Range-Price Trade-off in Sensor-cloud for Provisioning Sensors-as-a-Service

Arijit Roy*, *Student Member, IEEE*, Sudip Misra†, *Senior Member, IEEE*, and Farid Nait-Abdesselam‡, *Senior Member, IEEE*

Abstract—This work proposes an optimal pricing scheme for provisioning sensors-as-a-service (Se-aaS) for catering to applications with multi-tenancy requirements in a sensor-cloud platform. The scheme orchestrates a trade-off analysis between communication range and price in a sensor-cloud platform with range-reconfigurable nodes. The proposed scheme consists of two phases – (a) selection of a neighbor node of a source node, and determination of optimal price for the selected neighbor node. In the first phase, a source node adjusts its communication range and selects its best possible neighbor node using *selectivity factor* of all the neighbor nodes. The selectivity factor considers the determinants such as effective residual energy, effective power consumption, and the number of applications to which the neighbor nodes are associated in the neighbor selection process. In the second phase, we design a utility function to determine the optimal price of the selected neighbor node. We use the *Lagrangian* function to model the proposed problem as a mixed-integer linear program (MILP) and obtain the optimal solution using the Karush-Kuhn-Tucker (KKT) conditions. The existing works on pricing in sensor-cloud are deficient in considering the presence of the reconfigurable communication range of sensor nodes. Moreover, based on the value of the communication range, the charged price of the sensor nodes varies. Thus, in this work, we propose a pricing scheme with a trade-off of the reconfigurable communication range of sensor nodes and the charged price incurred in adjusting the communication range. Extensive experimental results show that the proposed scheme performs better compared to the existing pricing schemes for sensor-cloud. In precise, the proposed scheme is capable of increasing the average number of neighbor nodes by at least 1.38%. Further, the proposed scheme is capable of reducing the charged price by 10.55%, as compared to the existing pricing scheme, DOPH.

Keywords—Sensor-Cloud, Virtualization, Service Provisioning, Sensors-as-a-Service, Pricing, Wireless Sensor Networks, Range-reconfigurable Nodes

1 INTRODUCTION

TRADITIONAL wireless sensor networks (WSNs) are widely used in different application domains such as target tracking [1], healthcare [2], and wild-life monitoring [3]. Typically, traditional WSN deployments are single-user centric. The users procure WSN for serving specific applications and they may not agree to share the sensed data to other users. However, the single-user centric limitation of WSN can be alleviated with the evolution of the sensor-cloud platform [4]–[6], in which sensor nodes are virtualized among multiple users. A sensor-cloud architecture consists of three actors – sensor owner, sensor-cloud service provider (SCSP), and end-user. The sensor owners deploy the sensor nodes over different geographical locations for serving different applications, as requested by the end-users. In return, the sensor-owners earn monetary profit from the sensor-cloud platform. On the other hand, the end-users pay the rent to the sensor-cloud platform for the requested services. The SCSP is a centralized entity, that manages the entire platform. Traditionally, in a sensor-cloud architecture, multiple physical sensor nodes combine together to form a virtual sensor (VS), and further, multiple VSs combine to form a virtual sensor group (VSG). However, the end-users remain dormant about all the back-end processes of the platform. The sensor-cloud architecture is based on Service-Oriented Architecture (SOA), which follows the pay-per-use model. Therefore, the end-user pays the price for a service as per its usage. A portion of the payment made by the end-user is received by the sensor owners as rent for the sensor nodes they own. On the other hand, the SCSP gains a certain amount of profit and allocates the required amount for the maintenance of the sensor-cloud architecture.

The underlying layer of the sensor-cloud platform consists of sensor nodes [5], which collectively provision Sensors-as-a-Service (Se-aaS) among multiple end-users in a self-organized manner. The selection of the specific sensor nodes that cater to serve a specific use-case is spatiotemporally distributed. Typically, the nodes deployed by the sensor-owners are battery-powered and energy-constrained in nature. Further, the energy consumption of these nodes depends on the communication range.

- *Arijit Roy is with the Advanced Technology Development Center, Indian Institute of Technology Kharagpur, India (Email: arijitroy@iitkgp.ac.in).*
- †*Sudip Misra is with the Department of Computer Science and Engineering, Indian Institute of Technology Kharagpur, India (Email: smisra@sit.iitkgp.ernet.in).*
- ‡*Farid Nat-Abdesselam is with the Department of Computer Science and Engineering, University of Missouri Kansas City, USA (Email: naf@umkc.edu)*

A majority of the commercially available sensor nodes at present are range-reconfigurable either statically at deployment time or dynamically at run-time through power-level adjustment. Moreover, the increasing value of the communication range of a sensor node results in an increase in energy consumption, which causes faster depletion of its energy. Further, when the energy level reaches a threshold value, the sensor node is unable to communicate with other nodes. Such a situation encourages a sensor owner to replace the nodes to continue the normal operation of the sensor-cloud, which incurs certain amount of monetary loss for the owner. Therefore, we design a pricing scheme for the sensor-cloud architecture which is capable of considering the communication range of the sensor nodes and determining an optimal price to be charged from the end-users. The proposed scheme enables the node to select a suitable neighbor node among the available ones, considering effective residual energy, effective power consumption, and the number of applications to which the neighbor node is associated.

1.1 Motivation

All the existing works on sensor-cloud architecture consider the presence of the sensor nodes with static communication range. However, in reality, the communication range of a sensor node can be increased or decreased by adjusting its power level [7]. On the other hand, increased the communication range of a sensor node results in faster reachability of data to the sink node. As we discussed already, the underlying layer of sensor-cloud is sensor nodes, which are traditionally energy-constrained in nature. Therefore, adjusting the communication range of a sensor node to its maximum level for a long duration leads to the faster depletion of energy. Moreover, after the depletion of the energy level below a threshold value, the sensor node is unable to transmit data to other nodes in the network. In such a situation, the sensor owner needs to replace the sensor node, which incurs a certain cost. Consequently, in such a situation, the sensor owner experiences monetary loss. On the other hand, the source node transmits the sensed data to the sink through intermediate nodes by multi-hop connectivity among them. However, it is undesirable to adjust the communication range of these nodes to a random value for serving an application. We assert in this work that there exists a range-price trade-off, formulate an optimization problem, and then solve it to determine the optimum price for an increased range. We propose an algorithm for selecting an appropriate neighbor node of the source to forward the sensed data to the sink, by adjusting its communication range. Moreover, to design a pricing scheme considering the adjusted communication ranges of the nodes, which are associated to serve an application in a sensor-cloud platform, is essential from the business perspective.

1.2 Contribution

The core component of a sensor-cloud platform constitutes wireless sensor nodes, which are virtualized to provision Se-aaS among multiple end-users. However, these sensor nodes are energy-hungry in nature, and therefore, the communication range of the sensor nodes needs to be adjusted strategically to handle energy consumption efficiently. Thus, we propose a novel scheme to adjust the communication range of the sensor nodes and provide an optimal pricing strategy for a sensor-cloud platform. The specific *contributions* of this work are as follows:

- The communication range of a sensor node can be increased or decreased, by adjusting its power level. However, the selection of the maximum communication range of a sensor node for a long duration of the time results in its faster energy depletion. On the other hand, a sensor node senses its surroundings and transmits the sensed data to the sink through single/multi-hop connectivity. At each level of communication range of a sensor node, there is a possibility to present one or more neighbor nodes to forward the sensed data. Therefore, it is essential to select an appropriate neighbor node among the available ones. In this work we adjust the communication range of sensor node to select a suitable neighbor node, among the available ones, considering residual energy, power consumption, and Source Application Count (SAC) count. The total number of application served by a node at any time instant is denoted by SAC.
- A sensor-owner procures, deploys, and maintains the physical sensor nodes. The expenses of the sensor-owners depend on the types and number of sensor nodes deployed. Therefore, after the selection of a suitable neighbor node, the proposed scheme computes an optimal pricing strategy, considering the residual energy and power consumption of the neighbor nodes. Moreover, a sensor node may serve as the source node for other applications. Therefore, for computing the optimal price of the neighbor node, we define a new parameter, termed *Source Application Count* (*SAC*), to incorporate the importance of a neighbor node for being a source node for other applications.
- For the selection of an appropriate neighbor node, we consider different parameters such as residual energy, power consumption, and SAC of the neighbor nodes. Therefore, for considering these parameters for the selection of a suitable neighbor node selection, we define the term – *Selectivity Factor*. Further, considering the selectivity factor of the neighbor nodes of a source node, we model the proposed problem using mixed-integer linear programming (MILP) for *Lagrangian* functions [8]. We obtain an optimal solution for the proposed problem using KKT conditions [8].
- In this work, we attempt to design a pricing scheme

for sensor-cloud architecture after selecting a suitable neighbor node of a source node, considering its communication range. Moreover, the proposed pricing scheme is new, unique, and specifically designed for sensor-cloud platforms. We examine the proposed scheme with extensive simulation and rigorous mathematical analysis.

To precisely mention the contributions, we propose an adjustable communication range selection scheme for provisioning Sensors-as-a-Service (Se-aaS). The existing literature of sensor-cloud architecture do not consider the presence of such sensor nodes, which are capable of adjusting their communication range. Consequently, the pricing schemes in the existing literature do not take the adjustment of communication range in their account to determine the optimal price. We adjust the communication range for selecting the next-hop of a source node at an optimal price. In order to determine the optimal price, we apply the *Lagrangian* function [8] and Karush Kuhn Tucker (KKT) conditions [8].

2 Related Work

In this Section, we study the existing works on sensor-cloud, which form the backdrop of the present work. Existing literature [9]–[11] explored the concept of virtualization in traditional sensor networks. Yuriama *et al*. [5] adopted the concept of virtualization of physical sensor nodes and proposed the architecture of sensor-cloud for provisioning sensors-as-a-service among multiple users. Therefore, Misra *et al*. [4] designed the theoretical framework for sensor-cloud. In this work, the authors identified different actors and their roles in sensor-cloud. Moreover, the authors detailed the sensor-cloud architecture, in which multiple physical sensor nodes combine to form a Virtual Sensor (VS), and multiple VSs together serve certain end-user applications. The composition of a VS dynamically changes with the types of applications. Therefore, Chatterjee *et al*. [12] focused on the dynamic participation of physical sensor nodes in a VS and proposed a dynamic VS formation scheme for sensor-cloud. Aligned with the concept of VS formation, Roy *et al*. [13] presented a VS formation scheme, considering the overlapping deployment region of sensor nodes in a sensor-cloud platform. Sensor nodes are energy-constrained in nature, and therefore, allocating a sensor node to a VS for a long duration is not a feasible solution to serve an application. Thus, Banaie et al. [14] designed a Software-Defined Networking (SDN)-based load balancing mechanism for VSs in sensor-cloud architecture. On the other hand, the back-end processes in sensor-cloud must cater to be very fast in order to serve a time-critical application requirement. Therefore, Roy *et al*. [15] proposed a caching mechanism for the sensor-cloud architecture to ensure faster access to data for an end-user application. In this work, the authors aim to design the caching mechanism considering the destroyed virtual machines in sensor-cloud. Similar to dynamic VS formation, data caching, and load balancing, privacy is another important aspect that needs to be investigated. To address this issue Wang *et al*. [16] proposed an edge-based privacy mechanism for sensor-cloud. In another work, *Wang et al*. [17] considered the generation of huge data in an industrial sensor-cloud environment. The authors proposed a data cleaning model and established it by using Support Vector Machine (SVM). Finally, Madria *et al*. [18] presented the real implementation of the sensor-cloud platform while designing the client centric-layer of it.

In the existing literature, the authors considered economic transactions as an important aspect in different domains such as in Cyber-Physical System (CPS) and mobile networks [19]–[21]. Huang *et al*. [19] proposed a game-based economic model for CPS consisting of three actors – Big Data Collectors (BDCs), Service Organizers (SOs), and users. The proposed scheme is capable to make pricing decisions in a CPS architecture, considering these actors. Similarly, Liu *et al*. [20] designed for pricing competition among the SOs for determining the service pricing in CPS. Further, Dong *et al*. [21] discussed different price competition models for mobile networks. On the other hand, pricing is a major concern in both traditional cloud computing and sensor-cloud. Therefore, Shah-Mansouri *et al*. [22] presented a pricing scheme for cloud computing, which is capable of determining an optimal price for offering cloud services. The authors claimed that the proposed pricing scheme is non-convex in nature. Pricing in cloud computing depends on the usage of its resources. Therefore, considering the resources of a cloud environment, Mashayekhy *et al*. [23] designed an auction-based mechanism for determining the pricing for the cloud resources. The proposed scheme insists the users to reveal the actual requirement of the resources. Similarly, Bonacquisto *et al*. [24] proposed an auction-based scheme for selling the residual computing capacity, which is otherwise not possible to be allocated directly to the users. The authors claimed that the proposed scheme is capable to handle the underutilization of the resources. In another work, Prasad *et al*. [25] designed an auction-based scheme, named *CLOUD-CABOB*, for procuring multiple resources from the cloud vendors. CLOUD-CABOB enables the users to request the resources for which the cloud vendors bid with price, Quality of Service (QoS), and resources. The authors claimed that the proposed scheme provides scalability of the continuous appearance of multiple cloud vendors to bid for the user requests. The cloud computing architecture is based on the business model, in which the service providers earn a certain profit. Therefore, Dabbagh *et al*. [26] devised a scheme for maximizing the cloud profits with an aim to minimize energy consumption. In this work, the authors proposed a scheme for maximizing cloud profit by allocating an appropriate amount of resources to elastic tasks. Considering the *Stochastic* model, Kash *et al*. [27] explored the possibility of the revenue generation in cloud with simple approaches. As in traditional cloud computing, sensor-cloud is also based on a pay-per-

TABLE 1: Summary of the existing works on sensor-cloud

Aspect	SV	AR	DVS	LB	VM	EPM
Conceptualization [5]	✓	×	×	×	×	×
Theoretical Modelling [4]	✓	✓	×	×	×	×
Virtual Sensor Formation [12], [13]	✓	×	✓	×	×	×
SDN-based VS for sensor-cloud [14]	✓	×	×	✓	×	×
Caching [15]	✓	✓	✓	×	✓	×
Privacy [17]	✓	×	×	×	×	✓
Implementation [18]	✓	✓	✓	×	✓	×

Legend: Sensor Virtualization (SV), Actors and their roles (AR), Dynamic VS (DVS), Load balancing for VS (LB), Virtual Machine (VM), and Edge-based Privacy Mechanism (EPM)

TABLE 2: Summary of the existing works on pricing in cloud and sensor-cloud

Aspect	CPS	SP	PC	OP	AP
Economic model for CPS [19]	✓	×	×	×	×
Pricing among SOs [20]	✓	✓	✓	×	×
Pricing for mobile networks [21]	×	×	✓	×	×
Pricing for cloud [22]	×	×	×	✓	×
Pricing for cloud resources [23]–[25]	×	×	×	×	✓

Legend: CPS Architecture (CPS), Service Pricing (SP), Pricing Competition (PC), Optimal Price (OP), Auction-based Pricing (AP)

use model. Therefore, Chatterjee *et al*. [28] designed an optimal pricing scheme for a sensor-cloud platform. In this work, the authors primarily considered two types of price – (a) price for hardware, and (b) price for infrastructure. Further, the authors claimed that the proposed scheme is capable of satisfying user demand along with the maximization of the profit of the sensor owners. In another work, Chakraborty *et al*. [29] presented a pricing scheme for sensor-cloud with an aim to enforce trust among the sensor-owners, while ensuring the quality of Se-aaS.

Synthesis: The existing works addressed different issues such as theoretical modeling, VS composition, and caching in the traditional sensor-cloud architecture as depicted in Table 1. Further, the authors in the existing literature presented different pricing strategies for traditional cloud computing and sensor-cloud architecture as shown in Table 2. However, none of the works considered the presence of the sensor nodes with reconfigurable communication range. Moreover, the pricing strategies for sensor-cloud and other domain presented in the literature do not consider the selection of a suitable neighbor node of a source node, while offering an optimal price to the sensor-owners. Therefore, the existing schemes on pricing are neither suitable to select an appropriate neighbor sensor node by adjusting their communication range, nor are they suitable to determine the optimal price to be paid to their respective owners, depending on the adjusted communication range.

3 Problem Description

We consider a sensor-cloud architecture consisting of multiple sensor owners and end-users. The SCSP plays a centralized role to handle different monetary transactions along with the architecture management issues. The foundation layer of the sensor-cloud architecture consists of networked sensor nodes, which are typically procured by the respective sensor owners. We adapt the concept of range-reconfigurable sensor nodes, discussed by Kar *et al*. [7], and we consider the same for this work. However, the reconfiguration of the communication range of a sensor node depends on the adjustment of its power level. The source node transmits the sensed data to a centralized unit through single or multi-hop connectivity. Typically, the centralized unit is called a sink node. If a source node is not directly connected to the sink node, it uses the neighbor nodes as intermediate hops to deliver the sensed data. As the communication ranges of the sensor nodes are reconfigurable, the neighbor list of the sensor node varies with the increasing or decreasing communication range, as depicted in Fig. 1. In this figure, r_1, r_2, and r_3 are the communication ranges of the sensor node, X. At the communication range r_3 of the sensor node, X has the maximum number of neighbor nodes (with node ids 1 to 9), whereas, with the communication r_1, X has only two neighbor nodes (with ids 1 and 2).

End-users request for a certain services to the sensor-cloud system. On the other hand, the eligible sensor owners, who are able to serve the application, share the optimal price with the SCSP. Further, the SCSP includes

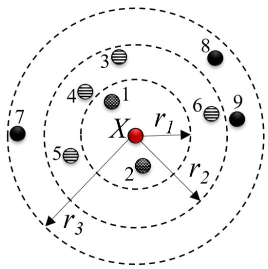


Fig. 1: Presence of neighbor nodes

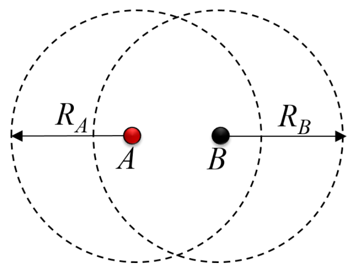


Fig. 2: Communication between two nodes

certain service charge with the price of the sensor-owner and share the same with the end-users. In the process, the end-users remain unaware of the node offering the service. The sensor owner charges an optimal price to an end-user by considering the communication range of the sensor nodes participating to serve the application. Therefore, in this work we target to design the optimal pricing scheme, which enables the sensor owners to charge the optimal price from the end-user, while considering the communication range of his/her owned sensor nodes.

Let the set of sensor owners present in our system be represented as $SO = \{so_1, so_2, so_3, \cdots, so_m\}$. Further, the set of sensor nodes owned by a sensor owner, so_i, is denoted as $S^i = \{s^i_1, s^i_2, s^i_3, \cdots, s^i_x\}$. Similarly, we define the set of end-users present in the system as $EU = \{u_1, u_2, u_3, \cdots, u_n\}$, where n is the maximum number of end-users present in the system. Any sensor node, s^i_j, owned by the sensor owner, j, is configurable to a set of communication ranges. The set of communication ranges of a node, s^i_j, and the set of corresponding power levels to achieve these ranges is denoted by the sets $R^i_j = \{r_1(s^i_j), r_2(s^i_j), r_3(s^i_j), \cdots, r_a(s^i_j)\}$ and $P^i_j = \{p_1(s^i_j), p_2(s^i_j), p_3(s^i_j), \cdots, p_a(s^i_j)\}$, respectively.

The initial communication range of a source sensor node is set to its minimum value. Thereafter, as per requirement, the source node increases the communication range. At every communication range level of the source node, multiple neighbor nodes may be present, as shown in Fig. 1. The neighbor nodes work as intermediate hop-node to deliver the sensed data of the source node to the destination or sink. However, the communication ranges of these neighbor nodes should be increased in order to forward the sensed data of the source node. For successful communication between two nodes, both the nodes need to be present within the communication ranges of each other, as depicted in Fig 2. In this figure, nodes A and B are within the communication range of each other. Therefore, when the source node increases its range, the available neighbor node must increase their respective communication ranges for successfully establishing connectivity.

Theorem 1. *Let M_R be a zero-one matrix, of the relation, R, on a set of k communication ranges of a sensor node, then M^*_R of the transitive closure R^* is:*

$$M^*_R = M_R \vee M^{[2]}_R \vee M^{[3]}_R \vee \cdots \vee M^{[k]}_R \tag{1}$$

Proof: Let the zero-one matrix of the communication ranges of any sensor node be denoted as:

$$M_R = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1k} \\ m_{21} & m_{22} & \cdots & m_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ m_{j1} & m_{j2} & \cdots & m_{jk} \\ \vdots & \vdots & \ddots & \vdots \\ m_{k1} & m_{k2} & \cdots & m_{kk} \end{bmatrix} \tag{2}$$

where the value of each m_{jk} is either 0 or 1. Also, j and k represent the number of possible communication ranges at time t and $(t+1)$, respectively. Therefore, M_R is the zero-one matrix of order $k \times k$. The zero-one matrix of the transitive closure R^* is expressed as:

$$M^*_R = M_R \vee M^{[2]}_R \vee M^{[3]}_R \vee \cdots \vee M^{[k]}_R \tag{3}$$

where $M^{[2]}_R = M_R \odot M_R$, which is represented as $(M_R \wedge M_R) \vee (M_R \wedge M_R)$ and $M^{[k]}_R$ is the Boolean product of k factors of M_R. □

Corollary 1. *If a given relation, R, from the set of k communication ranges from the time instant t to $(t+1)$, then there exists a connectivity relation, R^*, of at least one path length.*

Proof: Let R be a relation in the set of k communication ranges from time instant t to $(t+1)$. Composite of a relation between two sets, P and Q, signifies the presence of some ordered pairs, which is denoted as $P \circ Q$. Hence, the composite of the relation R signifies, $R' = R$, $R^2 = R \circ R$, $R^{(n+1)} = R^n \circ R$. In our scenario, R contains $(m_{i,j}, m'_{i,j})$. As, $R^2 = R \circ R$, therefore, R^2 always contains the pair $(m_{i,j}, m'_{i,j})$, where R^2 is a composite relation. Therefore, $(m_{i,j}, m'_{i,j}) \in R^2$. Then, R^* contains $(m_{i,j}, m'_{i,j})$. In other words, there exists a connectivity relation, R^*, of at least one path length due to the presence of the same ordered pair, which proves the statement. □

4 RP-Sense: The Solution Approach

It is required to address the problem of computing the optimum price for the sensor nodes so that the end-users requested applications are served. Based on the application requirements, each source node in the sensing plane chooses the suitable intermediate node out of the different options it has at its disposal. The process continues at each hop till the sensed data is transmitted to the destination. The source node adjusts its communication range and selects a suitable intermediate node among the available ones. We design a pricing scheme, named as RP-Sense, which determines the price required to be paid by the end-user for the sensor nodes involved in the application.

4.1 Selection of neighbor node

In existing literature [7], [30] discussed different schemes for intermediate neighbor node selection in the WSNs to transmit the sensed data from source to destination. However, the existing neighbor node selection scheme does not consider the virtualization of the sensor nodes. Moreover, the authors focus on the single-user centric approach of WSN and presented the intermediate node. Consequently, the existing node selection schemes are not suitable for sensor-cloud. In this Section, we explore the scheme for the selection of a suitable neighbor node of the source node. However, after making this selection, the process continues until the source node is able to connect and transmit the sensed data to the sink through a multi-hop network. We consider that the communication range of the sensor nodes is reconfigurable. The increase in the communication range of a sensor node increases its energy consumption. Therefore, a node with higher residual energy is given priority of choice as the next-hop node. We use effective residual energy (R^{eff}) as one of the parameters for selecting the next-hop node. The effective residual energy, R_k^{eff}, of the k^{th} neighbor node of a source node is derived as:

$$R_k^{eff} = \frac{RE_k}{E^{init}} \tag{4}$$

where RE_k and E^{init} are the current residual and initial energy of the k^{th} sensor node, respectively.

A sensor node achieves different communication ranges with the increasing or decreasing values of power levels. Therefore, we adopt the power level metric for selecting a neighbor node of a source node as the next hop. We define the parameter, effective power consumption (P_k^{eff}) of the k^{th} neighbor node, as:

$$P_k^{eff} = \frac{P_k^{c_i}}{P^{c_{max}}} \tag{5}$$

where $P_k^{c_i}$ and $P^{c_{max}}$ are the power consumption at the i^{th} communication range and the maximum power consumption of the k^{th} sensor node, respectively.

A neighbor node of a source node may participate as the source of multiple applications in the system. On the other hand, the increase in the communication range of the neighbor node may affect the service of the other applications. Therefore, we introduce the Source Application Count (SAC) parameter.

***Definition* 1.** *Source Application Count (SAC_k) of a neighbor node, k, counts the number of different applications for which it is serving as a source node.*

Practically, at each communication range, some of the neighbor nodes may be directly connected with the sink node. In such a scenario, the neighbor node with direct connectivity with the sink node receives an incentive as *connectivity incentive*.

***Definition* 2.** *Connectivity incentive ($\mathbb{I}_k$) of a node is defined as an extra benefit received in the selection mechanism of a neighbor node, k, as a next-hop node, considering the communication range of source code.*

Let a source node, s, is able to achieve its maximum communication range, $r_a(s_j^i)$ at the y^{th} step. We assign a weight for the 1^{st} to the y^{th} steps. Further, if at the p^{th} communication range of the source node, a neighbor node, k, increases its communication range and is able to connect directly to the sink node, then the connectivity incentive is derived as:

$$\mathbb{I}_k = \frac{1}{p} \tag{6}$$

At every communication range of the source node, a set of neighbor nodes is present. In such a situation, the source node must choose a suitable neighbor node among the available ones. We define a parameter, *selectivity factor*, in order to select the suitable neighbor node.

***Definition* 3.** *The selectivity factor (σ_k) of a neighbor node determines its capability for getting selected as a next hop of the source node, considering R^{eff}, P^{eff}, SAC, and $\mathbb{I}$, respectively.*

The selectivity factor of a neighbor node, k, is derived as:

$$\sigma_k = \begin{cases} \left(\frac{R_k^{eff}}{P_k^{eff}+SAC_k}\right)\mathbb{I}_k, & \text{if } \lambda = 1 \\ \left(\frac{R_k^{eff}}{P_k^{eff}+SAC_k}\right), & \text{otherwise} \end{cases} \tag{7}$$

where $\lambda = 1$ indicates that the neighbor node, k, is able to establish the connectivity with the sink node, after increasing the communication range.

$\mathbb{S} = \{\sigma_1, \sigma_2, \sigma_3, \cdots, \sigma_n\}$ denotes the set of selectivity factors of all the neighbor nodes of a source node. Finally, a neighbor node is selected with max$\{\mathbb{S}\}$. If a neighbor node is unable to connect to the sink node directly, it follows the same process of finding the suitable neighbor node.

4.2 Optimal pricing

A sensor owner procures and deploys the sensor nodes in different locations for provisioning Se-aaS to multiple end-users. In return, the sensor owner earns a certain amount of profit, based on the usage of his/her owned sensor nodes. However, the sensor owner bears the cost of procuring, deploying, and maintaining the sensor nodes. The procurement and deployment costs are one-time costs. After paying the one-time costs, the sensor-owner has to spend the maintenance cost in the long-run for its respective deployed sensor nodes. Therefore, we consider the maintenance cost as the expenses of the sensor owner. Let the total maintenance cost incurred by a sensor owner, so_i, for the j^{th} sensor node up to the last t instances is P_j^m. We compute the average expense, $\mathcal{E}_k$, of the k^{th} node for the last t instances as:

$$\mathcal{E}_k = \frac{\sum_{j=1}^{t} P_j^m}{t} \tag{8}$$

Let the total chargeable price for the k^{th} sensor node is $\mathcal{P}_k$. Further, we calculate the total income of sensor owner, so_i, for the k^{th} sensor node by Equation (9).

$$\mathcal{I}_k = \left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right)\mathcal{P}_k \tag{9}$$

Using Equations (8) and (9), we compute the profit of the sensor owner for the k^{th} sensor node as:

$$\mathbb{P}_k = \mathcal{I}_k - \mathcal{E}_k \tag{10a}$$

$$\mathbb{P}_k = \left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right)\mathcal{P}_k - \left(\frac{\sum_{j=1}^{t} P_j^m}{t}\right) \tag{10b}$$

Utility of the sensor owner

The satisfaction of the j^{th} sensor owner for the k^{th} sensor node is quantified by the utility function, $\mathcal{U}_{(j,k)}$, considering the price charged by the sensor owner. The utility function, $\mathcal{U}_{(j,k)}$, follows the *law of diminishing marginal utility* [31] as:

$$\mathcal{U}_{(j,k)} = \mathcal{P}_k\left[\frac{\mathbb{P}_k(1 - log\mathbb{P}_k)}{\mathbb{P}_k^{max}}\right] \tag{11}$$

where $\mathbb{P}_k^{max}$ denotes a predefined limit of the profit for the sensor owner, such that $\mathbb{P}_k < \mathbb{P}_k^{max}$. $\mathcal{P}_k$ denotes the chargeable price for the sensor node k. We obtain Equation (12), on substituting the values of $\mathbb{P}_k$, from Equation (10b) in Equation (11).

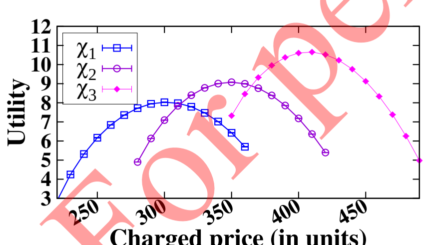


Fig. 3: Variation in utility

Justification for using the law of diminishing factor: Fig. 3 presents the plots of the utility values, with the increasing charged price. This figure represents the analysis of variations in the values of utilities, considering three price ranges – χ_1 $(220 - 360$ units), χ_2 $(280 - 420$ units), and χ_3 $(360 - 480$ units), respectively. Further, for each of the plots, we consider the constant values of R_k^{eff}, P_k^{eff}, and SAC_k. In each of the price ranges, we observe that the values of utility increase, initially, with the increasing value of the charged price. However, after a certain increment of the charged price (say $\mathcal{P}_{max}$), the values of the utility start to drop. The pattern of the utility values indicates that a sensor owner is able to claim the charged price up to a certain amount, beyond which the utility of the sensor owner starts to drop. Consequently, a sensor owner is able to charge the price for their respective deployed sensor node, considering the maximum utility value. Therefore, the use of the law of diminishing factor is justified for computing the utility. Further, Property 1 summarized the applicability of the law of diminishing factor in the proposed utility.

Property 1. *The proposed utility function in Equation (11) is based on the law of diminishing factor. The value of the utility function increases with the increment of the charged price up to $\mathcal{P}_{max}$. However, the value of the utility function starts to drop, if the sensor owner claims the charged price more than $\mathcal{P}_{max}$.*

Equation (12) gives the final utility of the sensor owner. Our aim is to maximize $\mathcal{U}_{(j,k)}$, such that $\mathcal{P}_k$ becomes optimal. Therefore,

$$\underset{\mathcal{P}_k}{argmax}\ (\mathcal{U}_{(j,k)}) \tag{13}$$

subject to,

$$0 \leq R_k^{eff} \leq 1, 0 \leq P_k^{eff} \leq 1, SAC_k \leq N, \text{ and } \mathcal{P}_k \leq \mathbb{P}_{max} \tag{14}$$

Theorem 2. *There exists an optimal solution of $\mathcal{U}_{(j,k)}$ for the constraints represented in Equation (14).*

Proof: In order to solve the given optimization problem in Equations (13) and (14), we use *Lagrangian multiplier* [8] and apply KKT conditions [8] to obtain $\mathcal{P}_k^*$.

The Lagrangian form of Equations (13) and (14) is represented as:

$$L = \mathcal{U}_{(j,k)} - \mu_1(E^{init} - R_k^{eff}) - \mu_2(P^{c_{max}} - P_k^{eff}) - \mu_3(N - SAC_k) - \mu_4(\mathbb{P}_{max} - \mathcal{P}_k) \tag{15}$$

Let Equation (15) be splitted into X, Y, and Z as:

$$X = \mathcal{P}_k \tag{16a}$$

$$Y = \mathbb{P}_k = \left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right)\mathcal{P}_k - \mathcal{E}_k \tag{16b}$$

$$\mathcal{U}_{(j,k)} = \frac{P_k}{\mathbb{P}_k^{max}}\left[\left\{\left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right)\mathcal{P}_k - \left(\frac{\sum_{j=1}^{t} P_j^m}{t}\right)\right\}\left\{1 - log\left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right)\mathcal{P}_k - \left(\frac{\sum_{j=1}^{t} P_j^m}{t}\right)\right\}\right] \tag{12}$$

$$Z = -\mu_1(1 - R_k^{eff}) - \mu_2(1 - P_k^{eff}) - \mu_3(N - SAC_k) - \mu_4(\mathbb{P}_{max} - \mathcal{P}_k) \tag{16c}$$

The partial derivative of Equation (15) with respect to $\mathcal{P}_k$ is represented in Equation (17), which provides the dual feasibility condition of KKT.

$$\frac{\partial \mathcal{L}}{\partial \mathcal{P}_k} = XY\frac{\partial Z}{\partial \mathcal{P}_k} + YZ\frac{\partial X}{\partial \mathcal{P}_k} + XZ\frac{\partial Y}{\partial \mathcal{P}_k} = 0 \tag{17}$$

In order to simplify Equation (17), we use the *Taylor Series* expansion and obtain Equation (18), where

$$\alpha = \left(\frac{R_k^{eff}}{P_k^{eff} + SAC_k}\right) \text{ and } \beta = \mathcal{E}_k \tag{19}$$

and e is the exponential term obtained after the application of Taylor's series expansion.

We observe that Equation (18) gives a polynomial function. Therefore, we apply the *Cardano's method* [32] to compute the optimal chargeable price, $\mathcal{P}_k^*$ as:

$$\mathcal{P}_k^* = S + T - \frac{b}{3a} \tag{20}$$

such that,

$$Q = \frac{3ac - b^2}{9a^2} \tag{21a}$$

$$R = \frac{9abc - 27a^2d - 2b^3}{54a^3} \tag{21b}$$

$$S = \sqrt[3]{R + \sqrt{Q^3 + R^2}} \tag{21c}$$

$$T = \sqrt[3]{R - \sqrt{Q^3 + R^2}} \tag{21d}$$

and the coefficients of $\mathcal{P}_k$, as obtained from Equation (18), are represented as:

$$a = -\frac{1}{2}\alpha^3 \tag{22a}$$

$$b = e^2\alpha^2 + 2\alpha^2\beta^2 - 3\alpha^2 + \frac{1}{2}\alpha^3 + \alpha^2\beta + \alpha^2 e \tag{22b}$$

$$c = 4\alpha\beta + 2e\alpha - 2\alpha\beta^2 - 4e\alpha\beta + \frac{1}{2}\alpha^2\beta - \alpha\beta^2 - e^2\alpha + e\alpha^2 \tag{22c}$$

$$d = \mu_4 - \beta^2 - e\beta + e\beta^2 + \frac{1}{2}\beta^3 + \frac{1}{2}e^2\beta \tag{22d}$$

□

Algorithm 1 represents the procedure to find the optimal price for a selected neighbor sensor node k of the source node. In order to deliver data from the source to the sink, the selected node at each hop execute Algorithm 1 and then acts as a source node.

Algorithm 1 Optimal pricing in RP-Sense

INPUTS:
R_k, E^{init}, $P_k^{c_i}$, $P^{c_{max}}$, SAC_k, $\mathcal{E}_k$
OUTPUTS:
Optimal price, $\mathcal{P}_k^*$, for the k^{th} sensor node with communication range s_j^i
PROCEDURE:
```
for j=1 to x do
    for k=1 to y do
        Compute R_k^eff                  ▷ Using Equation (4)
        Compute P_k^eff                  ▷ Using Equation (5)
        Obtain SAC_k                     ▷ as given in Definition 1
        if λ = 1 then
            Compute I_k                  ▷ Using Equation (6)
        else
            Set I_k = 1
        end if
        Compute S_k                      ▷ Using Equation (7)
        Find Max{S}
    end for
    Compute P_k    ▷ Using Equations (8), (9), and (10b)
    Compute U_k    ▷ Using Equations (11), (13), and (14)
    Compute P_k^*                        ▷ Using Equation (20)
end for
```

5 Performance Evaluation

In this Section, we discuss the performance of the proposed scheme, *RP-Sense*. First, we discuss the simulation design, based on which we analyze the performance of RP-Sense. We, then, elaborately discuss the results of the performance obtained.

5.1 Simulation Design

In order to evaluate the performance, we consider a simulation area of $10 \times 10\ KM^2$. In the simulation area, 5 distinct types of 100-$1,000$ sensor nodes are deployed by following uniform random distribution. These sensor nodes are owned by their respective sensor owners. Table 3 represents the values of different simulation parameters used for the evaluation of the performance of RP-Sense.

$$-\frac{1}{2}\alpha^3\mathcal{P}_k^3 + \mathcal{P}_k^2(e^2\alpha^2 + 2\alpha^2\beta^2 - 3\alpha^2 + \frac{1}{2}\alpha^3 + \alpha^2\beta + e\alpha^2) + \mathcal{P}_k(4\alpha\beta + 2e\alpha - 2\alpha\beta^2 - 4e\alpha\beta + \frac{1}{2}\alpha^2\beta - \alpha\beta^2 - e^2\alpha + \alpha^2 e) + (\mu_4 - \beta^2 - e\beta + e\beta^2 + \frac{1}{2}\beta^3 + \frac{1}{2}e^2\beta) = 0 \tag{18}$$

***Benchmark*:** As the concept of sensor-cloud is relatively new, only a very few works addressing different issues in the sensor-cloud architecture exist. Specifically, only two works – Dynamic Optimal Pricing for Heterogeneous Service-Oriented Architecture of Sensor-Cloud Infrastructure (DOPH) [28] and Dynamic Trust Enforcing Pricing Scheme for Sensors-as-a-Service in Sensor-Cloud Infrastructure (DETER) [29] – addressed the pricing issue for the sensor-cloud architecture. We already discussed these works in Section 2. For simplicity, we abbreviate the proposed pricing scheme by Chatterjee *et al*. [28] as *DOPH* and by Chakraborty *et al*. [29] as *DETER*. We consider different parameters to compare the proposed scheme, RP-Sense, with the benchmarks, DOPH and DETER.

TABLE 3: Simulation Parameters

Parameter	**Value**
Simulation area	$10Km \times 10Km$
Type of sensor nodes	5
Number of sensor nodes (N)	$100 - 1,000$
Number of sensor owners	5
Communication range (ρ)	$30 - 120m$
SAC count	$4 - 18$
Connectivity incentive	$1 - 15$

5.2 Results

As the communication range of the sensor nodes is considered to be reconfigurable. In this work, in order to evaluate the performance of the proposed scheme, we vary the communication range of the source nodes in increasing steps. Fig. 4 depicts the presence of the average number of neighbor nodes of a source node. We consider three different communication ranges – $30m$, $60m$, and $90m$ of the source nodes, while the number of source nodes varies from $2-12$. Additionally, we consider the presence of the total number of nodes in the network as 100, 500, and $1,000$, respectively. In this figure, first, we analyze the presence of the average number of the neighbor nodes, while the total number of nodes in the network is 100. We observe that the

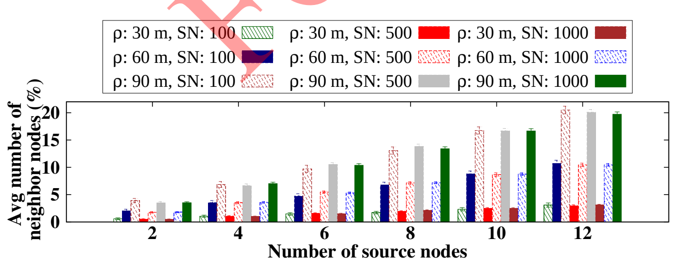


Fig. 4: Average number of neighbor nodes

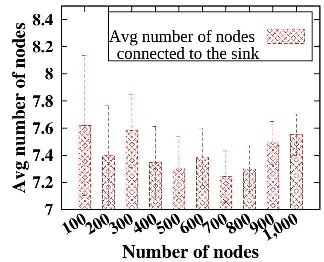


Fig. 5: Percentage of nodes connected to the sink

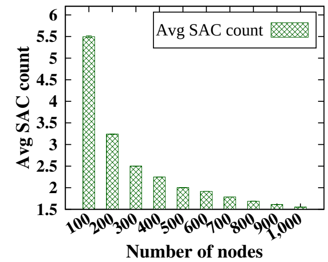
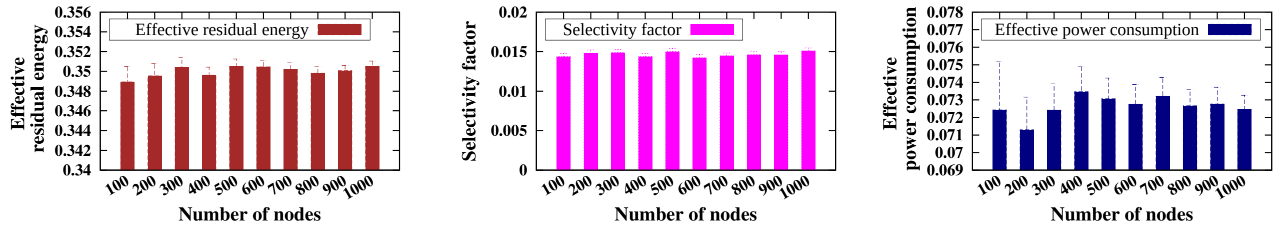


Fig. 6: Percentage of average SAC count

average number of neighbor nodes is more, when the communication range of the source nodes is $90m$, as compared to the cases when the communication ranges are $30m$ and $60m$, respectively. On the other hand, the average number of neighbor nodes decreases with the decrease in the communication range to $60m$. Finally, we observe the presence of the lowest average number of neighbor nodes of source nodes, when the communication range is $30m$. The possible reason for this trend is that the probability of the number of neighbor nodes of the source node increases with the increasing value of communication range from $30m$-$60m$. Due to the same reason, we observe a similar pattern in the plots, when the total number of nodes in the network are 500 and $1,000$. We also observe that the general trend of the plot of the presence of the number of neighbor nodes is increasing with the increasing number of sensor nodes in the network, while the communication range remains the same.

We also examine the number of nodes connected to the sink in our experiments. Fig. 5 shows the percentage of nodes connected to the sink. Along the x-axis, we vary the number of nodes present in the network from 100 to $1,000$. We observe that at least 7% of nodes are connected to the sink, irrespective of the total number of nodes present in the network. Further, we do not observe any smooth increasing, or decreasing trend in the plot.

As SAC is one of the important factors for the selection of an appropriate neighbor node of a source node, we analyze the average SAC count with the variations in the number of nodes in the network. In Fig. 6, we observe a



(a) Effective residual energy (b) Selectivity factor (c) Effective power consumption

Fig. 7: Variations in effective residual energy, selectivity factor, effective power consumption with number of nodes

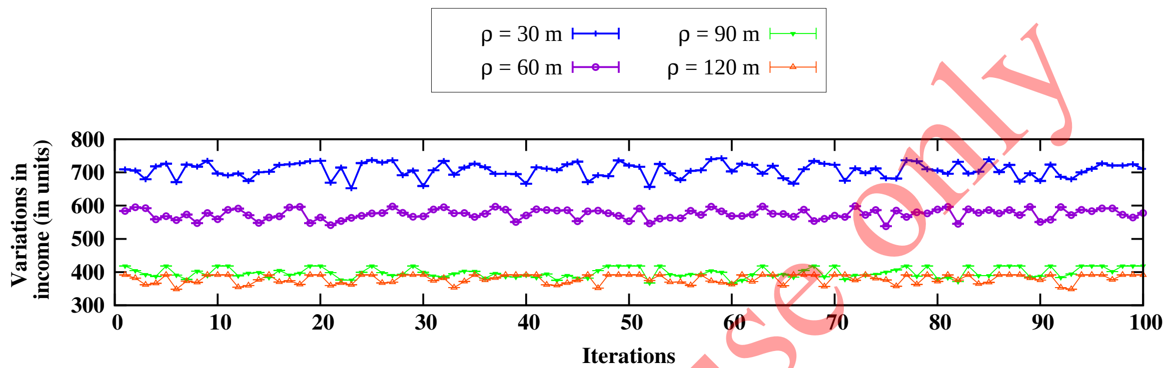
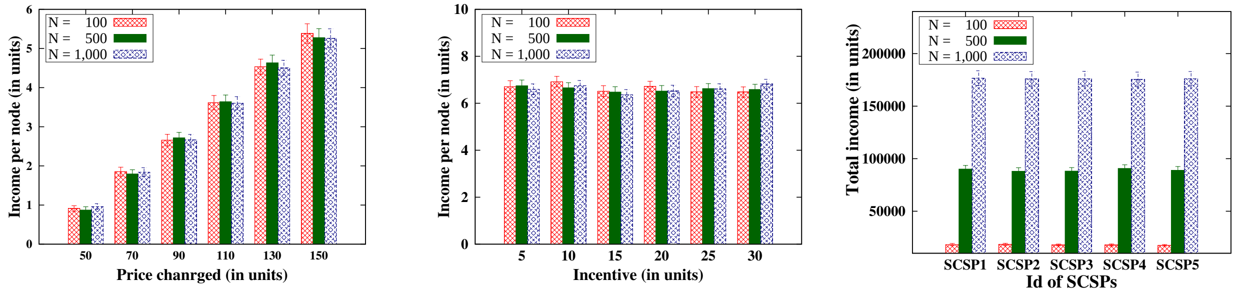


Fig. 8: Change in income with iterations

decreasing pattern in the plot with the increasing number of nodes in the network. As mentioned in Definition 1, the SAC count of a node represents the number of applications for which the node works as a source node. The total number of applications is fixed for a network. Consequently, we observe the highest and the lowest SAC count in the presence of 100 and $1,000$ nodes, respectively, in the network.

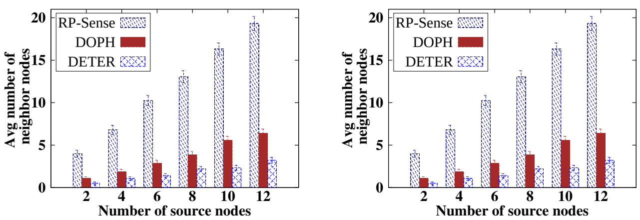
The proposed pricing scheme constitutes a few parameters such as effective residual energy (R^{eff}), selectivity factor (σ), and effective power consumption (P^{eff}). Thus, we evaluate the change in these parameters with the variations in the number of nodes in the network, as depicted in Fig. 7. In Figs. 7(a)-7(c), we notice a random change in the values of effective residual energy, selectivity factor, and effective power consumption of a node in the network. The possible reason for this is attributed to the fact that the communication range of different nodes is different. Consequently, the values of R^{eff} and P^{eff} randomly vary with the change in the communication range. Similarly, we observe a random variation in σ with the change in the communication range of these nodes.

The monetary transaction among multiple actors is an intrinsic part of the sensor-cloud architecture. Therefore, we examine the variations in the total income of a sensor owner. Fig. 8 depicts the change in the total income of a sensor owner with an increase in the number of experimental iterations, while considering the varying communication ranges of the sensor nodes between $30m$ and $120m$. In order to evaluate the total income, we consider that a random number of applications is served by the sensor nodes of the respective sensor owners. We observe that when the communication ranges are $90m$ and $120m$, the total income of the sensor owners varies between 350 and 450 units, respectively. On the contrary, the total income of the sensor owners varies between 500 and 625 units, when the communication range of the sensor nodes is $60m$. Finally, we notice that the total income varies between 650 and 750 units when the communication range of the sensor nodes. Therefore, we infer that for the $30m$ range, the total income of the sensor owners is the highest. This is attributed to the fact that when the communication range is less, the sensor nodes need not to spend more energy as compared to when the communication range varies between $60m$ and $120m$. For a similar reason, a reduced total income is observed with the communication range of $120m$ of the sensor nodes. We also evaluate the income of a sensor owner for a sensor node with the variation of the price charged to the end-users. Fig. 9(a) depicts the change in income per node with the variation of the price charged to an end-user to serve an application. We observe a gradual increase in the income per node with the increasing amount of price charged, irrespective of the price



(a) Income with charged price (b) Income with incentive (c) Total income of SCSP

Fig. 9: Income

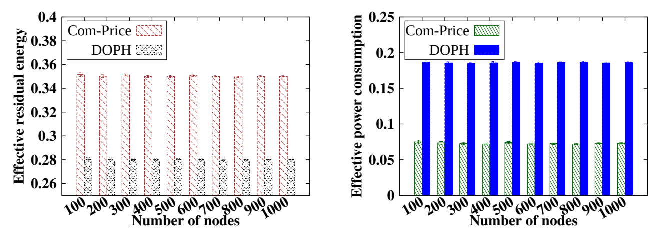


(a) Total nodes = 100 (b) Total nodes = 500

Fig. 10: Presence of average number of neighbor nodes in RP-Sense, DOPH, and DETER

charged to the end-user. Thus, we infer that the income of a sensor owner, for a node, depends directly on the charged price. On the other hand, in Fig. 9(b), we observe that the change in connectivity incentive does not result in any significant change in the income per node of a sensor owner. The incentive of a sensor node depends on its communication range as mentioned in Equation (6), which causes a change in the income. However, the income of a sensor node also has a significant effect on the other factors such as the effective residual energy, the SAC count, and the effective power consumption. Therefore, the income per node varies, independently with the change in the connectivity incentive of the node. The SCSPs are centralized entities, who earn profits for managing the sensor-cloud platform. Thus, we evaluate the income of the SCSPs considering the total number of nodes 100, 500, and $1,000$ in the network, considering five SCSPs with ids $SCSP1$-$SCSP5$. Fig. 9(c) depicts that the income of all the SCSPs is highest when the number of nodes in the network is $1,000$, whereas the total income drops to the minimum amount in the presence of 500 nodes in the network. From this trend, we infer that the presence of more number of nodes in the network yields increased income.

We compare the proposed scheme, RP-Sense, with the existing pricing schemes – DOPH and DETER, considering different aspects such as the presence of the average number of neighbor nodes, effective residual energy, effective power consumption, and charged price. Fig. 10 presents the variations in the average number of neighbor nodes of a source node, considering 100 and 500 sensor nodes in the network. In both Figs. 10(a) and 10(b), we observe that the presence of the average number of neighbor nodes is high in RP-Sense as compared to DOPH and DETER. Unlike DOPH and DETER, in RP-Sense, the sensor nodes have a provision to adjust their communication range. Moreover, in DOPH and DETER, the source node is able to get a fixed number of neighbor nodes in its communication range. In the case of RP-Sense, the source node has provision to increase the communication range to have more number of neighbor nodes within one-hop distance. Consequently, in all the cases, the source nodes achieved more number of neighbor nodes in RP-Sense, as compared to that in DOPH and DETER.



(a) Effective residual energy (b) Effective power consumption

Fig. 11: Comparison of RP-Sense with DOPH and DETER in terms of effective residual energy and power factor

The power consumption and the effective energy play a crucial role in the proposed scheme. Therefore, we compare the performance of the proposed scheme with DOPH and DETER, considering the effective residual energy and effective power consumption. Fig. 11 depicts a comparison of effective energy consumption and effective power consumption with the variations of 100-$1,000$ sensor nodes in the network. DOPH and DETER do not have the provision to adjust the communication range.

Consequently, the availability of the average number of neighbor nodes is less, which, in turn, increases the involvement of more intermediate sensor nodes to deliver a data packet from the source to the sink nodes. On the other hand, in RP-Sense, the source node is able to adjust the communication range to select a suitable neighbor node as an intermediate node to forward the sensed data. Thus, we notice that the effective residual energy is less and the effective power consumption is more in DOPH and DETER, as compared to those in RP-Sense.

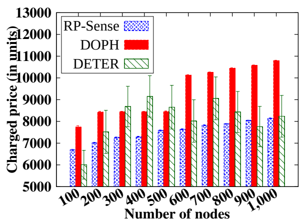


Fig. 12: Charged price in RP-Sense, DOPH, and DETER

One of the objectives behind the proposed pricing scheme is to provide an opportunity for the sensor owner to charge a suitable amount of price, considering the adjusted communication range of their respective sensor nodes. In the proposed scheme, a source node increases its communication range to select a suitable neighbor node. The process continues, till the sensed data is delivered to the sink. In the process, multiple nodes adjust their respective communication ranges, which incurs addressing monetary expenses. Thus, in such a scenario, the sensor owner should receive a price compensation for the utilization of sensor nodes. We consider the charged price and compare our proposed scheme, RP-Sense, with DOPH and DETER. Fig. 12 presents a comparison of charged prices in RP-Sense, DOPH, and DETER. In this figure, the y-axis denotes the total charged price, whereas the x-axis denotes the total number of nodes present in the network. We notice that the sensor owners charge higher amounts using DOPH and DETER, as compared to that using RP-Sense. The reason for charging a higher amount in DOPH and DETER is that in these schemes the authors do not consider the presence of reconfigurable communication range of the sensor nodes. Moreover, the sensor nodes are unable to increase the communication range as per requirement. Thus, in DOPH and DETER, the source nodes use more number of intermediate nodes to deliver data to the sink node. As a result, all the intermediate nodes, which participate in the transmission of data from source to the sink, incur an additional cost.

6 Conclusion

In this work, we designed a pricing scheme for sensor-cloud infrastructure, while considering the presence of a reconfigurable communication range of sensor nodes. The proposed scheme consists of two phases – the selection of an appropriate neighbor node of a source node and the design of a pricing scheme. In the first phase, we designed a metric the – *selectivity factor* – to select a best possible neighbor node of a source node among the available ones. On the other hand, the selected neighbor node continues, in turn, to select its neighbor node, using the selectivity factor. The process of node selection continues till the data of the source node reaches the sink. In the second phase, we designed the pricing scheme, based on the adjusted communication range of the sensor nodes. The results of the extensive experimental analysis support the requirement of the consideration of reconfigurable communication range of the sensor nodes.

In this work, we studied the presence of static sensor nodes with reconfigurable communication range in a sensor-cloud architecture. Practically, there exists the possibility of the presence of mobile sensor nodes in a sensor-cloud platform. Further, the mobility of the sensor nodes enables the dynamic allocation of the sensor nodes in a virtual sensor. Consequently, the existing pricing schemes for traditional sensor-cloud architecture are not applicable for use in sensor-cloud with the presence of mobile sensor nodes. Therefore, in the future, we plan to extend our work to design a pricing scheme for sensor-cloud architecture, considering the presence of mobile sensor nodes. Additionally, different channel conditions may affect the pricing in a sensor-cloud platform. Therefore, we plan to analyze the effect of different channel conditions on the pricing of the sensor-cloud.

7 Acknowledgment

The first author of this work is partially funded by grant no. IFC/4122/RCF2018/1371 of the Indo-French Centre for the Promotion of Advanced Research (IFC-PAR/CEFIPRA). The second author of this work is partially funded by grant no. INAE/121/AKF, Dt. 13-02-2019 of Indian National Academy of Engineering (INAE)

References

[1] U. Gosda, R. Weber, O. Michler, S. Zeisberg, and E. Mademann, "Target Tracking in Wireless Sensor Networks by Data Fusion with Video-based Object Detection," in *proceedings of the* 10^{th} *Workshop on Positioning, Navigation and Communication (WPNC)*, Mar 2013, pp. 1–6.

[2] C. R. Baker, K. Armijo, S. Belka, M. Benhabib, V. Bhargava, N. Burkhart, A. D. Minassians, G. Dervisoglu, L. Gutnik, M. B. Haick, C. Ho, M. Koplow, J. Mangold, S. Robinson, M. Rosa, M. Schwartz, C. Sims, H. Stoffregen, A. Waterbury, E. S. Leland, T. Pering, and P. K. Wright, "Wireless Sensor Networks for Home Health Care," in *Proceedings of the* 21^{st} *International Conference on Advanced Information Networking and Applications Workshops (AINAW'07)*, vol. 2, May 2007, pp. 832–837.

[3] J. P. Dominguez-Morales, A. Rios-Navarro, M. Dominguez-Morales, R. Tapiador-Morales, D. Gutierrez-Galan, D. Cascado-Caballero, A. Jimenez-Fernandez, and A. Linares-Barranco, "Wireless Sensor Network for Wildlife Tracking and Behavior Classification of Animals in Doana," *IEEE Communications Letters*, vol. 20, no. 12, pp. 2534–2537, Dec 2016.

[4] S. Misra, S. Chatterjee, and M. S. Obaidat, "On Theoretical Modeling of Sensor Cloud: A Paradigm Shift From Wireless Sensor Network," *IEEE Systems Journal*, vol. 11, no. 9, pp. 1–10, Nov 2014.

[5] M. Yuriyama and T. Kushida, "Sensor-Cloud Infrastructure - Physical Sensor Management with Virtualized Sensors on Cloud Computing," in *Proceedings of the* 13^{th} *International Conference on Network-Based Information Systems*, Sep 2010, pp. 1–8.

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

[7] P. Kar, A. Roy, and S. Misra, "Connectivity Reestablishment in Self-Organizing Sensor Networks with Dumb Nodes," *ACM Transactions on Autonomous and Adaptive Systems*, vol. 10, no. 4, pp. 28:1–28:30, Jan 2016.

[8] M. S. Bazaraa, *Nonlinear Programming: Theory and Algorithms*, 3^{rd} ed. Wiley Publishing, 2013.

[9] S. Abdelwahab, B. Hamdaoui, M. Guizani, and T. Znati, "Cloud of Things for Sensing-as-a-Service: Architecture, Algorithms, and Use Case," *IEEE Internet of Things Journal*, vol. 3, no. 6, pp. 1099–1112, Dec 2016.

[10] L. Guijarro, V. Pla, J. Vidal, and M. Naldi, "Game Theoretical Analysis of Service Provision for the Internet of Things Based on Sensor Virtualization," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 3, pp. 691–706, Mar 2017.

[11] C. Delgado, M. Canales, J. Ortn, J. R. Gllego, A. Redondi, S. Bousnina, and M. Cesana, "Joint Application Admission Control and Network Slicing in Virtual Sensor Networks," *IEEE Internet of Things Journal*, vol. 5, no. 1, pp. 28–43, Feb 2018.

[12] S. Chatterjee and S. Misra, "Optimal Composition of a Virtual Sensor for Efficient Virtualization within Sensor-cloud," in *In proceedings of the IEEE International Conference on Communications (ICC)*, Jun 2015, pp. 448–453.

[13] C. Roy, A. Roy, and S. Misra, "DIVISOR: Dynamic Virtual Sensor Formation for Overlapping Region in IoT-based Sensor-cloud," in *Proceedings of IEEE Wireless Communications and Networking Conference (WCNC)*, Apr 2018, pp. 1–6.

[14] F. Banaie, M. H. Yaghmaee, and S. A. Hosseini, "SDN-based Scheduling Strategy on Load Balancing of Virtual Sensor Resources in Sensor-cloud," in *the* 8^{th} *International Symposium on Telecommunications (IST)*, Sep 2016, pp. 666–671.

[15] A. Roy, S. Misra, and S. Ghosh, "QoS-Aware Dynamic Caching for Destroyed Virtual Machines in Sensor-Cloud Architecture," in *Proceedings of the* 19^{th} *International Conference on Distributed Computing and Networking (ACM ICDCN)*. NY, USA: ACM, 2018, pp. 1–7.

[16] T. Wang, Y. Mei, W. Jia, X. Zheng, G. Wang, and M. Xie, "Edge-based Differential Privacy Computing for Sensor-cloud Systems," *Journal of Parallel and Distributed Computing, Elsevier*, vol. 136, pp. 75–85, Nov 2020.

[17] T. Wang, H. Ke, X. Zheng, K. Wang, A. K. Sangaiah, and A. Liu, "Big Data Cleaning Based on Mobile Edge Computing in Industrial Sensor-Cloud," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 2, pp. 1321–1329, Sep 2020.

[18] A. Sen, V. P. Modekurthy, R. Dalvi, and S. Madria, "A sensor cloud test-bed for multi-model and multi-user sensor applications," in *IEEE Wireless Communications and Networking Conference (WCNC)*, Apr 2016, pp. 1–7.

[19] M. Huang, W. Liu, T. Wang, Q. Deng, A. Liu, M. Xie, M. Ma, and G. Zhang, "A Game-Based Economic Model for Price Decision Making in Cyber-Physical-Social Systems," *IEEE Access*, vol. 7, pp. 111 559–111 576, Aug 2019.

[20] X. Liu, M. Dong, K. Ota, P. Hung, and A. Liu, "Service Pricing Decision in Cyber-Physical Systems: Insights from Game Theory," *IEEE Transactions on Services Computing*, vol. 9, no. 2, pp. 186–198, Jun 2015.

[21] M. Dong, X. Liu, Z. Qian, A. Liu, and T. Wang, "QoE-ensured Price Competition Model for Emerging Mobile Networks," *IEEE Wireless Communications*, vol. 22, no. 4, pp. 50–57, Aug 2015.

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

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

[24] P. Bonacquisto, G. D. Modica, G. Petralia, and O. Tomarchio, "A Procurement Auction Market to Trade Residual Cloud Computing Capacity," *IEEE Transactions on Cloud Computing*, vol. 3, no. 3, pp. 345–357, Jul 2015.

[25] G. V. Prasad, A. S. Prasad, and S. Rao, "A Combinatorial Auction Mechanism for Multiple Resource Procurement in Cloud Computing," *IEEE Transactions on Cloud Computing*, vol. 6, no. 4, pp. 904–914, Oct 2018.

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

[27] I. A. Kash, P. Key, and W. Suksompong, "Simple Pricing Schemes for the Cloud," *ACM Transactions on Economics and Computation*, vol. 7, no. 2, pp. 7:1–7:27, Jun 2019.

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

[29] A. Chakraborty, A. Mondal, A. Roy, and S. Misra, "Dynamic Trust Enforcing Pricing Scheme for Sensors-as-a-Service in Sensor-Cloud Infrastructure," *IEEE Transactions on Services Computing*, Oct 2018.

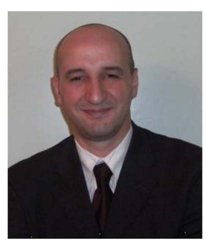
[30] H. Moosavi and F. M. Bui, "Optimal Relay Selection and Power Control With Quality-of-Service Provisioning in Wireless Body Area Networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 8, pp. 5497–5510, Aug 2016.

[31] E. Kauder, *A History of Marginal Utility Theory*. Princeton Legacy Library, 1965.

[32] L. Guilbeau, "The history of the solution of the cubic equation," *Mathematics News Letter*, vol. 5, no. 4, pp. 8–12, Dec 1930.

Arijit Roy is a senior research fellow in the Indian Institute of technology Kharagpur, India. Prior to that Mr. Roy completed an MS (by research) degree and B. Tech degree in Information Technology from Indian Institute of Technology Kharagpur. and the West Bengal University of Technology, respectively. After completion of B.Tech, he worked as a Network Engineer in IntecInfonet Pvt. Ltd., India. He has experiences of handling 3 different government funded national and international research projects. He is a Co-founder and Director of a Start-up, named- “SensorDrops Networks Pvt. Ltd.”. He is a student member of ACM and IEEE. His research works are published in different reputed SCI journals (including IEEE/ACM Transactions) and reputed conferences. Additionally, he has 6 Indian filed patents, which are along the same line of his research work. He received the Council of Scientific & Industrial Research Senior Research Fellowship (CSIR-SRF) in 2017. He has been recognized with several awards such as Samsung Innovation Award 2014 and IBM Day Award 2017. One of his research projects was selected (among the top 9 worldwide) in IEEE ComSoc Student competition in 2014. He received the prestigious Gandhian Young Technological Innovation (GYTI) Award-2018, for society relevant innovation (the award was received from honorable President of India). He was awarded with the prestigious Raman-Charpak Fellowship-2018 (only 4 students were selected in Engineering Sciences), for visiting a French university and pursuing a short-term collaborative research. He received different travel grants from IIT Kharagpur and Microsoft Research (MSR) for attending international conferences and research events. He was selected as a young researcher to participate in the 6th Heidelberg Laureate Forum 2018, organized in Heidelberg, Germany, in which only the 200 most qualified Young Researchers (world-wide) are given the opportunity to enrich and share the unique atmosphere of the Heidelberg Laureate Forum. His research interests include Internet of Things (IoT), Sensor-cloud Architecture, Wireless Sensor Networks, Cloud Computing, and Wireless Body Area Networks. He, along with his team, developed different societal impactful products and prototypes in the domain of healthcare and agriculture.

Sudip Misra (SM’11) is a Professor and Abdul Kalam Technology Innovation National Fellow in the Department of Computer Science and Engineering at the Indian Institute of Technology Kharagpur. He received his Ph.D. degree in Computer Science from Carleton University, in Ottawa, Canada. His current research interests include Wireless Sensor Networks and Internet of Things. Professor Misra has published over 350 scholarly research papers and 12 books. He has won nine research paper awards in different conferences. He was awarded the *IEEE ComSoc Asia Pacific Outstanding Young Researcher Award* at IEEE GLOBECOM 2012, California, USA. He was also the recipient of several academic awards and fellowships such as the *Faculty Excellence Award* (IIT Kharagpur), *Young Scientist Award* (National Academy of Sciences, India), *Young Systems Scientist Award* (Systems Society of India), *Young Engineers Award* (Institution of Engineers, India), (Canadian) *Governor Generals Academic Gold Medal* at Carleton University, the *University Outstanding Graduate Student Award* in the Doctoral level at Carleton University and the National Academy of Sciences, India *Swarna Jayanti Puraskar* (Golden Jubilee Award), *Samsung Innovation Awards-2014* at IIT Kharagpur, *IETE-Biman Behari Sen Memorial Award-2014*, and the *Careers360 Outstanding Faculty Award* in Computer Science for the year 2018 from the Honourable Minister for Human Resource Development (MHRD) of India. Thrice consecutively he was the recipient of the *IEEE Systems Journal Best Paper Award* in 2018, 2019, and 2020. He was awarded the Canadian Governments prestigious *NSERC Post Doctoral Fellowship* and the Alexander von *Humboldt Research Fellowship* in Germany. His team received the GYTI Award 2018 in the hands of the President of India for socially relevant innovations. Dr. Misra has been serving as the Associate Editor of different journals such as the IEEE Transactions on Mobile Computing, IEEE Transactions on Vehicular Technology, IEEE Transactions on Sustainable Computing, IEEE Network, and IEEE Systems Journal. He is the Fellow of the Indian National Academy of Engineering (INAE), India, the National Academy of Sciences (NASI), India, the Institution of Engineering and Technology (IET), UK, British Computer Society (BCS), UK, Royal Society of Public Health (RSPH), UK, and the Institution of Electronics and Telecommunications Engineering (IETE), India. Professor Misra is the distinguished lecturer of the IEEE Communications Society. He is the Director and Co-Founder of the IoT startup, SensorDrops Networks Private Limited (http://www.sensordropsnetworks.com). Further details about him are available at http://cse.iitkgp.ac.in/ smisra/.



Farid Nait-Abdesselam is a Professor of Computer Science and Engineering at the University of Missouri Kansas City, USA. He received his State Engineering degree in computer science from Bab-Ezzouar University (USTHB, Algeria) in 1993 and his MSc degree in computer science from Paris Descartes University (Paris 5, France) in 1994. After two years in the industry, working as a software and network engineer, he joined the University of Versailles (UVSQ, France) in 1996 where he obtained in 2000 his Ph.D degree in computer science. His research interests lie in the field of computer and communication networks with emphasis on architectures and protocols for quality of service and security in wireless and wired networks. Areas of current interest include future Internet, wireless networks, cyber physical systems, smart cities, Internet of Things, data analytics and smart mobile healthcare, network security, trust management and data privacy.