Q-Safe: QoS-Aware Pricing Mechanism for Provisioning Safety-as-a-Service

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Abstract—In this paper, we propose a Quality of Service (QoS)-aware pricing mechanism, termed as Q-Safe, for provisioning safety-related decisions to the end-users. Typically, a Safety-as-a-Service (Safe-aaS) platform provides real-time decisions to the customers, as per their requirement. At the time of registration of the use, customers provide the details of their source and destination locations, chose certain decision parameters, and make payment through the Web portal. Based on these selected decision parameters, the decision is generated. In the proposed pricing scheme, we consider the presence of multiple Safety Service Providers (SSPs) in the Safe-aaS platform. Therefore, the end-users possess the opportunity to select a SSP, depending on the price charged by the latter. On the other hand, the end-users may compromise with the quality of the decision provided through the selection of the available safety services at a low cost. Considering road transportation as the application scenario of Safe-aaS and to address these above-mentioned issues, we propose a dynamic pricing scheme, Q-Safe. We introduce the concept of varying prices to be charged by the SSPs for each of the decision parameters, based on the fluctuation in the value of these parameters with time. Each of the end-users selects certain decision parameters among the ones displayed in the Web portal. Thereafter, the SSPs suggest decision parameters to the end-users depending upon their present geographical location. To model these interactions between the SSPs and the end-users, we map the scenario with Non-Cooperative *Multiple Leader Multiple Follower Stackelberg* game, where the SSPs act as leaders and the end-users act as followers. Exhaustive analysis of our proposed scheme demonstrates that the average profit of the SSP is improved by 70.88%, 52%, and 77% compared to the Per-Subscriber model [1], PRIME [2], and RegPrice [3] in the presence of 200 sensor nodes in the simulation environment. Additionally, we characterize the errors during the estimation of energy consumed, utility, effective time, and total cost, with the increase in the number of end-users.

Index Terms—Road Transportation, Service Oriented Architecture (SOA), Decision Virtualization, Decision parameters, Quality of Service (QoS)

1 Introduction

With the recent advancements in the diverse Internet of Things (IoT)-based technologies such as Intelligent Transportation System (ITS) [4] and Advanced Driver Assistance System (ADAS) [5]–[7], the on-road traffic conditions, as well as the safety of drivers have improved. Further, the rate of increase in the number of on-road accidents has also reduced significantly. The prior intimation of the safety-related information to the drivers may result in minimizing the rate of accidents. Safe-aaS [8]–[10] is one of the unique platforms, which provides safety-related decisions to the end-users, as per their requirements. Considering road transportation as the application scenario of Safe-aaS, we design a QoS-aware pricing mechanism for provisioning customized, virtualized decisions to the end-users.

In Safe-aaS, the end-users provide the source and destination locations, select certain decision parameters, and make payment. Based on their selected decision parameters, the decision is provided to the end-users. Typically, in a road transportation environment the decision parameters such as the presence and depth of potholes, the location of manholes, and the sharp turnings on road, which do not fluctuate with time are termed as low-cost parameters. On the other hand, the decision parameters such as weather conditions and road congestion, whose value varies frequently with time are known as high-cost parameters. The end-users have the flexibility to select both high- and low-cost parameters. The SSPs suggest the end-users with certain decision parameters, as per their geographical location. Therefore, the SSPs may possess the tendency to suggest only the high-cost parameters to increase their profit. The end-users may select only the low-cost parameters to avail safety services at a cheaper price. To maintain a balance between the profit of SSPs, QoS of services provided, and prices charged from end-users, we propose a pricing scheme.

Existing researchers proposed certain schemes, real-time assistance systems, and infrastructures to minimize the number of on-road accidents, forecast and evaluate the traffic measures, provide alerts to the drivers, and recognize their driving pattern [4], [5], [11]. Safe-aaS [8] is a newly developed, unique platform which provides a customized safety-related decision to the end-users. Founded on the concept of decision virtualization, the same decision is shared among multiple end-users. The key actors of Safe-aaS are – end-users, sensor owners, vehicle owners, and SSPs. The end-users select certain decision parameters and make payments to the Safe-aaS platform. The value of some of these decision parameters does not fluctuate frequently with time. On the other hand, sensor and vehicle owners rent their sensor nodes and receive payment from SSP. The remaining amount from the payment received from end-users and rent paid to owners is the profit of the

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TABLE 1: Summary of the existing research works on road safety and pricing

Applications	IoT	Pricing	Fog/cloud	QoS	Latency
Safe-aaS [10], [24]	✓	D	✓	×	✓
mSe-aaS [11]	✓	D	✓	✓	✓
Se-aaS [16]	✓	D	✓	×	×
Smart road pricing [19], [20]	✓	D	✓	×	×
Resource allocation [26]	✓	D	×(edge)	×	✓

[Legend: Pricing - Static (S)/ Dynamic (D)]

SSP. Therefore, complex monetary transactions occur among these actors of Safe-aaS. The demand of end-users vary dynamically. Further, the SSPs may demand higher prices from the end-users to increase their profit. Therefore, to provide customized prices to the end-users maintaining the quality of service is challenging. None of the existing pricing schemes are applicable for the Safe-aaS platform. Motivated by these facts, we design a QoS-aware pricing scheme for Safe-aaS, which satisfies both the SSPs as well as end-users.

In this paper, we propose a QoS-aware pricing mechanism, Q-Safe, which satisfies both the SSPs and the end-users. The proposed scheme maintains a trade-off between the minimum price charged from the end-users and the QoS of the decision generated. The SSPs suggest certain decision parameters to the end-users, based on their present geographical location, after they have submitted their selected decision parameters. Depending upon the optimal number of low- and high-cost decision parameters selected, the minimum price to be charged from the end-users is estimated. Therefore, we primarily aim to address the following issues: (a) how to provide safety services to the end-users at a lower price such that the quality of service is maintained as well as the SSP is satisfied? (b) how to select the optimal number of low price and high price decision parameters to provide safety services at low prices? The specific *contributions* of this work are as follows:

- To maintain the QoS of the decision provided to the end-users, we design a suggestion-based pricing scheme. The SSPs suggest decision parameters to the end-users depending upon their geographical location. We categorize the decision parameters selected by the end-users as *low-cost* and *high-cost* decision parameters. Further, we estimate the effective total cost from the optimal number of selected decision parameters.
- We consider the presence of multiple SSPs in our scenario. To map the interactions among these SSPs and the end-users, we apply Non-Cooperative *Multiple-Leader-Multiple-Follower* Stackelberg game-theoretic fabric, where the SSPs act as leaders and the end-users act as followers. Additionally, we prove the existence of Stackelberg equilibrium in our scenario.
- In Safe-aaS, the end-users possess a tendency to avail the safety services at a cheaper price, while the SSPs desire to enjoy higher profit. To satisfy both the SSPs and the end-users, we formulate the total cost as an optimization function. Further, we apply the Lagrangian function and the Karush-Kuhn-Tucker (KKT) conditions to obtain the optimal number of low-cost and high-cost decision parameters, for which the price charged by the SSPs is minimum.
- We evaluate and analyze the proposed scheme, Q-Safe, in Python considering various metrics. Extensive analysis results of our proposed scheme proved to be beneficial in terms of the average profit of the service provider and the utility of the end-user, compared to the Per-Subscriber model [1], RegPrice [3], and Prime [2].

2 Related Work

In this section, we discuss some of the existing pricing mechanisms such as static [12] and dynamic [13] pricing schemes, resource utilization-based pricing mechanisms for cloud [1], [14], [15] and pricing schemes for sensor cloud platform [16]–[18]. Various smart road pricing schemes were also proposed to prevent toll evasions, optimal traffic flow management, optimal congestion control pricing, and dynamic parking management [19]–[23].

Certain schemes and real-time assistance systems were proposed to ensure the safety of drivers. A unique platform, Safety-as-a-Service (Safe-aaS), was proposed by Roy *et al*. [3], [8]–[10], [24], which provides customized safety-related decisions to the end-users. The authors introduced the concept of decision virtualization using which multiple end-users receive the same decision. Tian *et al*. [11] studied the various consequences associated with the detection of the drivers' distraction on road and upgrade their safety. The authors studied the various available data sets to study the probabilities of crash and near-crash events. On the other hand, to securely manage the traffic in smart cities and obstruct toll evasion violations, Bouchelaghem and Omar [19] proposed a smart road pricing scheme. The proposed approach works under fully distributed threshold-based control system. Similarly, Tettamanti *et al*. [20] designed a dynamic pricing scheme to optimally manage the traffic. The authors considered the time-delay effect of traffic forecasting and performed simulation on real-world traffic test networks applying various traffic control methods.

Various pricing schemes were designed by the researchers for WSNs utilizing cloud services [1], [25], at the network edge for low latency applications [26], and dynamic pricing in mobile social network [27]. Guijarro *et al*. [1] designed a platform, which acts as a broker between the human users and the WSNs. The proposed scheme maximizes the profit of both the users and the WSNs. Their proposed platform acts as a monopolist and circulates the price charged from the users and paid to the WSNs. Similarly, with the widespread emergence of edge computing for low-latency applications in the IoT scenario, the appropriate allocation of resources has become essential. Baek *et al*. [26] proposed three dynamic pricing mechanisms for resource allocation at the edge of the network. On the other hand, cloud service providers charge for the resources depending upon the assigned CPU frequency. Lucanin *et al*. [28] considered the CPU frequency, estimated the power dissipated in a multi-core CPU machine, and proposed a pricing scheme. On the other hand, in cloud computing the service providers primarily provide preservation of available resources and on-demand plans to the consumers. Ardagna *et al*. [29] proposed two solution approaches for provisioning services in the form of generalized Nash game and proved the existence of equilibrium. Further, there exists heterogeneous types of sensor nodes and multiple sensor owners in a sensor cloud platform. Considering such an oligopolistic market scenario, Chakraborty *et al*. [16] proposed a dynamic pricing scheme to impose trust among the sensor owners to maintain the QoS requirements for provisioning Se-aaS services. Similarly, Roy *et al*. [2] proposed a pricing scheme for provisioning mobile sensors-as-a-service (mSe-aaS) such that the profit is optimally distributed among the different actors.

Synthesis: The researchers addressed various problems related to pricing in the domain of Wireless Sensor Network (WSN) and cloud platform such as profit maximization of users and service providers [1], maintenance of QoS parameters [18], resource allocation [26], dynamic pricing for revenue maximization [27], and performance-based pricing [28]. However, none of these above pricing schemes provide customized prices to the end-users. Considering the road transportation scenario, various pricing schemes were proposed by researchers for on-road traffic flow management [20], optimal congestion control [21], and dynamic parking management [23]. Safe-aaS is a newly developed, unique platform, which provides customized safety services dynamically to the end-users. Founded on the concept of decision virtualization, these generated decisions are provided to multiple end-users simultaneously. Therefore, in case of Safe-aaS platform, providing customized prices to the end-users and maintain the QoS is a complicated task.

3 Q-Safe: The System Model

3.1 The System Architecture

Safe-aaS infrastructure is implemented in ITS application area. Typically, Safe-aaS is a five-layered architecture – device, edge, decision, decision virtualization, and application, as illustrated in Fig.1. The device layer comprises heterogeneous types of static and mobile sensor nodes, which sense and transmit their sensed data to the edge/cloud. Static sensor nodes are deployed at a particular geographical location, while mobile sensor nodes are placed into the vehicles. Based on their time-critical nature, these sensed data are primarily processed at the edge nodes. Further, these primarily processed data from the edge layer/cloud are transmitted to the decision layer, where the decision is generated. Finally, the logical mapping of the decision parameters requested by the end-users and the decision generated is done in the decision virtualization layer. On the other hand, the application layer acts as the interface between the end-users and the Safe-aaS infrastructure. The

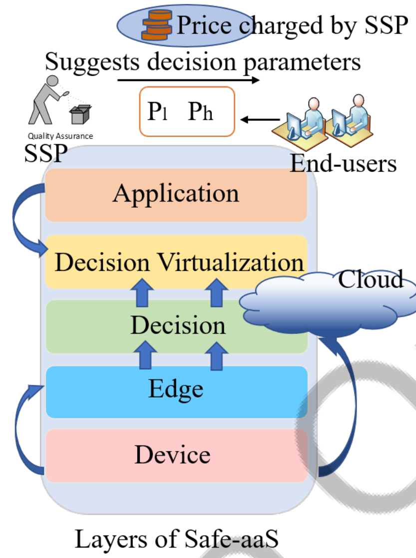


Fig. 1: Q-Safe: The System Architecture

end-users select certain decision parameters, register, and make payments through the Web portal.

On the other hand, various business entities such as sensor owners, vehicle owners, end-users, and safety service providers (SSPs) exist in the Safe-aaS platform, and monetary transactions take place among them. The sensor and vehicle owners rent their sensor nodes and receive an amount given by the SSPs. Further, the end-users are benefited from these safety services on pay-per-use basis. Therefore, the remaining amount from the payment done by the end-users and the rent paid by the sensor and vehicle owners is the profit of the SSP. The SSPs possess a tendency to maximize their profit, while the end-users expect to avail these services at a lower price. However, as safety-related decisions are delivered to the end-users, it is important to maintain the Quality of Service (QoS) of the decisions provided to them. In this scheme, Q-Safe, the SSPs suggest decision parameters to the end-users, based on their geographical location. We classify the decision parameters as *low-price* and *high-price*. The decision parameters whose values does not fluctuate frequently with time are termed as *low-price* parameters. On the other hand, the values of *high-price* parameters vary with time. Depending upon the decision parameters selected by the end-users and modifications done after incorporating the suggestion of the SSPs as illustrated in Fig. 1, the price is charged from the end-users. We propose this QoS-aware pricing scheme, Q-Safe, to minimize the total costs incurred by the end-users, through the optimal selection of high-price and low-price decision parameters.

3.2 Problem formulation

Let $\mathbb{E} = \{e_1, e_2, \cdots, e_n\}$ be the set of n registered end-users of the Safe-aaS platform. These registered end-users select certain decision parameters from the set $\mathbb{P}$, where $\mathbb{P} = \{p_1, p_2, \cdots, p_m\}$. On the other hand, $\mathbb{N}_s$ represents the set of heterogeneous sensor nodes present in the device layer of Safe-aaS. As discussed in Section 3.1, the SSPs set the price for each of these decision parameters, based on the fluctuation in the value of these parameters with time. Further, the SSPs maintain a mapping between the decision parameters and the price. We characterize this mapping as the one-to-one map. Each of the decision parameters possesses a unique price. On the other hand, based on the price of the decision parameters set by the SSPs, we classify these parameters as – (i) $\mathbb{P}_l$ - the set of decision parameters with low-price, and (ii) $\mathbb{P}_h$ - the set of decision parameters with high-price. $\mathbb{C}_h$ is the cost of a high-price decision parameter, $\mathbb{P}_h^i$. Similarly, $\mathbb{C}_{low}$ be the cost of a low-price decision parameter, $\mathbb{P}_l^i$. The proposed pricing scheme, Q-Safe, has two perspectives – (a) End-user/customer and (b) Safety Service Provider.

End-user's perspective: Suppose, the number of parameters selected by an end-user is $\mathbb{P}_s$. The properties of these selected parameters are characterized as follows:

Property 1. *$\mathbb{P}_l \subset \mathbb{P}$ and $\mathbb{P}_h \subset \mathbb{P}$. Therefore, $\mathbb{P} = \mathbb{P}_l \cup \mathbb{P}_h$, where $\mathbb{P}_l \cap \mathbb{P}_h$ is not possible, as there are no common parameters between these two sets.*

Property 2. *The cost of low-cost decision parameters are always lower than the cost of high-price decision parameters, such that $\mathbb{C}_{low} < \mathbb{C}_{high}$, and $(\mathbb{C}_{low}, \mathbb{C}_{high}) > 0$.*

Let $\mathcal{L}_a^i$ and $\mathcal{H}_b^i$ are the number of low- and high-cost decision parameters selected by the end-users from the set $\mathbb{P}_l$ and $\mathbb{P}_h$, respectively. Therefore, the total number of parameters selected by the i^{th} end-user is

$$\mathbb{P}_s^i = \mathcal{L}_a^i + \mathcal{H}_b^i \tag{1}$$

where $\mathcal{L}_a^i$ and $\mathcal{H}_b^i$ are the number of parameters from the set $\mathbb{P}_l$ and $\mathbb{P}_h$, respectively.

Safety Service Provider's perspective: The SSPs are responsible for the estimation of the final price for the end-users and check the utility of the available resources. The decision is generated from the data sensed by heterogeneous sensor nodes. We consider $\mathbb{N}_l$ as the number of sensor nodes involved to provide low-price decision parameters and $\mathbb{N}_h$ for the high-price decision parameters. Therefore, the total number of sensor nodes utilized for low-cost and high-cost decision parameter depend upon the selected decision parameters is described as,

$$\mathcal{N}_{tot} = \mathcal{L}_a^i \times \mathbb{N}_{la} + \mathcal{H}_b^i \times \mathbb{N}_{hb} \tag{2}$$

The SSP maintains a mapping between the decision parameters and price in $\mathbb{M}_{pp}$.

$$\mathbb{M}_{pp}[i][j] = \begin{cases} \mathbb{C}_{low}, & \text{parameter of } \mathbb{P}_l \\ \mathbb{C}_{high}, & \text{parameter of } \mathbb{P}_h \end{cases} \tag{3}$$

The sensor nodes in the device layer are mapped with the decision parameters using their unique identification number. This mapping is maintained by the SSPs, which is mathematically expressed as,

$$\mathbb{M}_{sp}[i][j] = \begin{cases} 1, & \text{if } p_i \text{ is generated from } \mathbb{N}_{sum_j} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Centralized Service Utility: In this proposed approach, we aim to satisfy both the SSPs and the end-users, such that both are benefited. The SSPs deliver the generated decisions to the end-users, and price is charged from them. Based on the number of active sensor nodes at any time instant, the effective energy of the j^{th} sensor node is estimated as,

$$\varepsilon_j^{eff} = \frac{\varepsilon_j^{resi} - (\varepsilon_j^{sense} + \varepsilon_j^{trans})}{\varepsilon_j^{init}} \tag{5}$$

where ε_j^{resi}, ε_j^{sense}, ε_j^{trans}, and ε_j^{init} represent the residual energy, energy consumed for sensing, energy required for transmission, and the initial energy of the j^{th} sensor node at any time instant. Therefore, effective energy consumed to deliver safety services to the i^{th} end-user for n sensor nodes being utilized to generate the decision is $\varepsilon_i^{eff} = \sum_{j=1}^{n} \varepsilon_{i,j}^{eff}$. Further, to provide real-time safety services, any delay may result in a hazardous situation.

Algorithm 1 Q-Safe: Price charged from end-users

INPUTS: $\langle$source, destination$\rangle = \langle S_i, d_i \rangle$, P_l, P_h, $\mathcal{L}_a^i$, $\mathcal{H}_b^i$.
OUTPUT: Price charged from i^{th} end-user.
PROCEDURE:
1: **for** i = 1 to n **do** ▷ n: Number of end-users
2: **for** $j = 1$ to k **do** ▷ k: Number of decision parameters displayed in the Web portal
3: i^{th} end-user selects decision parameters
4: $\mathbb{P}_s^i$ is computed
5: Estimate price charged from i^{th} end-user and his/er utility
6: **while** time = τ **do** ▷ τ: short time duration
7: SSP suggests j parameters to i^{th} end-user, based on $\langle S_i, d_i \rangle$
8: **if** i^{th} end-user agrees **then**
9: Price and Utility is estimated
10: Decision generated
11: **else**
12: Go to Step 5
13: **end if**
14: **end while**
15: **end for**
16: **end for**

Algorithm 1 provides an overview of the minimum price charged from the end-users. Steps $3-5$ computes the price charged by the end-users, as per the decision parameters selected. In Steps $6-14$, a periodic time is used for price re-evaluation. During this period, the minimum price charged from the end-users is estimated by incorporating the decision parameters suggested by the SSPs, until the optimal number of high-price and low-price decision parameters is computed.

The effective time required for this whole process of computation of price charged from the end-users is mathematically represented as,

$$\mathbb{T}_i^{eff} = \frac{\mathcal{N}_{p,i} \times \mathbb{T}_{fixed,i} + \mathbb{T}_{eval,i} + \mathbb{T}_{r,i}}{\mathbb{T}_{comp,i}} \tag{6}$$

where $\mathcal{N}_{p,i}$ is the number of times re-evaluation request is processed. $\mathbb{T}_{fixed,i}$ is the fixed amount of time required for each time of re-evaluation. $\mathbb{T}_{eval,i}$ is the utility evaluation time for each period, $\mathbb{T}_{r,i}$ is the response time, and $\mathbb{T}_{comp,i}$ represents the total computation time. Therefore, the utility of the safety service to be provided to the i^{th} end-user is represented as,

$$\mathcal{U}_i = \mathcal{N}^i_{tot} \times \left(\lambda_1 \times \varepsilon^{eff}_i + \frac{\lambda_2}{\mathbb{T}^{eff}_i}\right) \quad (7)$$

where λ_1 and λ_2 represent the constants for the rate of change of effective energy of the sensor nodes and effective time, such that $1 > (\lambda_1, \lambda_2) > 0$.

3.3 Pricing Strategies

The end-users and the SSPs interact among them and agrees to the pricing scheme when both are satisfied. The end-users have the intention to select the low-price parameters, such that the price charged by the SSPs is minimized. On the other hand, the SSPs may tend to increase their profit by suggesting high-price decision parameters to the end-users. Therefore, the price charged from end-users must satisfy both the end-users and the SSPs. Considering the above scenario, we design three cases which are discussed as follows.

- *Case 1:* When an end-user selects all low-price parameters, the end-user have to compromise with the real-time safety service, however they have the option to select other parameters. In such a case, the initial price charged by the SSP is represented as,

$$\mathcal{C}_{init} = \mathcal{L}_a \times \mathbb{C}_{low} + \mathbb{C}_{opt} + \mathbb{C}_p \quad (8)$$

  where $\mathbb{C}_{opt}$ represents the optional cost of other decision parameters selected by the end-users and $\mathbb{C}_p$ is the processing cost.
- *Case 2:* When an end-user selects mixed parameters – both low- and high-price parameters. This situation provides average quality of service to the end-users within affordable price. In this case, the initial price charged by the SSP is,

$$\mathcal{C}_{init} = \mathcal{L}_a \times \mathbb{C}_{low} + \mathcal{H}_b \times \mathbb{C}_{high} + \mathbb{C}_p \quad (9)$$

- *Case 3:* When an end-user selects only high-cost parameters, the initial price charged by the SSP is mathematically represented as,

$$\mathcal{C}_{init} = \mathcal{H}_b \times \mathbb{C}_{high} + \mathbb{C}_{opt} + \mathbb{C}_p \quad (10)$$

After all the above cases, we represent the total price charged by any SSP from an end-user for these above-mentioned cases as follows –

$$\mathcal{C}_{total} = \sum_{j=1}^{\mathcal{N}_p} (\mathcal{C}^j_{init} + \mathcal{C}^j_r) \quad (11)$$

where $\mathcal{C}^i_r$ is the re-evaluation cost for $\mathcal{N}_p$ re-evaluation requests. To maintain the quality of service (QoS) provided to the end-users, satisfy the utility of service provided to them, and select the appropriate number of high- and low-price decision parameters is an essential aspect of concern. Therefore, a trade-off is to be maintained between the satisfaction of the end-users and the price charged by the SSPs.

$$\mathcal{C}^i_{total} = \beta \times \mathcal{C}^i_{init} \times \mathcal{U}_i + \mathcal{C}^i_r \quad (12)$$

3.4 Quality of Service (QoS)

Typically, in Safe-aaS, depending upon the decision parameters selected, the end-users make payment. In Q-Safe, the SSPs suggest the end-users certain decision parameters. Further, QoS depends on the efficiency of the heterogeneous sensor nodes. In a recent research work, Roy *et al.* [2] proposed an optimal pricing scheme considering the quality of service. The authors designed QoS in terms of efficiency of sensor nodes. Further, the service return of the service provider (SCSP) is measured in terms of the type of end-users and time factor. Motivated by this concept, we mathematically define the efficiency, $\mathbb{E}^i$, and quality of service, $\mathcal{Q}^i$ for i^{th} end user as,

$$\mathbb{E}^i = \frac{\varepsilon^{eff}_j \times (\mathbb{T}_{c,j} + \mathbb{T}_{t,j})}{\mathbb{T}_{r,i}} \quad (13)$$

Therefore, $\mathcal{Q}^i$ is represented as,

$$\mathcal{Q}^i = \alpha \times \mathbb{E}^i \times \mathcal{U}_i \quad (14)$$

where $\mathbb{T}_{c,i}$ and $\mathbb{T}_{t,i}$ are the time required to collect and transmit data from edge layer by j^{th} sensor node for i^{th} end user. $\mathbb{T}_{r,i}$ is taken to response to i^{th} end user.

3.5 Game Formulation

In Safe-aaS, the customers register to the platform, select certain parameters and make payment through the Web portal. A decision is delivered to them. In our proposed pricing scheme, we introduce a suggestive method using which the end-users select their decision parameters. The SSPs suggest certain decision parameters to the customers, depending upon their selected source and destination details. To map the strategic interactions among the end-users and the SSPs, we apply *Non-Cooperative Multiple Leaders Multiple Followers Stackelberg* game-theoretic approach. The SSPs act as leaders and the end-users act as followers. Suppose, $\mathbb{E}^x$, such that $\mathbb{E}^x \subset \mathbb{E}$ and $(1 \leq x \leq n)$, set of end-users which act according to the pricing scheme declared by the SSPs, $\mathbb{Z}^y, 1 \leq y \leq q$.

Non-Cooperative Stackelberg Game-The Justification: The end-users first select certain decision parameters, among the ones displayed in the Web portal. Thereafter, based on their source and destination details given by the end-users and to maintain the Quality of Service (QoS), the SSPs suggest certain decision parameters. The price charged from the end-users and their utility is estimated during each re-evaluation. The SSPs possess the intention to increase their profit as well as satisfy the end-users with the price charged. Therefore, a dynamic scenario exists, where we map the interactions among the SSPs and the end-users with a non-cooperative game. Each of the players, the leaders and the followers, take their decisions independently in the game. The leaders first put forth their strategies or suggest the decision parameters. Based on their strategies or suggested decision parameters, the followers/end-users select their decision parameters.

Lemma 1. *The event of selection of the decision parameters by the end-users and those suggested by the SSPs is a pairwise, dependent event.*

Proof. We consider P^x as the decision parameters initially selected by the end-users and P^y as those suggested by the

SSPs. We design the selection of the decision parameters as an event. Suppose, the probability of occurrence of these events be denoted as $\mathbf{P}$. Therefore,

$$\mathbf{P}(P^y \cap P^x) = \mathbf{P}(P^x)\mathbf{P}(P^y|P^x) \tag{15}$$

where $\mathbf{P}(P^y|P^x)$ represents the probability of occurrence of the event P^y when P^x has already occurred. □

Therefore, the strategic form of the game is defined as –

$$\xi^i = (\mathbb{Z}^y \cup \mathbb{E}^x)_{(x\in n, y\in q)}), (\mathcal{S}_L^y, \mathcal{S}_F^i, \mathcal{U}_L^y, \mathcal{U}_F^i)_{(i\in n, y\in q)} \tag{16}$$

The various parameters of the game are – (i) $\mathbb{Z}^y$, set of leaders/SSPs,(ii) $\mathbb{E}^x$, set of followers/end-users, (iii)$\mathcal{S}_L^y$, strategies of the leaders, (iv)$\mathcal{S}_F^i$, strategies of the followers, (v) $\mathcal{U}_L^y$, the utility function of the leaders, and (vi) $\mathcal{U}_F^i$, the utility function of the followers.

Strategies of the leaders: The leaders put forth their strategies depending upon the different pricing strategies, which are described in Section 3.3. Therefore, strategy of the leaders is mathematically represented as, $\mathcal{S}_L^y = \{\mathcal{C}_{init}, \mathbb{C}_{low}, \mathbb{C}_{high}, \mathbb{C}_p\}$.

Strategies of followers: The followers place their strategies, $\mathcal{S}_F^i$, depending on the type of decision parameters selected by them. Therefore, $\mathcal{S}_F^i = \{\mathcal{L}_a, \mathcal{H}_b\}$.

To satisfy the end-users as well as the SSPs requests, we aim to minimize the total costs, depending on the optimal number of low-cost and high-cost decision parameters selected.

Theorem 1. *There exists a unique Stackelberg equilibrium, for the total costs charged by the SSPs from the end-users. To estimate the total cost, we consider a given re-evaluation cost, effective residual energy of the sensor nodes, number of sensor nodes used, and time required for the entire process of decision parameters selected by the end-users and suggestions provided by the SSPs.*

Proof. In our proposed pricing scheme, each of the end-users requests certain decision parameters, and decision is provided by the Safe-aaS platform. Further, the SSPs tend to minimize their utility and increase their profit, such that the decision is provided to the end-users, utilizing the minimum number of sensor nodes and their energy consumed, within a bounded time period. Therefore, the optimization function is mathematically represented as,

$$\underset{\mathcal{L}_a^i, \mathcal{H}_b^i}{argmin} \quad \mathcal{C}_{total}^i \tag{17}$$

subject to, $m \geq (\mathcal{L}_a^i + \mathcal{H}_b^i)$, $\mathcal{C}_{high} > \mathcal{C}_{low}$, $\mathcal{C}_r \geq 0$, $\mathcal{C}_p > 0$, $\mathcal{N}_{tot}^i > 0$, and $0 \leq (\varepsilon_i^{eff}, \mathbb{T}_i^{eff}) \leq 1$. The maximum number of decision parameters displayed in the Web portal is represented as m. In order to simplify the optimization function, we apply *Lagrangian* function, which is represented as,

$$\begin{aligned} L^i = &-\mathcal{C}_{total}^i - \mu_1(\mathcal{L}_a^i + \mathcal{H}_b^i - m) - \mu_2(\mathcal{C}_{low} - \mathcal{C}_{high}) \\ &- \mu_3(\mathcal{C}_p) - \mu_4(\mathcal{C}_r) - \mu_5(\mathcal{N}_{tot}^j) - \mu_6(\varepsilon_i^{eff} - 1) \\ &- \mu_7(\mathbb{T}_i^{eff} - 1) \end{aligned} \tag{18}$$

where $\mu_1, \mu_2, \mu_3, \mu_4, \mu_5, \mu_6$, and μ_7 represent the *Lagrangian Multipliers*. Further, to solve Equation 18, we use *Karush-Kuhn-Tucker* (KKT) conditions. The *dual feasibility* and *complementary slackness* conditions are represented as follows:

$$\frac{\partial L^i}{\partial \mathcal{L}_a^i} = -(\beta\mathcal{C}_{low} + \beta\mathcal{L}_a^i\mathbb{N}_{la}) + \mu_1 = 0 \tag{19a}$$

$$\mu_i(X) = 0 \quad \text{and } \mu_i \geq 0, \forall i = \{1, 2, \cdots, 7\} \tag{19b}$$

where X represent the constraints of the Equation 17. On solving Equation 19, we obtain the optimal value of $\mathcal{L}_a^i$. Similarly, we perform the first order derivative of Equation 18, with respect to $\mathcal{H}_b^i$ and applied the KKT conditions, to obtain the optimal number of high-cost parameters. Therefore, the optimal value of $\mathcal{L}_a^{i,*}$ and $\mathcal{H}_b^{i,*}$ are represented as:

$$\mathcal{L}_a^{i,*} = \frac{1}{\mathbb{N}_{la}}\left(\frac{\mu_1}{\beta\mathcal{C}_{low}} - 1\right) \tag{20a}$$

$$\mathcal{H}_b^{i,*} = \frac{1}{\mathbb{N}_{hb}}\left(\frac{\mu_1}{\beta\mathcal{C}_{high}} - 1\right) \tag{20b}$$

Based on the optimal values of $\mathcal{L}_a^{j,*}$ and $\mathcal{H}_b^{j,*}$, we obtain the minimum total cost charged by the SSP from the end-users. □

4 Performance Evaluation

4.1 *Simulation Design*

To evaluate and analyze the performance of the proposed pricing scheme, Q-Safe, we vary the user entities from 0 to 500 and the number of sensor nodes from 200 to 600, in a simulation area of $10 \times 10km^2$. We randomly deploy the sensor nodes in the simulation region. The various simulation parameters used are listed in Table 2.

TABLE 2: Simulation Parameters

Parameters	Values
$\mathbb{P}_l$, $\mathbb{P}_h$	10
$\mathbb{N}_l$, $\mathbb{N}_h$	200
Decision parameters	10
Cases for price charged	3
C_{low}	$100 - 500$
C_{high}	$501 - 1000$
C_r	100
λ_1, λ_1, β	$0 - 1$

4.2 Benchmark Solution

Existing research works discussed various dynamic pricing schemes to fulfill the demand of both SSP and customers, in terms of profit of SSP and maintain the quality of service (QoS). Guijarro *et al*. [1] proposed a two-sided payment scheme in a service platform, based on WSNs. Their designed platform acts as a mediator between the consumers and the WSNs, where both the service providers as well as consumers post their prices to maximize their profit. On the other hand, Roy *et al*. [2] proposed a dynamic pricing scheme for providing Sensors-as-a-Service (Se-aaS) in the mobile sensor cloud environment. They considered the quality of service provided by the sensor nodes in terms of service return, the price charged by the Sensor Cloud Service Provider (SCSP). Additionally, we compare another recent research work on pricing in the Safe-aaS platform as a benchmark scheme. Considering the type of road in different geographical regions and the presence of homogeneous sensor nodes, Roy *et al*. [3] proposed a region-based pricing scheme. The authors calculated the price charged from the end-users based on fixed cost, variable cost, and maintenance cost. We termed the pricing scheme proposed by Guijarro *et al*. [1], Roy *et al*. [2] and Roy *et al*. [3] as Per-Subscriber Model, PRIME, and RegPrice. However, none of these existing schemes consider the quality of service to be provided to the end-users in terms of their requirement, and suggestion is not given by the service provider.

We analyze the profit of SSP with the increase in the number of end-users, as illustrated in Fig. 2. We observe that the average profit in the proposed scheme, Q-Safe, is improved by 70.88%, 52%, and 77% compared to the Per-Subscriber model, PRIME, and Reg-Price in the presence of 200 sensor nodes. We increase the number of end-users from 50-500 along the x-axis. The possible reason behind the increase in the profit of SSPs is the rate of increase in the demand of safety services by the registered end-users. Moreover, these end-users select the optimal number of high- and low-cost decision parameters. We observe that the profit of the SSPs varies randomly with the increase in the number of customers. As the price charged to the customers varies with the number and type of selected parameters by them, therefore, the average profit of the SSPs also fluctuates.

Fig.3 demonstrates the variations in the utility of the proposed scheme, Q-Safe with the existing benchmark schemes, Per-Subscriber, PRIME, and RegPrice. We vary the number of end-users from 0 upto 500 with an interval of 50, along the x-axis. Interestingly, we observe that the average utility of Per-Subscriber model decreases with the increase in the number of end-users, whereas the utility of Q-Safe increases in the presence of 200 sensor nodes. We observe that the value of average utility is reduced by 5%, 16%, and 17% with respect to PRIME, Per-Subscriber, and RegPrice. One of the possible reasons behind this trend in the average utility is that the effective time required to generate a decision decreases with the increase in the number of end-users. The possibility of similarities among the decision parameters selected by the end-users increases with the rate of increase in their number. Therefore, the time required in processing, analysis, and generation of the decision reduces.

Fig. 4 illustrates the variations in the average cost of end-users in the presence of 200 sensor nodes in the environment. It is studied that the cost or price charged from end-users using our proposed scheme is quite low compared to the other existing schemes. The price charged from the end-users is highest in case of Per-Subscriber model, in contrast to PRIME and RegPrice. The possible reason behind this is that the concept of low- and high-price decision parameters and the suggestion provided by the service provider. Based on the selected type and number of decision parameters, the price is charged from the end-users. Further, the decision is provided to the them accordingly. Fig. 5 demonstrates the variations in the QoS of the proposed scheme with other existing schemes, PRIME, RegPrice, and Per-Subscriber model. It is shown that the QoS values follow raising trend with the increase in the number of customers. However, the rate of increment in QoS is comparatively high in Q-Safe with respect to other benchmark mechanisms. One of the possible

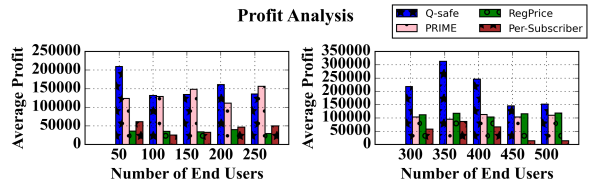


Fig. 2: Profit Analysis

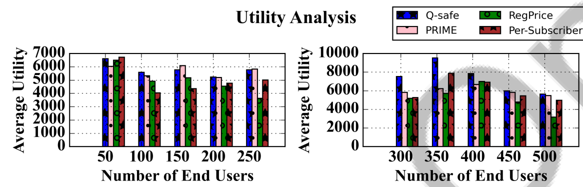


Fig. 3: Utility Analysis

reasons behind such a trend is that the value of utility and effective energy is high compared to the other existing schemes, as illustrated in Figs. 3 and 6.

4.3 *Result Analysis*

In our proposed approach we describe how price is charged from end users through maintaining the quality of service. To maintain QoS of the safety services, we consider various parameters involved in the proposed pricing scheme such as utility of service, total cost, energy consumed, time, error characteristics, and optimal number of selected parameters by the end-users, to characterize it. In this section, we study and analyze the behavior of these parameters for helping customers by delivering safety services at an optimal cost.

Effective Energy: Fig. 6 illustrates the variations in the effective energy consumed, with 200 sensor nodes. We vary the number of end-users from 20–200 at an interval of 40 along the x-axis. We observe an increasing trend in the average effective energy, both in case of high- and low-

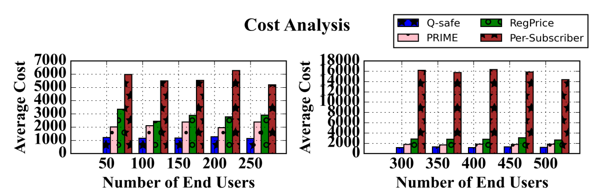


Fig. 4: Cost Analysis

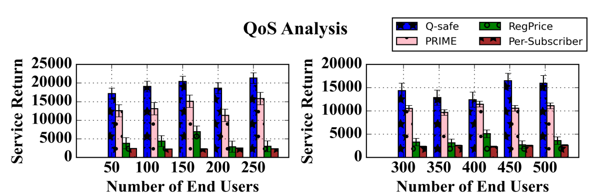


Fig. 5: QoS Analysis

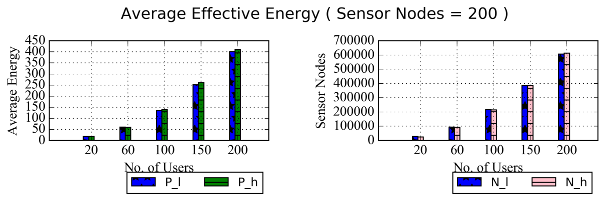


Fig. 6: Average Effective Energy

cost decision parameters. The probable reason behind this is that with the increase in the number of end-users, the number of decision parameters (high- and low-cost) selected by them increases. Therefore, the total sensor nodes in the decision generation process also increases. We consider the energy consumed by used sensor nodes for five iterations. As a result, the effective energy consumed increases. In another analysis of Fig. 6, we observe that with respect to the increase in the number of end-users, the number of sensor nodes involved in the decision generation correspondingly increases. As a result, the number of sensor nodes required to provide the information of the low- and high-cost decision parameters also increases.

Total Cost: Fig. 7(a) demonstrates the average total cost of the decision parameters incurred by an end-user at different iterations during the re-evaluation of the cost before optimization. In our proposed approach, the price is charged from the end-users, based on their selected decision parameters. SSP provides two types of parameters- high- and low-cost. Based on the decision parameters selected by the end-users, the total cost is estimated. We observe that the average total cost follows a decreasing pattern for different iterations and increasing pattern with the increase in the number of end-users. In Fig. 7(a), the total average cost after iteration 1 is quite high. It signifies that most of the end-users select high-cost decision parameters. However, after iteration 4, the average total cost is quite high compared to iteration 3. The possible reason behind this is that the end-users select more high-cost decision parameters than low-cost parameters in iteration 4. As a result, the utility of the service to be provided to the end-users changes. Further, selected parameters varies with the inclusion of decision parameters suggested by the SSPs. Moreover, as the decision parameters recommended by the SSPs are incorporated, the average total cost charged from the end-users decreases, after each re-evaluation.

Effective Time: Fig. 7(b) illustrates the variations in the average effective time with the increase in the number of end-users. We observe that the effective time decreases with the increase in the number of end-users by 58.12%, in the presence of 200 sensor nodes. Additionally, the effective time decreases with different iterations. The possible reason behind this trend is that the number and type of decision parameters selected by the end-users may overlap. Therefore, the time required to evaluate and generate the decision, and the number of times re-evaluation requests are processed, are minimized.

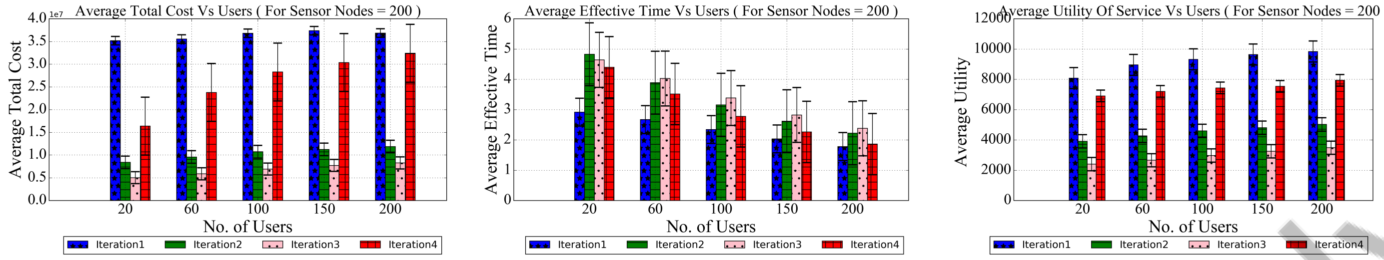
Utility: Fig.7(c) demonstrates the variation in the utility of safety services to be provided to the end-users. We observe that with the increase in the number of end-users, the utility of service increases by 34.35%. We estimate the utility of safety service as per Equation 7. The utility of the services provided to the end-users increases with the increase in the number of decision parameters selected and decreases with the increase in the time required for decision generation. From Figs. 6 and 7(b), we study that the effective energy consumption increases and the effective time required for estimation of total cost decreases with the increase in the number of end-users. Therefore, as per Equation 7, with the increase in the effective energy consumed and decrease in the effective time, the utility of service also increases.

Optimal number of parameters selected: Fig. 8 depicts one example of the optimal number of high-price and low-price decision parameters selected by the end-users, such that the total price charged by the SSPs is minimized.In Fig. 8, we consider the optimum number of high-range and low-range parameters are selected in the presence of 10 end users. We estimate the optimal value of $\mathcal{L}_a^{j,*}$ and $\mathcal{H}_b^{j,*}$ from the solution of the optimization function, as given in Equation 20. Therefore, the optimal number of decision parameters selected by the end-users vary. Fig. 9 demonstrates the variation of optimal cost and average utility with the increase in the number of end-users from 20 to 200. We observe that both the minimum total cost charged by the SSPs and average utility at different iteration vary randomly in the presence of 200 and 600 sensor nodes. In comparison with Fig. 7(a), the total cost is significantly minimized with every iteration for 200 sensor nodes. However, there exists a raising trend with the increase in the number of end users. The possible reason behind this trend is for similar number of high-range and low-range parameters, the number of end users are increased.

Error Characterization: Fig. 10 illustrates the characterization of error in the estimation of energy, utility, time, total cost, and the optimal number of high-price and low-price decision parameters selected. We compute the energy consumed based on selected parameters by the customers (error estimated in Energy1 graph) and used sensor nodes in the decision generation (error estimated in Energy2 graph) process. We observe that the error occurred during different iterations is significantly low in case of energy consumed, while the error is quite high in case of utility, effective time, total cost, and the optimal number of high- and low-cost decision parameters. Error characterization is required to provide the clear concept about the trend of variations in the parameters. We observe the outcome after five iterations and found that the error is minimum for every parameter. However, the total cost varies because of different types of parameters chosen by the customers. From the error characterization graphs, the future behavior of all the decision parameters can be predicted over the number of end-users.

5 Conclusion

In this work, we proposed a QoS-aware dynamic pricing scheme, Q-Safe, for provisioning customized safety services to the end-users. This proposed two-way pricing scheme satisfies both the end-users as well as the SSPs. We introduced the concept of high-price and low-price decision parameters, as displayed in the Web portal. The end-users first select certain decision parameters, then the SSPs suggest



(a) Average Total Cost (b) Effective Time (c) Utility

Fig. 7: Variation in average cost, time, and utility

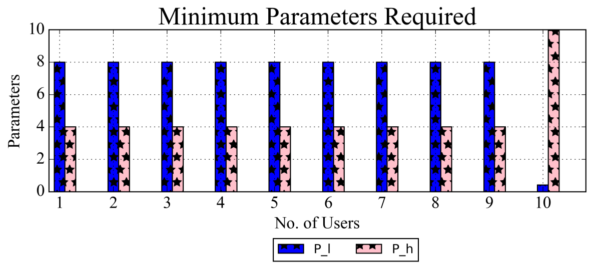


Fig. 8: Optimized Parameters per User

Fig. 9: Variation of optimum Cost with QoS

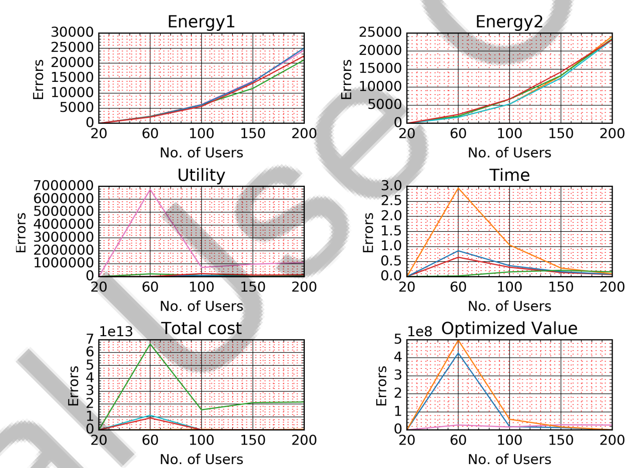


Fig. 10: Error Characterization of Optimization Parameters

them decision parameters depending upon their geographical location. Therefore, a dynamic scenario exists, which we map with the non-cooperative *Multiple-Leader-Multiple-Follower* Stackelberg game-theoretic approach. Based on the effective energy consumed, the effective time required for computation of total cost, and sensor nodes utilized to create the decision, we design the utility of service to be provided to the end-users. Further, we estimate the total cost incurred by the end-users, depending upon the utility of service and decision parameters selected. We design an optimization function to minimize the total cost charged from the end-users for an optimal number of high-cost and low-cost decision parameters, such that the QoS is ensured.

In the future, this pricing mechanism can be extended to propose another pricing scheme based on communication ranges of sensor nodes. As safety-related decisions are provided to the end-users, any form of wrongly sensed data may result in a hazardous situation. Therefore, we plan to incorporate the presence of malicious and misbehaving nodes in the scenario.

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