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# QoS-Aware Dispersed Dynamic Mapping of Virtual Sensors in Sensor-Cloud

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**Abstract**—In this paper, we study the problem of dynamic mapping of virtual sensors in sensor-cloud for provisioning high quality of Sensors-as-a-Service (Se-aaS) in the presence of multiple sensor-owners and heterogeneous sensor nodes. We divide this problem into two subproblems — optimal dispersed node selection and optimal data-rate distribution, and analyze that these problems are NP-complete. Hence, we propose a game theory-based online scheme, named QADMAP, to solve these two problems in polynomial time. For the optimal node selection problem, we design a dynamic coalition-formation game-based online scheme, while maximizing the *dispersion index* of the selected nodes. On the other hand, we propose an evolutionary game theory-based scheme for distributing the data-rate requirements of the services among the selected nodes, optimally. As per our knowledge, none of the existing works on dynamic mapping of virtual sensors considers the stochastic behavior of sensor-cloud for provisioning Se-aaS. From simulations, we observe that, using QADMAP, the energy consumption of the network reduces by $29.88$-$31.73\%$, thereby improving the QoS in terms of service availability by $11\%$ and increasing the profit of the SCSP by $3.63$-$9.82\%$, compared to the existing benchmark schemes.

**Index Terms**—Sensor-Cloud, Game Theory, p-Dispersion, Virtual Sensors, Se-aaS

## 1 Introduction

Sensor-Cloud is an emerging *service-oriented architecture* based on Wireless Sensor Networks (WSNs). This model extends the applicability of WSNs by combining it with cloud infrastructure. Thus, sensor-cloud emerges as a highly scalable and easily accessible system, which is capable of serving a huge number of users [1], [2]. Essentially, the Sensor-Cloud Infrastructure is built on the concept of *virtualisation* of hardware resources of cloud computing [3], thereby enabling the same physical sensor nodes to be used for serving multiple end-user applications simultaneously. Similar to other cloud-based infrastructures, a centralized *Sensor Cloud Service Provider* (SCSP) obtains physical wireless sensor nodes from their respective *sensor-owners*. With the help of cloud infrastructure, virtualized instances of these sensor nodes are created by the SCSP and provisioned to the end-users in the form of *ready-to-use* service, popularly known as "Sensors-as-a-Service" (Se-aaS) [4].

Thus, in sensor-cloud, there is a clear demarcation of the responsibilities of the various actors involved. The sensor-owners purchase, deploy and maintain their sensor nodes and register their information with SCSPs. The SCSPs maintain the necessary cloud infrastructure to virtualize these resources and provision Se-aaS to the end-users. On the other hand, the end-users register their service requirements with the SCSPs and utilize Se-aaS for running their WSN-based applications. Additionally, these three actors also earn financial benefits [5] from the system — the end-users only pay for the amount of service consumed based on *pay-per-use* model, while the sensor-owners and the SCSP earn revenue by providing the services.

In the existing literature, sensor-cloud is envisioned as a potential solution to the problem of remote management of a large number of WSNs. Misra *et al.* [4] justified the necessity of the paradigm shift from traditional WSNs to sensor-cloud by showing decreased resource consumption, and increased cost-effectiveness. Evidently, from the point of view of SCSP, the profitability of such a highly scaled infrastructure as sensor-cloud is largely dependent on the availability and efficient utilization of resources. In several existing works, researchers aimed to improve the resource utilization in terms of energy efficiency and the network lifetime of sensor-cloud, viz., dynamic duty scheduling [6], optimal gateway node selection [7], bridge node selection [8], optimal virtual sensor formation [9] and optimal cache selection [10]. However, to increase the availability of sensor nodes, the SCSP must try to increase the participation of sensor-owners in the sensor-cloud market by giving each sensor-owner equal chances to earn profit [11].

On the other hand, from the point of view of end-users, it is also essential that the high quality of seamless and uninterrupted Se-aaS is provided by the SCSP [12]. Since physical sensor nodes are highly constrained in terms of energy, computation and storage capabilities, the SCSP must ensure that the selected set of physical sensor nodes for a service request are capable of serving it. Additionally, the SCSP must also ensure that the service load is optimally distributed among the sensor nodes to prevent unwanted failures

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due to overburdening of nodes. However, as per our knowledge, none of the existing works considered the problem of optimal mapping of virtual sensors in sensor-cloud, while maintaining a high quality of delivered service and ensuring that the physical sensor nodes are not over-burdened.

In this paper, we propose a QoS-aware dynamic scheme, named QADMAP, for the mapping of virtual sensors to physical sensor nodes in sensor cloud. The major contributions of this work are listed as follows:

a) We address the problem of dynamic optimal mapping of virtual sensors to physical sensor nodes for ensuring high QoS of Se-aaS in terms of service availability and reduction in service disruptions.

b) We divide the aforementioned problem into two sub-problems — optimal sensor node selection and optimal data-rate distribution. Thereafter, we reduce these sub-problems from well-known NP-complete problems and show that these are NP-complete.

c) We model the two sub-problems using dynamic coalition formation game and evolutionary game theoretic approaches, respectively, and provide an online scheme to solve these in polynomial time.

d) Finally, we present the performance evaluation of the proposed scheme, *QADMAP*, in terms of certain parameters, viz., network lifetime, total energy consumption, bandwidth utilization, and network overhead while comparing with existing schemes.

## 2 Related Works

In this section, we discuss some of the works presented in the existing literature related to the mapping of virtual sensors in sensor-cloud. We divide the related works into two categories. First, we discuss the works related to the optimal selection of sensor nodes. Thereafter, the works related to the optimal data-rate distribution among sensor nodes are discussed.

There exist several works in the existing literature which propose schemes for the selection of physical sensor nodes for the creation of virtual sensors. Misra *et al.* [4] proposed the selection of the maximal subset of compatible nodes based on type, QoS level and location requirements of the services. However, this scheme is highly resource consuming and hence, an improvement of this scheme was proposed by Chatterjee *et al.* [9]. In [9], the authors proposed two schemes – COV-I and COV II – for the optimal composition of virtual sensors, while considering the resource-constrained behavior of the nodes and the geographical locations of the nodes. However, the economic aspects of the sensor-cloud market are not considered by the authors. Roy *et al.* [11] proposed another scheme for the dynamic mapping of virtual sensors in the presence of multiple sensor-owners having overlapping deployment region. The authors attempted to increase the participation of sensor-owners by giving them equal opportunities to earn profits. However, this work does not consider the possibility of multiple virtual sensors being served using the same sensor node. Kim *et al.* [13] proposed another game theoretic algorithm for sensor node selection in sensor-cloud while considering the possibility of untruthful behavior of the sensor owners. Ojha *et al.* [14] proposed another sensor node selection scheme for sensor-cloud while considering the energy consumption of the network and the profit of the SCSP and the sensor-owners. However, these works do not consider the capacity of the sensor nodes for service provisioning. In the existing literature, researchers proposed a few schemes for the optimal selection of physical sensor nodes in WSNs, viz., [15]–[17] and Internet-of-Things devices [18], [19]. However, these schemes are designed with the aim of solving specific issues such as coverage and event-detection. For example, Delicato *et al.* [16] proposed a scheme for the selection of an optimal subset of sensor nodes for serving a particular application. Based on the QoS requirement of the application, the duty cycle of the nodes in the network is varied to obtain energy savings. Bajović *et al.* [17] proposed a scheme for the selection of $p$ optimal sensor nodes for increasing the probability of event detection. However, none of these schemes are suitable for sensor-cloud because these schemes consider that the WSN supports only a single application, which is not the case for sensor-cloud.

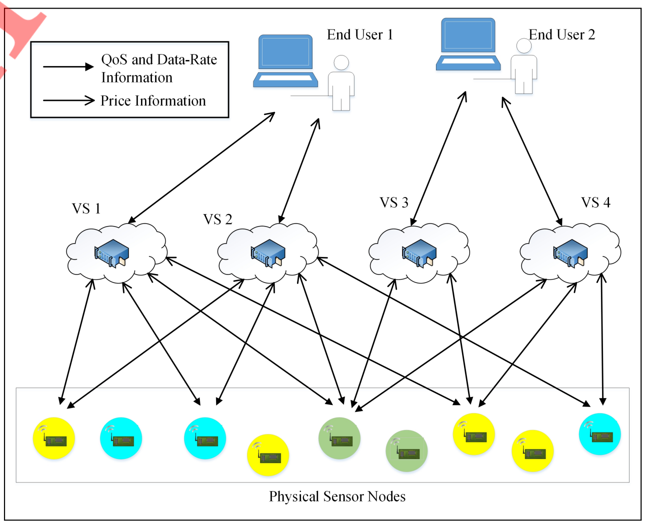



Fig. 1: Schematic Diagram of QADMAP

On the other hand, in existing literature, a few resource allocation schemes are proposed by the researchers for sensor-cloud. Delgado *et al.* [20] proposed an optimal resource allocation algorithm for sensor-cloud for maximizing the number of applications that can be served using the same sensor node while considering the limitations of the WSNs. Another heuristics-based hybrid resource allocation scheme for sensor-cloud was proposed by Santos *et al.* [21] which aims to reduce resource consumption by executing tasks common to multiple applications exactly once and share their results. However, these works neither consider the reduction of the number of activated nodes nor consider the presence of sensor-owners. In WSNs, there exist some works which propose schemes for optimal load distribution [22]. For example, clustering schemes proposed by Wajgi and Thakur [23] and Yournis and Fahmi [24] ensure distribution of load among the sensor nodes in the network by electing cluster heads and replacing them based on their energy level. However, these schemes are also not suitable for sensor-cloud as it comprises multiple WSNs where each WSN is owned and deployed by different sensor-owners. Additionally, in sensor-cloud, a single sensor node is used to serve multiple services, unlike traditional WSNs.

## 3 System Model

We consider a sensor-cloud infrastructure involving a single Sensor-Cloud Service Provider (SCSP) with multiple registered end-users and sensor-owners as shown in Figure 1. Each end-user $u \in \mathcal{U}(t)$ can request services from the SCSP at any time instant $T$, where $\mathcal{U}(t)$ is the set of registered end-users at time $t$ and $T \geq t$. The set of services requested by end-user $u$ is denoted by $\mathcal{S}_u(t)$ such that $\mathcal{S}_u(t) = \{s_1^u, s_2^u, \cdots, s_k^u\}$, where $k$ is the total number of services requested by end-user $u$. For each service $s \in \mathcal{S}(t)$, where $\mathcal{S}(t) = \bigcup_u \mathcal{S}_u(t)$, the corresponding end-user specifies the service requirements using the 5-tuple $< \tau_s, a_s, r_s, \eta_s, t_s >$, where $\tau_s$ is the type of service requested, i.e., type of the sensed data, $a_s$ is the region of interest, $r_s$ is the required data-rate, $\eta_s$ is the number of physical sensor nodes required, and $t_s$ is the start time of service $s$. Moreover, each end-user needs to ensure that $\eta_s \geq \eta_s^{min}$, where $\eta_s^{min}$, which is decided by the SCSP, denotes the minimum number of physical sensor nodes needed for ensuring complete sensing coverage of the region of interest.

Based on these requirements, the SCSP provisions virtual sensors for the requested services. We consider that the SCSP serves each service request using a single virtual sensor. Thus, the set of virtual sensors provisioned by the SCSP for each end-user $u$ is denoted by $\mathcal{V}_u(t) = \{v_1^u, v_2^u, \cdots, v_k^u\}$ where $k = |\mathcal{S}_u(t)|$. Thus, each virtual sensor $vs_s \in \mathcal{V}(t)$, where $\mathcal{V}(t) = \bigcup_u \mathcal{V}_u(t)$, needs to satisfy the requirements of service $s$. Due to this one-to-one correspondence between services and virtual sensors, we use the two terminologies interchangeably in the rest of the paper.

On the other hand, we consider that each sensor-owner $o \in \mathcal{O}(t)$, where $\mathcal{O}(t)$ is the set of registered sensor-owners at time $t$, owns $n_o$ number of physical sensor nodes which are rendered to the SCSP for provisioning Se-aaS. The set of physical sensor nodes associated with sensor-owner $o$ is represented as $\mathcal{P}_o(t) = \{p_1^o, p_2^o, \cdots, p_{n_o}^o\}$. Each physical sensor node $p \in \mathcal{P}(t)$, where $\mathcal{P}(t) = \bigcup_o \mathcal{P}_o(t)$, serves $\mathcal{V}^p(t) \subseteq \mathcal{V}(t)$ set of virtual sensors. Here, $|\mathcal{V}^p(t)| \geq 0$. Hence, each physical sensor $p$ is denoted using the tuple $< id_p, loc_p, \{(\tau_s, r_s) | vs_s \in \mathcal{V}^p(t)\} >$. Moreover, each virtual sensor $vs_s$ needs to be mapped to $\eta_s$ number of physical sensor nodes. We define an association parameter $x_{s,p}$ as follows:

$$x_{s,p} = \begin{cases} 1, & \text{if service } s \text{ is served by sensor node } p \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Therefore, we get — $|\mathcal{V}^p(t)| = \sum_{s \in \mathcal{S}(t)} x_{s,p}$. Additionally, the following condition holds:

$$\eta_s \leq \sum_{p \in \mathcal{P}(t)} x_{s,p} \tag{2}$$

From the above discussion, it follows that, in order to increase the resource utilization of the sensor-cloud infrastructure and earn high profits, it is necessary for an SCSP to determine the optimal mapping of end-user service requests with the physical sensor nodes. However, to sustain in the sensor-cloud market, the SCSP must simultaneously ensure that the high quality of seamless Se-aaS, in terms of service availability and reduced service failures, is delivered to the end-users as per their requirements and that the registered sensor owner is given equal opportunity to earn a profit. Hence, to achieve these objectives, the SCSP must choose and distribute the service requests among the physical sensor nodes in such a way that — (a) Nodes are not overburdened, (b) Minimum number of nodes are activated in the network at each time and (c) Each node is given equal opportunity to participate in provisioning Se-aaS. Therefore, in this work, we propose a dynamic mapping scheme for sensor-cloud to address the aforementioned problems. We divide our principal objective into two subparts:

**Objective 1:** Choose an optimal set of physical sensor nodes for serving the virtual sensors such that the requirements of the end-users are fulfilled and each sensor node, as well as each sensor-owner, obtains a fair chance to participate in Se-aaS provisioning.

**Objective 2:** Distribute the service load optimally among the chosen set of sensor nodes such that none of the sensor nodes are overburdened and the QoS of Se-aaS in terms of service availability is ensured.

## 4 Problem Formulation

In this section, we study and formulate the aforementioned problems, mathematically, while introducing two optimization problems — (1) Optimal node selection and (2) Optimal data-rate distribution. We discuss these two problems elaborately in the following sections.

### 4.1 Optimal Node Selection

Given the number of sensor nodes, $B$, to be activated for serving a given set of services, the SCSP needs to decide the optimal set of nodes to be selected such that each sensor node, as well as each sensor-owner, obtains a fair chance to participate in Se-aaS provisioning. Thereby, the SCSP must ensure that the selected sensor nodes — (1) are not concentrated within a small part of the region of interest, (2) do not belong to the same owner, and (3) cover most part of the region of interest. In other words, the SCSP needs to ensure that the selected nodes are dispersed in terms of location, ownership, and hop count, respectively. To quantify the dispersion of the sensor nodes, we define the dispersion index $d_{p_i,p_j}$ of two nodes $p_i$ and $p_j$ as defined in Definition 1.

**Definition 1.** *The dispersion index $I_{p_i,p_j}$ of two nodes $p_i$ and $p_j$ is defined as the Euclidean distance between the two points, i.e., $p_i$ and $p_j$, in a three-dimensional space, in which X-axis represents the magnitude $\delta_{p_i,p_j}$ of the normalized physical distance vector, Y-axis represents the dissimilarity in ownership $\theta_{p_i,p_j}$, and Z-axis represents the normalized hop-count difference $h_{p_i,p_j}$ between nodes $p_i$ and $p_j$. Mathematically,*

$$I_{p_i,p_j} = \sqrt{\delta^2_{p_i,p_j} + \theta^2_{p_i,p_j} + h^2_{p_i,p_j}} \tag{3}$$

*where $\delta_{p_i,p_j} = \frac{d_{p_i,p_j}}{\max\{d_{p_i,p_j} | 1 \leq i < j \leq |\bigcup_t \mathcal{P}(t)|\}}$, $d_{p_i,p_j}$ is the Euclidean distance between sensor nodes $p_i$ and $p_j$, $h_{p_i,p_j} = \frac{h_{p_i} - h_{p_j}}{\max\{h_{p_n} | 1 \leq n \leq |\bigcup_t \mathcal{P}(t)|\}}$, $h_{p_i}$ is the hop-count of node $p_i$ from the base-station and $\theta_{p_i,p_j}$ is a binary variable and defined as follows:*

$$\theta_{p_i,p_j} = \begin{cases} 1, & \textit{if } p_i \in \mathcal{P}_o(t),\ p_j \in \mathcal{P}_{\tilde{o}}(t), \textit{ and } o \neq \tilde{o} \\ 0, & \textit{otherwise} \end{cases} \tag{4}$$

The objective of the SCSP is to select the optimal set of nodes $P \subseteq \bigcup_t \mathcal{P}(t)$ having cardinality $B$ while maximizing the minimum dispersion index between any two pair of nodes. Mathematically, we have:

$$\max f(P) \tag{5}$$

where $f(P) = \min\{I_{p_i,p_j} : 1 \leq i < j \leq |\bigcup_t \mathcal{P}(t)|\}$. Equation (5) needs to satisfy the following constraints:

$$P \subseteq \bigcup_t \mathcal{P}(t) \text{ and } |P| = B \tag{6}$$

We observe that the aforementioned problem is an NP-complete problem as discussed in Theorem 1.

**Theorem 1.** *The problem of selecting the optimal dispersed subset of sensor nodes in sensor-cloud is NP-complete.*

*Proof:* Refer to the supplementary file. □

### 4.2 Optimal Data-Rate Distribution

We consider that the sequence of service requests of the end-users are known to the SCSP a priori. The set of registered sensor-nodes available to the SCSP for service provisioning also remains fixed and known to the SCSP. We denote the state of each sensor node $p$ using a variable $y_p$, which is defined as follows:

$$y_p = \begin{cases} 1, & \text{if sensor node } p \text{ is in } \textit{active} \text{ state,} \\ & \text{i.e., } \{s | x_{s,p} = 1 \ \&\ \forall s \in \bigcup_t \mathcal{S}(t)\} \neq \{\emptyset\} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Hence, the SCSP tries to minimize the number of activated nodes in the system to serve the given set of service requests. Mathematically,

$$B = \min \sum_p y_p \tag{8}$$

while satisfying the following constraints along with the constraints given in Equations (1) and (7):

$$\sum_p y_p \sum_s r_s x_{s,p} = \sum_s \eta_s r_s \tag{9}$$

$$\sum_s r_s x_{s,p} \leq R_{max} \text{ and } \sum_p x_{s,p} = \eta_s \tag{10}$$

where $R_{max}$ is the maximum data-rate supported by each node. Using Equation (9), the SCSP ensures that the data-rate requirement of each service-request is satisfied. We observe that the problem of optimal data-rate distribution is an NP-complete problem as discussed in Theorem 2.

**Theorem 2.** *The problem of optimal data-rate distribution among sensor nodes in sensor-cloud is NP-complete.*

*Proof:* Refer to the supplementary file. □

In addition to the NP-completeness of the problems discussed in this work, it is not feasible for an SCSP to obtain the prior knowledge of the service request sequence in the sensor-cloud scenario. Hence, we propose a *cooperative game theory*-based *online* scheme to reduce the complexity of the optimal data-rate distribution and node selection problems and solve these in polynomial time, as discussed in Section 5.

## 5 Proposed QADMAP Scheme

In this work, we model the problem of optimal dynamic mapping of virtual sensors in sensor-cloud using *cooperative game theory* and propose an online scheme, named QADMAP, to ensure high quality of Se-aaS in terms of increased service availability and reduced service failures. To achieve the overall objective of optimal mapping of virtual sensors in polynomial time, we address Objective 1 mentioned in Section 3 first, followed by Objective 2. Thus, using the proposed scheme, the SCSP receives the service requests from the end-users and forms the candidate set of the nodes to be selected using dynamic coalition formation game as discussed in Section 5.1. Thereafter, SCSP distributes the data-rate among the selected dispersed set of sensor nodes using an evolutionary game as discussed in Section 5.2.

## 5.1 Optimal Node Selection Game

We model the problem of optimal sensor node selection for service provisioning in sensor-cloud using a *dynamic coalition formation cooperative game with transferable utility* [25]. Based on the incoming service requests of the end-users, the SCSP decides the number of sensor nodes that need to be activated while satisfying the following constraint:

$$|\mathbb{P}(t)| \geq \max\{\max\{\eta_s|\forall s\}, \lceil(\sum_s r_s\eta_s)/R_{max}\rceil\} \quad (11)$$

where $s \in \mathcal{S}(t)$ and $\mathbb{P}(t)$ is the set of nodes to be activated. The components of the proposed game are discussed as follows:

**Players and Strategies**: The set of available physical sensor nodes are considered to be the players of this game. The sensor nodes which are used to serve the end-user service requests form a coalition set $\mathbb{P}(t)$. Each player has two different strategies — either to join the coalition or to remain in the sleep state.

### 5.1.1 Utility Function of Players

The utility function $U_{j,i}(t)$ of each player or physical sensor node, $p_j$, signifies the dispersion index of the sensor node with respect to another sensor node $p_i \in \mathbb{P}(t)$ in the coalition. The payoff of the utility function $U_{j,i}(t)$ is considered to be same as the dispersion index mentioned in Definition 1. Therefore, we get:

$$U_{j,i} = I_{p_j,p_i}$$

Thereby, each sensor node $p_j$ calculates a utility vector $\mathbf{U}_j(t)$ having length $|\mathbb{P}(t)|$. Therefore, we define $\mathbf{U}_j(t)$ as follows:

$$\mathbf{U}_j(t) = [\cdots \; U_{j,i} \; \cdots], \quad \forall p_i \in \mathbb{P}(t) \quad (12)$$

### 5.1.2 Utility Function of Coalition

The utility function $C(p_j, t)$ of the coalition of physical sensor nodes signifies the transferable payoff value of the players, i.e., sensor nodes, in the coalition, while adding sensor node $p_j$ into the coalition. $C(p_j, t)$ is calculated as the cumulative dispersion value of the set of sensor nodes belonging to the coalition. Therefore, we define the utility function $C(p_j, t)$ as a function of the utility vector of ${}^{|\mathbb{P}(t)|+1}\mathbf{P}_2$ pairs of elements from the set $(\mathbb{P}(t) \bigcup \{p_j\})$ of sensor nodes in the coalition. Hence, we define $C(p_j, t)$ as follows:

$$C(p_j, t) = \sum_{p_k \in (\mathbb{P}(t) \bigcup \{p_j\})} ||\mathbf{U}_k(t)|| \quad (13)$$

where $||\mathbf{U}_k(t)||$ is the Manhattan Norm [26] of utility vector $\mathbf{U}_k(t)$. We argue that high payoff of $C(p_j, t)$ implies that the sensor nodes belonging to the coalition having sensor node $p_j$ have high cumulative dispersion value. Therefore, the SCSP tries to maximize the payoff of the utility function $C(p_j, t)$ of the coalition based on a preference relation among the possible coalitions as defined in Definition 2.

**Definition 2.** *Given a set of physical sensor nodes $\mathcal{P}(t)$ and an existing coalition $\mathbb{P}(t)$, the preference relation among two possible coalitions $\mathcal{A} = (\mathbb{P}(t) \bigcup \{p_j\})$ and $\mathcal{B} = (\mathbb{P}(t) \bigcup \{p_k\})$ follows $\mathcal{A} \triangleright \mathcal{B}$, if and only if the following inequality holds:*

$$C(p_j, t) \geq C(p_k, t) \quad (14)$$

*where $p_j, p_k \in \mathcal{P}(t)$ and $j \neq k$. Hence, $p_j$ has a higher chance of merging into the coalition $\mathbb{P}(t)$ compared to $p_k$.*

Using this optimal node selection game, SCSP ensures that an optimal set of dispersed nodes are activated while satisfying the constraints given in Equation (11).

## 5.2 Optimal Data-Rate Distribution Game

We use an evolutionary game theoretic approach to formulate the problem of optimal data-rate distribution in QADMAP. The different components of this game are discussed as follows.

**Players**: In QADMAP, each virtual sensor $vs_k$ needs to be mapped to at least $\eta_k$ number of sensor nodes. We consider that the SCSP creates $\eta_k$ instances for virtual sensor $vs_k$. Each virtual sensor instance $vs_i^k$ of virtual sensor $vs_k$ is considered as a player in QADMAP. Hence, the total number of players in the proposed scheme is $\sum_{vs_k \in \mathcal{V}(t)} \eta_k$.

**Strategies**: The strategy of a virtual sensor instance in the evolutionary game is to choose a particular sensor node $p_j \in \mathbb{P}(t)$ for being served. We consider that no two instances of the same virtual sensor can be mapped to the same sensor node.

**Population and Population Share**: The set of virtual sensor instances determines the population in this evolutionary game. One or more instances of the different virtual sensors may choose the same physical sensor node for serving them. Such a group of virtual sensor instances choosing the same physical sensor node form the population share of that node. Moreover, in sensor-cloud, the virtual sensors have varied data rate requirements. Hence, we define the population share $w_j$ of each sensor node $p_j \in \mathbb{P}(t)$ in terms of the data-rate supported by the node as follows:

$$w_j(t) = (\sum_{s\in\mathcal{S}(t)} r_s x_{s,j})/(\sum_j \sum_{s\in\mathcal{S}(t)} r_s x_{s,j}) \tag{15}$$

At any time instant, the state of the entire population of virtual sensor instances is specified completely using the vector $\mathbf{W}(t)$, defined as follows:

$$\mathbf{W}(t) = [\ \cdots\ w_j(t)\ \cdots\ ] \tag{16}$$

The population share given in Equation (15) must satisfy the following constraint:

$$\sum_{p_j\in\mathbb{P}(t)} w_j(t) = 1 \tag{17}$$

### 5.2.1 Fitness Function of each Strategy in QADMAP

In QADMAP, we define the fitness function of each strategy, i.e., physical sensor node, as the payoff obtained by each player, i.e, virtual sensor instance, for selecting that particular strategy. It is calculated as the difference between the utility yield and the cost incurred for choosing a particular strategy. Hence, the fitness function of strategy $j$, i.e, mapping of physical sensor node $p_j$ to virtual sensor instance, $vs_i^k$ of virtual sensor $vs_k$, is expressed as follows:

$$\pi_j(\cdot) = \mathcal{U}_j(\cdot) - \mathcal{C}_j(\cdot) \tag{18}$$

where $\mathcal{U}_j(\cdot)$ is the utility function, and $\mathcal{C}_j(\cdot)$ is the cost function for selecting physical sensor node $p_j$.

We define the parameters to be used for the calculation of the fitness function in the following sections.

5.2.1.1 *Average Duration of Service* ($\bar{\tau}(t)$): We calculate the mean service time $\bar{\tau}(t)$ based on the service duration of the incoming applications over past $h$ time instants. Therefore, we define $\bar{\tau}(t)$ as follows:

$$\bar{\tau}(t) = \begin{cases} \dfrac{\sum_{vs_i\in\Theta_1(t)} \tau_i}{\sum_{vs_i\in\Theta_1(t)} 1}, \Theta_1(t) = \bigcup_{t'=(t-h)}^{t} \mathcal{V}(t) \text{ and } t \geq h \\ \dfrac{\sum_{vs_i\in\Theta_2(t)} \tau_i}{\sum_{vs_i\in\Theta_2(t)} 1}, \Theta_2(t) = \bigcup_{t'=0}^{t} \mathcal{V}(t') \text{ and } t < h \end{cases} \tag{19}$$

where $\tau_i$ is the time duration of virtual sensor $vs_i$ is served by the SCSP. We consider that the sensor-cloud follows the pay-per-user model [5], and the duration of services are not specified beforehand by the end-user. Hence, the SCSP uses mean service time $\bar{\tau}(t)$ to estimate the average cost of serving a virtual sensor using a particular physical sensor node.

5.2.1.2 *Effective Data-Rate* ($\mathrm{R}_j^{\mathtt{eff}}(t)$): In sensor-cloud, each physical sensor node $p_j$ serves multiple virtual sensors, having different data-rate requirements. Thus, each sensor node sources multiple independent streams [27] of data to serve multiple virtual sensors. Hence, we define the effective data stream rate $\mathrm{R}_j^{\mathtt{eff}}(t)$ of each physical sensor node $p_j$ as the summation of the data-rates of the streams supported by it. Mathematically, we have:

$$\mathrm{R}_j^{\mathtt{eff}}(t) = \sum_s r_s x_{s,j} \tag{20}$$

where $\sum_{s\in\mathcal{S}(t)} r_{s,j} x_{s,j} = w_j(t) \sum_j \sum_{s\in\mathcal{S}(t)} r_{s,j} x_{s,j}$.

5.2.1.3 *Data-Rate Utilization Factor* ($\zeta_j(t)$): The data-rate utilization factor $\zeta_j(t)$ of a physical sensor node $p_j$ is defined as the fraction of the maximum data-rate supported by $p_j$, $R_{max}$, used for serving the set of virtual sensors $\mathcal{V}^j(t)$. Mathematically,

$$\zeta_j(t) = \frac{\mathrm{R}_j^{\mathtt{eff}}(t)}{R_{max}} \tag{21}$$

In QADMAP, we ensure high value of $\zeta_j(t)$ for active nodes. Therefore, in sensor-cloud, active node consolidation is achieved using QADMAP. Thereby the efficiency of the sensor-cloud is improved.

5.2.1.4 *Average Energy Consumption* ($\Delta E_j(t)$): Physical sensor nodes are energy constrained devices. Hence, energy consumption plays an important role in determining the number of applications that can be served by a node. We define the average energy consumption of a node $p_j$ as the amount of energy consumed by the node for serving the set of virtual sensors $\mathcal{V}^j(t)$ for average service duration $\bar{\tau}(t)$. The total energy consumed by a node is decomposed into several components, described as follows:

a. *Sensing Energy* ($E_{sn}$): We define $E_{sn}$ the amount of energy consumed per unit time for sensing data at a constant rate by a sensor node. Here, we assume that the sensor nodes, which are in the *active* state, since data at the same rate irrespective of the end-user applications. Hence, $E_{sn}$ is considered to be the same for the active sensor nodes.

b. *Transmission Energy* ($E_{tx}$): It is the amount of energy spent by a sensor node for transmitting each data packet, and is assumed to be constant.

c. *Computation Energy* ($E_{pc}$): $E_{pc}$ is defined as the amount of energy consumed for each packet by a sensor node for performing computations and aggregation, on the raw sensed data to generate a processed data to be transmitted to the base station.

Thus, we define the average energy consumption of a physical sensor node $p_j$ for serving the set of virtual sensors, $\mathcal{V}^j(t)$, as follows:

$$\Delta E_j(t) = \left(E_{sn} + E_{tx}\mathbb{R}_j^{\mathtt{eff}}(t) + E_{pc}RS\right)\bar{\tau}(t) \tag{22}$$

where, $RS$ is the sensing rate. For providing uninterrupted service, the SCSP needs to ensure that:

$$\Delta E_j(t) \leq E_{res}^j(t) \tag{23}$$

where $E_{res}^j(t)$ is the residual energy of node $p_j$.

5.2.1.5 *Average Buffer Usage* ($\Delta M_j(t)$): The amount of buffer memory that must be possessed by a physical sensor node, $p_j$ in order to serve the set of virtual sensors $vs_j$ successfully for average service duration, $\bar{\tau}(t)$ is defined as the average memory requirement of the node. Considering the amount of data generated per sensing to be $\mu$, we have:

$$\Delta M_j(t) = (\mu RS)/(\mathrm{R}_j^{\mathtt{eff}}(t)) \tag{24}$$

To reduce the chances of loss of data, the SCSP needs to satisfy the following constraint:

$$\Delta M_j(t) \leq M_{max}^j \tag{25}$$

where $M_{max}^j$ is the maximum buffer size of sensor node $p_j$.

5.2.1.6 *Utility Function* ($\mathcal{U}_j(\cdot)$): The utility function of a virtual sensor for selecting a particular physical sensor node is defined in terms of the data-rate utilization factor of the node. We define the utility function as follows:

$$\mathcal{U}_j(\cdot) = \gamma_1 \zeta_j(t) \tag{26}$$

Hence, with the increase in the value of the data-rate utilization factor, the value of the utility function also increases.

5.2.1.7 *Cost Function* ($\mathcal{C}_j(\cdot)$): We define the cost incurred for selecting physical sensor node $p_j$ in terms of the average energy consumption and the average memory requirement of the node, as follows:

$$\mathcal{C}_j(\cdot) = \gamma_2 \frac{\Delta E_j(t)}{E_{res}^j}(t) - \gamma_3 \frac{M_{max}^j}{\Delta M_j}(t) \tag{27}$$

Hence, we evaluate the fitness function of the strategy $p_j$ for being selected by player $vs_i^k$, as follows:

$$\pi_j(\cdot) = \alpha_j(t) w_j(t) - \beta_j(t) \tag{28}$$

where $\beta_j(t) = \gamma_2[\frac{(E_{pc}RS+E_{sn})\bar{\tau}(t)}{E_{res}^j(t)}]$, $\alpha_j(t) = \gamma_1[\frac{\lambda_j}{R_{max}}] - \gamma_2[\frac{E_{tx}\bar{\tau}(t)}{E_{res}^j(t)}]\lambda_j + \gamma_3 \leq [\frac{\lambda_j M_{max}^j}{\mu RS}]$, and $\lambda_j = \sum_j \sum_{s \in \mathcal{S}(t)} r_s x_{s,j}$.

#### *5.2.2 Replicator Dynamics and Evolutionary Equilibrium*

The evolution of the state of the population over time in an evolutionary game is modeled using the replicator dynamics equation. In an evolutionary game, the population share of the various strategies changes based on the value of the corresponding fitness function. The strategies having a higher value of fitness function compared to others are replicated at a faster rate, resulting in higher population share. This property is very similar to that of biological evolution, in which individuals having traits more fit for survival compared to others, reproduce or replicate and increase in number. On the other hand, the replication rate of the fewer fit individuals decreases eventually leading them to become extinct.

In order to define the replicator dynamics, we first calculate the average fitness value $\bar{\pi}(\cdot)$ of the entire population, as follows:

$$\bar{\pi}(\cdot) = \sum_j w_j(t)\pi_j(\cdot) = \sum_j \left[\alpha_j(t)w_j^2(t) - \beta_j(t)w_j(t)\right]$$

We define the replicator dynamics of the evolutionary game considered in QADMAP as follows:

$$\dot{w}_j(t) = \sigma w_j(t)\left(\pi_j(\cdot) - \bar{\pi}(\cdot)\right) \tag{29}$$

where $\sigma$ is a constant signifying the evolution controlling parameter. It is evident from Equation (29) that a high value of $\pi_j(\cdot)$ results in a greater change in the value of $w_j(t)$ and the change is positive, if $\pi_j(\cdot) > \bar{\pi}(\cdot)$. It is also evident that the population dynamics cease to change, when the value of $\dot{w}_j(t)$ becomes equal to zero. At this time instant, the state of the population becomes fixed and the system reaches *evolutionary equilibrium*. For the solution of the evolutionary equilibrium of QADMAP using the replicator dynamics, the reader is requested to refer to the supplementary file.

### 5.3 Proposed Algorithms

As mentioned earlier, the proposed QADMAP scheme is composed of two parts — optimal node selection and optimal data-rate distribution. Initially, the SCSP calculates the dispersion index between each pair of available nodes and stores these values in a matrix. This matrix is updated whenever a new node is registered with the SCSP or a node leaves the network. On receiving each service request, the SCSP determines the set of available sensor nodes for service provisioning, while considering that the residual energy of each sensor node is above a threshold value. Then, the SCSP decides whether the requirement of the end-users can be fulfilled using the set of already active sensor nodes using a greedy approach. If the total data-rate requirement of the received service requests exceeds the total data-rate capacity of the active sensor nodes, at least $n$ new nodes are activated where $n$ = (total data-rate requirement - total data-rate capacity of the active sensor nodes)/(max capacity of each node). In addition to that, we consider that the SCSP activates $\delta$ number of new nodes, where $\delta \geq 0$, such that the SCSP can accommodate sudden changes in the requirements of the service requests. Thereafter, the SCSP determines the set of nodes to be selected using Algorithm 1. The optimal service load distribution among the set of selected nodes, i.e., the population share of each node, is obtained using Algorithm 2. Then, using a general brute-force algorithm, the SCSP decides the mapping of the virtual sensors with the physical sensor nodes, while ensuring that the maximum data-rate allocated to a node does not exceed its calculated population share.

**Algorithm 1** Optimal Node Selection

**INPUTS:**
1: $n$ ▷ Number of Nodes to be Activated
2: $\mathcal{P}(t)$ ▷ Set of available sensor nodes
3: $\mathbb{P}(t-1)$ ▷ Set of active sensor nodes
4: $I_{p_i,p_j} \quad \forall p_i, p_j \in \mathcal{P}(t)$ ▷ Dispersion Index
**OUTPUT:**
1: $\mathbb{P}(t)$
**PROCEDURE:**
1: $\mathbb{P}(t) \leftarrow \mathbb{P}(t-1)$;
2: $\Delta\mathbb{P}(t) \leftarrow \{\emptyset\}$
3: **while** $|\Delta\mathbb{P}(t)| \le n$ **do**
4: **for** $\forall p_j \in \mathcal{P}(t)/\mathbb{P}(t-1)$ **do**
5: Obtain $\mathbf{U}_j(t)$ using Equation (12);
6: Calculate $C(p_j, t)$ using Equation (13);
7: **end for**
8: Choose $\max_{p_j} C(p_j, t)$;
9: $\Delta\mathbb{P}(t) \leftarrow \Delta\mathbb{P}(t) \bigcup \{p_j\}$;
10: **end while**
11: $\mathbb{P}(t) \leftarrow \mathbb{P}(t) \bigcup \Delta\mathbb{P}(t)$;
12: **return** $\mathbb{P}(t)$;

**Algorithm 2** Optimal Data-Rate Distribution

**INPUTS:**
1: $\mathcal{S}(t)$ ▷ The set of virtual sensors
2: $\mathbb{P}(t)$ ▷ Set of active sensor nodes
**OUTPUT:**
1: $\mathbf{w}(t)$ ▷ Population share
**PROCEDURE:**
1: **for** each $p_i \in \mathbb{P}(t)$ **do**
2: Decide $w_j(t)$ randomly, while satisfying the constraint in Equation (17);
3: **end for**
4: **do**
5: **for** each $p_j \in \mathbb{P}(t)$ **do**
6: Calculate $\pi_j(t)$ using Equation (18);
7: **end for**
8: Calculate $\overline{\pi}(t)$ using Equation (30);
9: **for** each $p_j \in \mathbb{P}(t)$ **do**
10: Calculate $\dot{w}_j(t)$ using Equation (31);
11: $w_j(t) \leftarrow w_j(t) - \dot{w}_j(t)$
12: **end for**
13: **while** $\dot{w}_j(t) \neq 0$, $\forall p_j \in \mathbb{P}(t)$
14: **return** $\mathbf{w}(t)$;

### *Complexity Analysis*

We present the asymptotic complexity analysis of Algorithms 1 and 2 in this section. As QADMAP is an online scheme, these two algorithms are performed by the SCSP whenever a new service request is received. Based on the service requirements, the value of $n$ is determined and Algorithm 1 is performed. The *while* loop (Lines 3-10) in Algorithm 1 is executed $\theta(n)$ and $O(|\mathcal{P}(t)|)$ times. The inner *for* loop (Lines 4-7) needs to be computed for all idle nodes, i.e., $O(|\mathcal{P}(t)| - |\mathbb{P}(t-1)|) \equiv O(|\mathcal{P}(t)|)$ times. The computational complexity to execute Line 9 of Algorithm 1 is $O(\ln|\mathcal{P}(t)|)$. Hence, the overall time complexity of Algorithm 1 is computed as $O(n|\mathcal{P}(t)|) + O(n \ln|\mathcal{P}(t)|) = O(n|\mathcal{P}(t)|)$, where $n \le |\mathcal{P}(t)|$. Additionally, the space complexity of Algorithm 1 is $O((|\mathcal{P}(t)|)^2)$, which is required to store the matrix of the dispersion indices of the nodes. On the other hand, each of the *for* loops (Lines 1-3, 5-7, and 9-12) of Algorithm 2 are executed $O(|\mathbb{P}(t)|)$ times. The *do-while* loop (Lines 4-13) is iterated $K$ times in order to reach evolutionary equilibrium state. Therefore, the overall time complexity of Algorithm 2 is $O(K|\mathbb{P}(t)|)$.

TABLE 1: Simulation Parameters

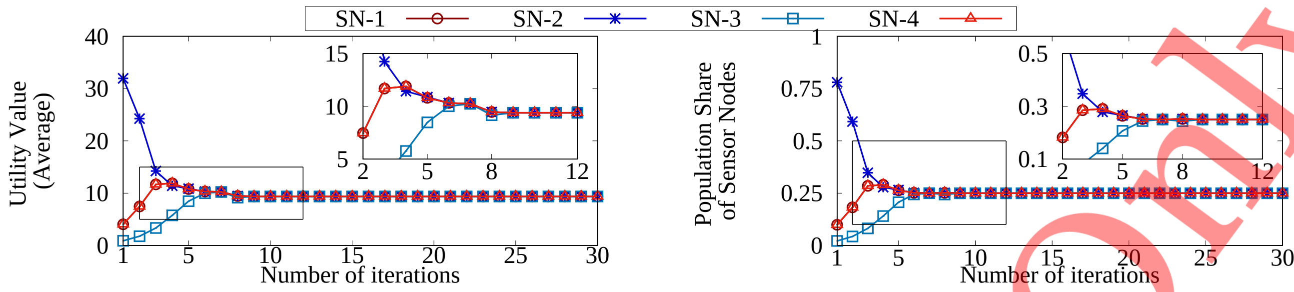
| Parameter | Value |
|---|---|
| Simulation area | $500\ m \times 500\ m$ |
| Number of sensor owners | 5 |
| Number of sensor nodes | $50 - 250$ |
| Communication protocol | IEEE 802.15.4 |
| Initial energy of each node | $20\ J$ [28] |
| Communication range | $100\ m$ |
| Packet Header size | $6\ bytes$ |
| Packet Payload size | $128\ bytes$ |
| Maximum data-rate | $250\ kbps/\text{node}$ |
| Tx-Rx energy | $50\ nJ/bit$ [29] |
| Amplifier energy | $100pJ/bit\text{-}m^2$ [29] |
| Processing energy | $70\ nJ/bit$ [9] |
| State-transition energy | $30\ nJ/bit$ [9] |
| Sensing energy | $10\ nJ/bit\text{-}m^2$ [9] |
| Number of service requests | 10-30 |
| Maximum data-rate/service | $20\ packets/sec$ |

## 6 Performance Evaluation

In this work, we attempt to increase the profit of SCSP by reducing the resource consumption of sensor-cloud and increasing the number of services that it can support while ensuring high quality of delivered service. To evaluate the performance of our proposed scheme QADMAP, we conduct extensive simulations and present our results in this section.

### 6.1 Simulation Parameters

We perform the simulation experiments in MATLAB. We consider that wireless sensor nodes are deployed by multiple sensor-owners in a $500 \times 500\ m^2$ terrain, randomly. The base station is located at the center of the terrain. The sensor-owners are registered with the SCSP having multiple registered end-users. The SCSP receives service requests having varied requirements from the end-users. Without loss of generality, we consider that the service requests arrive at the SCSP after $\tau$ seconds and have a fixed requirement of $10$ physical sensor nodes. For simplicity, we consider that each sensor node is equipped with multiple sensors and supports all types of service requests. Additionally, we consider that maximum data-rate supported by each sensor node is $250$ *kbps* and each data packet has a payload of $128$ *bytes*. Thereafter, we varied the total number of physical sensor nodes from $50$ to $150$ and the number of virtual sensors from $10$ to $30$ to study the performance of QADMAP. Motivated by the works [9], [28]–[30] in the existing literature, the values of the various parameters considered for simulations are shown in Table 1.




(a) Evolution of Population Share of Nodes

(b) Convergence of Node Utility

Fig. 2: Evolutionary Game Dynamics for QADMAP

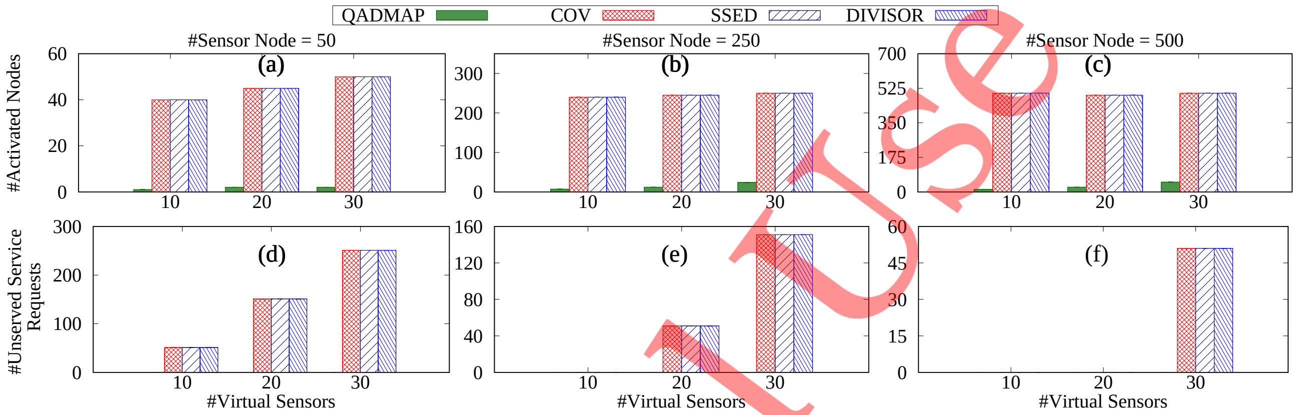



Fig. 3: Performance Analysis: (a), (b), (c) – Activated Nodes; (d), (e), (f) – Unserved Service Requests

## 6.2 Benchmarks

The performance of the proposed QADMAP scheme is evaluated through comparisons with three existing benchmark schemes. Two of these schemes, viz., optimal composition of virtual sensors (COV) by Chatterjee *et al.* [9] and dynamic virtual sensor formation in the overlapping region (DIVISOR) by Roy *et al.* [11], are proposed in the context of sensor-cloud for addressing the problem of virtual sensor composition, i.e., mapping of virtual sensors to physical sensor nodes. The third one, i.e., sensor selection for event detection (SSED) by Bajovic *et al.* [17], is designed for event-driven WSNs for addressing the problem of selecting the optimal subset of physical sensor nodes for event detection.

In COV, the authors proposed an optimal virtual sensor formation scheme, COV-I, which is concerned with sensor nodes deployed over a single region of interest. In the proposed scheme, the authors determine the goodness of each node based on its physical parameters and optimize the quality-of-information based on requirements of end-users. In DIVISOR, the authors proposed a dynamic scheme for the composition of virtual sensors while taking into consideration the number of times each sensor node is rented. This scheme is designed to ensure that each sensor-owner gets equal opportunity to earn a profit. In SSED, the authors proposed a scheme for the selection of an optimal subset from a given set of sensor nodes for event detection using WSNs. However, none of the afore-mentioned schemes consider the possibility of selection of a single sensor node for serving more than one applications, which is an inherent advantage of sensor-cloud. Additionally, in these schemes, the authors did not consider the optimal distribution of service load among the sensor nodes for reducing energy consumption and ensuring high profit of SCSP.

## 6.3 Performance Metrics

We evaluate the performance of QADMAP based on the following performance metrics:

**Number of Activated Nodes:** For a fixed number of services, lower value of activated nodes indicates improved resource utilization and hence, increased profit of SCSP. We calculate the number of activated nodes, $N_{act}$, as — $N_{act} = |\cup \mathbb{P}(t)|$.

**Network Energy Consumption:** The total energy consumption of the network for serving a fixed number of services is measured by the difference of the cumulative initial energy of the nodes and the cumulative residual energy of the nodes after serving the services. In addition to the components mentioned earlier, it also includes the energy required for the activation of the sensor nodes. Mathematically, we have — $E^{nw}_{cons} = \sum_{p_j}(E^j_{init} - E^j_{res}) \quad \forall p_j \in \cup\mathbb{P}(t)$. Lesser values of energy consumption imply lesser chances of node failure and higher QoS.

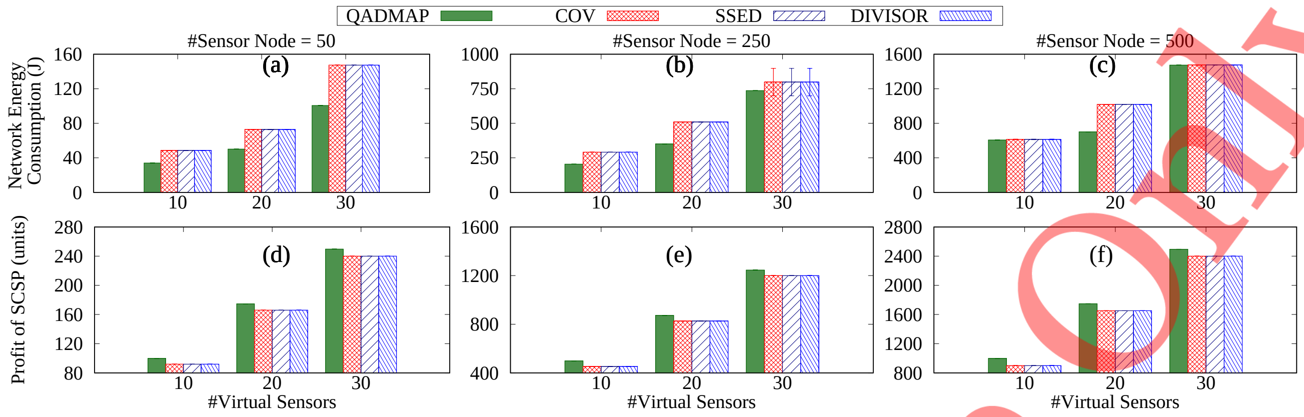



Fig. 4: Performance Analysis: (a), (b), (c) – Network Energy Consumption; (d), (e), (f) – Profit of SCSP

**Profit of Sensor-Owners:** Profit earned by each sensor-owner is directly proportional to the number of times the sensor nodes belonging to the sensor-owner are utilized by the SCSP for providing services. We estimate the profit of each sensor-owner as — $\texttt{Profit}_{o_i} = \rho \sum_{\cup \mathbb{P}_{o_i}(t)} \sum_{s \in \cup \mathcal{S}(t)} x_{s,j}$, where $\rho$ is the per unit profit earned by a sensor-owner per service per active sensor node and $\mathbb{P}_{o_i}(t)$ is the set of activated nodes belonging to sensor-owner $o_i$. Higher profits earned by sensor-owners induce more participation of sensor-owners in the sensor-cloud market, which, in turn, improves service availability for end-users.

**Unserved Service Requests:** When the compatible sensor nodes are completely utilized or are busy serving other allocated virtual sensors, and no sensor nodes are available to the SCSP for provisioning services, the service requests of the end-users are dropped due to service unavailability. This directly affects the QoS of Se-aaS delivered by the SCSP, thereby resulting in losses for the SCSP. Therefore, the number of unserved service requests is considered to be indirectly proportional to the service availability, i.e., QoS of Se-aaS, and directly proportional to the loss of the SCSP.

**Profit of SCSP:** The profit earned by an SCSP, $\texttt{Profit}_{scsp}$, is calculated as the difference of the revenue earned by the SCSP, $P_s$, for providing Se-aaS to the end-users and the cost borne by the SCSP for service provisioning. We calculate the profit of the SCSP as — $\texttt{Profit}_{scsp} = \sum_{s \in \cup \mathcal{S}(t)} (P_s - C_s^{vs} - C_s^{psn} \sum_p x_{s,p})$, where, $C_s^{vs}$ and $C_s^{psn}$ are the costs for virtual sensor creation and maintenance and price paid to sensor-owners for physical sensor nodes, respectively. With the increase in the number of services served, the profit of the SCSP also increases.

## 6.4 Results and Discussions

To study the evolution of load distribution among sensor-nodes, we simulated with 20 virtual sensors and 4 selected physical sensor nodes. From Figures 2(a) and 2(b), we observe that the population share and the utility of each of the selected nodes converge to the same value after $6-7$ iterations and the evolutionary equilibrium is reached. Thus, even distribution of service load is achieved using QADMAP.

Figures 3(a)-(c) depict the variation in the number of activated nodes in the network for a varying number of virtual sensors and registered sensor nodes. We observe that, compared to the existing schemes COV, DIVISOR, and SSED, there is 90-97.5% reduction in the number of active sensor nodes in the network using QADMAP. This is due to that fact that, unlike existing schemes, more than one virtual sensors are served by the same physical sensor node using QADMAP and hence, the requirement of the number of active nodes reduces significantly in case of QADMAP. Thus, using QADMAP, the same number of physical sensor nodes can be used to serve a higher number of services by the SCSP at any time compared to using the existing schemes, thereby resulting in increased service availability of Se-aaS and increased QoS. Figures 3(d)-(f) also support the aforementioned argument as we can see that there are no unserved service requests in case of QADMAP, while in case of the other three schemes, approximately 10% of the services cannot be served by the SCSP due to resource exhaustion. In other words, to ensure the same level of service availability using the existing schemes, the SCSP has to maintain a higher number of sensor nodes as compared to using QADMAP, thereby reducing his/her profit.

Additionally, we observe from Figures 4(a)-(c) that the energy consumption of the network reduces by 29.88-31.73% using QADMAP, compared to using COV, DIVISOR, and SSED, for a fixed number of nodes and a fixed number of service requests. This is mainly attributed to the fact that using QADMAP since the number of activated nodes in the network is reduced, the energy consumption for node activation and for the node remaining in the active state also reduces thereby reducing the energy consumption of the

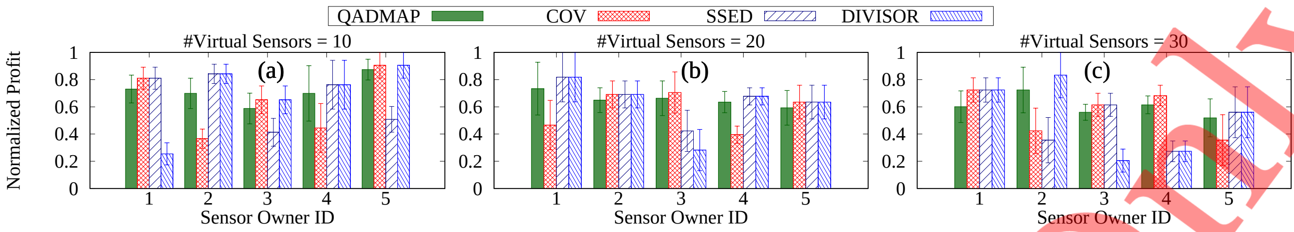



Fig. 5: Profit of Sensor Owners

network. Thereby, we argue that the network lifetime is increased which, in turn, leads to the increase in service availability and decrease in chances of service disruptions. Figures 4(a)-(c) also depict the variation of energy consumption with varying number of virtual sensors and sensor nodes. As the number of virtual sensors increases, the energy consumption also increases. It is to be noted that with the increase in the number of sensor nodes in the network, we considered that the node requirement of each virtual sensor increases, resulting in an increase in the number of virtual sensor instances. Thus, with the increase in the number of nodes, the energy consumption of the network increases.

In Figures 4(d)-(f), we observe that, for a fixed number of virtual sensors and the fixed number of sensor nodes, the profit earned by the SCSP using QADMAP is 3.63-9.82% higher than using COV, DIVISOR, and SSED. This is due to the fact that, using QADMAP, the SCSP is able to improve the network resource utilization efficiency by serving the same number of services using less number of nodes, compared to existing schemes, thereby incurring less cost for service provisioning. With the increase in the number of physical sensor nodes in the network, the profit of the SCSP increases due to the corresponding increase in the number of end-user service requests being served.

The distribution of profits among the sensor owners in the sensor-cloud market is depicted in Figure 5. In this figure, we observe that the proposed scheme ensures minimum sustainable profit for each sensor-owner in sensor-cloud. For the other existing schemes, the profits of the sensor-owners vary abruptly. Thus, we argue that QADMAP motivates the sensor-owners increases their participation in the sensor-cloud market. This, in turn, increases the availability of sensor nodes for provisioning Se-aaS, thereby increasing the service availability of Se-aaS.

## 7 Conclusion

In this work, we proposed a dynamic scheme, named QADMAP, for optimal mapping of virtual sensors to physical sensor nodes in sensor-cloud, while ensuring decreased resource consumption and increased QoS in terms of service availability and reduced service failures. We divided the afore-mentioned problem into two subproblems — optimal node selection and optimal data-rate distribution, which were shown to be NP-complete. Hence, we addressed the two subproblems individually using dynamic coalition-formation game theory and evolutionary game theory, respectively and presented an online scheme which solves the problem in polynomial time. To demonstrate the performance of QADMAP, we conducted simulations on MATLAB and compared it with three existing benchmark schemes. Experimental results show 29.88-31.73% decrease in energy consumption of the network as compared to existing schemes. Additionally, we observe that using QADMAP, the profits of the SCSP and the sensor-owners also increase while ensuring high QoS of Se-aaS.

In this work, we observed that other service parameters such as data freshness and service delay can also impact the QoS of Se-aaS. Hence, we plan to design an optimal virtual sensor mapping scheme while incorporating the aforementioned parameters. Additionally, this work can be extended to ensure uniform load distribution among the intermediate nodes in the network. It can also be extended to study the dynamics of load distribution if the sensor-nodes support only specific application types.

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## 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] I. L. Santos, L. Pirmez, F. C. Delicato, S. U. Khan, and A. Y. Zomaya, "Olympus: The Cloud of Sensors," *IEEE Cloud Comp.*, vol. 2, no. 2, pp. 48–56, Mar 2015.

[3] V. Moysiadis, P. Sarigiannidis, and I. Moscholios, "Towards Distributed Data Management in Fog Computing," *Wire. Comm. and Mob. Comp.*, vol. 2018, pp. 1–14, Sep 2018.

[4] S. Misra, S. Chatterjee, and M. S. Obaidat, "On Theoretical Modeling of Sensor Cloud: A Paradigm Shift From Wireless Sensor Network," *IEEE Syst. J.*, vol. 11, no. 2, pp. 1084–1093, Jun. 2017.

[5] S. Chatterjee, R. Ladia, and S. Misra, "Dynamic Optimal Pricing for Heterogeneous Service-Oriented Architecture of Sensor-cloud Infrastructure," *IEEE Trans. on Serv. Comp.*, vol. 10, no. 2, pp. 203–216, Mar. 2017.

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

[7] S. Misra, S. Bera, A. Mondal, R. Tirkey, H. C. Chao, and S. Chattopadhyay, "Optimal Gateway Selection in Sensor-Cloud Framework for Health Monitoring," *IET Wireless Sens. Syst.*, vol. 4, no. 2, pp. 61–68, Jun. 2014.
[8] S. Chatterjee, S. Sarkar, and S. Misra, "Energy-Efficient Data Transmission in Sensor-Cloud," in *Proc. of App. and Innov. in Mob. Comp.*, Feb. 2015, pp. 68–73.
[9] 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.
[10] A. Chakraborty, A. Mondal, and S. Misra, "Cache-Enabled Sensor-Cloud: The Economic Facet," *Proc. of IEEE WCNC*, pp. 1–6, 2018.
[11] C. Roy, A. Roy, and S. Misra, "DIVISOR: Dynamic Virtual Sensor Formation for Overlapping Region in IoT-based Sensor-Cloud," *Proc. of IEEE WCNC*, pp. 1–6, 2018.
[12] A. Sen and S. Madria, "Risk Assessment in a Sensor Cloud Framework Using Attack Graphs," *IEEE Trans. on Serv. Comp.*, 2016.
[13] 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.
[14] 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.
[15] P. Sarigiannidis, T. Zygiridis, A. Sarigiannidis, T. D. Lagkas, M. Obaidat, and N. Kantartzis, "Connectivity and Coverage in Machine-Type Communications," in *Proc. of IEEE ICC*, May 2017, pp. 1–6.
[16] F. Delicato, F. Protti, L. Pirmez, and J. F. de Rezende, "An Efficient Heuristic for Selecting Active Nodes in Wireless Sensor Networks," *Comp. Net.*, vol. 50, no. 18, pp. 3701 – 3720, 2006.
[17] D. Bajovic, B. Sinopoli, and J. Xavier, "Sensor Selection for Event Detection in Wireless Sensor Networks," *IEEE Trans. on Sig. Proc.*, vol. 59, no. 10, pp. 4938–4953, 2011.
[18] M. Vogler, J. Schleicher, C. Inzinger, and S. Dustdar, "Optimizing Elastic IoT Application Deployments," *IEEE Trans. on Serv. Comp.*, pp. 1–1, 2016.
[19] A. Triantafyllou, P. Sarigiannidis, and T. D. Lagkas, "Network Protocols, Schemes, and Mechanisms for Internet of Things (IoT): Features, Open Challenges, and Trends," *Wire. Comm. and Mob. Comp.*, vol. 2018, pp. 1–24, Sep 2018.
[20] 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.
[21] 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.
[22] D. Pliatsios, P. Sarigiannidis, S. Goudos, and G. K. Karagiannidis, "Realizing 5G Vision Through Cloud RAN: Technologies, Challenges, and Trends," *EURASIP J. Wire. Comm. and Net.*, vol. 2018, no. 1, p. 136, May 2018. [Online]. Available: https://doi.org/10.1186/s13638-018-1142-1
[23] D. Wajgi and N. V. Thakur, "Load Balancing Based Approach to Improve Lifetime of Wireless Sensor Network," *Int. J. of Wireless & Mob. Net.*, vol. 4, no. 4, p. 155, 2012.
[24] O. Younis and S. Fahmy, "HEED: A Hybrid, Energy-efficient, Distributed Clustering Approach for Ad Hoc Sensor Networks," *IEEE Trans. on Mobile Comp.*, vol. 3, no. 4, pp. 366–379, Oct 2004.
[25] Z. Han, D. Niyato, W. Saad, T. Baar, and A. Hjrungnes, *Game Theory in Wireless and Communication Networks: Theory, Models, and Applications*. New York, NY, USA: Cambridge University Press, 2012.
[26] R. E. Wendell and A. P. Hurter Jr, "Location Theory, Dominance, and Convexity," *Oper. Res.*, vol. 21, no. 1, pp. 314–320, 1973.
[27] J. Paek and R. Govindan, "RCRT: Rate-Controlled Reliable Transport Protocol for Wireless Sensor Networks," *ACM Trans. on Sen. Net.*, vol. 7, no. 3, p. 20, 2010.
[28] S. Misra, G. Mali, and A. Mondal, "Distributed Topology Management for Wireless Multimedia Sensor Networks: Exploiting Connectivity and Cooperation," *Int. J. of Comm. Syst.*, vol. 28, no. 7, pp. 1367–1386, 2015.
[29] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. on Wireless Comm.*, vol. 1, no. 4, pp. 660–670, Oct 2002.
[30] 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.

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