-Safe. We consider the $opel\_corsa\_1$ csv file present in the dataset. Further, we use the dataset for representing the on-road sensed data and analyze the effectiveness of implementing DNN with the change in the internal parameters. These internal parameters encompass the learning rate and the activation function. The dataset consists of 14 numeric attributes which represent road and vehicle sensed data and 3 target attributes including "road surface condition classes", "traffic congestion condition class", and "driving style class" which are predicted using DNN. We obtain the classification report for various activation functions such as 'reLU', 'logistic', and 'tanh', and 'adam' as the solver for weight optimization. We modify the learning rate of DNN and perform a comparative analysis as illustrated in Table IV. Additionally, Table IV provides information of the classification report on the training and testing data set consisting of 504125 and 216055 tuples, respectively. We observe that the overall accuracy increases for a learning rate of 0.001. Moreover, with the increase in the learning rate, precision, recall, and F1-score value increase. We also observe that the precision, recall, and F1-score trend does not fluctuate significantly with the change in activation function on testing dataset. As per the existing literature, 'ReLU' activation function performs better [24]. Thus, we infer that DNN with 'ReLU' as an activation function and with a learning rate of 0.001 is suitable for supplying safety-related decisions to the registered end-users.

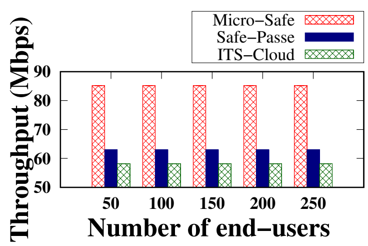
Latency: We define latency as the total time required in processing the decision parameters requested by the registered end-users. The proposed scheme, Micro-Safe introduces the concept of microservices in the traditional Safe-aaS architecture to minimize the latency incurred in generating a decision. Fig. 4(a) depicts the changes in the overall network latency in case of Micro-Safe and other existing schemes. We observe that as the number of registered end-users increases, the number of flows within the network also increases significantly.

TABLE IV: Classification report for DNN

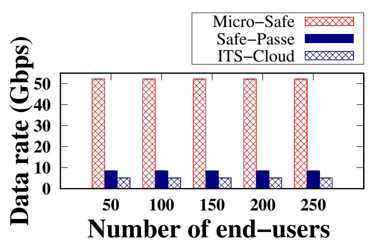
Activation function	Learning rate	Data set	Precision	Recall	F1-score	Support
ReLU	0.01	Training set	0.96	0.96	0.96	504125
ReLU	0.01	Testing set	0.96	0.96	0.96	216055
ReLU	0.001	Training set	0.97	0.97	0.97	504125
ReLU	0.001	Testing set	0.97	0.97	0.97	216055
Logistic	0.01	Training set	0.97	0.97	0.97	504125
Logistic	0.01	Testing set	0.97	0.97	0.97	216055
Logistic	0.001	Training set	0.98	0.98	0.98	504125
Logistic	0.001	Testing set	0.97	0.97	0.97	216055
tanh	0.01	Training set	0.96	0.96	0.96	504125
tanh	0.01	Testing set	0.96	0.96	0.96	216055
tanh	0.001	Training set	0.97	0.98	0.97	504125
tanh	0.001	Testing set	0.97	0.97	0.97	216055



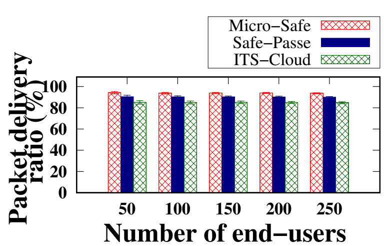
(a) Delay incurred



(b) Throughput



(c) Data rate



(d) Packet delivery ratio

Fig. 4: Variation of various network parameters

However, the integration of 6G network infrastructure with microservices-based Safe-aaS resulted in the improvement of the overall latency to transmit the data packets and execution of the complex task. Hence, Micro-Safe shows a significant decrease in the reduction of latency by 26.1% and 31.2% respectively, compared to Safe-Passé and ITS-Cloud.

Energy consumption: We represent the energy consumption of the network as the cumulative sum of energy required in transferring the sensed data acquired by the sensor nodes to the edge nodes/cloud, processing it, extraction of the information, and finally transmitting the generated decision to the registered end-users. Fig. 5 depicts the variations in the overall energy consumption in the network with the surge in the number of end-users. We observe that the proposed scheme, Micro-Safe shows a significant decrease in the energy consumption by 22.1% and 29.9% respectively, compared to Safe-Passé and ITS-Cloud. One of the possible reasons behind this is that the combination of microservices in a 6G environment leads to the reduction in overall energy consumption within the network. On the other side, the energy consumed by the existing schemes is comparatively higher because Safe-Passé [7] is designed for 5G infrastructure and ITS-Cloud [8] use the traditional 4G infrastructure. Therefore, Micro-Safe demonstrates comparatively better performance compared to the existing state-of-the-art.

Data rate: We represent data rate as the number of bits transmitted from one device to another present within the network. Fig. 4(c) represents the changes in the data rate with the surge in the number of registered end-users. We notice that the data rate of our proposed scheme, Micro-Safe increases by 83.8% and 90.3% respectively, compared to the existing state-of-the-art. The possible reason behind this is that Micro-Safe works in the 6G network infrastructure, which utilizes a higher spectrum by allowing a higher data rate of information transformation. On the other hand, the data rate of the existing schemes, Safe-Passé and ITS-Cloud, is low compared to Micro-Safe, because they utilize 5G and 4G network environment.

Packet delivery ratio: We define packet delivery ratio as the ratio of the total number of data packets received by the edge nodes/cloud to the original number of data packets transmitted by the sensor nodes. Fig. 4(d) demonstrates the variations in the packet delivery ratio with the surge in the number of registered end-users within the network. We see that the packet delivery ratio in Micro-Safe increases with respect to the existing state-of-the-art schemes by 3.7% and 8.9% respectively. This is because the proposed scheme, Micro-Safe, works in a 6G environment that leads to faster processing and results in an increase in the overall packet delivery ratio.

Throughput: We estimate throughput of the proposed scheme in terms of the total volume of data transmitted in a specified time duration within the network. Fig. 4(b) represents the change in the throughput experienced by Micro-Safe and the existing benchmark schemes with the surge in the number of registered end-users. We observe that the throughput is notably increased by 26.1% and 31.7% respectively in our proposed scheme, Micro-Safe, in comparison to the existing schemes, Safe-Passé and ITS-Cloud. This is because the proposed scheme, Micro-Safe, provisions safety services in a 6G environment, which results in the increased throughput. On the other hand, Safe-Passé and ITS-Cloud consider 5G environment and traditional network infrastructure respectively, which results in the lower throughput compared to Micro-Safe scheme.

Price charged: Fig. 6 depicts the change in the overall price charged with the rise in the overall decision parameters selected at 15 different time instants. We observe that as the number of selected decision parameters (DP) increases, the price charged increases. However, there exist slight randomness in the price charged at every instant of time. The probable reason behind this pattern is that with the surge in the number of decision parameters selected, the accuracy of the decision generated increases. On the other hand, the price charged from the end-users is dependent upon the number of decision parameters opted by them. The demand of these end-users may fluctuate depending upon their requirement, up to their destination. Hence, the price charged from them also fluctuates.

Profit: Profit of a SSP is the outstanding amount of the payment received from the end-users and the rental fee paid to the sensor owner and vehicle owners. Further, the maintenance and other associated charges are also deducted from the profit of the SSP. Fig. 7 represents the variations in the profit of SSP with the change in the location and time of end-user, as per the service requirement. We consider LT_1 as the most common destination location at a particular time instant, followed by LT_2, LT_3, and LT_4 which are the least expected destination location. Additionally, the price charged for traveling to these location is more compared to the LT_1. We observe that the profit significantly increases when the equal number of end-users travel to the least expected location compared to the most frequent ones. This is because the end-user is charged more while traveling to the least expected destination site for any particular time instant. However, due to the increase in the number of end-users traveling to the most common destination, the overall profit of SSP does not hamper with less price charged from these end-users. Fig. 8 represents the profit of the SSP with the variations in the number of registered end-users from 50 to 250. We observe that in Figs. 8(a)-8(c), with the rise in the number of decision parameters in the simulation environment, the profit of SSP increases significantly. One of the probable reason behind such a trend is with the rise in the number of selected decision parameters, the end-users possess options to select multiple decision parameters. As a result, the price charged from the registered end-users increases and the profit of SSP improves. However, with the rise in the number of sensor/vehicle owners, the profit of a SSP decreases.

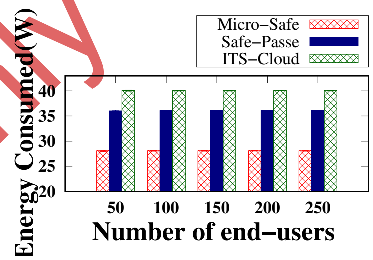


Fig. 5: Energy consumed

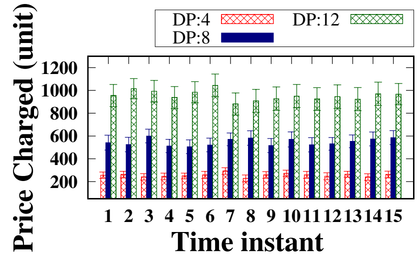


Fig. 6: Price charged from end-users [DP: Number of decision parameters]

V. Conclusion

In this paper, we addressed the problems of scalability and accuracy of generated decisions of the Safe-aaS platform and designed a microservices- and deep learning-based Safe-aaS. The decisions provided to the registered end-users are time-critical, hence, timely delivery and maintaining the accuracy of generated decisions is necessary. Considering these facts, we establish the concept of microservices in the Safe-aaS platform. We apply state space model to design the microservice-enabled application layer. We also group the locations and time duration based on the demand of end-users. Furthermore, we implement a deep neural network (DNN) for improving the accuracy of the generated decision.The simulation-based analysis of Micro-Safe demonstrates that the incorporation of microservices and deep learning in a 6G-enabled environment results in reduced latency and increased throughput. Additionally, the accuracy of the generated decision has improved significantly.

In the succeeding work, we tend to implement a deep reinforcement learning algorithm to eliminate the requirement

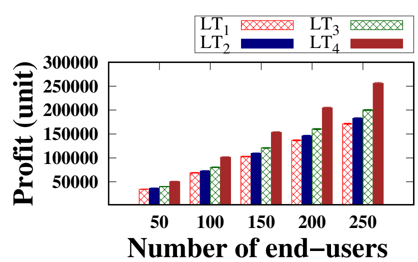
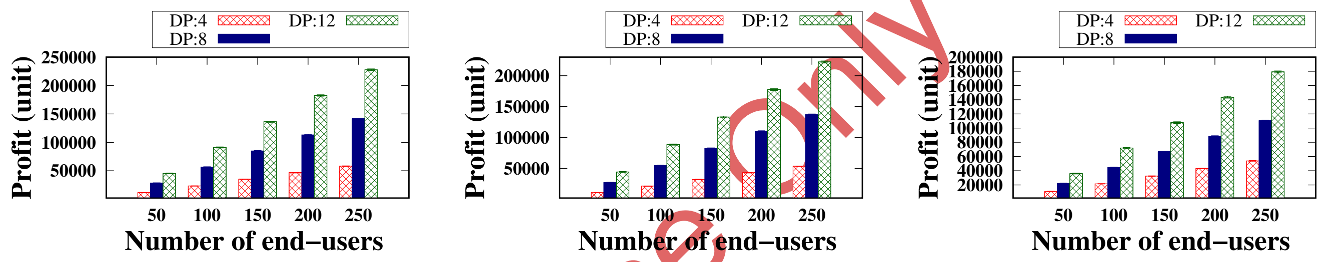


Fig. 7: Profit of SSP with variation in location and time [LT: Location and time of end-users]



(a) 3 sensor owners

(b) 6 sensor owners

(c) 9 sensor owners

Fig. 8: Variation of profit with respect to number of sensor/vehicle owners [DP: Number of decision parameters]

of training data set for prediction and improvement of the learning capability. Furthermore, we plan to implement SDN infrastructure to remove the heterogeneity that exists within the edge layer. The SDN-based edge layer provides the view of the entire network to the controller, which improves the overall decision-making process. Finally, we plan to incorporate the quality of sensed data. Based on the sensed data, the decision is generated. Therefore, the quality of raw sensed data is an important aspect. We plan to introduce an incentive for the vehicle owners for providing accurate data to the Safe-aaS platform and propose a differentiated pricing scheme.

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