RACE: QoI-Aware Strategic Resource Allocation for Provisioning Se-aaS

Sudip Misra†, *Senior Member, IEEE*, Robert Schober‡, *Fellow, IEEE*, and Aishwariya Chakraborty†, *Student Member, IEEE*

Abstract—In this work, the problem of ensuring profitability for multiple sensor-owners in sensor-cloud, while satisfying the service requirements of end-users, is studied. In traditional sensor-cloud, Sensor-Cloud Service Provider (SCSP) solely dictates the service provisioning process. However, the SCSP cannot always ensure high profits for sensor-owners, who incur significant maintenance costs for their sensor-nodes. Contrarily, it is highly essential to meet the Quality-of-Information (QoI) requirements of end-users to ensure their service satisfaction. In the existing literature, researchers proposed few node allocation schemes which neither consider the cost incurred by sensor-owners nor the QoI of sensed-data in sensor-cloud. To address this problem, a strategic resource allocation scheme, named RACE, is proposed, which introduces the participation of sensor-owners in the node allocation process. Firstly, utility theory is used to calculate the optimum number of nodes to be allocated for a service. Thereafter, single leader multiple followers Stackelberg game is formulated to decide the number of nodes to be contributed by each sensor-owner and the price to be charged. Through simulations, we observed that, using RACE, the profits of the sensor-owners and those of the SCSP increase by 86.11–89.26% and 41.95–80.82%, respectively, as compared to existing benchmark schemes, while considering that each sensor-node is capable of serving multiple applications simultaneously. Moreover, service availability in sensor-cloud increases by 31.70–96.96% using RACE.

Index Terms—Sensor-Cloud, Se-aaS, Game Theory, Utility Theory, Resource allocation.

1 Introduction

To meet the increasing global demands for wireless sensor network (WSN)-based applications, conventional WSNs are coupled with cloud infrastructure to offer Sensors-as-a-Service (Se-aaS). This integrated platform, referred to as *sensor-cloud* [1], [2], follows a Service-Oriented Architecture (SOA) comprising of three entities — sensor owners, sensor-cloud service provider (SCSP), and end-users [3]. With the help of cloud technology, the SCSP enables the virtualization of physical sensor nodes, which are obtained on rental basis from their respective sensor owners, for provisioning WSNs in the form of service units to the end-users. On the economic side, sensor-cloud adopts a *pay-per-use* model, in which the end-users make payments to the SCSP as per their service consumption and the sensor owners are compensated by the SCSP for the usage of their sensor nodes. Similar to other SOAs, the SCSP and the end-users are bound by the terms of a Service Level Agreement (SLA) specifying various service-related parameters decided based on mutual agreement for a particular service.

Owing to the merger of heterogeneous types of services, i.e., hardware and infrastructure, and the involvement of multiple commercial entities, efficient allocation of sensor-cloud resources while satisfying the financial interests of each entity is a significant yet challenging task. Moreover, the utility of sensor-cloud is strongly influenced by the quality and the characteristics of the sensed information provided by the sensor nodes as these parameters decide the fitness of the information for serving a particular end-user application [4]. Thus, it is also essential for an SCSP to simultaneously meet the Quality-of-Information (QoI) requirements of the service requests of the end-users while provisioning Se-aaS [3]. Existing literature on sensor-cloud fail to address the issue of ensuring the profitability of Se-aaS for both the SCSP and the sensor owners while simultaneously ensuring the service satisfaction of the end-users. Therefore, in this work, we propose a QoI-aware strategic resource allocation scheme, named RACE, for sensor-cloud to address the aforementioned issues.

From the economic perspective, sensor-cloud infrastructure can be visualized as a competitive market, in which the end-users act as the consumers of Se-aaS, the SCSP acts as the prosumer (producer of Se-aaS and consumer of sensor nodes), while the sensor owners act as the suppliers of sensor nodes. In this market, the SCSP and the sensor owners try to earn high profits while ensuring service satisfaction of the end-users. In the existing literature, few works [3], [5], [6] focused on the economic aspects of sensor-cloud and the effects of market competition on its functioning. In the traditional sensor-cloud architecture, once the sensor

- † *Sudip Misra and Aishwariya Chakraborty are with the Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur, India (Email: smisra@sit.iitkgp.ac.in; aishwariya.chakraborty@iitkgp.ac.in).*
- ‡ *Robert Schober is with the Department of Electrical-Electronic-Communication Engineering, Institute for Digital Communications (IDC), Germany. (Email: robert.schober@fau.de)*

owners register their sensor nodes with the SCSP, the SCSP obtains full control of using the sensor nodes. However, the responsibility of the maintenance of the sensor nodes resides with sensor owners throughout. As the revenue earned by the sensor owners depends solely on the usage of their nodes, which, in turn, is decided by the SCSP, high profits cannot always be ensured for the sensor owners using the existing schemes. However, for the proper functioning of sensor-cloud, it is essential to satisfy the interests of the sensor owners for maintaining their participation in the sensor-cloud market.

On the other hand, the profit earned by the SCSP in sensor-cloud is influenced significantly by the service satisfaction of the end-users, and hence, the quality-of-service (QoS) of Se-aaS. Since sensor-cloud is designed to provision sensor network-based services, an important aspect of the QoS of Se-aaS is its QoI, which deals with several attributes of sensed information such as context, coverage, accuracy, timeliness, and security. To ensure high revenue, it is also essential for an SCSP to ensure that the QoI demands of end-user applications are satisfied at all times. In the existing literature, Chatterjee *et al.* [3] considered the QoI of Se-aaS for deciding the price to be paid to sensor owners by the SCSP. However, the authors neither considered the possibility of having varying QoI requirements for each service-request, nor contemplated the allocation of resources based on these specific QoI demands. Therefore, in this work, we aim to address the aforementioned lacuna of the sensor-cloud architecture by proposing RACE, a QoI-aware resource allocation scheme, which encourages the active participation of the sensor owners along with the SCSP in the Se-aaS provisioning process. We present a practical scenario which depicts the necessity of addressing the aforementioned problem as follows.

Motivating Scenario: We consider a Smart City in which an SCSP provides environmental monitoring services using sensor nodes deployed by various sensor-owners. End-users such as weather stations, farmers, and common people, can obtain these services easily in exchange of a nominal service charge, using the sensor-cloud infrastructure. Let us consider two end-users – (a) User A, who is a farmer and requires accurate information of daily weather conditions and emergency alarms in case of events such as rainfall, and (b) User B, who is a office-goer and requires weather information before his daily commute to and from the office. Evidently, User A has a higher QoI requirement in terms of accuracy, coverage, and sensing rate, compared to User B, and hence, different amounts of resources are needed to provide these services. Further, we consider that, to provide these services, the SCSP utilizes sensor nodes belonging to two sensor-owners, X and Y, who incur maintenance costs of c_1 and c_2 units per node, respectively, where $c_1 > c_2$. In such circumstances, as the SCSP is unaware of the node maintenance costs, the resource allocation decision solely taken by the SCSP is not always profitable to the sensor-owners. Hence, the active participation of sensor-owners in the resource allocation process is necessary to ensure their profit and maintain their involvement in the Se-aaS market.

In this work, we propose a QoI-aware strategic resource allocation scheme, named RACE, for ensuring the profitability of the sensor owners and the SCSP, and service satisfaction of the end-users in sensor-cloud. In the proposed scheme, on receiving the service requirements from an end-user, the SCSP informs the minimum and the maximum number of nodes that can be allocated for the request and their corresponding prices for achieving a desired QoI level. Based on these, the end-user decides the optimal number of nodes to be allocated. Thereafter, the SCSP declares its demand for sensor nodes for the service to the sensor owners, depending on which, the sensor owners decide the optimal number of their sensor nodes to be used for serving the request to earn maximum profit. Finally, the SCSP decides the optimal price to be paid to the sensor owners while considering the price paid by the end-users, to ensure high profits for itself. The main contributions of this work are listed as follows:

1) We introduce a modified sensor-cloud architecture, in which the sensor owners actively participate in the Se-aaS provisioning process along with the SCSP, thereby giving them control over the revenue earned by them.

2) We propose a dynamic resource allocation scheme, named RACE, for provisioning Se-aaS as per the end-users' requirements, while considering the market competition among the sensor owners and its effects on the profits earned by the SCSP and the sensor owners.

3) We model the decision-making process of the end-users and the SCSP using *utility theory* in order to obtain the optimal number of nodes to be allocated and the price to be charged for each service for achieving maximum end-user satisfaction.

4) We model the interactions between the SCSP and the sensor owners in the Se-aaS market using a *single leader multiple followers Stackelberg game* in which the SCSP acts as the leader, and the sensor owners act as the followers. Thereafter, we reduce the aforementioned problem into two inter-dependent utility maximization problems and show the existence of an equilibrium.

5) We present extensive simulation results to evaluate the performance of the proposed scheme, RACE, in comparison with the existing schemes for sensor-cloud in the literature.

2 Related Works

In the past few years, several works have studied the sensor-cloud architecture. Yuriama *et al.* [1] first proposed the sensor-cloud architecture and stated its various possible applications. Misra *et al.* [2] proposed the theoretical modelling of the architecture along with the characterization of virtualization, followed by Madria *et al.* [7] and Bose *et al.* [8], who further described the functioning and implementation of the architecture. Chatterjee *et al.* [9] proposed the development of a big sensor-cloud infrastructure for efficient handling of big sensor data for Se-aaS. Several schemes were proposed for improving the performance of the sensor-cloud architecture. Chatterjee *et al.* [10] proposed a scheme for the selection of an optimal data center for minimizing service delay and maximizing QoS based on the *optimal decision rule*. Another scheme was proposed by Misra *et al.* [11] for optimal duty scheduling in sensor-cloud for improving its energy consumption efficiency.

Researchers also proposed several schemes for ensuring efficient virtualization in sensor-cloud. Chatterjee *et al.* [12] proposed a scheme for the optimal composition of virtual sensors in sensor-cloud for ensuring reduced resource consumption while maintaining coverage. In this work, the authors proposed that the selection of sensor nodes is done based on the requirements of the end-user and the geographical location of the nodes. In another work, an optimal resource allocation scheme was proposed by Delgado *et al.* [13] where the resource-constrained behavior of the sensor nodes was considered, to increase the number of services that can be provided by an SCSP simultaneously. Kim *et al.* [14] proposed a game-theoretic algorithm for sensor node allocation in sensor-cloud fanning into account the malicious behavior of sensor owners. Guerreiro *et al.* [15] proposed a resource allocation model for sensor-cloud in which each service request is composed of multiple set of requirements, or *mashups*. The authors proposed a heuristics-based algorithm to obtain the optimal resource allocation under the considered settings. Santos *et al.* [16] also proposed to reduce resource consumption with an heuristics-based algorithm which optimally shares multiple similar tasks among the same set of compatible sensor nodes. However, none of the aforementioned schemes considered the economic aspects of sensor-cloud for resource allocation.

There are several schemes in the existing literature which deal with the economic aspects of sensor-cloud. Chatterjee *et al.* [3] proposed a dynamic pricing scheme for sensor-cloud in which the authors introduced two schemes – pricing due to hardware and pricing due to infrastructure – and maximized the profit of the SCSP and the satisfaction of the end-users. Zhu *et al.* [17] proposed several pricing schemes while considering different service parameters. Chakraborty *et al.* [5] proposed a dynamic trust enforcing pricing scheme to enforce trust among oligopolistic sensor owners and maximize the profits of the SCSP. Another dynamic pricing scheme

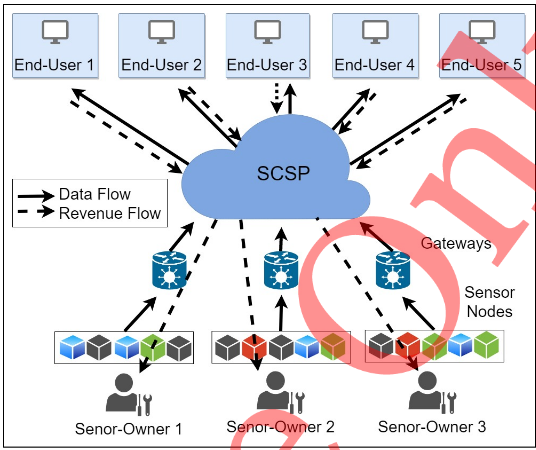


Fig. 1: Schematic Diagram of Sensor-Cloud.

for cache-enabled sensor-cloud was proposed by Chakraborty *et al.* [18] to obtain the optimal service load distribution and maximize the profit of SCSP. However, these works do not consider resource allocation for sensor-cloud.

In the existing literature, few works consider resource allocation schemes that take into account the economic aspects of sensor-cloud. An optimal sensor node selection scheme was proposed by Ojha *et al.* [6] to reduce the energy consumption of the network and increase the profit of the SCSP and the sensor owners. Misra *et al.* [19] proposed another QoS-aware dynamic virtual sensor selection and mapping scheme where the authors used cooperative game theory to maximize the profits of SCSP and sensor owners. However, in these works, the SCSP is considered to be the sole controller of the service-provisioning process, and hence, these schemes fail to ensure the maximum profit of the sensor owners.

Synthesis: The schemes proposed for sensor-cloud in the existing literature mostly focus on pricing and efficient resource management of virtual sensors for maximizing the revenue earned by the different involved entities. These schemes assume that the SCSP solely takes the decisions regarding resource allocation for Se-aaS provisioning. Thus, the maximum profit of the sensor owners cannot be ensured using these schemes, as they do not consider the possibility of dynamic procurement of physical sensor nodes from the sensor owners. On the other hand, the cloud-based resource management and capacity planning schemes, viz. [20]–[23], proposed in the existing literature are also not suitable for sensor-cloud, as sensor-cloud follows a heterogeneous SOA [3] which is a combination of hardware and infrastructural services. Hence, the existing cloud-based schemes cannot ensure profitable Se-aaS provisioning in sensor-cloud.

3 System Model

In this work, we consider a sensor-cloud comprising of a single SCSP, a set $\mathcal{O}$ of registered sensor owners, and a set $\mathcal{E}$ of end-users, as shown in Figure 1. At a particular time instant, an end-user $e \in \mathcal{E}$ places a set of service-requests, R_e, to the SCSP through its web portal specifying the types $\mathcal{T} = \{t_i | r_i^e \in R_e\}$ of services, the data-rates $\mathcal{D} = \{d_i | r_i^e \in R_e\}$, the concerned geographical regions $\mathcal{G} = \{g_i | r_i^e \in R_e\}$, and the desired QoI $\mathcal{I} = \{I_i | r_i^e \in R_e\}$. Based on these parameters, the SCSP decides the minimum and maximum number of nodes that can be allocated for the service and the maximum price $P_i^{max,e}$ of each service $r_i^e \in R_e$ per unit time that has to be paid by the end-user e. Based on this information, the end-user decides the number q_i^e of sensor nodes to be allocated for serving the request. Thereafter, an SLA is prepared between the two entities for each service r_i^e and the service provisioning process is initiated.

On the other hand, we consider that each sensor owner $o_n \in \mathcal{O}$ registers a set M_n of heterogeneous sensor nodes equipped with different types of sensors and deployed over different geographical regions. Hence, the overall set $\mathcal{M}$ of sensor nodes available through the SCSP is given as $\mathcal{M} = \bigcup_{o_n \in \mathcal{O}} M_n$. For serving request r_i^e, the SCSP initializes a set of virtual sensors $\mathcal{V}_i$ where each virtual sensor $v_j^i \in \mathcal{V}_i$ is formed using a subset of physical sensor nodes. We assume that the total set $\mathcal{N}_i$ of physical sensor nodes required to serve the set of virtual sensors $\mathcal{V}_i$ is a combination of nodes belonging to different sensor owners. Let $q_{n,i}^e$ be the number of sensor nodes contributed by owner o_n. To fulfill the requirements of r_i^e, the following constraint must be satisfied:

$$\sum_{o_n \in \mathcal{O}_i^e} q_{n,i}^e \geq q_i^e, \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}, \tag{1}$$

where $\mathcal{O}_i^e$ denotes the set of sensor owners whose nodes are used to serve r_i^e. Each sensor owner $o_n \in \mathcal{O}_i^e$ is paid by the SCSP a price of p_i^e units for each sensor node contributed by him/her. To ensure the profit of SCSP, the following constraint needs to be satisfied.

$$\sum_{o_n \in \mathcal{O}_i^e} p_i^e q_{n,i}^e < P_i^{max,e}, \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}. \tag{2}$$

Moreover, we assume that, for each active sensor node, each sensor owner o_n bears a maintenance cost of c_n units. Hence, to ensure profit, each sensor owner must satisfy the following constraint at all times:

$$p_i^e > c_n, \quad \forall o_n \in \mathcal{O}, \forall r_i^e \in R_e, \forall e \in \mathcal{E}. \tag{3}$$

Thus, to ensure QoI, each user needs to maintain a trade-off between the number of nodes required for serving each request and the price charged by the SCSP. On the other hand, to earn high profits, the sensor owners must decide the optimal number of sensor nodes that should be provided to the SCSP for serving request r_i^e. At the same time, the SCSP must also decide the optimum price to be paid to the sensor owners for their nodes for ensuring its profit. Hence, we argue that the aforementioned optimization problems are inter-dependent. Hence, in order to solve this problem, we propose a strategic resource allocation scheme, named RACE, the details of which are discussed in the subsequent sections.

Assumptions: The assumptions considered in designing RACE are – (a) the SCSP coordinates the service provisioning process as a centralized controller; (b) multiple sensor-owners are registered with the SCSP and involve in the Se-aaS provisioning; (c) the deployed sensor nodes are heterogeneous and are capable of serving all types of requests; (d) each active sensor node incurs a fixed maintenance cost to its respective owner; (e) each sensor-owner and the SCSP behave rationally, maximize their individual profits, and their decisions are mutually dependent; (f) sensor-owners are trustworthy, i.e., they do not misbehave; and (g) the system is considered to be secured to external security attacks.

4 RACE: The Proposed Strategic Resource Allocation Scheme

For modeling the decision-making process of the end-users in the sensor-cloud architecture[1], we use utility theory, by which the end-users decide the optimal node requirement for their service-request in order to achieve maximum service satisfaction. Here, utility theory ensures a trade-off between the number of nodes required for serving each request and the price charged by the SCSP. On the other hand, for modeling the interactions between the SCSP and the sensor owners, we use a *single leader multiple followers Stackelberg game*, which is a non-cooperative game. The objective of the game is to guarantee high profits for both the SCSP and the sensor owners while fulfilling the service requirements of the end-users.

Justification For Using Utility Theory and Stackelberg Game

Utility theory is an essential tool in economics which is used to model the satisfaction derived by a customer through service or product consumption. In sensor-cloud, the service satisfaction of the end-users increases with the increase in QoI. Generally, as the number of nodes allocated increases, the QoI of Se-aaS increases. However, as sensor-cloud follows a pay-per-use model, with the increase in the number of nodes allocated, the price charged by the SCSP also increases, which, in turn, results in a decrease in the satisfaction of the end-users. Hence, each end-user needs to ensure a trade-off between the desired QoI and the price to be paid, which is not explored by

1. As mentioned earlier, the sensor-cloud architecture follows a cloud-based hetergenous SOA.

the researchers in the existing literature. Therefore, we argue that utility theory is the most suitable tool to model the decision-making process of the end-users.

On the other hand, as mentioned earlier in Section 1, sensor-cloud infrastructure gives rise to a market scenario involving multiple competitive sensor owners offering deployed sensor nodes for rent to the SCSP. In a particular geographic region, *a few* registered sensor owners may deploy similar types of sensor nodes which can be used by the SCSP for serving the end-users. As a result, these sensor owners tend to compete among themselves to earn high revenue, thereby, giving rise to an *oligopolistic* market scenario. Moreover, in sensor-cloud, the SCSP is responsible for ensuring that each service request of the end-users is served with high QoS. For this, the SCSP relies on the sensor nodes belonging to the different sensor owners who are chosen to serve the request. As the sets of sensor nodes owned by the sensor owners are mutually exclusive, each sensor owner needs to decide the optimum number of nodes for serving a request to ensure high revenue. This, in turn, affects the strategy of the SCSP of deciding the unit price to be paid to the sensor owners for serving the request. Hence, we observe that, in sensor-cloud, the decisions taken by the sensor owners and the SCSP are mutually dependent. Hence, we argue that, a single leader multiple follower Stackelberg game is the most suitable approach for modeling this competitive market scenario.

4.1 Service Requirement Calculation for End-Users

In this work, we design a game theoretic-scheme to decide the service requirement of each end-user service-request in terms of the number of nodes to be allocated based on the price charged by the SCSP, using utility theory. For each request r_i^e, end-user e informs his/her QoI requirements to the SCSP. Based on this, the SCSP informs the minimum $q_i^{min,e}$ and the maximum $q_i^{max,e}$ number of nodes that can be allocated for the service and the maximum price $P_i^{max,e}$ that the end-user will be charged for the service. Needless to say, $P_i^{max,e} > 0$ and $q_i^{max,e} = \sum_{o_n \in \mathcal{O}_i^e} |\mathcal{Q}_n^{comp}|$, where $|\mathcal{Q}_n^{comp}|$ denotes the number of compatible sensor nodes available from sensor owner o_n. For simplicity, in this work, we assume that each registered sensor node is capable of serving all types of requests and hence, $|\mathcal{Q}_n| = |\mathcal{Q}_n^{comp}|$. Additionally, we assume that the SCSP follows a polynomial function in order to decide the price P_i^e to be charged for serving a request r_i^e for q_i^e nodes. Motivated by the work of Misra *et al.* [24], we define the pricing function of the SCSP as – $P_i^e = \alpha q_i^e + \beta {q_i^e}^2 + \gamma, \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}$, where α, β, and γ are constants and decided by the SCSP. Here, γ signifies the virual sensor maintenance cost incurred by the SCSP. Additionally, based on the constraint in (3), we argue that $\alpha \geq c_n$. On the other hand, we consider that each end-user calculates his/her satisfaction factor f_i^e for service request r_i^e as defined in Definition 1.

Definition 1. *The satisfaction factor f_i^e of end-user e for service request r_i^e is defined as the ratio of the number of nodes q_i^e allocated for the service and the maximum number of nodes available for allocation through the SCSP. Therefore, we have –* $f_i^e = \frac{q_i^e}{\sum_{o_n \in \mathcal{O}_i^e} |\mathcal{Q}_n|}, \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}$.

As mentioned earlier, each end-user tries to maximize the number of nodes to be allocated for each service request while paying optimally. Thus, we define the utility function $\mathcal{E}_e^i(f_i^e, P_i^e)$ as follows:

$$\mathcal{E}_e^i(f_i^e, P_i^e) = \rho_e f_i^e - \pi_e \frac{P_i^e}{P_i^{max,e}}, \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}, \tag{4}$$

where ρ_e and π_e are constants decided by end-user e and $0 \leq \rho_e, \pi_e \leq 1$. The values of these constants depend on the preference of the end-user. If the end-user has a higher preference for paying less or for maximizing the QoI, we have $\rho_e < \pi_e$ or $\rho_e > \pi_e$, respectively. On the other hand, if the end-user e is unbiased towards these choices, we have $\rho_e = \pi_e = 1$. Each end-user e tries to maximize the satisfaction derived by him/her from the service request r_i^e by maximizing the utility function $\mathcal{E}_e^i(f_i^e, P_i^e)$ mentioned in (4).

In order to obtain a definite expression for the optimal value of the number of nodes q_i^e, we consider q_i^e to be a continuous variable. Thereafter, using the gradient descent approach, we maximize $\mathcal{E}_e^i(f_i^e, P_i^e)$ with respect to q_i^e, while assuming that Proposition 1 is true.

Proposition 1. *In order to ensure the existence of a global optimum value of the number of nodes q_i^e which maximizes the function $\mathcal{E}_e^i(f_i^e, P_i^e)$, the following constraint needs to be satisfied.*

$$\beta \geq 0. \tag{5}$$

Proof: Refer to supplementary file. □

Thereby, we obtain the optimal number of nodes q_i^e to be requested for provisioning service request r_i^e, as follows:

$$q_i^e = \frac{1}{\beta \pi_e} \left[\frac{\rho_e P_i^{max,e}}{\sum_{o_n \in \mathcal{O}_i^e} |\mathcal{Q}_n|} - \alpha \pi_e \right], \quad \forall r_i^e \in R_e, \forall e \in \mathcal{E}. \tag{6}$$

Practically, as q_i^e is discrete and can only assume integer values, we evaluate the actual value of optimal q_i^e to be either the ceiling or the floor of the obtained value based on which among the two results in a higher value for $\mathcal{E}_e^i(f_i^e, P_i^e)$. After receiving the information regarding the number of nodes, i.e., q_i^e, to be allocated, the SCSP interacts with the sensor owners for deciding the subset of nodes to be selected for each service request r_i^e and the corresponding price to be paid, as discussed in the subsequent sections.

4.2 Interaction Between SCSP and Sensor owners

As mentioned earlier in this work, we use a single leader multiple followers game to model the complex interdependent decision-making process of the SCSP and the sensor owners. The theoretical analysis of the game is presented in the following sections.

4.2.1 Game-theoretic Analysis

In the proposed game, the SCSP acts as a leader and the sensor owners act as the followers. Firstly, the SCSP identifies the set of sensor owners $\mathcal{O}_i^e \subseteq \mathcal{O}$ capable of serving the request r_i^e and informs the minimum requirement of sensor nodes. Based on this, each sensor owner $o_n \in \mathcal{O}_i^e$ decides the number of sensor nodes, $q_{n,i}^e$, to be allocated for serving the request r_i^e, non-cooperatively. After getting the responses from the sensor owners, the SCSP decides the optimal unit price p_i^e to be paid to the sensor owners for borrowing a single sensor node. Thereby, the components of the proposed Stackelberg game in RACE are as follows:

(i) The SCSP acts as the leader and decides the unit price p to be paid to a sensor owner for borrowing each of his/her sensor nodes.

(ii) Each sensor owner o_n acts as a follower and decides the number of sensor nodes, $q_{n,i}^e$, to be allocated for serving a request r_i^e, considering that the SCSP needs at least q_i^e sensor nodes to serve that request.

(iii) The SCSP maximizes its utility function $\psi_i(\cdot)$ and ensures its maximum profit by deciding the unit price p_i^e to be paid to each owner.

(iv) Each sensor owner o_n tries to maximize his/her utility function $\mathcal{U}_{n,i}(\cdot)$, while satisfying the following constraint:

$$q_{n,i}^e \leq |\mathcal{Q}_n|, \tag{7}$$

where $\mathcal{Q}_n$ is the set of sensor nodes owned by o_n.

Now, in order to design the utility functions of the SCSP and the sensor owners, we define a parameter termed as the *throughput factor*, $\chi_{n,i}$, for each service request r_i^e, as mentioned in Definition 2.

Definition 2. *The throughput factor $\chi_{n,i}$ of each service request r_i^e is defined as the ratio of the data-rate request of the service, d_i, and the average remaining data-rate capacity, D_n, of the nodes belonging to the sensor owner o_n as follows:*

$$\chi_{n,i} = \frac{d_i}{D_n}, \tag{8}$$

where $D_n = \frac{\sum_{k \in \mathcal{Q}_n} (D - \sum_{r_j^e \in \mathcal{R}_{k,n}, e \in \mathcal{E}} d_j)}{|\mathcal{Q}_n|}$, D is the maximum data rate supported by each sensor node, and $\mathcal{R}_{k,n}$ represents a set of service requests already served by the sensor node k owned by sensor owner o_n.

Here, it is noteworthy that each sensor owner needs to ensure that none of his/her sensor nodes are oversubscribed. In other words, if a sensor node $k \in \mathcal{Q}_n$ of sensor owner o_n is serving a set of service requests, $\mathcal{R}_{k,n}$, s/he needs to satisfy the following constraint:

$$\sum_{r_i^e \in \mathcal{R}_{k,n}} d_i \leq D, \quad \forall k \in \mathcal{Q}_n. \tag{9}$$

4.2.2 Utility Function of Each Sensor Owner

Each sensor owner $o_n \in \mathcal{O}_i^e$ aims to maximize his/her utility function $\mathcal{F}_{n,i}(q_{n,i}^e, q_{-\boldsymbol{n},i}^e, p_i^e)$, where $q_{-\boldsymbol{n},i}^e = \{q_{1,i}^e, \cdots, q_{n-1,i}^e, q_{n+1,i}^e, \cdots, q_{|\mathcal{O}|,i}^e\}$, and decides an optimal value for the number of nodes $q_{n,i}^e$ to be allocated for service r_i^e. However, the price p_i^e, which is decided by the SCSP, depends on $q_{\boldsymbol{n},i}^e$, where $q_{\boldsymbol{n},i}^e = \{q_{1,i}^e, \cdots, q_{n,i}^e, \cdots, q_{|\mathcal{O}|,i}^e\}$. Therefore, the decision, i.e., $q_{n,i}^e$, of each sensor owner o_n depends indirectly on the number of nodes supplied by the other sensor owners, i.e., $q_{-\boldsymbol{n},i}^e$. Hence, each sensor owner o_n decides the optimal value of $q_{n,i}^e$ non-cooperatively. We argue that the utility function $\mathcal{F}_{n,i}(q_{n,i}^e, q_{-\boldsymbol{n},i}^e, p_i^e)$ of sensor owner o_n needs to satisfy the following properties:

(1) To maximize his/her revenue in the oligopolistic Se-aaS market, each sensor owner tries to supply a large number of nodes to the SCSP. Thus, the utility function of a sensor owner increases as the number of nodes supplied increases.

(2) However, to ensure high profits, the sensor owners need to have a trade-off between the supply and the revenue. Hence, there exists a marginal payoff value for which $q_{n,i}^e$ is optimal.

(3) When the price p_i^e paid by the SCSP increases, the payoff of the utility function of the sensor owners increases, thereby motivating them to increase the number of allocated nodes $q_{\boldsymbol{n},i}^e$.

(4) When the throughput factor for service r_i^e increases, the payoff of $\mathcal{F}_{n,i}(q_{n,i}^e, q_{-\boldsymbol{n},i}^e, p_i^e)$ decreases due to the fact that the energy consumption of each node increases linearly with the increase in the data-rate.

(5) When $q_{n,i}^e$ increases, the cost incurred for maintenance also increases linearly, as we consider that the maintenance cost c_n incurred for each sensor node is fixed for each sensor-owner o_n.

Therefore, we design $\mathcal{F}_{n,i}(q_{n,i}^e, q_{-\boldsymbol{n},i}^e, p_i^e)$ as a concave function which is given as follows:

$$\mathcal{F}_{n,i}(q_{n,i}^e, q_{-\boldsymbol{n},i}^e, p_i^e) = (p_i^e - c_n)\frac{q_{n,i}^e}{q_i^e} - \frac{1}{2}\chi_{n,i}\left(\frac{q_{n,i}^e}{q_i^e}\right)^2. \tag{10}$$

In RACE, each sensor owner tries to maximize his/her payoff by deciding an optimal value for $q_{n,i}^e$.

Therefore, the objective of each sensor owner n is defined as follows:

$$\arg\max_{q^e_{n,i}} \mathcal{F}_{n,i}(q^e_{n,i}, q^e_{-\boldsymbol{n},i}, p^e_i), \tag{11}$$

subject to the constraints in (1) and (3).

Proposition 2. *The utility function $\mathcal{F}_{n,i}(q^e_{n,i}, q^e_{-\boldsymbol{n},i}, p^e_i)$ is a convex function with respect to $q^e_{n,i}$.*

Proof: Refer to the supplementary file. □

4.2.3 Utility Function of the SCSP

The utility function $\psi_i(q^e_{\boldsymbol{n},i}, p^e_i)$ of the SCSP primarily signifies the profit earned by the SCSP by serving request r^e_i. This, in turn, depends on the price charged from the end-user making the request r^e_i, the price paid to the sensor owners for their sensor nodes, and the cost incurred by the SCSP for provisioning cloud infrastructure. We argue that the utility function $\psi_i(q^e_{\boldsymbol{n},i}, p^e_i)$ of the SCSP must satisfy the following properties:

(1) The price P^e_i charged from an end-user e for request r^e_i is decided by the SCSP based on the service requirements prior to service initiation. When the value of P^e_i increases, the payoff of the utility function of the SCSP increases.

(2) The price P^o_i that the SCSP has to pay to the set of sensor owners $\mathcal{O}^e_i$ for contributing sensor nodes for serving r^e_i is given as, $P^o_i = p^e_i \sum_{o_n \in \mathcal{O}^e_i} q^e_{n,i}$. The payoff of the SCSP decreases with the increase in P^o_i.

(3) The utility function of the SCSP decreases with the increase in the cost $\mathcal{C}_i$ incurred by the SCSP for provisioning cloud infrastructural resources for serving r^e_i. For each service r^e_i, we consider that, a fixed infrastructural cost $\mathcal{C}_i$ is incurred by the SCSP.

Therefore, we design the utility function $\psi_i(q^e_{\boldsymbol{n},i}, p^e_i)$ of the SCSP as a linear function depicted as follows:

$$\psi_i(q^e_{n,i}, p^e_i) = P^e_i - P^o_i - \mathcal{C}_i. \tag{12}$$

In RACE, the SCSP tries to maximize the profit earned by itself when serving a request r^e_i. Hence, the objective of the SCSP is as follows:

$$\arg\max_{p^e_i} \psi_i(q^e_{n,i}, p^e_i), \tag{13}$$

subject to the constraint in (7).

4.2.4 Existence of Stackelberg Equilibrium

In a hierarchical game with leader-follower structure, for reaching the equilibrium point of the system, the followers initially decide their optimal strategy set or response set, non-cooperatively, to reach the Nash Equilibrium (NE) point. The NE point is defined as a point at which any subset of players cannot obtain higher gains by deviating from his/her (their) chosen strategy (strategies), also termed as the *optimal response set*. Thereafter, using the optimal response set of the followers, the leader decides his/her optimal strategy for obtaining maximum utility. This point is termed as the Stackelberg Equilibrium (SE) point. We define the SE point of the proposed RACE scheme as in Definition 3. To prove the existence of the SE, we first prove the existence of the NE for the followers, or the sensor owners by the applying Karush-Kuhn-Tucker (KKT) conditions, as mentioned in Theorem 1. We argue that the local optimum solutions may satisfy some of the KKT conditions. However, satisfying all the KKT conditions ensures that there exists a global optima in the proposed scheme, RACE. Thereafter, we show the existence of the SE for the proposed RACE scheme in Lemma 1. We also present the solution of the SE in Section 4.2.5.

Definition 3. *In the proposed scheme, RACE, we define the Stackelberg Equilibrium point as the optimal point $(q^{e*}_{\boldsymbol{n},i}, p^{e*}_i)$, at which the following conditions are satisfied $\forall r^e_i \in R_e, \forall o_n \in \mathcal{O}^e_i, \forall e \in \mathcal{E}$:*

$$\psi_i(q^{e*}_{\boldsymbol{n},i}, p^{e*}_i) \geq \psi_i(q^{e*}_{\boldsymbol{n},i}, p^e_i), \tag{14}$$

$$\mathcal{F}_{n,i}(q^{e*}_{n,i}, q^{e*}_{-\boldsymbol{n},i}, p^{e*}_i) \geq \mathcal{F}_{n,i}(q^e_{n,i}, q^{e*}_{-\boldsymbol{n},i}, p^{e*}_i). \tag{15}$$

Theorem 1. *Given a price p^e_i for service r^e_i, there exists at least one NE for the sensor owners in the proposed scheme, RACE.*

Proof: Refer to the supplementary file. □

Lemma 1. *From Theorem 1, we conclude that SE exists for the proposed scheme, RACE, as there exists at least one NE for the followers in the proposed game.*

Proof: Refer to the supplementary file. □

4.2.5 Solution for Stackelberg Equilibrium

We use the KKT conditions to obtain the SE solution for the proposed scheme, RACE. By applying the *stationary and primal feasibility* conditions, we get:

$$\left.\begin{array}{l} \lambda_{n,1} = 0, \forall o_n \in \mathcal{O} \\ \lambda_2 = \frac{(p^e_i - c_m) + \chi_{m,i}\frac{x}{y}}{q^e_i} \\ \lambda_3 = 0 \end{array}\right\}, \tag{16}$$

where $x = 1 - \sum\limits_{o_m \in \mathcal{O}/\{o_n\}} \frac{c_m - c_n}{\chi_{n,i}}$ and $y = \sum\limits_{o_m \in \mathcal{O}/\{o_n\}} \frac{\chi_{m,i}}{\chi_{n,i}}$. Additionally, we argue that the constraint mentioned in Theorem 2 needs to be satisfied.

Theorem 2. *Considering that $\lambda_2 \neq 0$, the game between two sensor owners m and n needs to satisfy the following constraint:*

$$\frac{1}{\chi_{n,i}} - \frac{1}{\chi_{m,i}} < \frac{1}{c_n - c_m}. \tag{17}$$

Proof: Refer to the supplementary file. □

Therefore, as $\lambda_2 \neq 0$, we have — $q^e_i = \sum\limits_{o_n \in \mathcal{O}} q^{e*}_{n,i}$.

Hence, from *complementary slackness condition*[2] and (16), we get:

$$q^{e*}_{n,i} = \frac{(c_m - c_n) \sum\limits_{o_m \in \mathcal{O}/\{o_n\}} q^{e*}_{m,i} + \chi_{m,i} q^{e*}_{m,i}}{\chi_{n,i} - (c_m - c_n)}. \tag{18}$$

Additionally, from *dual feasibility and complimentary slackness* conditions, we get, $\lambda_3 \neq 0$. Thus, we have:

$$p^{e*}_i = \frac{\chi_{n,i} q^e_{n,i} \sum\limits_{o_m \in \mathcal{O}} \frac{1}{\chi_{m,i}} - \sum\limits_{o_m \in \mathcal{O}} q^e_{m,i} - \sum\limits_{o_m \in \mathcal{O}} \frac{c_m}{\chi_{m,i}} + c_n}{1 + \sum\limits_{o_m \in \mathcal{O}} \frac{1}{\chi_{m,i}}}. \tag{19}$$

In the proposed scheme, RACE, $(q^{e*}_{n,i}, p^{e*}_i)$ denotes the Stackelberg equilibrium point.

4.3 Algorithms

In RACE, each end-user places his/her service requirements to the SCSP, based on which the SCSP presents the various possible pricing schemes. Thereafter, using (6), the end-users decide the optimal number of sensor nodes to be used to serve the request and inform their decision to the SCSP. The SCSP, in turn, forwards this information to the sensor owners of the compatible sensor nodes. Using Algorithm 1, each sensor owner decides the optimal number of nodes to be contributed for serving the request. It is noteworthy that, in the presence of only a single sensor-owner, the outcomes of Algorithm 1 and any greedy algorithm are the same, i.e., they result in the same solution. On obtaining the decision of each sensor owner, the SCSP decides the optimal price to be paid to each sensor owner for the service using Algorithm 2. Since Stackelberg game is repetitive and played in multiple iterations, the two Algorithms continue to be executed sequentially until an equilibrium point is reached at which neither the sensor owners nor the SCSP change their strategies or decisions. At this point, Stackelberg equilibrium is reached.

Complexity Analysis: We present the complexity analysis of Algorithms 1 and 2 in this section. The objective of both the aforementioned algorithms is to obtain the optimum value of a certain variable. To achieve this aim, the values of the optimisation variables are iteratively modified while taking into consideration the corresponding change in the value of the objective function is observed. To ensure convergence, the number of iterations of the *do-while* loops in Algorithms 1 and 2 are limited to K_1 and K_2, respectively. Thus, the computational complexity of Algorithm 1 is calculated to be $O(K_1)$. On the other hand, in case of Algorithm 2, in addition to the *do-while* loop, a *for* loop is also executed, which iterates over the number of sensor-owners. Hence, the

2. Refer to the supplementary file.

Algorithm 1 Optimum Contribution of Sensor Owner

INPUTS:
$p^e_i, q^e, c_n, d_i, D_n$
δ ▷ Increment factor
K_1 ▷ Maximum Number of Steps
OUTPUT:
$q^{e*}_{n,i}$ ▷ Optimum node contribution of sensor owner o_n for service r^e_i
PROCEDURE:
Set $temp \leftarrow 0$, $steps \leftarrow K$, $q^e_{n,i} \leftarrow 0$, and $\mathcal{F}_{n,i} \leftarrow 0$;
Calculate $\chi_{n,i}$ using (8);
do
  Set $temp_{old} \leftarrow temp$, $q^{e*}_{n,i} \leftarrow q^e_{n,i}$, $\mathcal{F}^{old}_{n,i} \leftarrow \mathcal{F}_{n,i}$, and $q^e_{n,i} \leftarrow q^e_{n,i} - \delta * delta_{temp}$;
  Calculate $\mathcal{F}_{n,i}$ for service r^e_i using (10);
  Set $temp \leftarrow \mathcal{F}_{n,i} - \mathcal{F}^{old}_{n,i}$ and $delta_{temp} \leftarrow temp - temp_{old}$;
  if $delta_{temp} \geq 0$ **then**
    Break;
  end if
  Set $steps \leftarrow steps - 1$;
while $steps > 0$;
Return $q^{e*}_{n,i}$;

Algorithm 2 Optimum Price Determination by SCSP

INPUTS:
$P^e_i, C_i, q^e_{n,i}, \forall o_n \in \mathcal{O}_i$
ω ▷ Increment factor
K_2 ▷ Maximum Number of Steps
OUTPUT:
p^{e*}_i ▷ Optimum price paid by SCSP to sensor owners for service r^e_i
PROCEDURE:
Set $temp \leftarrow 0$, $p^e_i \leftarrow 0$, $P^o_i \leftarrow 0$, and $steps \leftarrow K$;
for $o_n \in \mathcal{O}_i$ **do**
  $P^o_i \leftarrow P^o_i + q^e_{n,i}$;
end for
do
  Set $temp_{old} \leftarrow temp$, $p^{e*}_i \leftarrow p^e_i$, $\psi^{old}_i \leftarrow \psi_i$, and $p^e_i \leftarrow p^e_i + \omega * delta_{temp}$;
  Calculate ψ_i for service r^e_i using (12);
  Set $temp \leftarrow \psi^{old}_i - \psi_i$ and $delta_{temp} \leftarrow temp - temp_{old}$;
  if $delta_{temp} \geq 0$ **then**
    Break;
  end if
  Set $steps \leftarrow steps - 1$;
while $steps > 0$;
Return p^{e*}_i;

computational complexity of Algorithm 2 is calculated to be $O(|\mathcal{O}_i| + K_2)$. Moreover, as mentioned earlier, Stackelberg game is an iterative game executed in multiple steps by the leader and the followers. Hence, considering that the proposed scheme converges after N iterations, the overall computational time complexity of the scheme is $ON(K_1 + |\mathcal{O}_i| + K_2)$ and the message overhead is $O(N|\mathcal{O}_i|)$.

5 Performance Evaluation

To evaluate the performance of the proposed scheme, RACE, we performed simulations in a Python-based simulation platform and evaluated the results in comparison to a few existing benchmark schemes. We present the detailed discussion on the simulation and the performance results in the following subsections.

5.1 Simulation Parameters

For simulations, we considered a geographical region of area $1000 \times 1000\ m^2$, over which multiple sensor owners have deployed heterogeneous types of sensor nodes. The sensor nodes communicate with each other using the IEEE 802.15.4 Zigbee protocol, and hence, their maximum supported data-rate is 250 kbps. These sensor nodes are used to serve $1000-3000$ end-user service-requests. We argue that, to handle such a huge number of services in a small geographic region, there is a requirement of sensor-cloud for provisioning sensor network-based services. It is noteworthy that, we considered the presence of only 5-10 sensor-owners as they geographical area considered is small. For larger areas, it is suggested to consider a higher number of sensor-owners in order to accurately replicate the practical scenarios. We assume that, at a particular time instant, a single end-user requests for the service of the SCSP. The duration of the service is not known *a priori*, and hence, is determined randomly. Additionally, we considered that each service-request demands for a single type of sensor data. Thereafter, we varied the number of sensor owners and that of end-users, and observed the performance of the proposed scheme. The detailed simulation parameters are presented in Table 1.

TABLE 1: Simulation Parameters

Parameter	Value
Simulation Area	1000×1000 m^2 [5]
Number of SCSP	1
Number of sensor-owners	5-10
Maximum number of sensor nodes	50/owner
Communication protocol	IEEE 802.15.4
Maximum data-rate	250 $kbps$/node
Maintenance cost for active sensor node	1-10 units/unit time
Number of end-users	100-300
Number of service requests	1-10/user
Data-rate per service	100-250 $kbps$
Node requirement	1-100/service
Types of Services	5
Price paid by end-users	100 units/service
Cost for infrastructural resources	10 units/service
α, β, γ	1
π_e, ρ_e	0.5

5.2 Benchmarks

To evaluate the performance of the proposed scheme, RACE, we compared its performance with two existing benchmark schemes — dynamic optimal pricing for heterogeneous SOA for sensor-cloud (DOP) [3] and dynamic trust enforcing pricing scheme for Se-aaS in sensor-cloud (DETER) [5] — in an ologpolistic[3] sensor-cloud infrastructure. In DOP, Chatterjee *et al.* [3] proposed a dynamic pricing scheme for sensor-cloud comprising of two components — pricing due to hardware and pricing due to infrastructure. Pricing due to hardware is the price paid by the SCSP to the sensor owners for the usage of their nodes and is decided based on the quality of sensed information provided by their nodes. Pricing due to infrastructure is decided by the SCSP based on the cost of cloud resources utilized for serving the end-user. On the other hand, in DETER, Chakraborty *et al.* [5] proposed another pricing scheme for sensor-cloud in order to enforce trust among the oligopolistic sensor owners. In DETER, the price to be paid to the sensor owners is decided based on their trust value, which is calculated based on the distributed opinions of other sensor owners and the centralized opinion of the SCSP.

In both the aforementioned works, the proposed pricing schemes influence the sensor-node allocation decision of the SCSP. This is due to the fact that, in both the works, the pricing schemes are designed to maximize the profit of the SCSP while ensuring the profit of the sensor-owners. Both these parameters depend on the resource allocation strategy of the SCSP. However, none of these works, or the other works in existing literature, considers the possibility of involving the sensor owners in the resource allocation process in sensor-cloud. Hence, we compared our work with these two existing works for performance evaluation as only these two works focus on pricing-based resource allocation in sensor-cloud.

5.3 Performance Metrics

We evaluate the performance of the proposed scheme, RACE, based on the following performance metrics:

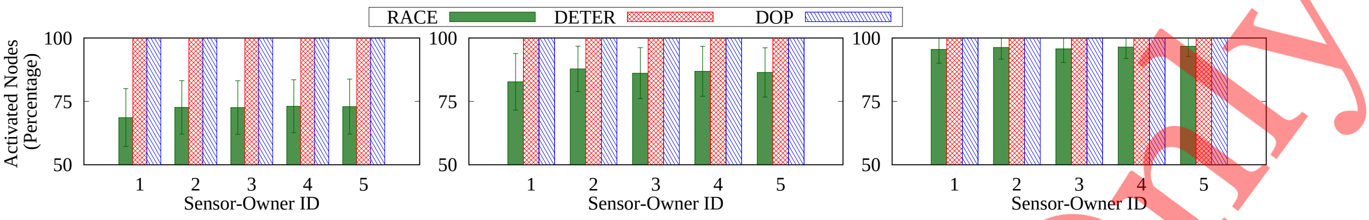
(1) *Number of activated sensor nodes:* The number of activated sensor nodes directly influences the resource consumption of the network as a significant amount of additional energy is consumed for activation of the nodes. Moreover, the nodes consume energy to remain in the active state. This, in turn, reduces the network lifetime, thereby reducing the profit of the sensor owners and the SCSP.

(2) *Profit of sensor owners:* The profit of the sensor owners is defined as the difference between the price earned by them from the SCSP and the cost incurred by them for service provisioning. Therefore, it varies directly with the number of services provided by them. It also depends on the number of sensor nodes used for provisioning Se-aaS and the maintenance cost of the nodes. High profits motivate sensor owners to participate in Se-aaS provisioning.

(3) *Number of unserved applications:* The SCSP is unable to serve the requests of the end-users in case of unavailability of compatible sensor nodes as per their requirements. This implies that, if the set of available sensor nodes run out of resources, i.e., energy and memory, required for serving the requested application, the SCSP is unable to provide the service to the corresponding end-user, thereby increasing the number of unserved applications. This, in turn, negatively impacts the profit of the SCSP.

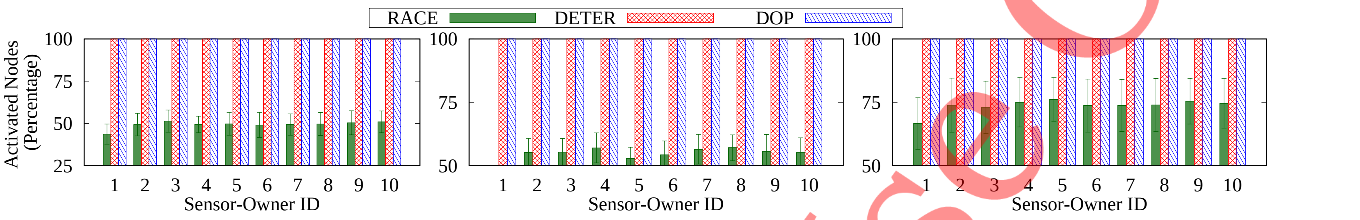
(4) *Profit of SCSP:* The profit earned by the SCSP depends on the price charged by him/her for serving

3. Oligopolistic market is defined by the presence of more than 1 suppliers. Therefore, for simulation, we considered the presence of more than 1 sensor owners for the three schemes – RACE, DOP, and DETER. While implementing DETER, we considered that, each sensor-owner has a trust value of 1. On the other hand, for DOP, we considered that, for each service, the price charged by the owner of an intermediate node is determined based on the price charged by the previous node in the path.



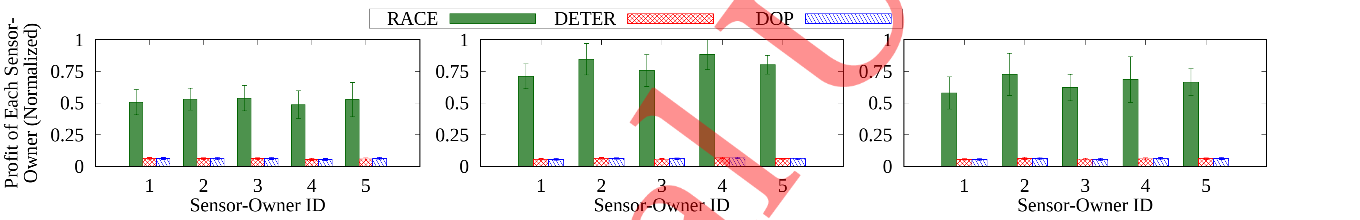
(a) Number of Users = 100 (b) Number of Users = 200 (c) Number of Users = 300

Fig. 2: Activated Sensor Nodes when #sensor owners = 5.



(a) Number of Users = 100 (b) Number of Users = 200 (c) Number of Users = 300

Fig. 3: Activated Sensor Nodes when #sensor owners = 10.



(a) Number of Users = 100 (b) Number of Users = 200 (c) Number of Users = 300

Fig. 4: Profit of sensor owners, when #sensor owners = 5.

the end-user requests and the price paid by the SCSP to the sensor owners. In order to increase its profits, the SCSP tries to serve the maximum possible number of requests while using a limited amount of resources.

5.4 Results and Discussions

Figures 2 and 3 depict the variation of the percentage of activated sensor nodes belonging to each sensor owner for different numbers of end-user service requests and different numbers of sensor owners. We observe that the number of activated nodes decreases by 9.92-42.82% using RACE compared to using the existing schemes DETER and DOP. This is due to the fact that in DETER and DOP, a single sensor node is used to serve only one service-request at a particular time. Thus, using these schemes, the number of sensor nodes, that the SCSP has to activate, must be at least equal to the number of service requests. However, using RACE, multiple applications can be served using the same node, which decreases the required number of activated nodes in the system. Moreover, we observe that, unlike the other two schemes, the number of activated sensor nodes per owner decreases as the number of sensor owners in the system using RACE increases. This is due to the fact that each sensor owner is given an opportunity to decide his/her participation in the Se-aaS provisioning process in RACE. This fact is also evident from Figures 2 and 3, where we observe that the percentage of activated sensor nodes for each sensor owner is almost equally distributed in case of RACE.

The variation in the profit of each sensor owner for different numbers of end-user service-requests and different numbers of registered sensor owners is shown in Figures 4 and 5. Here, we observe that the profit of the sensor owners increases by 86.11-89.26% using RACE, compared to the existing schemes DETER and DOP. This can be attributed to the fact that, in RACE, the sensor owners are given an opportunity to decide the optimal number of nodes to contribute for providing a service in order to ensure high profits for themselves. However, in the other two schemes, the SCSP solely controls the service provisioning process and decides the number of sensor nodes to be used for a particular service while ensuring high profit for itself. Thus, high profits are not ensured for the sensor owners using DETER and DOP. Moreover, from Figures 4 and 5, we also observe that the profit of the sensor owners is independent of the number of end-user service requests. This is because, in RACE, the number of sensor nodes to be activated depends on the requirements of the service-requests, and not on the number of service-requests, due to the consolidation of the nodes for provisioning Se-aaS. However,

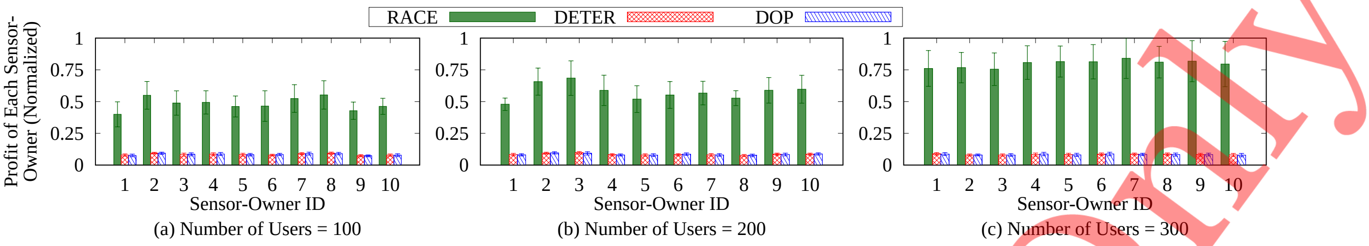


Fig. 5: Profit of sensor owners, when #sensor owners = 10.

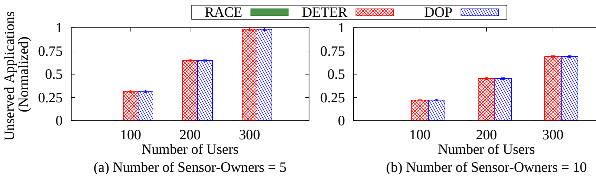


Fig. 6: Unserved Applications.

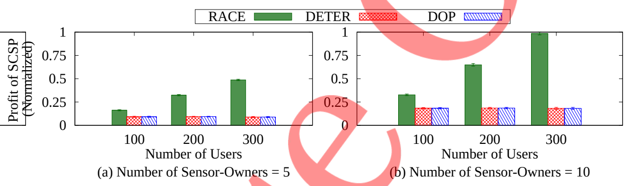


Fig. 7: Profit of the SCSP.

this is not the case for DETER and DOP.

Figure 6 shows the number of unserved applications or service-requests that the SCSP was unable to serve due to resource exhaustion, for different numbers of requests and different numbers of sensor owners for the three considered schemes — RACE, DETER, and DOP. In both Figures 6(a) and 6(b), we observe that using DETER and DOP, the SCSP is unable to serve nearly 31.70-96.96% of the service-requests, respectively, and the number of unserved service-requests increases as the number of end-users increase. On the other hand, using RACE, there are no unserved service-requests. This is also due to the fact that, in RACE, the same sensor node is used to serve multiple applications having similar requirements, unlike the other two schemes in which each sensor node is used to serve only a single application. Thus, we argue that the number of unserved service-requests varies almost linearly with the number of sensor nodes in the system. This argument is also supported by Figure 6, in which we observe that, as the number of sensor owners increases, the number of unserved requests decreases for DETER and DOP. In this case, with the increase in the total number of available sensor nodes, the SCSP is able to support a higher number of applications.

The same outcome is observed in Figure 7, which shows the effect of the variation of the number of end-users and that of sensor owners on the profit of the SCSP for the three schemes. Here, we observe that using RACE, the profit of the SCSP increases almost linearly with the increase in the number of services as the SCSP earns more revenue by serving a large number of applications using a fixed amount of resources or sensor nodes. On the other hand, using DETER and DOP, the profit of the SCSP remains almost the same as the number of services increases. This is because the SCSP is unable to serve more than a fixed number of applications using its limited resources and earns no revenue for the unserved service requests. From this figure, we observe that the profit earned by the SCSP increases by 41.95-80.82% using RACE, compared to using DETER and DOP, while considering that each sensor node is capable of serving multiple applications simultaneously.

6 Conclusion and Future Directions

In this work, we proposed a strategic resource allocation scheme, RACE, for sensor-cloud in order to improve the profitability of Se-aaS to the sensor owners while considering the QoI requirements of the end-users. In the proposed scheme, first, we used utility theory to decide the optimal number of nodes to be allocated for a particular service to ensure user satisfaction. Thereafter, we used a single leader multiple followers Stackelberg game to model the interactions between the sensor owners and the SCSP. In the proposed game, the SCSP acts as a leader and decides the optimum price to be paid to the sensor owners for using their sensor-nodes for provisioning a particular service, whereas, the sensor owners act as followers and decide the optimum number of nodes to be allocated for providing the service while satisfying the QoI requirement of the end-user. Thereby, RACE ensures high profits for the SCSP and the sensor owners, and service satisfaction of the end-users. Through simulations, we observed that RACE outperforms the existing benchmark schemes, DOP and DETER, in terms of resource consumption and profitability.

This work can be extended while considering the effects of variable maintenance cost for different types of sensor nodes on the decision of the sensor owners. It can also be extended by considering service delay as a deciding parameter for QoI of Se-aaS. Moreover, the procurement of intermediate hop nodes for Se-aaS provisioning can also be a future research direction. Furthermore, this work can be extended to study the effects of various security attacks on the performance of sensor-cloud and evaluate the counter-measures.

References

[1] M. Yuriyama, T. Kushida, and M. Itakura, “A New Model of Accelerating Service Innovation with Sensor-Cloud Infrastructure,” in *Ann. SRII Glob. Conf.*, Mar 2011, pp. 308–314.

[2] S. Misra, S. Chatterjee, and M. S. Obaidat, “On Theoretical Modeling of Sensor Cloud: A Paradigm Shift From Wireless Sensor Network,” *IEEE Sys. J.*, no. 99, pp. 1–10, 2014.

[3] S. Chatterjee, R. Ladia, and S. Misra, “Dynamic Optimal Pricing for Heterogeneous Service-Oriented Architecture of Sensor-cloud Infrastructure,” *IEEE Trans. on Serv. Comp.*, no. 99, 2015.

[4] C. Bisdikian, L. M. Kaplan, and M. B. Srivastava, “On the quality and value of information in sensor networks,” *ACM Trans. Sen. Netw.*, vol. 9, no. 4, pp. 48:1–48:26, Jul. 2013.

[5] A. Chakraborty, A. Mondal, A. Roy, and S. Misra, “Dynamic Trust Enforcing Pricing Scheme for Sensors-as-a-Service in Sensor-Cloud Infrastructure,” *IEEE Trans. on Serv. Comp.*, pp. 1–12, 2018.

[6] T. Ojha, S. Misra, N. S. Raghuwanshi, and H. Poddar, “DVSP: Dynamic Virtual Sensor Provisioning in Sensor-Cloud based Internet of Things,” *IEEE IoT J.*, pp. 1–8, 2019.

[7] S. Madria, V. Kumar, and R. Dalvi, “Sensor Cloud: A Cloud of Virtual Sensors,” *IEEE Soft.*, vol. 31, no. 2, pp. 70–77, Mar 2014.

[8] S. Bose, A. Gupta, S. Adhikary, and N. Mukherjee, “Towards a Sensor-Cloud Infrastructure with Sensor Virtualization,” in *Proc. of Wrkshp on Mob. Sens., Comp. & Comm.*, New York, USA, 2015, pp. 25–30.

[9] S. Chatterjee, A. Roy, S. K. Roy, S. Misra, M. Bhogal, and R. Daga, “Big-Sensor-Cloud Infrastructure: A Holistic Prototype for Provisioning Sensors-as-a-Service,” *IEEE Trans. on Cloud Comp.*, pp. 1–1, 2019.

[10] S. Chatterjee, S. Misra, and S. Khan, “Optimal Data Center Scheduling for Quality of Service Management in Sensor-cloud,” *IEEE Trans. on Cloud Comp.*, no. 99, 2015.

[11] T. Ojha, S. Bera, S. Misra, and N. S. Raghuwanshi, “Dynamic Duty Scheduling for Green Sensor-Cloud Applications,” in *Proc. of the IEEE CloudCom*, Dec 2014, pp. 841–846.

[12] S. Chatterjee and S. Misra, “Optimal Composition of a Virtual Sensor for Efficient Virtualization within Sensor-Cloud,” in *Proc. of IEEE ICC*, Jun 2015, pp. 448–453.

[13] C. Delgado, J. R. Gállego, M. Canales, J. Ortín, S. Bousnina, and M. Cesana, “On Optimal Resource Allocation in Virtual Sensor Networks,” *Ad Hoc Net.*, vol. 50, no. C, pp. 23–40, Nov 2016.

[14] S. Kim, “An Effective Sensor Cloud Control Scheme Based on a Two-Stage Game Approach,” *IEEE Acc.*, vol. 6, pp. 20 430–20 439, 2018.

[15] J. Guerreiro, L. Rodrigues, and N. Correia, “Resource Allocation Model for Sensor Clouds under the Sensing as a Service Paradigm,” *Computers*, vol. 8, no. 1, p. 18, Feb 2019.

[16] I. L. Santos, L. Pirmez, F. C. Delicato, G. M. Oliveira, C. M. Farias, S. U. Khan, and A. Y. Zomaya, “Zeus: A Resource Allocation Algorithm for the Cloud of Sensors,” *Future Gen. Comp. Sys.*, vol. 92, pp. 564 – 581, 2019.

[17] C. Zhu, X. Li, V. C. M. Leung, L. T. Yang, E. C. H. Ngai, and L. Shu, “Towards Pricing for Sensor-Cloud,” *IEEE Trans. on Cloud Comp.*, no. 99, pp. 1–12, 2017.

[18] A. Chakraborty, A. Mondal, and S. Misra, “Cache-Enabled Sensor-Cloud: The Economic Facet,” in *IEEE WCNC*, Apr 2018, pp. 1–6.

[19] S. Misra and A. Chakraborty, “QoS-Aware Dispersed Dynamic Mapping of Virtual Sensors in Sensor-Cloud,” *IEEE Trans. on Ser. Comp.*, pp. 1–12, 2019.

[20] D. Ardagna, M. Ciavotta, and M. Passacantando, “Generalized Nash Equilibria for the Service Provisioning Problem in Multi-Cloud Systems,” *IEEE Trans. on Ser. Comp.*, vol. 10, no. 3, pp. 381–395, May 2017.

[21] S. Chaisiri, B. S. Lee, and D. Niyato, “Optimization of Resource Provisioning Cost in Cloud Computing,” *IEEE Trans. on Ser. Comp.*, vol. 5, no. 2, pp. 164–177, Apr 2012.

[22] A. Comi, L. Fotia, F. Messina, G. Pappalardo, D. Rosaci, and G. M. L. Sarné, “A Reputation-Based Approach to Improve QoS in Cloud Service Composition,” in *IEEE Int. Conf. on Enab. Tech.: Infra. for Collab. Ent.*, 2015, pp. 108–113.

[23] A. Comi, L. Fotia, F. Messina, D. Rosaci, and G. M. Sarné, “A Partnership-Based Approach to Improve QoS on Federated Computing Infrastructures,” *Inf. Sci.*, vol. 367, no. C, p. 246–258, Nov. 2016.

[24] S. Misra, S. Bera, and T. Ojha, “D2P: Distributed Dynamic Pricing Policyin Smart Grid for PHEVs Management,” *IEEE Trans. on Par. & Dist. Sys.*, vol. 26, no. 3, pp. 702–712, Mar 2015.

Sudip Misra (SM'11) is a Professor at IIT Kharagpur. He received his Ph.D. degree from Carleton University, Ottawa, Canada. Prof. Misra is the author of over 350 scholarly research papers. He has won several national and international awards including the IEEE ComSoc Asia Pacific Young Researcher Award during IEEE GLOBECOM 2012. He was also the recipient of several academic awards and fellowships such as the NASI Fellow Award (National Academy of Sciences, India), the Young Scientist Award (National Academy of Sciences, India), Young Systems Scientist Award (Systems Society of India), and Young Engineers Award (Institution of Engineers, India). He was invited to deliver keynote/invited lectures in over 30 international conferences in USA, Canada, Europe, Asia and Africa.

Robert Schober (S'98-M'01-SM'08-F'10) was born in Neuendettelsau, Germany, in 1971. He received the Diplom and Ph.D. degrees in electrical engineering from the Friedrich-Alexander-Universität Erlangen-Nänberg, Erlangen, Germany, in 1997 and 2000, respectively. From 2001 to 2002, he was a Post-Doctoral Fellow with the University of Toronto, Canada, sponsored by the German Academic Exchange Service. Since 2002, he has been with The University of British Columbia, Vancouver, Canada, where he is currently a Full Professor. Since 2012, he has been an Alexander von Humboldt Professor and the Chair for Digital Communication with the Friedrich-Alexander-Universität Erlangen-Närnberg. His research interests fall into the broad areas of communication theory, wireless communications, and statistical signal processing.

Aishwariya Chakraborty (S'17) is pursuing her Ph.D. at Indian Institute of Technology Kharagpur, India. Her research interests include algorithm design for sensor-cloud, service-oriented architecture, and wireless sensor networks. She received her B.Tech. from West Bengal University of Technology in 2015. She is a student member of IEEE and ACM.