QoS-Aware Dynamic Cost Management Scheme for Sensors-as-a-Service

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Abstract—In this paper, we study the problem of quality of service (QoS)-aware cost management of sensor-cloud comprising multiple sensor-cloud service providers (SCSPs) and sensor-owners. The rapid adaptation of the wireless sensor network (WSN) and Internet-of-Things (IoT) technology led to the conceptualization of the sensor-cloud infrastructure which primarily aims to reduce the complexities associated with operating WSN-based applications by rendering Sensors-as-a-Service (Se-aaS). However, the oligopolistic market scenario of sensor-cloud involving multiple SCSPs and sensor-owners significantly impacts its profitability and QoS. Thus, there is a need to explore the dynamics of this market competition elaborately in order to maintain the usability of sensor-cloud. The existing works fail to address the aforementioned issues in sensor-cloud. Hence, in this work, we analyze the interactions among the sensor-owners and the SCSPs using a game-theoretic approach. We propose a QoS-aware dynamic cost management scheme, named QUEST, to determine the optimal strategies of the various actors in sensor-cloud market. Through simulations, we observe that, using QUEST, the price paid by the end-users decreases by 10.31-20.43% and the revenue of sensor-owners improves by 66.83-89.94%. Moreover, QUEST ensures the service satisfaction of the end-users while optimally distributing the services among the SCSPs and the sensor-owners.

Index Terms—Sensor-Cloud, Se-aaS, Wireless sensor networks, IoT, sensor services, Service-Oriented Architecture, Game Theory, Stackelberg Game.

1 Introduction

SENSOR-CLOUD is an emerging technology which aims to revolutionize the way in which wireless sensor networks (WSNs) are utilized by end-user organizations employing Internet-of-Things (IoT) and WSN-based applications [1]. In sensor-cloud, with the help of cloud infrastructure, WSN resources are virtualized to form *virtual sensors* (VSs) which are provisioned *on-demand* through the Internet as *Sensors-as-a-Service* (Se-aaS) [2]. Thus, sensor-cloud infrastructure enables the sharing of WSN-based resources as well as computing resources among multiple end-user applications, thereby improving resource utilization and reducing investment costs of the end-users. In particular, sensor-cloud follows a heterogeneous Service-Oriented Architecture (SOA) comprising a combination of sensor network hardware and cloud infrastructural services. Similar to other cloud-service-based systems such as Infrastructure-as-a-Service (IaaS) and Platform-as-a-Service (PaaS), sensor-cloud involves the participation of three types of entities — end-users or the consumers, sensor-cloud service provider (SCSP), and sensor-owners or the WSN infrastructure providers. The SCSP obtains WSN resources on rental basis from the respective sensor-owners and provide Se-aaS to the end-users following the *pay-per-use* model [3]. Thus, sensor-cloud relieves the end-users from the duties and responsibilities associated with using WSNs while providing the SCSPs and the sensor-owners with an opportunity to earn revenue.

As the sensor-cloud follows a SOA, two factors of paramount importance that determine the sustainability of sensor-cloud are — end-users' satisfaction of the service and the revenue earned by the sensor-owners and the SCSP. To ensure high service satisfaction, the SCSP must deliver high quality of Se-aaS as per the requirements of the end-users at fair prices. On the other hand, the sensor-owners and the SCSP must charge sufficient prices for their services to ensure high profits, while considering their resource utilization cost and their ability to meet the service demands of the end-users. Furthermore, similar to the case of cellular or other cloud service-based systems, the coexistence of multiple SCSPs and sensor-owners delivering similar services has a substantial impact on the pricing model and and QoS of Se-aaS. Here, the SCSPs compete among themselves and try to maximize their profits by attracting large number of end-users by providing higher QoS at low prices. The sensor-owners, on the other hand, compete among themselves to earn more revenue by serving higher number of requests from the SCSPs and charging less rental. This competitive behavior results in an *oligopolistic* market scenario in which both the SCSPs and the sensor-owners are motivated to act based on their self-interests instead of the social benefit. This may eventually lead to the overburdening of the resources belonging to certain SCSPs and sensor-owners while under-utilization in case of others. Therefore, there is a need to consider the effects of the Se-aaS market competition, while deciding their resource allocation strategies for ensuring QoS and the prices to be charged by them to maintain their individual market preferences.

In the existing literature, researchers did not consider the existence of such oligopolistic market competition in sensor-cloud. Therefore, in this work, we attempt to study the

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underlying rationale of the competition among the various entities of the Se-aaS market and its effect on the price and QoS of Se-aaS. We present QUEST – a QoS-aware dynamic cost management scheme – for sensor-cloud based on Stackelberg game theory. As per our knowledge, this is the first work in this direction. To motivate the problem studied in this work, we further present a real-life application scenario in the following section.

Application Scenario: Let us consider a smart city scenario in which sensor nodes of different types (such as temperature, gas, camera, and proximity) are deployed throughout the city by multiple sensor-owners on traffic lights, streets, and buildings. These sensor-owners register their nodes with different SCSPs offering sensor-cloud services in the city. Thus, each SCSP is capable of provisioning Se-aaS for different types of applications such as environmental and traffic monitoring, and surveillance. An end-user possessing any of these types of applications in the concerned smart city, thus, can obtain the services of either of the operating SCSPs, who can use the nodes belonging to either of the registered sensor-owners. Clearly, in this scenario, the choices of the end-users and the SCSPs are primarily influenced by the prices and the QoS offered. For example, if SCSPs A and B offer service availabilities of 99% and 95%, respectively, at the same price, the end-user will request for the services of A. However, if A charges a price $100/hour$ and B charges a price $50/hour$ for the aforementioned QoS level, then the end-user may decide to opt for the services of B depending on his/her service requirements. Therefore, the SCSPs, who behave non-cooperatively, need to decide the optimal prices for Se-aaS provisioning in order to attract more end-users and ensure their high profit. Similarly, sensor-owner X offering a service response time of 10 milliseconds is preferred by the SCSPs over sensor-owner Y offering a service response time of 100 milliseconds at the same price. However, if X and Y charge $1/unit$ and $0.1/unit$ of sensed data, respectively, an SCSP may opt for the nodes of Y for low latency-sensitive applications. Therefore, similar to the SCSPs, the non-cooperative sensor-owners also need to decide the optimal rental price for their sensor nodes for attracting more SCSPs and ensuring their high profit. Thus, the presence of multiple SCSPs and sensor-owners in the Se-aaS market gives rise to an oligopoly in which the various entities aim to maximize their profits by serving a large customer base and the end-users try to maximize their service satisfaction by paying less. Thus, it is essential for the SCSPs and the sensor-owners to decide their priced optimally to obtain a fair chance to earn profits in the Se-aaS market. Hence, we argue that, there is a need for designing an optimal scheme to tackle the aforementioned application scenario in sensor-cloud.

Therefore, in this work, we propose a QoS-aware dynamic cost management scheme, named *QUEST*, for Se-aaS in sensor-cloud. We model the interactions among the various actors involved in oligopolistic sensor-cloud market using a two-tiered Stackelberg game theoretic approach. In the first tier, a *Single-Leader-Multiple-Followers Stackelberg game* is formulated in which (a) an end-user, acting as the leader, aims to maximize his/her service satisfaction in terms of price and QoS by choosing the optimum SCSP, and (b) multiple oligopolistic SCSPs, acting as the followers, aim to maximize their revenue by deciding an optimum price for the request. In the second tier, a *Multiple-Leaders-Multiple-Followers Stackelberg game* is formulated in which (a) the SCSPs, acting as the leaders, aim to minimize their cost by choosing the optimal sensor-owners for a request and (b) the sensor-owners, acting as the followers, aim to maximize their revenue by charging an optimal rental for the usage of their nodes. These two tiers are executed sequentially in order to obtain a sub-optimal solution in QUEST. The major *contributions* of this work are listed as follows:

1) In this work, the dynamics of the market competition among the various entities, viz., end-users, SCSPs and sensor-owners, in the Se-aaS market are modeled using two-tiered Stackelberg game theory. It is mathematically shown that the Stackleberg equilibrium exists for both the tiers.

2) Three utility maximization problems for the end-users, the SCSPs, and the sensor-owners, respectively, are formulated. The analytical expressions for the equilibrium prices to be charged by the SCSPs and the sensor-owners as well as the optimal QoS and data-rate of a service for the end-users are determined.

3) Four distinct algorithms are proposed for determining the aforementioned optimal decisions of the end-users, the SCSPs and the sensor-owners, respectively.

4) Finally, detailed performance evaluation of QUEST is performed and comparative analysis of QUEST with respect to two existing benchmark schemes is presented in this work.

2 Related Work

The tremendous applicability of sensor-cloud for supporting WSN-based applications has led to a significant increase in the research works related to sensor-cloud in the recent years. Researchers addressed several design issues in sensor-cloud, while focusing on its technical and the economic aspects, separately. The architectural, theoretical, and practical conceptualization of sensor-cloud were proposed by Misra *et al.* [1], Yuriama *et al.* [4], and Bose *et al.* [5], respectively. Based on these works, Madria *et al.* [6] developed a test-bed of sensor-cloud. Several other works addressed the hardware and networking-related problems in sensor-cloud for ensuring high QoS. For example, Chatterjee *et al.* [7] studied a data-center scheduling scheme for improving QoS in terms of service delay and end-user satisfaction. The cache-enabled architecture was proposed by Chatterjee *et al.* [8] to reduce redundant data transmissions while provisioning Se-aaS. Another scheme for improving energy efficiency was studied by Misra *et al.* [9], in which the authors addressed the problem of obtaining the optimal duty scheduling scheme for sensor nodes in sensor-cloud. Sen *et al.* [10] studied the security aspects of sensor-cloud and proposed an attack graph-based framework to assess the vulnerabilities associated with the architecture. On the other hand, researchers also explored the economic particulars of sensor-cloud in the existing literature. A dynamic pricing scheme is proposed by Chatterjee *et al.* [3] while taking into consideration the heterogeneity of the SOA of sensor-cloud and the end-user satisfaction. Zhu *et al.* [11] studied five pricing schemes while considering several service parameters in sensor-cloud. However, none of these works considered the effect of the market competition among multiple

SCSPs and multiple sensor-owners on the QoS, prices and service satisfaction of Se-aaS.

Contrarily, there are several works in the existing literature which considered the effects of market competition among service-providers in cloud-service based systems. Petri *et al.* [12] presented a model for federated clouds market in the presence of multiple resource and service providers to determine the services to be hosted and the tasks to be outsourced to other sites in the federation. Revenue maximization in cloud federations was also studied by Hadji and Zeghlache [13]. The authors proposed a linear integer program-based scheme for obtaining the optimum distribution of service load across federations for ensuring maximum profit of the service providers. In another work, Sharma *et al.* [14] proposed a pricing architecture for cloud services named Clabacus using fuzzy logic and genetic algorithms and financial option theory. The authors also studied the effects of economic conditions such as inflation and depreciation on the price and QoS of the services and presented the optimal bounds of the prices to ensure satisfaction of both the service providers and the end-users. Simão and Veiga [15] studied resource allocation problem in cloud using partial utility, to ensure high revenue and resource utilization. In another work, Ardagna *et al.* [16] proposed a profit maximization scheme for service provisioning using associated Software-as-a-Service (SaaS) and IaaS providers. In another work, Chichin *et al.* [17] presented a double sided mechanism for deciding the optimal resource allocation strategy and pricing schemes for buyer-seller market of IaaS providers. However, none of these schemes are suitable to be used in sensor-cloud because, unlike other cloud-based systems, sensor-cloud follows a heterogeneous SOA comprising hardware and infrastructural services. Thus, in addition to the SCSPs and their cloud infrastructure, sensor-cloud involves multiple oligopolistic sensor-owners and highly resource-constrained wireless sensor nodes. Therefore, in this work, we make an attempt to address the problem of cost management of competitive Se-aaS market for ensuring high quality and profitability of Se-aaS, and end-users' service satisfaction.

3 System Model

We consider an Se-aaS market with multiple sensor-owners, multiple SCSPs, and multiple end-users. The schematic diagram of sensor-cloud is presented in Figure 1. Each sensor-owner $o_i \in \mathcal{O}$, where $\mathcal{O}$ denotes the set of sensor-owners, purchases and deploys multiple sensor nodes having different types of sensors, in different geographical regions.

The sensor-owners register and render their sensor nodes to a subset of the available SCSPs on rental basis. The set of SCSPs in sensor-cloud market is denoted by $\mathcal{S}$. We consider that each sensor node $d_j^i \in \mathcal{D}_i$, where $\mathcal{D}_i$ denotes the set of sensor nodes owned by sensor-owner o_i, is registered with the subset of SCSPs $\mathcal{S}_{i,j} \subseteq \mathcal{S}$, where $\mathcal{S}_{i,j} \neq \{\emptyset\}$. It is to be noted that if d_j^i is serving any requests from SCSP $s_z \in \mathcal{S}_{i,j}$, the SCSP obtains partial control of d_j^i for the entire service duration. Using the technique of virtualization, each SCSP creates virtualized instances of these sensor-nodes, termed as *virtual sensors*, and provisions them in the form of Se-aaS units to the end-users.

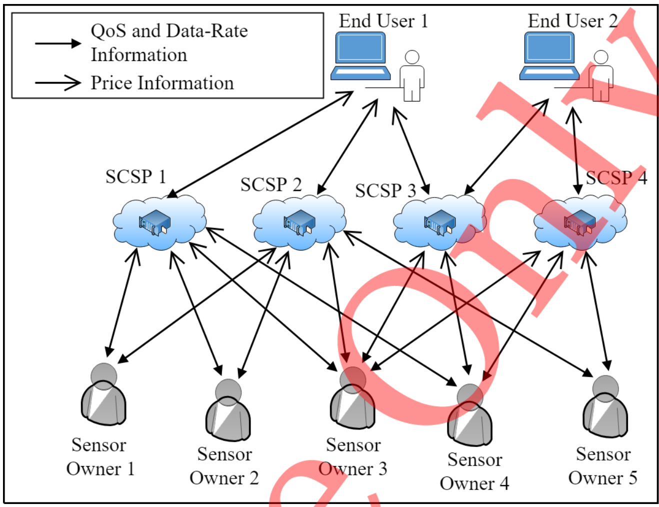

Fig. 1: Schematic Diagram of Service-Oriented Sensor-Cloud

On the other hand, each end-user $u_x \in \mathcal{U}$, where $\mathcal{U}$ denotes the set of end-users, communicates his/her service demands with the SCSPs and obtains the pricing-related information from them. At time t, the super set of services requested by the end-users is denoted by $\mathcal{R}$, where $R_x \in \mathcal{R}$ is the set of services requested by user u_x. We represent each service-request $r_y^x \in R_x$ using a three-tuple specified as follows:

$$r_y^x \equiv < T_y^x, Q_y^x, B_y^x >,$$

where T_y^x, Q_y^x and B_y^x are the type, desired QoS, as defined in Definition 1, and data-rate of the requested service r_y^x, respectively, and are specified by the end-user u_x.

Definition 1. *QoS Q_y^x of service request r_y^x is a measure of the freshness or timeliness of the sensed data delivered in the form of Se-aaS to an end-user. We calculate Q_y^x as –*

$$Q_y^x = \frac{h - \psi_y^x}{h}, \tag{1}$$

where h is a constant which denotes the maximum tolerable staleness and ψ_y^x is the amount of staleness that can be tolerated by user u_x for request r_y^x such that $0 \leq \psi_y^x \leq h$.

The service specifications of the end-users and the deliverables of the chosen SCSPs are mentioned in the Service Level Agreement (SLA). We argue that the Q_y^x and B_y^x values specified by an end-user must satisfy the *service requirement* constraints mentioned in Constraint 1.

Constraint 1. *QoS Q_y^x and data-rate B_y^x of each service r_y^x must meet the minimum service requirements of the end-user application while ensuring that their values are well within the maximum possible limits. Thus, we have the following service requirement constraints.*

$$(Q_{y,min}^x \leq Q_y^x \leq Q_{max}) \text{ and } (B_{y,min}^x \leq B_y^x \leq B_{max}), \tag{2}$$

where $Q_{y,min}^x$ and $B_{y,min}^x$ denote the minimum QoS and data-rate requirement of the service, respectively. Q_{max} and B_{max} are the maximum possible QoS and data-rate for any service.

We define an association parameter $\tau_{x,y,z}$ of service-request r_y^x with SCSP s_z as follows:

$$\tau_{x,y,z} = \begin{cases} 1, & \text{if service-request } r_y^x \text{ is served by SCSP } s_z \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Considering that service-request r_y^x is served by a single SCSP and the set of service requests served by SCSP s_z is represented by R_{s_z}, we have:

$$\sum_{\forall s_z \in \mathcal{S}} \tau_{x,y,z} = 1 \quad \text{and} \quad |R_{s_z}| = \sum_{u_x \in \mathcal{U}} \sum_{r_y^x \in R_x} \tau_{x,y,z} \tag{4}$$

On the other hand, we consider that, for service-request r_y^x, SCSP s_z provisions $\mathcal{V}_y^x$ set of virtual sensors, where $\tau_{x,y,z} = 1$ and $\mathcal{V}_y^x \neq \{\emptyset\}$. Each virtual sensor $v_q \in \mathcal{V}_y^x$ is served by a set of sensor nodes, $\mathcal{D}_q \subseteq \bigcup_{o_i \in \mathcal{O}} \mathcal{D}_i$, such that each sensor node $d_j^i \in \mathcal{D}_q$ may belong to any sensor-owner o_i. We define another association parameter $\omega_{z,q,i}$ among SCSP s_z, virtual sensor v_q, and sensor-owner o_i as follows:

$$\omega_{z,q,i} = \begin{cases} 1, & \text{if } v_q \text{ of SCSP } s_z \text{ is served by } o_i \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Hence, considering that virtual sensor v_q may be served using multiple senor-owners and $\mathcal{G}_{z,i}$ denotes the set of virtual-sensors associated with SCSP s_z being served by senor-owner o_i, we have:

$$\sum_{o_i \in \mathcal{O}} \omega_{z,q,i} \geq 1 \text{ and } |\mathcal{G}_{z,i}| = \sum_{u_x \in \mathcal{U}} \sum_{r_y^x \in R_x} \sum_{v_q \in \mathcal{V}_y^x} \omega_{z,q,i} \tag{6}$$

In this work, we assume that the resources possessed by the SCSPs and the sensor nodes deployed by the sensor-owners are enough to serve the service-requests of the end-users. Additionally, for simplicity, we assume that each request is served using a single virtual sensor. Therefore, we have the *resource sufficiency* constraints as mentioned in Constraint 2 and 3.

Constraint 2. *At any time instant, the SCSPs are capable of serving the service-requests made by the end-users. Thus, we have:*

$$\sum_{s_z \in \mathcal{S}} |R_{s_z}| = \sum_{u_x \in \mathcal{U}} |R_x| \tag{7}$$

Constraint 3. *The total number of virtual sensors served by the sensor nodes is equal to the total number of service-requests made by the end-users at any time. Thus, we have:*

$$\sum_{s_z \in \mathcal{S}} \sum_{o_i \in \mathcal{O}} |\mathcal{G}_{z,i}| = \sum_{u_x \in \mathcal{U}} |R_x| \tag{8}$$

3.1 Problem Statement

For the sustainability of the sensor-cloud infrastructure, it is essential to ensure the end-users' service satisfaction, while maintaining high revenue for the SCSPs and the senor-owners. To achieve these objectives, each of the three aforementioned entities needs to make the optimal decision *distributedly*, i.e., the end-users must obtain the optimal subset of SCSPs and the corresponding optimal QoS and data-rate values for serving their requirements; the SCSPs need to decide the optimal subset of senor-owners for provisioning Se-aaS and the optimal price to be charged from the end-users; and the sensor-owners need to decide the optimal price to be charged from the SCSPs for their sensor nodes. This scenario leads to a multi-objective multi-tier optimization problem in which the decision of each individual influences that of the others. Thus, in the absence of any centralized entity, Se-aaS provisioning in the presence of multiple SCSPs and sensor-owners becomes an NP-hard problem [18]. Therefore, to capture the dynamics of the complex decision making process of the entities participating in Se-aaS market and to obtain a sub-optimal solution of the aforementioned problem in polynomial time, we design an optimized cost management scheme for sensor-cloud in this work using a game-theoretic approach.

4 QUEST: The Proposed QoS-Aware Dynamic Cost Management Scheme

In this work, we propose a two-tiered Stackelberg game theory-based dynamic cost management scheme, named QUEST, to model the interactions among various entities in sensor-cloud. The justification for using this approach and the detailed game theoretic formulation are presented in the subsequent sections.

4.1 Justification for Stackelberg Game

The Se-aaS market follows a hierarchical structure with the sensor-owners at the bottom, the SCSPs in the middle, and the end-users at the top. Multiple sensor-owners compete among themselves to earn high profit, while ensuring cost-effective utilization of their sensor nodes and maintaining high preferability in Se-aaS market. Similarly, multiple SCSPs compete among themselves for obtaining high share of end-users by satisfying their service requirements with high QoS at competitive prices. On the other hand, each end-user aims to select the optimal SCSP with respect to service cost and quality for serving their applications. Thus, in sensor-cloud, the sensor-owners and the SCSPs behave *non-cooperatively* amongst each other resulting in the formation of two separate oligopolistic markets, such that the outcomes of these two competitive markets are interdependent. We argue that Stackelberg game [18] is the most appropriate mathematical tool to model the hierarchical dynamics of an oligopolistic market scenario. Hence, in order to model the interactions among different entities in the hierarchical Se-aaS market scenario, we use *two-tiered Stackelberg game theory*. The detailed theoretical analysis is discussed in the subsequent sections.

4.2 Game Formulation

The proposed hierarchical game comprises of two tiers which are described as follows:

Tier-I: In this tier, a *Single-Leader-Multiple-Followers Stackelberg game* is played among each end-user, who acts as the leader, and the multiple oligopolistic SCSPs, who act as the followers. Each end-user informs his/her service demands, i.e., $< type, qos, data\text{-}rate >$, to the available SCSPs. Based on these values, the SCSPs, which support the specified type of requested service, calculate the optimal price to be charged from the end-user, given the price charged by the sensor-owners for provisioning the service. On obtaining prices from multiple compatible SCSPs, each end-user decides the optimal SCSPs, and the corresponding optimal QoS and data-rate values for obtaining the services.

Tier-II: In this tier, a *Multiple-Leaders-Multiple-Followers Stackelberg game* is played among the multiple SCSPs, who act as the leaders, and the multiple sensor-owners, who act as the followers. Here, each SCSP propagates the service requirements of each end-user to the registered sensor-owners. Based on these, the sensor-owners calculate and inform the optimal rental price to be charged from the respective SCSPs for using their sensor nodes. Thereafter, the SCSPs choose the optimal subset of sensor-owners for provisioning Se-aaS.

We discuss the utility functions of the players in the proposed game as follows.

4.2.1 Utility function of End-User

For each service request r^x_y of end-user u_x, the utility function $\mathcal{U}_{x,y,z}(\cdot)$ signifies the satisfaction of the end-user by obtaining the service from SCSP s_z. It varies inversely with the price $p_{x,y,z}$ charged by SCSP s_z for providing the service and directly with the QoS Q^x_y and data-rate B^x_y. Based on the *law of diminishing marginal utility* [19], we define $\mathcal{U}_{x,y,z}(\cdot)$ as follows:

$$\mathcal{U}_{x,y,z}(\cdot) = \left(1 - \frac{p_{x,y,z}}{p_{max}}\right)\eta_{x,y}, \tag{9}$$

where $\eta_{x,y} = \log\left(1 + \frac{Q^x_y}{Q_{max}}\right)\log\left(1 + \frac{B^x_y}{B_{max}}\right)$ and p_{max} is the maximum price that can be charged by the SCSPs for serving a request having QoS Q_{max} and data-rate B_{max}. Each end-user u_x tries to maximize the pay-off of his/her utility function, and calculates the optimal Q^x_y and B^x_y for a given price $p_{x,y,z}$, while satisfying Constraint (1).

4.2.2 Utility function of SCSP

The utility function $\mathcal{S}_{x,y,z}(p_{x,y,z}, \boldsymbol{p}_{x,y,-z})$ of SCSP s_z varies directly with the revenue of the SCSP earned while serving request r^x_y. Here, $\boldsymbol{p}_{x,y,-z} = \{\cdots, p_{x,y,(z-1)}, p_{x,y,(z+1)}, \cdots\}$. This implies that, $\mathcal{S}_{x,y,z}(p_{x,y,z}, \boldsymbol{p}_{x,y,-z})$ rely on the price charged by the other SCSPs for Se-aaS in the sensor-cloud market. We define $\mathcal{S}_{x,y,z}(p_{x,y,z}, \boldsymbol{p}_{x,y,-z})$ as follows:

$$\mathcal{S}_{x,y,z}(\cdot) = log\left[p_{x,y,z}\log\left(1 + \frac{p_{x,y,z} - c_{x,y,z}}{p_{max}}\right)\right], \tag{10}$$

where $c_{x,y,z}$ is the cost incurred by SCSP s_z for serving request r^x_y and is determined as follows:

$$c_{x,y,z} = c'_{x,y,z} + c''_{x,y,z}, \tag{11}$$

Here, $c'_{x,y,z}$ denotes the infrastructural cost for creating and maintaining virtual machines and sensors for service r^x_y, and is considered to be fixed. $c''_{x,y,z}$ denotes the total price that SCSP s_z pays as rent to the sensor-owners for serving r^x_y and is dependent on the total service load R_{s_z} on SCSP s_z and the QoS and data-rate requirements of request r^x_y. It is determined as follows:

$$c''_{x,y,z} = \left[\frac{|R_{s_z}|}{p_{max}}\sum_{v_q\in\mathcal{V}^x_y}\sum_{o_i\in\mathcal{O}}\tilde{p}_{i,z}\eta_{x,y}\right], \tag{12}$$

where $\tilde{p}_{i,z}$ is the price to be paid by SCSP s_z per service to the sensor-owner o_i for using his/her sensor nodes. Given the value of the price being charged by the sensor-owners, each SCSP aims to maximize $\mathcal{S}_{x,y,z}(\cdot)$ while satisfying Constraint 2 along with the *profitability constraint* introduced in Constraint 4.

Constraint 4. *To ensure profits for the SCSPs, the price charged $p_{x,y,z}$ by each SCSP s_z for service r^x_y must fulfil the following profitability constraint.*

$$\tilde{p}_{i,z} < c_{x,y,z} \le p_{x,y,z} \le p_{max} \tag{13}$$

4.2.3 Utility function of Sensor-Owner

The utility function $\mathcal{E}_{i,z}(\tilde{p}_{i,z}, \tilde{\boldsymbol{p}}_{-i,z})$ of sensor-owner o_i represents the profit earned by leveraging his/her sensor nodes to SCSP s_z for providing Se-aaS. Here, $\tilde{\boldsymbol{p}}_{-i,z} = \{\cdots, \tilde{p}_{(i-1),z}, \tilde{p}_{(i+1),z}, \cdots\}$. Similar to Equation (10), we define the utility function $\mathcal{E}_{i,z}(\tilde{p}_{i,z}, \tilde{\boldsymbol{p}}_{-i,z})$ as follows:

$$\mathcal{E}_{i,z}(\cdot) = log\left[\tilde{p}_{i,z}\log\left(1 + \frac{\tilde{p}_{i,z} - \tilde{c}_{i,z}}{p_{max}}\right)\right], \tag{14}$$

where $\tilde{c}_{i,z}$ is the cost incurred by sensor-owner o_i for leveraging his/her sensor nodes to SCSP s_z for providing Se-aaS. It depends on the set of service-requests being served by the nodes belonging to sensor-owner o_i and their QoS and data-rate requirements. It is defined as follows:

$$\tilde{c}_{i,z} = \tilde{c}_0 B^{max}_{i,z,t} + \tilde{c}_1 Q^{max}_{i,z,t} + \tilde{c}_2|\mathcal{G}_{z,i}| \tag{15}$$

where $\tilde{c}_0$ and $\tilde{c}_1$ are constants. $\tilde{c}_2$ is the inverse of the total number of services requested by the end-users and defined as $\tilde{c}_2 = \frac{1}{\sum_{u_x\in\mathcal{U}}|R_x|}$. The coefficient of $\tilde{c}_2$ is defined in Equation (6). $B^{max}_{i,z,t}$ and $Q^{max}_{i,z,t}$ signify the maximum data-rate and QoS of particular type t of services that sensor-owner o_i is currently serving for SCSP s_z. Mathematically,

$$\begin{aligned} B^{max}_{i,z,t} &= \max\left\{B^{max}_{i,z,t}, B_{z,t}\right\} \ \&\ B_{z,t} = max\left\{B^x_y | \tau_{x,y,z} = 1\right\} \\ Q^{max}_{i,z,t} &= \max\left\{Q^{max}_{i,z,t}, Q_{z,t}\right\} \ \&\ Q_{z,t} = max\left\{Q^x_y | \tau_{x,y,z} = 1\right\} \end{aligned} \tag{16}$$

In QUEST, we consider that sensor-owner o_i is eligible to serve a service-request r^x_y, if and only if, s/he possess compatible physical sensor nodes which satisfy the *hardware constraint* mentioned in Constraint 5. Moreover, the price charged by the sensor-owners must ensure the *profitability constraint* mentioned in Constraint 6. Each sensor-owner aims to maximize $\mathcal{E}_{i,z}(\cdot)$, while satisfying the aforementioned constraints.

Constraint 5. *To ensure that a sensor node is capable of serving request r^x_y, it must satisfy the following constraints.*

$$E^{res}_{d^i_j} \ge E^{th},\ B^{ef}_{d^i_j} \le B^{d^i_j}_{max},\ and \sum_{d^i_j\in\mathcal{D}_i} B^{ef}_{d^i_j} = \sum_{s_z\in\mathcal{S}}\sum_t B^{max}_{i,z,t} \tag{17}$$

where $B^{ef}_{d^i_j} = \sum_z \sum_x \sum_y \sum_q B^x_y \tau_{x,y,z} \rho_{z,q,i,j}$ and $\rho_{z,q,i,j}$ is a binary variable, which is defined as, $\rho_{z,q,i,j} = 1$, iff $\omega_{z,q,i} = 1$ and SCSP s_z has allocated service r^x_y to physical sensor node d^i_j. $E^{res}_{d^i_j}$ and $B^{d^i_j}_{max}$ denote the residual energy and the maximum data-rate capacity of node $d^i_j \in \mathcal{D}_i$, respectively. E^{th} represents the minimum energy requirement of a node to serve a request.

Constraint 6. *To ensure profits for the sensor-owners, the price charged must be greater than the cost incurred. Hence, we define the profitability constraint for the sensor-owners as follows –*

$$\tilde{c}_{i,z} < \tilde{p}_{i,z} < p_{max} \tag{18}$$

4.3 Theoretical Analysis

In this section, we discuss the theoretical analysis of QUEST. We determine the two sub-game perfect equilibria for the two tiers of QUEST using *backward-induction* method. Firstly, given the QoS and data-rate requirements of the end-users, we determine the optimum price to be charged by each sensor-owner from the SCSPs. Secondly, using the price vector decided by the sensor-owners, we calculate the optimum price to be charged by each SCSP from the end-users. Finally, each end-user decides the optimal QoS and data-rate values for the service, and chooses the optimum subset of SCSPs by analyzing a trade-off between these two parameters and the price of the service. Thereby, we define the Stackelberg equilibrium of the hierarchical game in QUEST as mentioned in Definition 2.

Definition 2. *The Stackelberg equilibrium of QUEST is defined as the point ($B^{x*}_y, Q^{x*}_y, p^*_{x,y,z}, \tilde{p}^*_{i,z}$), which denotes the optimal strategies of the end-users, the SCSPs and the sensor-owners in terms of data-rate and QoS, price to be charged by the SCSPs, and rental to be charged by the sensor-owners, respectively. Thereby, for a given service-request r^x_y, QUEST needs to ensure that the following conditions are satisfied at equilibrium –*

$$\begin{aligned}
&\mathcal{E}_{i,z}(\tilde{p}^*_{i,z}) \geq \mathcal{E}_{i,z}(\tilde{p}_{i,z}) \\
&\mathcal{S}_{x,y,z}(p^*_{x,y,z}, \tilde{p}^*_{i,z}) \geq \mathcal{S}_{x,y,z}(p_{x,y,z}, \tilde{p}^*_{i,z}) \\
&\mathcal{U}_{x,y,z}(B^{x*}_y, Q^{x*}_y, p^*_{x,y,z}, \tilde{p}^*_{i,z}) \geq \mathcal{U}_{x,y,z}(B^x_y, Q^x_y, p^*_{x,y,z}, \tilde{p}^*_{i,z})
\end{aligned} \tag{19}$$

Hence, in order to the achieve the Stackelberg equilibrium solution of QUEST, the following objective function needs to be optimized —

$$\begin{cases}
\arg\max_{B^x_y, Q^x_y} \mathcal{U}_{x,y,z}(\cdot) \\
\quad \text{subject to } \arg\max_{p_{x,y,z}} \mathcal{S}_{x,y,z}(\cdot) \\
\quad\quad \text{subject to } \arg\max_{\tilde{p}_{i,z}} \mathcal{E}_{i,z}(\cdot)
\end{cases} \tag{20}$$

while satisfying the Constraints 1–6. Generally, non-cooperative game-theoretic approach does not necessarily ensure the existence of Stackelberg equilibrium. Hence, prior to determining the Stackelberg equilibrium solution, we evaluate the necessary conditions for the existence of equilibrium strategies for the sensor-owners, the SCSPs, and the end-users using Theorems 1, 2, and 3, respectively. From the theorems, we observe that Stackelberg equilibrium always exists for QUEST, while considering that the optimal QoS and data-rate values for each service are provided by the end-users.

Theorem 1. *Given QoS Q^{x*}_y and data-rate B^{x*}_y requirements of each service request r^x_y and maximum price p_{max}, there exists a unique Stackelberg equilibrium for the sensor-owners in QUEST.*

Proof. In QUEST, the payoff of the utility function $\mathcal{E}_{i,z}(\cdot)$ of each sensor-owner o_i is to be maximized. Hence, in order to identify the existence of unique Stackelberg equilibrium in QUEST, the payoff values for each sensor-owner needs to be maximized to obtain their Nash equilibrium strategies. Therefore, in QUEST, we maximize the overall utility function of the sensor-owners present in the system. Hence, we obtain:

$$\arg\max_{\tilde{p}_{i,z}} \sum_{o_i \in \mathcal{O}} \mathcal{E}_{i,z}(\cdot), \tag{21}$$

subject to Constraints 3 and 4. We solve this problem using Lagrangian Multipliers with Karush-Kuhn-Tucker (KKT) conditions. For detailed analysis, please refer to the supplementary file. □

Theorem 2. *Given QoS Q^{x*}_y and data-rate B^{x*}_y requirements of each service request r^x_y, a fixed price $p^*_{i,z}$ charged by the sensor-owners, and maximum price p_{max}, there exists a unique Stackelberg equilibrium for the SCSPs in QUEST.*

Proof. In QUEST, each SCSP tries to maximize the payoff of his/her utility function after obtaining the optimized value of price $\tilde{p}^*_{i,z}$ charged by each sensor-owner $o_i \in \mathcal{O}$. Thus, similar to Theorem 1, we maximize the overall utility function for the SCSPs to obtain their Nash equilibrium strategies, as mentioned below:

$$\arg\max_{p_{x,y,z}} \sum_{s_z \in \mathcal{S}} \mathcal{S}_{x,y,z}(\cdot) \tag{22}$$

while satisfying Constraints 2 and 6. Similar to Theorem 1, we can prove that there exists a unique Stackelberg equilibrium for the SCSPs in QUEST. For detailed analysis, please refer to the supplementary file. □

Theorem 3. *Given the price $p^*_{x,y,z}$ to be charged by SCSP s_z for service-request r^x_y, there exists a unique global equilibrium solution for an end-user who acts as the leader of the Tier-I sub-game in QUEST.*

Proof. In QUEST, from Theorem 2, we get that there always exists a unique Nash equilibrium for the SCSPs. On obtaining the optimized value of price $p^*_{x,y,z}$ charged by each SCSP $s_z \in \mathcal{S}$, each end-user tries to maximize the payoff of his/her utility function $\mathcal{U}_{x,y,z}(\cdot)$. Thereby, each end-user determines the optimal values of Q^x_y and B^x_y while satisfying the following objectives:

$$\arg\max_{Q^x_y, B^x_y} \mathcal{U}_{x,y,z}(\cdot) \tag{23}$$

subject to Constraint 1. We can prove that there exists a unique equilibrium for the end-users in QUEST using Lagrangian multipliers with KKT conditions. For detailed analysis, please refer to the supplementary file. □

4.3.1 Equilibrium Solutions for QUEST

We determine the sub-game perfect Nash equilibrium solutions for the proposed scheme in this subsection.

Optimal Solution for Each Sensor-Owner: In order to determine the optimum price $\tilde{p}^*_{i,z}$ to be charged from SCSP s_z by each sensor-owner o_i, we obtain the Nash Equilibrium solution for the non-cooperative game existing among the sensor-owners. Hence, we get:

$$\begin{aligned}&3\tilde{p}^{*3}_{i,z} + 3(p_{max} - \tilde{c}_{i,z})\tilde{p}^{*2}_{i,z} + (4p^2_{max} - 6p_{max}\tilde{c}_{i,z}\\&+3\tilde{c}^2_{i,z})\tilde{p}^*_{i,z} + (3p_{max}\tilde{c}^2_{i,z} - 2p^2_{max}\tilde{c}_{i,z} - \tilde{c}^3_{i,z}) = 0\end{aligned} \tag{24}$$

We rewrite the Equation (24) in the form $ag^3 + bg^2 + cg + e = 0$. Here, $g = \tilde{p}^*_{i,z}$, $a = 3$, $b = 3(p_{max} - \tilde{c}_{i,z})$, $c = (4p^2_{max} - 6p_{max}\tilde{c}_{i,z} + 3\tilde{c}^2_{i,z})$, and $e = (3p_{max}\tilde{c}^2_{i,z} - 2p^2_{max}\tilde{c}_{i,z} - \tilde{c}^3_{i,z})$. Thereafter, using Cardano's method [20], we obtain the value of $\tilde{p}^*_{i,z}$ which is mentioned below:

$$\tilde{p}^*_{i,z} = \sqrt[3]{-\frac{B}{2} + \sqrt{\frac{B^2}{2} + \frac{A^3}{27}}} + \sqrt[3]{-\frac{B}{2} - \sqrt{\frac{B^2}{2} + \frac{A^3}{27}}} - \frac{a}{3} \tag{25}$$

where $A = (\frac{c}{a} - \frac{b^2}{3a^2})$ and $B = \frac{e}{a} + \frac{2b^3}{27a^3} - \frac{bc}{3a^2}$.

Optimal Solution for Each SCSP: On obtaining the optimal values of $\tilde{p}_{i,z}$, we obtain the optimal price $p^*_{x,y,z}$ to be charged by SCSP s_z from each end-user u_x for serving request r^x_y which is as follows:

$$\begin{aligned}&3p^{*3}_{x,y,z} + 3(p_{max} - c_{x,y,z})p^{*2}_{x,y,z} + (4p^2_{max} - 6p_{max}c_{x,y,z}\\&+3c^2_{x,y,z})p^*_{x,y,z} + (3p_{max}c^2_{x,y,z} - 2p^2_{max}c_{x,y,z} - c^3_{x,y,z}) = 0\end{aligned} \tag{26}$$

Using Cardano's method, we obtain the solution for $p^*_{x,y,z}$ similar to $\tilde{p}^*_{i,z}$ as mentioned in Equation (25), where $a = 3$, $b = 3(p_{max} - \tilde{c}_{x,y,z})$, $c = (4p^2_{max} - 6p_{max}\tilde{c}_{x,y,z} + 3\tilde{c}^2_{x,y,z})$, and $e = (3p_{max}\tilde{c}^2_{x,y,z} - 2p^2_{max}\tilde{c}_{x,y,z} - \tilde{c}^3_{x,y,z})$.

Optimal Solution for Each End-User: Given the optimum price $p^*_{x,y,z}$ charged by each SCSP s_z, each end-user u_x determines the optimum QoS Q^{x*}_y and data-rate B^{x*}_y following similar procedures as mentioned earlier. By neglecting the higher order terms, we approximate the expression of η^x_y, as follows:

$$\eta^x_y = \frac{Q^x_y B^x_y}{Q_{max} B_{max}}$$

Using gradient descent method, we obtain:

$$\frac{\partial u_{x,y,z}}{\partial Q^x_y} = \frac{(1-w)(1+v)}{(1+u)Q_{max}} + \frac{\eta^x_y}{p_{max}} \frac{\partial p_{x,y,z}}{\partial Q^x_y} = 0 \tag{27}$$

$$\frac{\partial u_{x,y,z}}{\partial B^x_y} = \frac{(1-w)(1+v)}{(1+u)B_{max}} + \frac{\eta^x_y}{p_{max}} \frac{\partial p_{x,y,z}}{\partial B^x_y} = 0 \tag{28}$$

where $\frac{\partial p_{x,y,z}}{\partial Q^x_y} = \frac{\beta v}{Q_{max}}\left[\frac{3(1+w)^2-(1+3\xi)^2-6\xi(1-2\xi)}{(3w-2\xi+2)^2-\xi(\xi+2w)}\right]$ and $\frac{\partial p_{x,y,z}}{\partial B^x_y} = \frac{\beta u}{B_{max}}\left[\frac{3(1+w)^2-(1+3\xi)^2-6\xi(1-2\xi)}{(3w-2\xi+2)^2-\xi(\xi+2w)}\right]$. Here, we have, $u = Q^x_y/Q_{max}$, $v = B^x_y/B_{max}$, $w = p_{x,y,z}/p_{max}$ and $\xi = c_{x,y,z}/p_{max}$. By solving Equation (27), we obtain another cubic equation in the form of $a'g^3 + b'g^2 + c'g + d' = 0$, where

$$\begin{aligned}a' &= -3(\tfrac{c''_{x,y,z}}{Q^x_y})^2\\ b' &= -\tfrac{a'}{3}(1 + 6p_{max}(1+w) + 6c'_{x,y,z})\\ c' &= 2(2-(7w+4)p_{max})p_{max}(1-w)(c'_{x,y,z} - \tfrac{a'}{3})\\ &\quad - \tfrac{a'}{3}c'_{x,y,z}(2 - 6p_{max}(1+w) + 3c'_{x,y,z})\\ &\quad - \tfrac{a'}{3}p^2_{max}(1 - 3(1+w)^2)\\ d' &= p^3_{max}w(1-w)(2+3w)^2 + c'^2_{x,y,z}\end{aligned} \tag{29}$$

We solve this equation using Cardano's method, as mentioned earlier, to obtain Q^{x*}_y. We obtain similar results for B^{x*}_y. Following the aforementioned solution approaches, each end-user u_x makes a trade-off between the price charged, the QoS and the data-rate to decide upon the most suitable SCSP s_z for Se-aaS.

Algorithm 1 QUEST for each sensor-owner

INPUTS:
$T^x_y, B^x_y, Q^x_y, p_{max}, \tilde{c}_0, \tilde{c}_1, \tilde{c}_2, B^{max}_{i,z,t}, Q^{max}_{i,z,t}, \mathcal{G}_{z,i}, \forall s_z \in \mathcal{S}$
δ ▷ Price increment factor
OUTPUT:
$\tilde{p}^*_{i,z}$
PROCEDURE:
Set $temp \leftarrow -\inf$;
do
  Calculate $\tilde{c}_{i,z}$ for SCSP s_z using Equation (15);
  Calculate $\mathcal{E}_{i,z}$ for SCSP s_z using Equation (14);
  if $temp < \mathcal{E}_{i,z}$ **then**
    Set $temp \leftarrow \mathcal{E}_{i,z}$ and $\tilde{p}^*_{i,z} \leftarrow p_{i,z}$;
    Set $p_{i,z} \leftarrow p_{i,z} + \delta$;
  else
    break;
  end if
while (true);
  Return $\tilde{p}^*_{i,z}$;

Algorithm 2 QUEST for each SCSP

INPUTS:
$T^x_y, B^x_y, Q^x_y, \tilde{p}_{i,z}, p_{max}, R_{s_z}, \forall s_z \in \mathcal{S}$
δ ▷ Price increment factor
OUTPUT:
$p^*_{x,y,z}$
PROCEDURE:
Set $temp \leftarrow -\inf$;
do
  Calculate $c''_{x,y,z}$ for service r^x_y using Equation (11);
  Calculate $\mathcal{S}_{x,y,z}$ for service r^x_y using Equation (10);
  if $temp < \mathcal{S}_{x,y,z}$ **then**;
    Set $temp \leftarrow \mathcal{S}_{x,y,z}$ and $p^*_{x,y,z} \leftarrow p_{x,y,z}$;
    Set $p_{x,y,z} \leftarrow p_{x,y,z} + \delta$;
  else
    break;
  end if
while (true);
  Return $p^*_{x,y,z}$;

Algorithm 3 QUEST for optimum QoS of each end-user

INPUTS:
$T_y^x, B_y^x, Q_y^x, p_{max}, \delta, p_{x,y,z}, \forall s_z \in \mathcal{S}$
OUTPUT:
Q_y^{x*}
PROCEDURE:
Set $temp \leftarrow -\inf$;
do
    Calculate $\mathcal{U}_{x,y,z}$ using Equation (9) $\forall s_z \in \mathcal{S}$;
    if $temp < \mathcal{U}_{x,y,z}$ **then**;
        Set $temp \leftarrow \mathcal{U}_{x,y,z}$ and $Q^*_{x,y,z} \leftarrow Q_{x,y,z}$;
        Set $Q_{x,y,z} \leftarrow Q_{x,y,z} + \delta$;
    else
        break;
    end if
while (true);
    Return Q_y^{x*};

Algorithm 4 QUEST for optimum data-rate of each end-user

INPUTS:
$T_y^x, B_y^x, Q_y^x, p_{x,y,z}, p_{max}, \delta$
OUTPUT:
B_y^{x*}
PROCEDURE:
Set $temp \leftarrow -\inf$;
do
    Calculate $\mathcal{U}_{x,y,z}$ using Equation (9) $\forall s_z \in \mathcal{S}$;
    if $temp < \mathcal{U}_{x,y,z}$ **then**;
        Set $temp \leftarrow \mathcal{U}_{x,y,z}$ and $B^*_{x,y,z} \leftarrow B_{x,y,z}$;
        Set $B_{x,y,z} \leftarrow B_{x,y,z} + \delta$;
    else
        break;
    end if
while (true);
    Return B_y^{x*};

4.4 Algorithms

In this work, for QoS-aware dynamic cost management of sensor-cloud, we propose distinct algorithms for each of the three optimization problems. These are online algorithms and are executed each time an end-user requests for a service with new requirements. Initially, each end-user makes a service request to each SCSP by providing his/her service requirements in terms of type, QoS, data-rate, and the maximum price to be paid. Thereafter, each SCSP examines whether the active sensor nodes can fulfil these requirements. This is done by checking whether $T_y^x = T_q$, $Q_y^x \leq Q_q$, and $B_y^x \leq B_q$, for any active virtual sensor v_q being served by the SCSP. If such a virtual sensor v_q can be found, the SCSP creates a new virtual sensor v_r for the request with the same physical sensors as v_q and informs the corresponding sensor-owner(s) about the creation of v_r. Thereafter, the price to be charged by the SCSP for the service is decided using Algorithm 2. However, if such a virtual sensor is not found, the SCSP propagates the request to the sensor-owners who are capable of providing the required service. Thereafter, the sensor owners check if one or more of their nodes of the required type satisfy the hardware constraints mentioned in Constraint 5. Eventually, in case of the availability of such node(s), the sensor-owners calculate the optimum rental to be charged from each SCSP while ensuring high profits and maintaining their market preference using Algorithm 1. Based on the rental information provided by the sensor-owners, each SCSP chooses the most suitable sensor-owner for each service. Subsequently, using Algorithm 2, the SCSPs calculate the optimum price to be charged from each end-user for maximizing its profit while retaining his/her market share. It is to be noted that, in addition to the local information of the sensor-owners and the SCSPs, respectively, both Algorithms 1 and 2 consider the service requirements of the incoming request as inputs, thereby ensuring minimal communication overheads. Based on the optimum price values obtained from each SCSP, each end-user determines the optimum QoS and data-rate values for each service using Algorithms 3 and 4, respectively, and chooses the optimum SCSP for serving the request.

5 Performance Evaluation

In this section, the performance of QUEST is analyzed through simulations, while comparing it with two existing benchmark schemes, as discussed in the subsequent sections.

5.1 Simulation Parameters

We simulated QUEST in a MATLAB-based simulation platform and considered the Se-aaS market scenario comprising multiple SCSPs and multiple sensor-owners in which each end-user requests for one or more services from the SCSPs. The end-users specify their service-requests to each SCSP in terms of type, QoS, and data-rate. In our experiments, we considered that the service-requests are of 5 different types and each SCSP and each sensor-owner is capable of providing each type of services. The QoS is a randomly generated value within the range $[0, 1]$, thereby, having a maximum value of 1. On the other hand, the data-rate is a randomly generated real number having a maximum value of 250 kbps, which is the maximum possible data-rate that is supported by the Zigbee-enabled (IEEE 802.15.4) wireless sensor nodes. During simulations, we varied the number of sensor-owners, SCSPs, and end-users in the Se-aaS market, as mentioned in Table 1, to analyze the performance of QUEST in terms of the metrics mentioned in Section 5.3.

TABLE 1: Simulation Parameters

Parameter	Value
Number of end-users	$100, 250, 500$
Maximum number of service/end-user	5
Types of service	5
Maximum data-rate per service	250 $kbps$
QoS Requirement for each service	$[0, 1]$
Number of sensor owners	$5, 10, 20$
Number of SCSP	$3, 10, 20$
Number of sensor nodes/owners	100
Maximum Energy per sensor node	20J [18]
Maximum data-rate per node	250 $kbps$
Maximum price per service (p_{max})	100 $units$

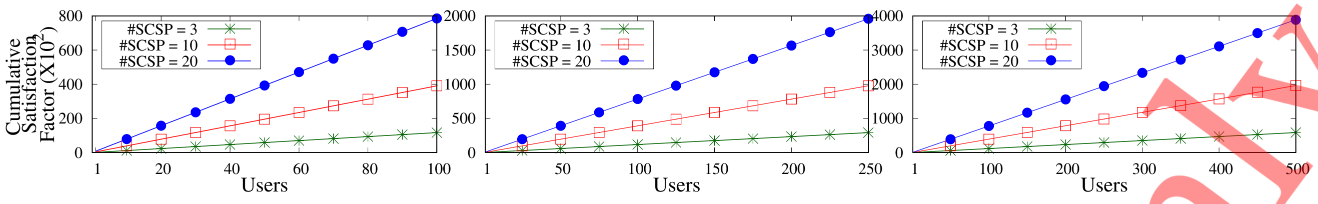

Fig. 2: Satisfaction Factor of End-Users (#Sensor-Owners = 5)

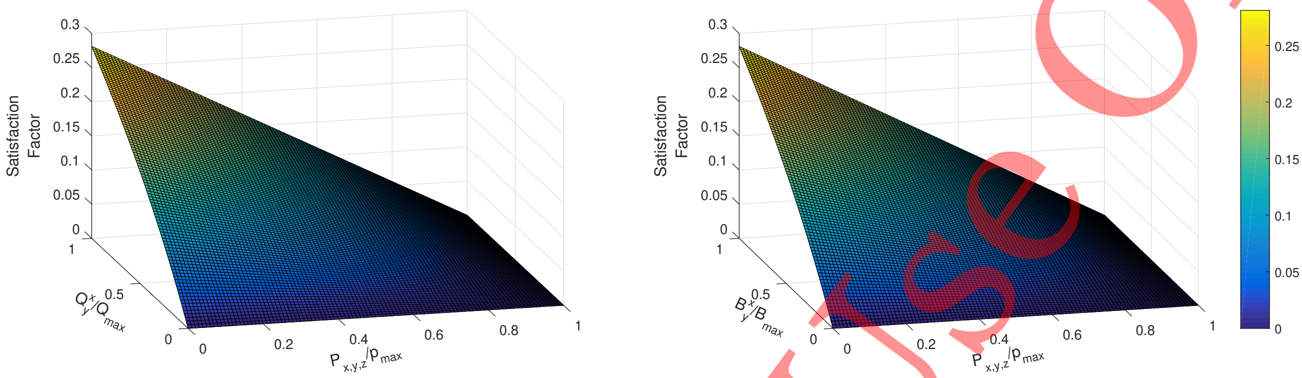

Fig. 3: Satisfaction Factor of End-User

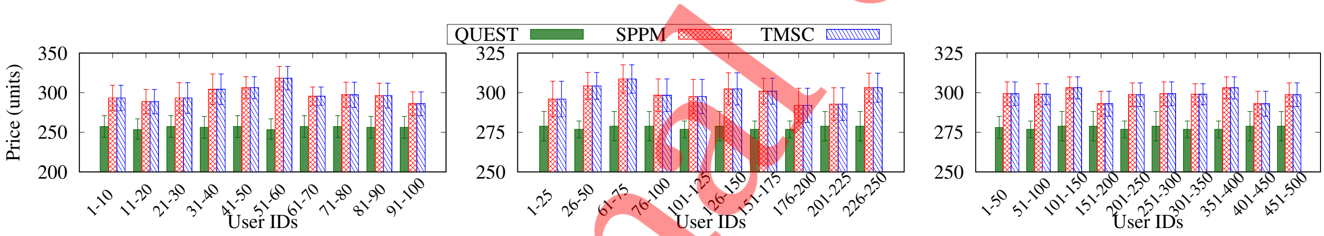

Fig. 4: Price Paid by End-Users (#SCSP = 3, #Sensor-Owners = 5)

5.2 Benchmarks

As mentioned earlier, the effect of the market competition among multiple SCSPs and multiple sensor-owners on the pricing and the quality of Se-aaS is not considered in the existing research works. As per our knowledge, this is the first work in this direction. However, to evaluate the performance of QUEST, we consider two existing benchmark schemes.

The first one is the theoretical modeling of sensor-cloud (TMSC) [1], in which Misra *et al.* presented the basic mathematical modeling of a sensor-cloud infrastructure. The authors proposed an allocation function for the mapping of each virtual sensor to each physical sensor node for provisioning Se-aaS. Using the proposed scheme, a random set of compatible sensor nodes are allocated to each service irrespective of the ownership of the nodes, the rental charged, or the current service load of the node. It must be noted that, in this work, the authors did not consider the market competition among multiple SCSPs and multiple sensor-owners. On the contrary, a more generalized framework to study the technical and economic aspects of sensor-cloud is presented by the authors in TMSC.

The second scheme considered for comparative analysis is the generalized Nash equilibria for theservice provisioning problem in multi-cloud systems (SPPM) [16]. The multi-cloud scenario comprising multiple IaaS and SaaS providers considered in this work is mapped to the oligopolistic Se-aaS market comprising multiple competitive SCSPs and sensor-owners. In both these scenarios, the success of each competing entity is dependent on the other entities. In SPPM, an optimal resource management scheme with revenue maximization is proposed by Ardagna *et al.* [16]. The authors used a game-theoretic approach based on generalized Nash equilibrium to ensure minimum service cost while maintaining the QoS. However, SPPM is not suitable to be used in sensor-cloud infrastructure due to the difference in the type of resources utilized.

5.3 Performance Metrics

To evaluate the performance of QUEST, we used the following performance metrics:

Satisfaction factor of each end-user: Satisfaction factor of each end-user is calculated as a function of the service requirements and the price to be paid for the services using Equation (9). It varies inversely with the price charged by the SCSPs and directly with the QoS and data-rate values. The cumulative satisfaction factor is the additive value of the satisfaction factors of the end-users, as new users enter the system.

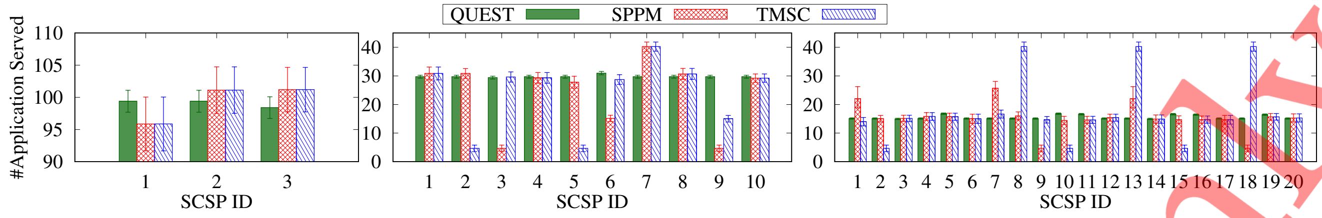

Fig. 5: Number of Applications Served by each SCSP (#End-Users = 100, #Sensor-Owners = 5)

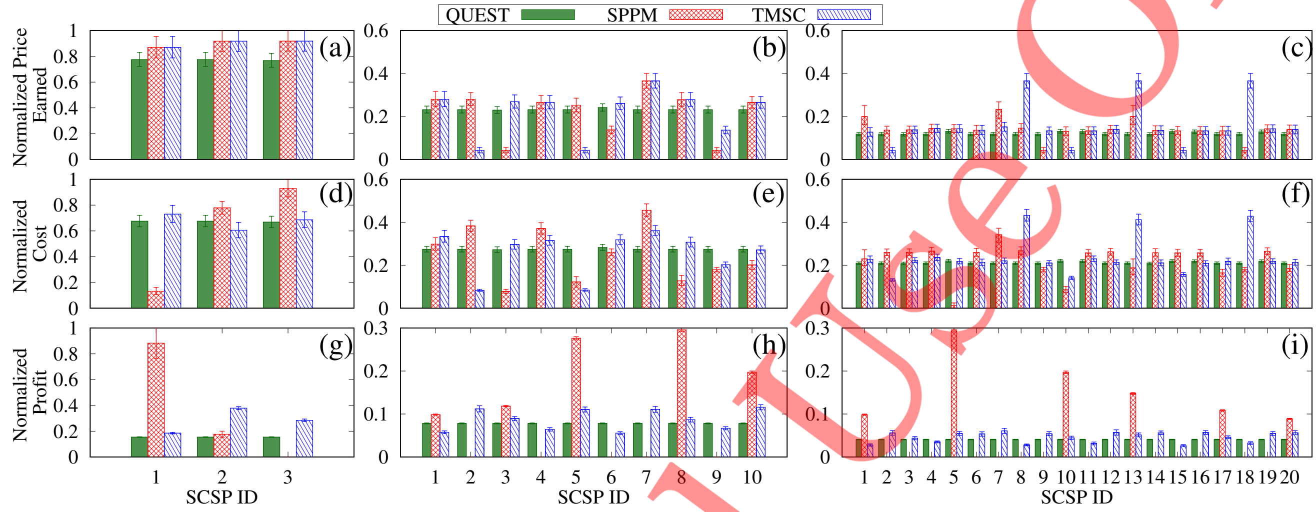

Fig. 6: (a-c) Price Charged, (d-f) Cost Incurred, and (g-i) Profit Earned by the SCSPs (#End-User = 100, #Sensor-Owner = 5)

Price paid by each end-user: The price paid by each end-user for each service is equal to the price $p_{x,y,z}$ charged by the chosen SCSP s_z. An SCSP charging low price for each unit of Se-aaS is more preferable to an end-user compared to the other SCSPs.

Profit of each SCSP: It is the cumulative sum of the profits earned by each SCSP to provision the allocated set of services for unit duration. The profit earned by serving each service-request is calculated using Equation (10). It is varies proportionally with the total number of services served and the corresponding price charged by the SCSP.

Applications Served by each SCSP: The number of service requests provisioned by each SCSP signifies the proportion of the end-user base captured by each SCSP and thus, provides a measure of his/her share in the Se-aaS market. An optimum number service-requests must be served by each SCSP at any time instant to ensure high profits of the SCSP while prohibiting the over-burdening of its resources.

Profit of each sensor-owner: It is calculated as the cumulative profit acquired by each sensor-owner by serving the requests of the SCSPs using his/her sensor nodes for unit time duration. The profit earned by each sensor-owner by serving each service-request is calculated using Equation (14) and is directly proportional to the rental price being charged and the maximum QoS and data-rate requested by that particular SCSP.

5.4 Results and discussions

In this section, we discuss the simulation results of the comparative analysis of QUEST.

Figure 2 depicts the variation of the cumulative satisfaction factor of the end-users with the change in the number of SCSPs and the total number of registered end-users. Using QUEST, the cumulative satisfaction factor increases almost linearly with a constant slope indicating that the satisfaction factor remains unaffected with the increase in the number of end-users in the system. Hence, we argue that QUEST is scalable. Additionally, we yield that with the increase in the number of SCSPs in the system, the satisfaction factor increases significantly. This can be attributed to the fact that the price charged by each SCSP for Se-aaS decreases with the increase in market competition, thereby resulting in an increase in satisfaction factor. Additionally, from Figure 3, we observe that the satisfaction factor of each end-user increases with the increase in QoS and data-rate for a fixed price charged by the SCSPs, and decreases with the increase in price charged by the SCSPs with the QoS and the data-rate remaining constant. Therefore, we argue that each end-user aims to obtain Se-aaS with high QoS and data-rate at low price for achieving high service satisfaction. On the other hand, in the other two schemes TMSC and SPPM, the service satisfaction of the end-users is not considered and hence, the comparative analysis of QUEST with existing schemes in terms of this parameter is not presented.

From Figure 4, we observe the cumulative price paid by each end-user for Se-aaS and its variation with the increase in the number of end-users, for a fixed number of SCSPs and sensor-owners in the market. We yield that using QUEST, the price paid for each unit of Se-aaS is fixed for each end-user and remains almost unchanged with the increase

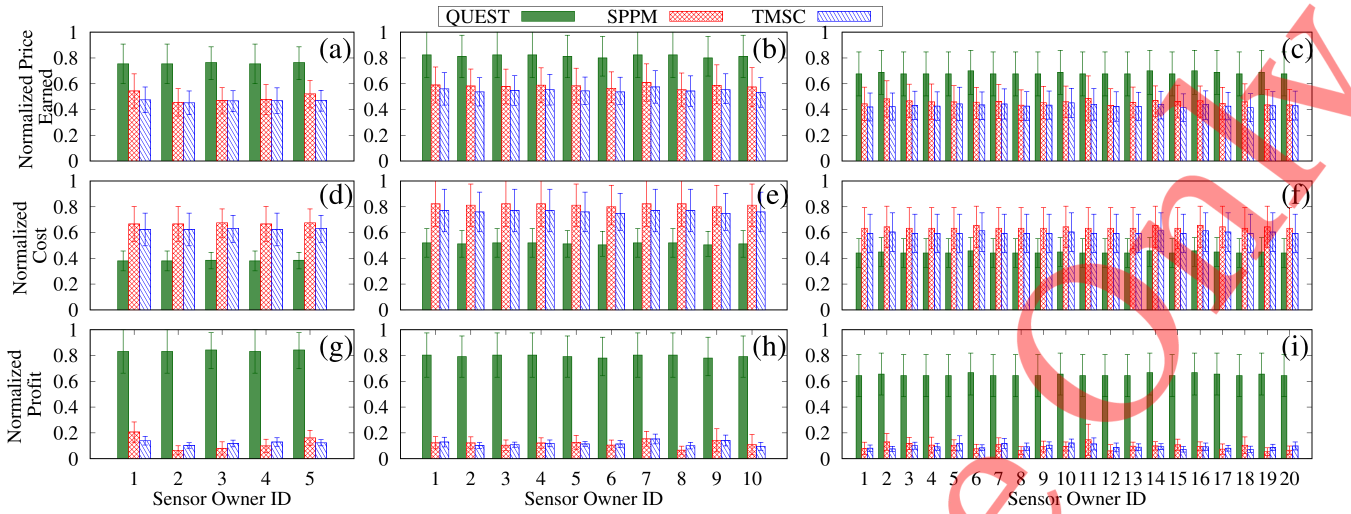

Fig. 7: (a-c) Price Charged, (d-f) Cost Incurred, and (g-i) Profit Earned by the Sensor-Owners (#End-User = 100, #SCSP = 3)

in the number of end-users in the system. Therefore, the scalability argument of QUEST is also supported by Figure 4. Additionally, using QUEST, a decrease of 10.31–20.43% in the price paid by each end-user is achieved, than using the existing schemes — TMSC and SPPM. This is attributed to the fact that unlike the other two schemes, optimized prices are charged by the sensor-owners and the SCSPs using QUEST, while considering that the end-users' satisfaction and the profitability of Se-aaS is maintained. Additionally, QUEST ensures that monopoly of the sensor-owners and the SCSPs is prevented in Se-aaS market, unlike the other two schemes.

Figure 5 presents the number of applications served while Figure 6 depicts the price charged, cost incurred, and profits earned by each SCSP. For a fixed number of end-users and sensor-owners, the variation of the aforementioned parameters with the increase in the number of SCSPs in the market is also shown. We observe that these parameters follow almost equal distributions using QUEST. Using SPPM and TMSC, the distribution of each of these parameters are random. This is due to the fact that using QUEST, with the increase in the service load of each SCSP, the resource consumption costs increase, thereby leading to an increase in the prices charged. As a result, the preference of the SCSP in the Se-aaS market decreases, leading to a corresponding decrease in the probability of him/her being chosen by the end-users for further services. Thus, the service load on each SCSP is regulated. On the other hand, using TMSC and SPPM, the selection of SCSPs is performed randomly, resulting in randomly distributed service loads and profits earned. Hence, we argue that the SCSPs are less vulnerable to losses using QUEST, compared to using the existing schemes, TMSC and SPPM.

Similarly, from Figure 7, we observe the distributions of the price charged, cost incurred, and profit earned by each sensor-owner for fixed number of SCSPs and end-users, while varying the total number of available sensor-owners. We yield that the profits earned by the sensor-owners increases by 66.83–97.57% and 77.97–89.94% using QUEST, compared to using TMSC and SPPM, respectively. Moreover, we observe that, similar to Figure 6, the overall market revenue is shared almost equally among the sensor-owners using QUEST. This is due to the fact that, using QUEST, each sensor-owner takes an active role in deciding his/her own profit as well as the price to be charged from the end-users. Additionally, with the increase in QoS and data-rate requirements of the request, the resource consumption of the sensor nodes increases, thereby increasing the cost incurred by the sensor-owners. This leads to an increase in the price charged by the sensor-owners which eventually, decreases his/her preference in the Se-aaS market. Therefore, using QUEST, we observe a trend of even distribution of the service requests and the profits among the sensor-owners. On the other hand, using TMSC and SPPM, the selection process of the sensor-owners is random and the pricing decision for Se-aaS is completely controlled by the SCSP. Thus, only a small percentage of the profits earned by each SCSP is paid to the sensor-owners. Hence, we argue that, using QUEST, each sensor-owner obtains an opportunity to participate in the decision making process of Se-aaS market alongside the SCSPs.

6 Conclusion

In this work, we proposed QUEST – a QoS-aware dynamic scheme – for the cost management of the oligopolistic Se-aaS market comprising multiple competitive SCSPs and sensor-owners. We adopted a game theoretic approach based on two-tiered Stackelberg game to model the dynamics of the market competitions among the entities and studied its effects on the economic as well as qualitative aspects of sensor-cloud. In Tier-I of the proposed game, each end-user and the SCSPs play a Single-Leader-Multiple-Followers Stackelberg game to determine the optimal strategies in terms of the choice of SCSP, QoS, and data-rate for a service, and the price to be charged, respectively. In Tier-II, a Multiple-Leaders-Multiple-Followers Stackelberg game is played among the SCSPs and the sensor-owners to determine the optimal strategies with respect to the choice of sensor-owners, and the rental price for sensor nodes, respectively. Through detailed mathematical analysis, we proved the existence of Stackelberg Equilibrium for each tier of QUEST and also, presented the Nash Equilibrium solution for each of the participating entities. Through simulations, we observed that QUEST outperforms the benchmark schemes – TMSC and SPPM, in terms of the end-users' satisfaction and the profitability of Se-aaS to the SCSPs and the sensor-owners.

This work can be further extended to include the dynamics of the sensor node selection by the sensor-owners, while ensuring optimum resource utilization of the nodes. It can also be extended by incorporating the actual determination of the other QoS parameters such as duration of service and geographical locations of the requested services. Furthermore, these works can be validated using a real test-bed, in future, while evaluating different network parameters.

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