RegPrice: Region-Based Pricing Scheme for Provisioning Safety-as-a-Service in IoT Applications

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***Abstract*—In this paper, we propose a region-based pricing scheme, named as RegPrice, for provisioning safety-related decisions dynamically to the end-users. Typically, heterogeneous type of sensor nodes are present in the device layer of Safe-aaS. Considering the case of safety in road transportation, we compute the fixed and variable costs incurred in procurement, deployment, and maintenance for each of these different types of sensor nodes. We introduce the concept of tariff cost, which varies with the type of road in different regions and presence of similar homogeneous sensor nodes deployed in that region. Finally, we estimate the utility of a sensor node, which is a function of the sensing area, ratio of the fixed cost to total cost incurred, responsiveness factor, and rating given by an end-user for that sensor node. The SSPs provide rent to the sensor/vehicle owners for taking their sensor nodes on lease. In order to formulate the interactions among the SSPs and sensor owners, we apply *first-price, sealed-bid auction-based* game theoretic approach, where SSPs act as bidders. Based on the outcome of the auction, the sensor owners decide to which SSP their sensor nodes are to be rented. Exhaustive simulation results depict that the proposed pricing scheme, RegPrice, is capable of reducing the expenses of a SSP by 7.51% and 9.71% compared to the existing pricing schemes [1] and [2].**

Keywords*—Safety-as-a-Service (Safe-aaS), Region-based pricing, Tariff cost, Auction, Feedback, Road transportation, IoT.

I. Introduction

In the past few years, a growing interest is observed across the different industries for integration of diverse IoT-based technologies to improve product quality, efficiency, and reduce downtime of machines [3]. On the other hand, in case of road transportation industry, with the increase in number of on-road vehicles, the number of road accidents have increased significantly. Therefore, provisioning of safety services to the end-users is an important aspect of concern [4]. Various advanced technologies such as Advanced Driver Assisstance Systems (ADAS) [5] and Intelligent Transportation Systems (ITS) [6] are developed for traffic management and congestion control. However, prior intimation of safety-related information may reduce on-road accidents. Safety-as-a-Service (Safe-aaS) [4] infrastructure provides safety-related customized virtualized decisions as services to multiple end-users simultaneously. Therefore, we consider road transportation as an application scenario of the Safe-aaS platform and propose a region-based pricing scheme.

The end-users register to the Safe-aaS infrastructure and request for certain decision parameters through a Web portal. Depending upon these selected decision parameters, the decisions are provided to them. A SSP is a centralized entity which manages the different activities of the Safe-aaS platform. Additionally, the SSP pays certain amount of money as rent to the sensor/vehicle owners and receives payment from the end-users for delivering the decisions to them. Therefore, complex monetary transactions are controlled by the SSP. The complexity increases further in the presence of multiple SSPs, where some of the SSPs may possess the tendency to exploit the sensor/vehicle owners. Considering these issues, we propose a pricing scheme to meet the requirements of the SSPs as well as sensor/vehicle owners. The vehicle owners may be active or passive. Active vehicle owners possess inbuilt sensor nodes in their vehicles. On the other hand, sensor nodes are externally placed into the vehicles of passive vehicle owners. Based on the type of road and number of homogeneous sensor nodes present in the region, we introduce the concept of region-based cost, termed as tariff cost, which varies for each of the passive vehicle owners. The proposed scheme, RegPrice, imposes a fair price offered by the SSPs and demanded by the sensor node owners.

The Safe-aaS architecture provides customized safety-related decisions dynamically to the end-users, as per their requests. These decisions are generated after processing, analysis, and combination of multiple sensor data. Further, the sensed data are generated from the sensor nodes taken on lease by the SSP from various sensor/vehicle owners. The SSP provides rent to these sensor/vehicle owners and receives payment from the end-users. Therefore, complex monetary transactions are involved among the actors of Safe-aaS. In the presence of multiple SSPs, the situation becomes complicated. The sensor owners may cumulatively set a high price and unethically force SSPs to pay them the amount. On the other hand, the SSPs may cumulatively set a lower price for the sensor nodes and the sensot/vehicle owners may incur substantial loss. Additionally, with the variations in the mobility of the passive vehicles, the presence of homogeneous sensor nodes and type of road may also vary across different regions. Therefore, to address these issues, we propose a region-based pricing scheme, which optimizes the profit of the sensor/vehicle owners and the SSPs.

In this paper, we aim to address the following questions: (a) How the fixed and variable costs change with different types of sensor nodes? (b) How much amount is demanded by the passive vehicle owners, which vary with the different road conditions? and (c) How the sensor/vehicle owners select the appropriate SSP among the multiple SSPs to rent their sensor nodes? To address these questions, the proposed region-based pricing scheme for provisioning safety services is useful, while considering the profit of SSPs and rent paid by the end-users. The specific contributions of this work are as follows:

- We propose a region-based pricing scheme among multiple SSPs and sensor owners, considering the presence

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of both the static and the mobile sensor nodes. Further, we compute the fixed and the variable costs associated with the static and mobile sensor nodes, respectively.
- The Safe-aaS architecture comprises various actors such as sensor/vehicle owners, SSPs, and end-users. Additionally, the vehicle owners are categorized as active and passive. We introduce the concept of tariff cost paid to passive vehicle owners, which vary with the road conditions of a particular region and the number of homogeneous sensor nodes preset in that region.
- We compute the utility for each type of sensor nodes based on (a) the effective sensing area, (b) the effective evaluation element, (c) the responsiveness factor, (d) the costs incurred due to procurement and maintenance, and (e) the service cost for each sensor nodes. As the responses provided by an active sensor node is continuous in nature, we apply the beta distribution function to estimate the expected value of responsiveness factor for each of these nodes. Based on the feedback provided by the end-users, we rate the performance of each sensor node and compute the effective evaluation element.
- In order to formulate the interactions among the SSPs and sensor node owners, we apply *first-price sealed bid* auction-based game theoretic approach, where the SSPs act as *bidders*. The winner SSP at the previous time instant acts as the *auctioneer*. Based on the outcome of the auction, the sensor owners decide to which SSP these sensor nodes are to be rented.
- Extensive simulation results illustrate that the proposed scheme, RegPrice, helps to reduce the expenditure of service provider, and ratio of fixed cost to total cost of the sensor nodes, compared to the existing pricing schemes DOPHS [1] and CLABACUS [2].

II. Related Work

This section discusses the prior research works done in the domain of safety services in road transportation [3]–[5], [7]–[9] and pricing for cloud services [2], [10]–[14], in general. Certain schemes were proposed for maintenance of trust in distributed networks [15], [16]. Safety is an essential aspect of concern for both drivers and vehicles on rural as well as urban roads. Further, the presence of horizontal curves on rural roads act as one of the potential threats for drivers. Karaduman *et al*. [9] proposed a model for prediction of risks associated with curved roads using rear and front end cameras installed on the vehicle. On the other hand, in urban environment, the presence of pedestrians on road may affect the vehicle platoons. Flores *et al*. [8] proposed a cooperative system to predict the trajectory of the pedestrians to execute speed reduction or emergency braking system. Similarly, Roy *et al*. [3], [4], [7] proposed a unique platform, Safety-as-a-Service (Safe-aaS), for provisioning customized safety-related decisions to the end-users, as per their request. The authors consider the presence of both static and mobile sensor nodes.

In the mobile cloud computing (MCC) environment, the computational tasks are offloaded to the servers. Shah-Mansouri *et al.* [10] addressed the problem of taking decision regarding the scheduling of tasks and price of services provided. From the mobile users perspective, the authors consider energy consumption, delay, and price of cloud services, and for cloud service provider (CSP), their profit was considered. Therefore, the authors jointly optimize the task scheduler and pricing strategy of the CSP in a dynamic MCC scenario. Similarly, Son and Sim [11] proposed a negotiation mechanism for reservation of price and time slot between CSPs and consumers. They allowed multiple agents to concurrently make multiple proposals during a negotiation round for different time slots. Further, Dabbagh *et al.* [12] proposed an online pricing scheme for resource allocation in cloud. The authors considered minimizing the energy consumption, while maximizing the profit of the service provider through the reduction of on-time of the servers. Therefore, a trade-off is maintained between the energy consumption and profit of a service provider. In another similar online pricing mechanism proposed by Mashayekhy *et al.* [13], different type of resources are considered and VM instances are allocated dynamically. Further, in the domain of cloud computing, the service provider possesses a tendency to increase their profit and end-users have the desire to pay fair prices for the resources. Sharma *et al.* [2] proposed a pricing scheme termed as Clabacus (Cloud-Abacus) to satisfy the service providers and clients. They proposed a general formula to record the technological advances of cloud resources, ad inflation and depreciation rate. In a service market model, a reverse auction occurs, where any service provider gains profit, if the prices set by that CSP is cheaper compared to the other CSPs. Considering this scenario, Tanaka and Murakami [17] proposed a possible solution based on Vickrey-Clarke-Groves mechanism. They solved the service selection problem in quasi-polynomial time and provided a satisfactory solution.

Synthesis : In the above discussed research works related with pricing for provisioning cloud services in the IoT scenario reveal that there exists a research lacuna on region-based pricing. Further, Safe-aaS is a unique platform, which is based on the concept of decision virtualization. With the change in location of the vehicles, the sensor nodes attached with the vehicles of passive vehicle owners attain mobility. Additionally, the road conditions vary with different regions. Therefore, the price charged by these passive vehicle owners differ with the regions, where they provide services. None of the existing pricing schemes consider mobility of the sensor nodes or change in prices with regions. Therefore, we design a region-based pricing scheme for provisioning customized safety services to the end-users.

III. Problem Description

A. Problem Scenario

We consider the case of Intelligent Transportation System (ITS) scenario with Safe-aaS infrastructure implemeted. Safe-aaS architecture is a unique platform in providing customized safety-related decisions as services to multiple end-users. The main actors of Safe-aaS are sensor owners, vehicle owners, safety service provider (SSP), and end-users. The sensor and vehicle owners rent their sensor nodes and vehicles to the Safe-aaS architecture. Based on their profit and necessity, the SSPs lease these sensor nodes and provide safety services to the end-users. There are five layers in Safe-aaS – device, edge, decision, decision virtualization, and application. The device layer comprises heterogeneous types of static and mobile sensor nodes, which sense and transmit data to the edge node/cloud, based on the time-sensitive nature of the data. Therefore, these sensor nodes may possess non-identical sensing range and data transmission/reception rate. Static sensor nodes are mostly used for continuous monitoring purposes, therefore, the expenses incurred in their maintenance and energy consumed is quite high compared to the mobile sensor nodes. The mobile sensor nodes are active only with the variation in the geographical location of the vehicles. The primarily processed sensor data are transmitted to the decision layer, where the decision is generated. The logical mapping of the decision parameters requested by the end-users and decision to be delivered to them is done at the decision virtualization layer. Further, the end-users register to the Safe-aaS infrastructure and request certain decision parameters through a Web portal. The application layer acts as the interface between the end-users and the infrastructure. In real-life, the road conditions may vary with various geographical regions, as illustrated in Fig. 1. Therefore, the amount to be paid to the passive vehicle owners belonging to different regions such as hills and planes, fluctuates. Considering, the presence of different types of roads, the sensing radius of sensor nodes, and fluctuation of different fixed and variable costs associated with these sensor nodes, we propose a pricing scheme for the selection of the appropriate sensor node to provide safety services. In addition to this, we compute the profit of the SSPs depending upon the decisions to be virtualized.

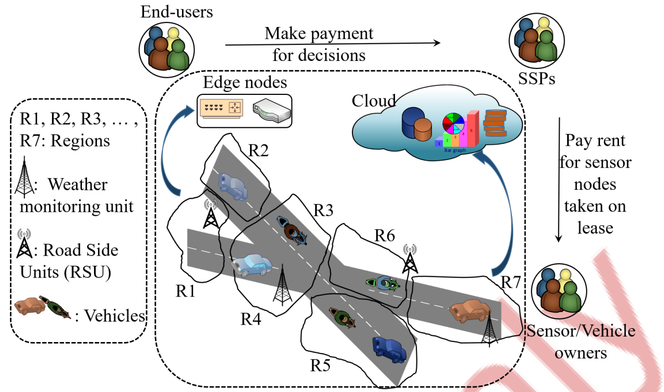

Fig. 1: RegPrice: The System Architecture

B. Problem Formulation

We consider the presence of heterogeneous types of sensor nodes in the device layer of the Safe-aaS architecture. These nodes are either deployed at different geographical locations or placed into the vehicles. We represent the set of sensor nodes as $\mathbb{S} = \{s_1, s_2, \cdots, s_n\}$, where s_i is the i^{th} sensor node. In our problem scenario, we consider sensor/vehicle owners and multiple SSPs as the preliminary participants. Let k sensor owners rent their n sensor nodes to the Safe-aaS infrastructure. The set of sensor owners is denoted as $O = \{o_1, o_2, \cdots, o_k\}$. Further, each of the sensor owners owns multiple sensor nodes of different types. However, we consider that each of the sensor nodes is not owned by multiple sensor owners. These sensor owners rent their sensor nodes to the SSPs. We denote any SSP as p_i, such that $\forall p_i \in \mathbb{P}$ and $1 \leq p_i \leq m$, where $\mathbb{P}$ denotes the set of SSPs. The sensor owners may rent their sensor nodes to multiple SSPs. Based on the type of sensor node, the price incurred by a sensor owner varies. Therefore, the total expenses, $\mathbb{C}_T^{i,j}$, for the deployment, procurement, and other associated costs of the i^{th} sensor node incurred by the j^{th} sensor owner is mathematically expressed as:

$$\mathbb{C}_T^{i,j} = \begin{cases} C_T^{s,i} = C_{fixed}^{s,i} + C_{vari}^{s,i}, & \text{static} \\ C_T^{me,i} = C_{fixed}^{me,i} + C_{vari}^{me,i}, & \text{externally-placed} \\ C_T^{mi,i} = C_{fixed}^{mi,i} + C_{vari}^{mi,i}, & \text{innate} \end{cases} \tag{1}$$

In case of static sensor nodes, there are two types of fixed costs – procurement ($C_p^{s,i}$) and deployment ($C_d^{s,i}$) associated with the purchase and deployment of the i^{th} sensor node. Therefore, $C_{fixed}^{s,i} = (a\%$ of $C_p^{s,i} + C_d^{s,i})$. The procurement costs may vary by $a\%$, depending upon the time duration for which the sensor node is active during the past t time instants. The variable costs (C_{vari}) associated with the static sensor nodes involve maintenance costs ($C_m^{s,i}$), which is the amount required for maintenance, and the expenses corresponding to the i^{th} sensor node, which may vary with time. On the other hand, the mobile sensor nodes are categorized as – innate and externally placed. The fixed costs associated with the innate sensor nodes are significantly low or may be neglected. The vehicles which have inbuilt sensor nodes incur only maintenance costs ($C_m^{mi,i}$). Therefore, $C_{vari}^{mi,i} = C_m^{mi,i}$. In case of externally placed type sensor nodes, fixed costs, $C_{fixed}^{me,i}$ include procurement ($C_p^{me,i}$) and deployment ($C_d^{me,i}$) costs. $C_{fixed}^{me,i} = (x\%$ of $C_p^{me,i} + C_d^{me,i} + C_t^{me,i})$, where x denotes the variation in the procurement costs every time the sensor node is rented. This fluctuation in the procurement cost of an externally placed sensor node depends upon the condition of the vehicle and the time duration for which the sensor node was active during the past time instants. The variable costs for externally placed sensor nodes comprise tariff ($C_t^{me,i}$) and maintenance ($C_m^{me,i}$) costs, which is expressed as $C_{vari}^{me,i} = (C_t^{me,i} + C_m^{me,i})$.

***Definition* 1.** *Tariff cost refers to the amount claimed by a passive vehicle owner from the sensor owners for deploying and carrying the externally placed sensor nodes to various geographical locations.*

Theorem 1. *The tariff cost demanded by the passive vehicle owners for the sensor nodes externally placed on their vehicles vary with different regions.*

Proof: In Safe-aaS, passive vehicle owners possess vehicles with sensor nodes externally placed on them. The passive vehicle owners receive rent from the sensor owners for carrying their node to the respective locations. With the variation in the geographical region, the maintenance and other associated costs fluctute. Therefore, the tariff cost demanded by the passive vehicle owners also change. The driving and maintenance of vehicle is easier in plane regions compared to hilly areas. In addition to this, the maintenance costs associated with these externally placed sensor nodes are more for hilly regions. Therefore, based on the road conditions, the passive vehicle owner may demand different rents. We compute tariff cost, $C_t^{me,i}$, depending on two factors – (a) route-grade (road conditions), and (b) presence of alternate nodes in the region.

Route-Grade (R_G): This represents the type of road and friction between the road and vehicles. The various factors that affect on-road friction are – (a) the type of pavement (such as bituminous, concrete, and gravel), (b) the maximum radii of road curves (ρ), and (c) super elevation (ϱ) of the road. With the decrease in friction, R_G increases. However, on-road friction lies within the specified range (f^{max}, f^{min}). On the other hand, the vehicle owners maintain a certain velocity, ν, to avoid accidents. As discussed in [18], the relationship between ν and ρ, ϱ, and f is expressed as – $\varrho + f = \frac{\nu^2}{127\rho}$. With the increase in the radii of road curves and super elevation, R_G decreases. Therefore, R_G is represented as a four tuple, $\langle \rho, \varrho, f, T_p \rangle$, where T_p is the type of pavement. Mathematically:

$$T_p = \begin{cases} a - x, & \text{for bituminous} \\ x - y, & \text{for concrete} \\ y - b, & \text{for gravel} \end{cases} \tag{2}$$

where $a > 0, b < 1$. The values of x and y ($a < (x, y) < b$) are determined through mutual agreement between the passive vehicle owner and the sensor owner.

Alternate-nodes (α_e): With the mobility of the passive vehicle owner through any geographical region, the other homogeneous sensor nodes present in that region are termed as alternate-nodes. With the increase in the number of alternate-nodes, the sensor owners possess multiple options to acquire the sensed data from these nodes. Therefore, the vehicle owners demand increased amount of rent for regions with fewer number of alternate-nodes. The tariff cost varies directly with R_G and inversely with α_e. Therefore, $C_t^{me,i} = \kappa \frac{R_G}{\alpha_e}$, where κ is a weight factor such that $0 \leq \kappa \leq 1$. As the value of R_G and α_e vary with regions, the tariff cost also fluctuates with the change in the location of the vehicle. ■

Utility Computation: The sensor owners rent their nodes to the SSPs. On the other hand, the SSPs utilize the data sensed from these rented nodes to provide customized safety services to the end-users. Therefore, the SSPs analyze the quality of the sensor nodes, before they lease them. We measure the quality of a node using the utility of the node. Further, we denote the utility of a sensor node as a function of the effective sensing area (A_s^e), responsiveness factor (R_f), effective evaluation element (E_e^{eff}), and the total cost incurred by the sensor owner ($\mathbb{C}_T^{i,j}$). We have, $U = f(A_s^e, R_f, E_e^{eff}, \mathbb{C}_T^{i,j})$.

***Definition* 2.** *Effective Sensing Area (A_s^e): The effective sensing area of a node is defined as the ratio of the sensing area of the node to the maximum possible sensing area of any sensor node present in that region. Therefore, $A_s^{e,i} = \frac{A_s^i}{A_{s,max}}$, where, $A_s^i = \pi r^2$ and $A_{s,max} = \pi r_{max}^2$, r and r_{max} represent the sensing radius of the i^{th} sensor node and the maximum sensing radius of any sensor node present in that region, respectively.*

In order to generate a decision for the decision parameters selected by the end-users, the SSPs request data from the sensor node. Practically, a sensor node may not respond properly due to adverse atmospheric conditions or any fault. Therefore, we define a parameter, the responsiveness factor (R_f^i), of the i^{th} sensor node. The responsiveness nature of the i^{th} sensor node is represented as: $RF_i = \langle 0, 1 \rangle$, where 1 or 0 denotes that the sensor node is responsive or not. The amount of positive and negative responses of any i^{th} sensor node is denoted as α_i and β_i, respectively. We use the beta distribution function to compute the responsiveness factor of any sensor node. The beta distribution function is expressed as, $f(p|\alpha_i, \beta_i) = \frac{\Gamma(\alpha_i+\beta_i)}{\Gamma(\alpha_i)\Gamma(\beta_i)} p^{\alpha_i - 1}(1-p)^{\beta_i - 1}$, where $0 \leq p \leq 1$ and $(\alpha, \beta) \geq 0$, such that the probability $p \neq 0$, if $\alpha < 1$, and $p \neq 1$, if $\beta < 1$ [19]. Therefore, the expected value of the beta distribution function, which gives the value of R_f^i, is expressed as:

$$R_f^i = E(p) = \frac{\alpha_i}{\alpha_i + \beta_i} \tag{3}$$

Thus, the responsiveness factor predicts the response of the sensor nodes. The feedback provided by the end-users also act as an important factor to improve the efficiency of the safety services. Considering this fact, we design a feedback system to rate the performance of the sensor nodes. The feedback provided by an end-user is processed to estimate the rating of the sensor nodes involved in the decision generation process.

Feedback System: In order to compute the individual performances of the active sensor nodes, we define a parameter termed as evaluation element (E_e^i). Based on the feedback of the end-users, the evaluation element is computed. The end-users rate the decision provided to them in the form of numeric values $\{1, 2, 3, 4, 5\}$, such that 1 and 5 denote the minimum and highest rating, respectively. As the experience of the end-user improves, the rating increases. Further, the SSP updates the rating of the sensor nodes involved in the particular decision generation process. Therefore, each time the end-users receive decision, the grade of the sensor nodes related with decision generation is updated. Let us consider that the i^{th} sensor node is involved in the generation of n decisions during the past D days. Therefore, the ratings for n decisions are represented as: $r^i = \{r_1^i, r_2^i, \cdots, r_n^i\}$. The rating, r_k corresponds to the k^{th} decision, where $k = 1, 2, \cdots, n$, where the value of r_k^i varies from 1 upto 5. The evaluation element for the i^{th} node is, $E_e^i = \frac{1}{n}\sum_{k=1}^{n} r_k^i$.

***Definition* 3.** *Effective evaluation element (E_e^{eff}): Effective evaluation element of a node is the ratio of the evaluation element of the node to the maximum rating (r_{max}) that the end-user provides. Therefore, $E_e^{eff,i} = \frac{E_e^i}{r_{max}}$.*

The utility (U_i) of a sensor node is directly proportional to the effective sensing zone (A_s^e), responsiveness factor (R_f^i), effective evaluation element ($E_e^{eff,i}$), and indirectly proportional to the expenses incurred in deployment and maintenance of that node. We have,

$$U_i^t = \frac{A_s^e \times R_f^i \times E_e^{eff,i}}{e^{\left(1 + \frac{C_{fixed}^{x,i}}{C_T^{x,i}}\right)}} \tag{4}$$

where x in $C_{fixed}^{x,i}$ and $C_T^{x,i}$ represent the static, innate, and externally placed type sensor nodes.

Algorithm 1 Computation of utility for each sensor node

INPUTS:
1: $C_{fixed}^{s,i}$, $C_{vari}^{s,i}$, $C_{fixed}^{me,i}$, $C_{vari}^{me,i}$, $C_{fixed}^{mi,i}$, $C_{vari}^{mi,i}$

OUTPUT:
1: U_i^t - utility for each sensor node

PROCEDURE:
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1: for i = 1 to n do        ▷ n - total number of sensor nodes
2:     Compute C^i_fixed and C^i_vari costs, based on their type, as per Equations 1 and 7.
3:     Compute A^{e,i}_s as per Defn. 2
4:     Compute R^f_i as per Equation 3.
5:     Compute E^{eff,i}_e as per Defn. 3.
6:     Compute U^t_i as per Equation 4
7: end for
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Distribution of sensor nodes among multiple SSPs: We design our pricing scheme considering the profit of sensor owners and SSPs. Based on the decision parameters selected by the end-users, the safety-related decisions are generated and provided to them from the Safe-aaS infrastructure. On the other hand, the sensed data are processed at the edge/cloud to generate the decisions. Using the concept of decision virtualization, a single decision is delivered to multiple end-users at the same time. However, the end-users are completely unaware of the back-end process of decision generation. Motivated by the concept of the costs incurred for the creation and maintenance of virtual machines, as proposed by Chatterjee *et al.* [1], we design the expenses incurred by the SSP to generate a virtual decision as $\Phi_i^v = (\Phi_i^c + \Phi_i^m(t - t_o))$. The combination of virtual decision creation (Φ_i^c), and virtual decision maintenance cost $\Phi_i^m(t - t_0)$ during the time period $(t - t_0)$ results in Φ_i^v. If b_i represents the number of sensor nodes involved in the generation of the i^{th} decision, the SSP spends $\frac{\Phi_i^v}{b_i}$ amount for each virtual decision. In order to provide virtual decisions to multiple end-users, the only expense incurred by the SSP is the maintenance of virtual decisions. With the increase in the number of end-users' requests for the same decision, the profit of the SSP increases. As the same decision is virtualized among multiple end-users, the amount charged by the SSP for that decision at different time instants is miimized. In case the same decision is virtualized to the i^{th} and u^{th} end-user at the time instant t and $(t + 2)$, the amount paid by the u^{th} end-user reduces by $a\%$. Therefore, the amount paid by the u^{th} end-user,

$$\mathcal{P}_u^j = P_i^j \left(1 - \frac{\frac{a \times P_i^j}{100}}{P_i^j}\right)^u \tag{5}$$

In Safe-aaS, various sensed data are collected, analyzed, processed, and combined to generate a decision. On the other hand, different decisions may be produced utilizing the same sensor data. The net profit earned by a SSP for the i^{th} sensor node depends on the number of decisions generated using the data of the i^{th} sensor node. During the registration process, the end-users select certain decision parameters and make payment. As per the initial and destination points selected by the end-users, decisions are delivered to them. However, each of these end-users have the illusion that the decision is generated only for them. Let n number of decision parameters are present in the Safe-aaS architecture, which are represented as a set, $\rho = \{\rho_1, \rho_2, \cdots, \rho_n\}$. Suppose, the per unit price for each of these decision parameters be denoted as, $\omega = \{p_1, p_2, \cdots, p_n\}$. If the j^{th} end-user selects k decision parameters, the price paid by him/her per unit distance is $\mathbb{P}_k^j = \sum_{j=1}^{k} p_j$. The payment given by the j^{th} end-user as,

$$P_i^j = \begin{cases} (F_r + d \times \mathbb{P}_k^j \times t), \text{for newly registered end-user} \\ (d \times \mathbb{P}_k^j \times t), \text{for already registered end-user} \end{cases} \tag{6}$$

where, d is the distance for which safety service is requested by the j^{th} end-user and F_r is the registration fee charged from the end-users. If the i^{th} virtual decision is delivered to e end-users, and each of them pays an amount, P_i^j, then the total profit of the k^{th} SSP for the i^{th} virtual decision is $P_{i,k}^T = \sum_{j=1}^{e}(P_i^j) - \Phi_i^v$. Therefore, for Θ sensor nodes involved with the generation of the i^{th} virtual decision, the total profit of the SSP per sensor node is $P_{i,k}^T = \frac{P_{i,k}^T}{\Theta}$.

As the Safe-aaS platform provides safety-related decisions to the end-users, any form of delay occurring during the data transmission is undesirable. Considering this and motivated by the concept of penalty cost [4], we consider service cost, $C_S^{i,k}$, for each of the sensor nodes. Based on the timely data transmitted by the i^{th} sensor node, the k^{th} SSP pays $C_S^{i,k}$ to the associated sensor owner. After evaluating the performance of the i^{th} sensor node for the entire day (24 hours), the amount is paid by the SSP to the sensor owner. However, when the i^{th} sensor node is not capable of transmitting data during the $(0 - t^{th})$ time duration, the SSP deducts a part of the amount to be paid to the sensor owner. Let the time required for data transmission be denoted as t. Further, let t^{th} be the threshold time up to which the delay is allowed by the SSP. Therefore, the total amount of fine levied upon the sensor owner by the SSP for ν days is,

$$C_S^{i,k} = \left(C_f^i \frac{(t - t^{th})}{t^{th}}\right) \times \nu \tag{7}$$

where, C_f^i represents the fine amount for per unit delay. Therefore, the profit of the j^{th} sensor owner at time instant, t, is $P_t^{j,k} = \sum_{i=1}^{x} \left(C_S^{i,k} + \mathcal{R}_k^i - C_T^{i,j}\right)$, where x denotes the number of sensor nodes rented by that sensor owner and $\mathcal{R}_k^i$ is the rent paid to the SSP.

IV. Solution Approach: Game theory - Auction with incomplete information

In our problem scenario, we formulate the interactions among the SSPs and the sensor owners using *first-price, sealed-bid* auction. Each of the SSPs acts as the *bidders* and decides the price to be paid by them to the sensor owners. The price/bid set by the SSPs are sealed and handed over to the *auctioneer*. On the other hand, the SSP who was declared as the *winner* in the auction, during the previous time instant, $(t - 1)$, acts as the *auctioneer*.

***Definition* 4.** *The process of bid submission done by the bidders to the auctioneer is termed as action. Therefore, action space for each of the k^{th} bidders is denoted as the $A_k = [0, \infty)$.*

***Definition* 5.** *Type, $\mathcal{T}$, for each of the bidder/SSP participating in the first-price, sealed-bid auction is the bidding value submitted by each of the players. Therefore, type space for the k^{th} bidder is $\mathcal{T}_k = [0, v_{max}]$.*

The maximum valuation provided by any bidder/SSP is denoted as v_{max}. Therefore, based on the bids of other bidders, the k^{th} SSP/bidder tries to maximize its payoff. Moreover, each of the bidders gives a bidding value, which is assumed to be uniform and independent. We discuss in Section IV-A the justification for adopting an auction-based game theoretic approach.

A. Auction with incomplete information: Justification

As discussed in Section III, we consider a problem scenario with heterogeneous sensor nodes belonging to different sensor/vehicle owners. These sensor nodes sense and transmit data to the edge layer/cloud, based on the time-critical nature of data. Further, the decision is generated from the primarily processed data and provided to the end-users. On the other hand, the SSP rents these sensor nodes from the sensor owners to provide safety services. The SSP may possess the tendency to earn higher amount of profit and rent these sensor nodes at a lower price. In the presence of multiple SSPs, a competition

$$b_k^*(v_k) = \beta(v_k, b_{-k}(.)) = \underset{b_{i,k}}{argmax} \int_0^{v_{max}} \mathbb{PF}_k(b,v) f(v_{-k}) dv_{-k} = \underset{b_{i,k}}{argmax} (v_{i,k} - b_{i,k}) Pr(b_{i,k} > b_{i,-k}(v_{i,-k})) + \frac{1}{n}(v_{i,k} - b_{i,k}) Pr(b_{i,k} = b_{i,-k}(v_{i,-k})) \quad (9)$$

exists among the SSPs for the price charged by them. As a result, the amount earned by the sensor owners decreases. Therefore, there exists a competitive market scenario among the sensor owners and the SSPs. The amount paid by any of the SSPs to the sensor owners and the conditions involved may be publicly available to the other SSPs. Considering these facts, we position our problem scenario in an auction based framework with incomplete information. The SSPs submit non-negative sealed bids simultaneously. Thus, the chances of using unfair means by these SSPs are avoided.

B. Game Formulation

In our problem scenario, the SSPs compete among one another to rent a sensor node from the sensor owners. A SSP participating in the auction submits the non-negative sealed bid, $b_{i,k}$. However, the other bidders/SSPs are aware of the bid put forth by that SSP. Depending upon (a) the amount end-users agree to pay for the decision generation, and (b) the profit of the SSP, the bid is submitted by that SSP. The SSP who submits the highest bid is declared as the *winner*. In case multiple SSPs submit the same bid, the auctioneer randomly selects the winner. However, both the SSPs and sensor owners are bounded by some bidding rules such as maximum/ceil price p_c[1] and minimum/floor price, p_f[2]. We consider that the k^{th} bidder/SSP sets a value $v_{i,k}$ for the i^{th} sensor node. Further, the price paid to the auctioneer is represented as – $p = b_{i,k}$. Therefore, the utility of the k^{th} SSP is $(v_{i,k} - b_{i,k})$. The valuation, $v_{i,k}$, for the i^{th} sensor node placed by the k^{th} SSP is dependent on the minimum price demanded by the sensor owner, $C_{i,k}$, and the utility of the sensor node. Therefore, $v_{i,k} = (C_{i,k} + \gamma_k U_i^t)$, where γ_k is the weight factor that varies for different SSPs, and depends on the maximum amount to be charged for the i^{th} sensor node. Based on the bidding value and valuation, the pay-off function for the k^{th} SSP is computed. Thus, we have,

$$\mathbb{PF}(b,v) = \begin{cases} v_{i,k} - b_{i,k}, b_{i,k} > b_{i,-k} \\ \frac{v_{i,k} - b_{i,k}}{n}, b_{i,k} = b_{i,-k}, \\ 0, b_{i,k} < b_{i,-k} \end{cases} \quad (8)$$

[1]The maximum price above which none of the SSPs claims to rent a sensor node is termed as the *ceil price*

[2]The minimum price below which none of the SSPs pays rent for a sensor node is termed as the *floor price*

where, $b_{i,-k}$ is the bid value submitted by the other SSPs/bidders for the i^{th} sensor node and n is the number of sensor nodes present. We consider B as the set of bidders participating in the auction, except the k^{th} SSP, such that $B \in \mathbb{P}$. Further, the action of the k^{th} bidder is represented as $b_k(v_k)$. Therefore, the best response of the k^{th} bidder is shown in Equation (9). $f(v_{-k})$ denotes the probability density function of the bidding values of other bidders, (v_{-k}) and m is the number of bidders/SSPs participating in the auction at that time instant. Further, $b_{i,-k}(v_{i,-k})$ is the action of the other bidders participating in the auction. The valuation of other bidders/SSPs is denoted as $v_{i,-k}$. Therefore, the Bayesian equilibrium is expressed as: $b_k^*(v_k) = \beta(v_k, b_{-k}^*(.))$ and the $b_{-k}^*(v_{-k}) = \beta(v_{-k}, b_k^*(.))$. In case other bidders place their valuation, therefore, $Pr(b_{i,k} = b_{i,-k}) = 0$. The strategies of the i^{th} player/SSP in auction is denoted as,

$$b_k(v_{i,k}) = \theta_k(v_{i,k} - C_{i,k}^L) \quad (10)$$

where $C_{i,k}^L$ is the lease cost for the i^{th} sensor node offered by the k^{th} SSP and θ_k is a positive constant ($\theta_k > 0$). Similarly, the strategies of other SSPs participating in the auction is expressed as: $b_{-k} = (v_{i,-k}) = \theta_{-k}(v_{i,-k} - C_{i,-k}^L)$. Therefore, the best response of the k^{th} SSP is

$$b_k^*(v_k) = \underset{b_{i,k}}{argmax} (v_{i,k} - b_{i,k}) Pr(b_{i,k} > b_{i,-k}(v_{i,-k})) \quad (11)$$

Further, on solving Equation (11), we obtain Equation (12). Therefore, the best response of the k^{th} bidder is obtained from the optimality conditions computed after solving Equation (11). The first order derivative of Equation (11) with respect to $b_{i,k}$ is expressed as follows:

$$\frac{\partial \left((v_{i,k} - b_{i,k}) \left(\frac{\left(b_{i,k} + \theta_{-k} C_{i,-k}^L\right)}{\theta_{-k}} \right)^{(n-1)} \right)}{\partial b_{i,k}} = 0 \quad (13)$$

On solving Equation (13), we obtain the optimal value of the bid put forth by the k^{th} SSP, as given in Equation (14).

Algorithm 1 provides insight regarding the computation of utility for each sensor node. In order to find utility of sensor nodes, the fixed and variable costs associated with their type are estimated. Further, the effective sensing area, effective evaluation element, and responsive factor, for each of the sensor node is estimated in steps 3–6. This value of utility acts as the input to the computation of $v_{i,j}$ for each of the sensor nodes, as mentioned in the step 2 of Algo. 2. Additionally, the

$$Pr\big(b_{i,k} > b_{i,-k}(v_{i,-k})\big) = Pr\big(b_{i,k} > (\theta_{-k}(v_{i,-k} - C_{i,-k}^L))^{(n-1)}\big) = Pr\left(v_{i,-k} < \left(\frac{b_{i,k} + \theta_{-k} C_{i,-k}^L}{\theta_{-k}}\right)^{(n-1)}\right) = \frac{\left(b_{i,k} + \theta_{-k} C_{i,-k}^L\right)^{(n-1)}}{\theta_{-k}} \quad (12)$$

$$b_k^*(v_k) = \beta(v_k, b_{-k}(.)) = \begin{cases} \frac{\theta_{-k} C_{i,-k}^L - (n-1) v_{i,k}}{(n-2)}, \text{ if } \theta_{-k} C_{i,-k}^L > v_{i,k} \text{ and } n > 2 \\ \frac{\theta_{-k} C_{i,-k}^L}{(n-2)}, \text{ if } \theta_{-k} C_{i,-k}^L < v_{i,k} \text{ and } n > 2 \end{cases} \quad (14)$$

payoff function and best response of the bidder is determined in the steps 3 and 4. The optimal value of the bid placed by each of the bidders is computed in step 5 of Algo 2.

Algorithm 2 Auction-based game-theoretic approach

INPUTS:
1: U_i^t, $C_{i,k}$
OUTPUT:
1: Appropriate SSP is declared as winner by auctioneer
PROCEDURE:
1: **for** j = 1 to k **do** ▷ k - total number of SSPs
2: Compute $v_{i,j}$ for each i^{th} sensor node put forth by j^{th} SSP, based on $C_{i,k}$ and U_t^i
3: Compute $\mathbb{PF}(b, v)$ for each of the SSPs
4: Compute best response for each SSP, as per Equation 11
5: Find the optimal value of the bid set by the j^{th} bidder/SSP
6: **end for**

V. Performance Evaluation

A. Simulation design

In real-life evironment, there are three types of road – concrete, bituminous, and gtavel, depending upon the construction material used. We consider two types of geographical region – plane and hilly. To analyze and evaluate the performance of our proposed scheme, we combine the types of road and regions into six types – (a) $R1$: plane region with bituminous road, (b) $R2$: hilly region with bituminous road, (c) $R3$: plane region with concrete road, (d) $R4$: hilly region with concrete road, (e) $R5$: plane region with gravel road, and (f) $R6$: hilly region with gravel road. We estimate the tariff cost incurred by any sensor owner for these six different regions. We use Matlab R2020B to simulate our proposed scheme. In our simulation environment, we consider the presence of both static and mobile sensor nodes, which vary from 100–1000, within a simulation area of 10×10 km^2. The mobile type sensor nodes attain mobility with the variation in the geographical location of the vehicles. In order to model the mobility of the vehicles and compute their speed and velocity, we apply the *Gauss-Markov mobility* [20] model. The speed (V_j^t) and direction (D_j^t) of the j^{th} vehicle is:

$$V_j^t = \alpha V_j^{(t-1)} + (1-\alpha)\bar{V}_j + \sqrt{(1-\alpha^2)}V_j^{r(t-1)} \tag{15a}$$

$$D_j^t = \alpha D_j^{(t-1)} + (1-\alpha)\bar{D}_j + \sqrt{(1-\alpha^2)}D_j^{r(t-1)} \tag{15b}$$

where α is the tuning parameter and $0 < \alpha \leq 1$. The mean value of speed and direction of the j^{th} vehicle is represented as $\bar{V}_j$ and $\bar{D}_j$. The velocity and direction of the vehicle in the immediate preceding time instant, $(t-1)$ is denoted by $V_j^{(t-1)}$ and $D_j^{(t-1)}$ respectively. The Gaussian random variables are represented as $V_j^{r(t-1)}$ and $D_j^{r(t-1)}$, respectively. Additionally, we consider 95% confidential interval to reveal the variance in the results for 100 simulation runs.

B. Benchmark Solution:

We compare the proposed pricing scheme, *RegPrice*, with the existing dynamic and optimal pricing scheme for provisioning Sensors-as-a-Service (Se-aaS) [1] and cloud-based pricing scheme, considering both the service providers and customers [2]. We termed the pricing schemes as DOPHS [1] and CLABACUS [2]. The pricing scheme proposed by Chatterjee *et al.* [1] considers the quality of information received to determine the expenses and the service cost. On the other hand, Sharma *et al.* [2] computed the cloud resource prices through mapping of the cloud parameters with the option pricing parameters. However, sharing the similar decision among multiple end-users using the concept of decision virtualization is not considered in the existing pricing schemes.

TABLE I: Simulation Parameters

Parameter	Value
Simulation area	$10 \times 10 Km^2$
Number of sensor nodes	100–1000
Range of payment	100–1500
Range of bituminous	0.10–0.25
Range of concrete	0.25–0.50
Range of gravel	0.50–0.75
sensing region	100–200

C. Results

We evaluate the performance of RegPrice, after detailed experimentation, using the following metrics:
Total payment by end-users: Fig. 2, illustrates the variations in the total payment done by an end-user with the increase in the number of end-users from 10–200, while the initial amount paid by an end user is varied from 500–1500 units. Further, we consider the presence of three different SSPs - SSP1, SSP2, and SSP3, who provided reduction factor of 1%, 3%, and 5% respectively. We observe that with the increase in the number of end-users, the total amount paid by an end-user follows a decreasing trend. Additionally, we observe that in case of initial payment of the end-user as 1500 units and allowable reduction factor as 5%, the slope of reduction in the total amount paid by the end-users is greater compared to the reduction factor of 1% and 3%. As the number of end-users increases, the decision parameters selected by them may overlap. The time required for processing and generation of decision reduces. Therefore, the expenses incurred for generation and maintenance of virtual decisions decreases. This is one of the possible reasons behind the drop in the total payment with the increase in the number of end-users. Therefore, we conclude that the region-based pricing scheme is beneficial for the end-users. Further, Fig. 3 depicts the variation of total amount paid by the end-users for a virtual decision with time. We vary the time from 10– 200 seconds along the x-axis, in case of initial payment of 500, 1000, and 1500 units done by the end-user. We observe random variations in the total amount paid by the end-users. The number and type of decision parameters requested by the end-users may change with time. Further, same decision parameters may be requested by different end-users. However, with time, the decision parameters requested by the end-users may change. On the other hand, through decision virtualization, a generated decision may be simultaneously shared among multiple end-users. Therefore, as the number of end-users requesting the same decision parameter/s vary, randomness is also observed in the amount paid by them.

Utility of a sensor node: As described in Equation 4, the cost of the sensor nodes acts as one of the important factors in determining the utility of that sensor node. Fig. 4 depicts the variation in average utility of the sensor nodes with the

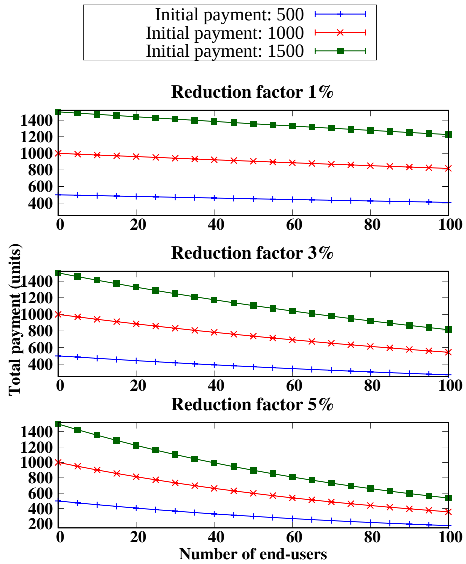


Fig. 2: Variation of total payment done by end-users

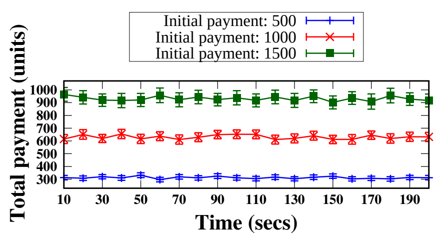


Fig. 3: Variation of payment by end-users with time

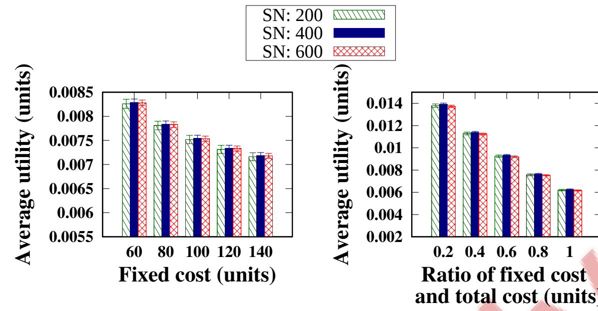
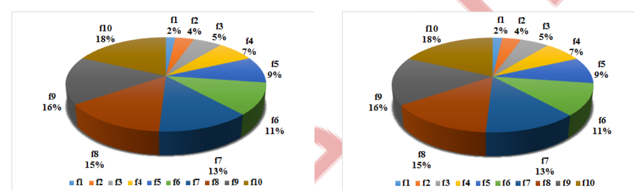


Fig. 4: Variation of utility with ratio of fixed and total cost of sensor owner



(a) Sensor nodes = 500 (b) Sensor nodes = 1000

Fig. 5: Variation of utility with effective evaluation element

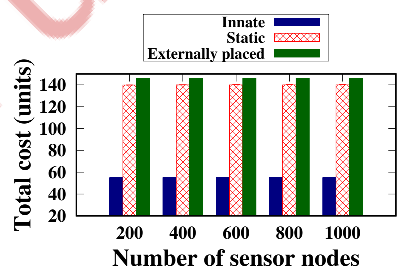


Fig. 6: Variation of total cost with the number of sensor nodes

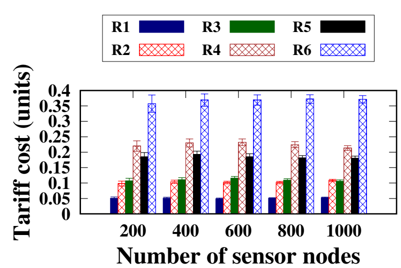


Fig. 7: Variation of tariff cost for different regions

increase in fixed cost associated with that node, and the ratio of the fixed cost to total cost. We observe that in both the plots, the average utility follows a decreasing trend in the presence of 200, 400, and 600 sensor nodes. The average utility reduces by 0.4% and 0.6% with the increase in fixed cost, in the presence of 400 and 600 sensor nodes, compared to 200 sensor nodes. On the other hand, the average utility reduces by 0.06% and 0.07% with the increase in the ratio of fixed cost to total cost incurred for a sensor node, in the presence of 400 and 600 sensor nodes, compared to 200 sensor nodes. One of the possible reasons behind such variation of average utility is that the utility of any sensor node is independent of the presence of other sensor nodes.

Figs. 5(a) and 5(b) illustrate the effect of effective evaluation on utility, with the help of pie charts, in the presence of 500 and 1000 sensor nodes. In both the cases, we observe that, with the increase in the value of effective evaluation element, its effect on utility increases from 2% to 18%. The reason behind such behavior is that, with the increase in the value of effective evaluation element, the rating provided by the end-users for the decisions provided to them is high. Further, each of the decisions is generated after combining different data of sensor nodes. Therefore, these sensor nodes is more likely to be trusted and selected for decision generation, and its utility increases. However, both the pie charts illustrate similar variations, which confirm the fact that the utility of single sensor node does not depend upon the total number of sensor nodes participating in the bidding process.

Total cost: Fig. 6 demonstrates the variations in the total cost incurred by a sensor owner for innate, static, and externally placed sensor nodes. We vary the number of sensor nodes in the range 200–1000 along the x-axis. We observe that the total cost is minimum for innate type sensor nodes. The probable reason behind this is that the fixed costs incurred for innate sensor nodes are negligible or minimum, as these types of nodes are inbuilt into the vehicles. On the other hand, the fixed costs incurred for static and externally placed sensor nodes include procurement, deployment, and

TABLE II: Summary of performance evaluation of benchmarks compared to RegPrice

Parameter	DOPHS	CLABACUS	Remarks
Service cost	0.78%	0.37%	reduced
Expenditure of SSP	9.71%	7.51%	reduced

maintenance costs. Therefore, we conclude that the total costs incurred in case of static and externally placed sensor nodes is always greater compared to the innate type sensor nodes. Moreover, the total cost of a sensor node is independent of the number of sensor nodes present in the simulation environment. Additionally, it is inferred that the sensor owners do not interact among themselves during bidding.

Tariff cost: One of the objectives of the proposed solution is that the proposed pricing scheme should vary in different geographical regions. In our simulation environment, we considered 6 different regions over which the heterogeneous types of sensor nodes are deployed. Fig.7 illustrates the variations in the tariff cost of any sensor node with the increase in the total number of sensor nodes for the regions – $R1$, $R2$, $R3$, $R4$, $R5$ and $R6$, as described in Section V-A. We observe that the tariff cost varies negligibly with the increase in the total number of sensor nodes. However, the value of tariff cost fluctuates region-wise. The possible reason behind this phenomenon is that the tariff cost demanded by the passive vehicle owners belonging to different regions is different. Additionally, the tariff cost increases in case the road construction material is bituminous, gravel, or, concrete. We also observe that the tariff cost is higher for hilly regions, as compared to the planes, probably due to the presence of less number of homogeneous sensor nodes in that region.

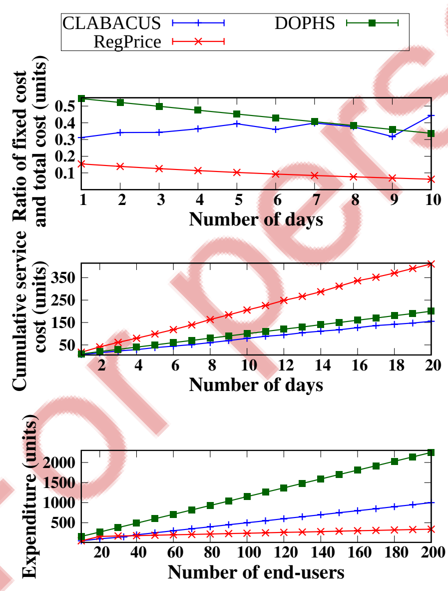


Fig. 8: Variation of expenses with end-users

Expenses of end-users: Fig. 8 illustrates the comparison of the proposed pricing scheme, RegPrice, with the existing pricing schemes [1], [2]. We observe that the cumulative service cost increases with the increase in the number of service days. Further, the cumulative service cost reduces by 0.78% and 0.37% compared with DOPHS and CLABACUS. However, in case of our proposed scheme, the cumulative service cost increases due to the fine amount charged by a SSP for per unit delay. On the other hand, the expenditure of the service provider is reduced by 9.71% and 7.51% compared to DOPHS and CLABACUS. On the other hand, in case of RegPrice, the ratio of fixed cost to total cost follows a decreasing trend with the increase in the number of days. The ratio of fixed costs to total cost follows a decreasing trend for DOPHS and seems to be increasing in case of CLABACUS.

TABLE III: Summary of performance evaluation of RegPrice

Parameter	Remarks
Total payment (Reduction factor 1%, 3%, and 5%)	reduces with increase in number of end-users
Total payment	randomly varies with time
Average utility	reduces with increase in fixed costs and ratio of fixed and total costs
Total cost	innate $<$ static $<$ externally placed sensor nodes
Tariff cost	$R1 < R2 < R3 < R4 < R5 < R6$

VI. Conclusion

In this paper, we proposed a region-based pricing scheme, RegPrice, for provisioning customized safety services to the end-users. Based on the different regions, the rent demanded by the passive vehicle owners may fluctuate. Considering this fact, we introduced the concept of tariff cost. After finding the cost of each sensor nodes, we estimate their utility. We considered the presence of multiple SSPs in our scenario. In order to model the interactions among the sensor owners and SSPs, we applied first-price sealed bid auction-based game-theoretic approach, where SSPs act as bidders. For the distribution of sensor nodes, we considered auction with incomplete information, where the SSPs only possess information about their own bid and do not have any information regarding the other bidders. The bidding process distributes the sensor nodes among SSPs maximizing the profit of both owners and SSPs. Extensive simulation results showed that the proposed scheme reduces the expenses incurred by a SSP compared to the existing pricing schemes.

In future, we plan to extend our work by considering the dynamic distribution of sensor nodes among the SSPs. Our proposed pricing scheme increases the feasibility of real world implementation of Safe-aaS as it optimizes the profit of SSPs as well as sensor owners. Therefore, we plan to implement the proposed pricing scheme with the Safe-aaS infrastructure in real-life environment.

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References

[1] S. Chatterjee, R. Ladia, and S. Misra, "Dynamic Optimal Pricing for Heterogeneous Service-Oriented Architecture of Sensor-Cloud Infrastructure," *IEEE Transactions on Services Computing*, vol. 10, no. 2, pp. 203–216, March 2017.

[2] B. Sharma, R. K. Thulasiram, P. Thulasiraman, and R. Buyya, "Clabacus: A Risk-Adjusted Cloud Resources Pricing Model Using Financial Option Theory," *IEEE Transactions on Cloud Computing*, vol. 3, no. 3, pp. 332–344, July 2015.

[3] C. Roy, S. Misra, and S. Pal, "Blockchain-Enabled Safety-as-a-Service for Industrial IoT Applications," *IEEE Internet of Things Magazine*, vol. 3, no. 2, pp. 19–23, 2020.

[4] C. Roy, A. Roy, S. Misra, and J. Maiti, "Safe-aaS: Decision Virtualization for Effecting Safety-as-a-Service," *IEEE Internet of Things Journal*, vol. 5, no. 3, pp. 1690–1697, June 2018.

[5] K. P. Divakarla, A. Emadi, and S. Razavi, "A Cognitive Advanced Driver Assistance Systems Architecture for Autonomous-Capable Electrified Vehicles," *IEEE Trans. on Transportation Electrification*, vol. 5, no. 1, pp. 48–58, March 2019.

[6] M. Chowdhury and K. Dey, "Intelligent Transportation Systems-A Frontier for Breaking Boundaries of Traditional Academic Engineering Disciplines [Education]," *IEEE Intelligent Transportation Systems Magazine*, vol. 8, no. 1, pp. 4–8, Spring 2016.

[7] C. Roy, S. Misra, J. Maiti, and M. S. Obaidat, "DENSE: Dynamic Edge Node Selection for Safety-as-a-Service," in *IEEE Global Communications Conference (GLOBECOM)*, 2019, pp. 1–6.

[8] C. Flores, P. Merdrignac, R. de Charette, F. Navas, V. Milans, and F. Nashashibi, "A Cooperative Car-Following/Emergency Braking System With Prediction-Based Pedestrian Avoidance Capabilities," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 5, pp. 1837–1846, May 2019.

[9] O. Karaduman, H. Eren, H. Kurum, and M. Celenk, "Road-Geometry-Based Risk Estimation Model for Horizontal Curves," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 6, pp. 1617–1627, June 2016.

[10] H. Shah-Mansouri, V. W. S. Wong, and R. Schober, "Joint Optimal Pricing and Task Scheduling in Mobile Cloud Computing Systems," *IEEE Transactions on Wireless Communications*, vol. 16, no. 8, pp. 5218–5232, Aug 2017.

[11] S. Son and K. M. Sim, "A Price- and-Time-Slot-Negotiation Mechanism for Cloud Service Reservations," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 3, pp. 713–728, June 2012.

[12] M. Dabbagh, B. Hamdaoui, M. Guizani, and A. Rayes, "Exploiting Task Elasticity and Price Heterogeneity for Maximizing Cloud Computing Profits," *IEEE Transactions on Emerging Topics in Computing*, vol. 6, no. 1, pp. 85–96, Jan 2018.

[13] L. Mashayekhy, M. M. Nejad, D. Grosu, and A. V. Vasilakos, "An Online Mechanism for Resource Allocation and Pricing in Clouds," *IEEE Transactions on Computers*, vol. 65, no. 4, pp. 1172–1184, April 2016.

[14] M. Aazam, E. N. Huh, M. St-Hilaire, C. H. Lung, and I. Lambadaris, "Cloud Customer's Historical Record Based Resource Pricing," *IEEE Transactions on Parallel and Distributed Systems*, vol. 27, no. 7, pp. 1929–1940, July 2016.

[15] A. S. Khan, Y. Rahulamathavan, B. Basutli, G. Zheng, B. Assadhan, and S. Lambotharan, "Blockchain-Based Distributive Auction for Relay-Assisted Secure Communications," *IEEE Access*, vol. 7, pp. 95 555–95 568, 2019.

[16] A. S. Khan, G. Chen, Y. Rahulamathavan, G. Zheng, B. Assadhan, and S. Lambotharan, "Trusted UAV Network Coverage Using Blockchain, Machine Learning, and Auction Mechanisms," *IEEE Access*, vol. 8, pp. 118 219–118 234, 2020.

[17] M. Tanaka and Y. Murakami, "Strategy-Proof Pricing for Cloud Service Composition," *IEEE Transactions on Cloud Computing*, vol. 4, no. 3, pp. 363–375, July 2016.

[18] D. L. R. Kadiyali, *Traffic Engineering and Transport Planning*. Khanna publisher, 1999.

[19] R. Ismail and A. Jøsang, "The Beta Reputation System," in *Bled eConference*, 2002.

[20] J. Ariyakhajorn, P. Wannawilai, and C. Sathitwiriyawong, "A Comparative Study of Random Waypoint and Gauss-Markov Mobility Models in the Performance Evaluation of MANET," in *International Symposium on Communications and Information Technologies*, Oct 2006, pp. 894–899.

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