Optimal Composition of a Virtual Sensor for Efficient Virtualization Within Sensor-cloud

Subarna Chatterjee, *Student Member*, *IEEE*, Sudip Misra, *Senior Member*, *IEEE*
School of Information Technology
Indian Institute of Technology
Kharagpur, 721302, India
Email: {subarna, smisra}@sit.iitkgp.ernet.in

***Abstract*—The work focuses on optimal formation of virtual sensors (VSs) within a sensor-cloud infrastructure. Existing work on sensor-cloud have considered the formation of VS with the maximal set of compatible physical sensor nodes. However, as these underlying nodes are highly resource constrained, inefficient and redundant utilization of the nodes takes a toll on the entire performance of the cloud and the network. In this work, we propose algorithms for efficient virtualization of the physical sensor nodes and optimal composition of VSs — within the same geographic region (*CoV-I*) and spanning across multiple regions (*CoV-II*). Experimental results demonstrate that, compared to the existing strategy of maximal composition of VSs, *CoV-I* improves the cumulative energy consumption and the network lifetime by** 34.9% **and** 61.04%**, respectively, and *CoV-II* enhances the parameters by** 68.4% **and** 29.59%**, respectively.**

***Index Terms*—Sensor-cloud, Virtualization, Wireless Sensor Network**

I. Introduction

Recent research has spawned the emerging concept of sensor-cloud as a potential substitute for traditional Wireless Sensor Networks (WSNs) [1], [2]. Sensor-cloud infrastructure is defined as an interface between the physical and the cyber world that functions as a platform for remote data management, monitoring, and provisioning [3], [4]. It is a new dimension of cloud computing that thrives on the virtualization of physical sensor nodes [5] thereby provisioning the physical sensor nodes as an on-demand service to remote applications [6]. This enables the end-users to envision the physical sensors simply as an easily obtainable, and accessible service — *Sensors-as-a-Service* (*Se-aaS*) [7], rather than as a typical hardware.

In sensor-cloud infrastructure, the physical sensor nodes are allocated as per the demand of the applications at the user end, and are accordingly grouped to form virtual sensors (VSs). The VSs are further grouped to form the virtual sensor groups (VSGs). Se-aaS is provisioned to the end-users through the VSs or the VSGs [8]. In the existing work on sensor-cloud, applications are served by a VS comprising of the maximal set of the physical sensor nodes that satisfy the requirements of that application. However, keeping in mind the resource constrained behavior of the underlying sensor network, the membership within a VS should be done optimally, and efficiently. This work focuses on dynamic, optimal, and resource efficient algorithms for selection of components of a VS, based on the application-demand.

A. Motivation

This work is strongly motivated by the constrained behavior of the underlying physical network in terms of the battery-life of the individual sensor nodes, as well as the lifetime of the network. Within the sensor-cloud infrastructure, when a particular application requests for Se-aaS, the compatibility of the physical sensor nodes are examined on the basis of the type, location, Quality of Service (QoS), and other application specific requirements. A subset of compatible sensor nodes are chosen to make up the corresponding VS of that particular application. As of now, all of the works on sensor-cloud have assumed every member of the compatible subset to account for the formation of the VS. However, allocation of the largest subset of compatible sensor nodes effectively leads to redundant utilization of the resources, and, consequently, unnecessary consumption of the same.

B. Contributions

The goal of this work is to address the above-mentioned problem of maximal allocation of sensor nodes for a particular VS. The work focuses on an optimal selection of sensor nodes, that are compatible to the requirements of an application, and preserve the efficiency of resource utilization, simultaneously. The work proposes two distinct algorithms to compose a VS optimally — i) *CoV-I* - *Composition of VS* when the sensor nodes bear homogeneous sensing hardware and belong to the same geographical boundary (as shown in Figure 1(a)), and ii) *CoV-II* - *Composition of VS* when the sensor nodes with heterogeneous sensing hardware span across multiple geographical regions, thereby comprising of multiple VSs, which, in turn, form a VSG (shown in Figure 1(b)). The aforesaid algorithms are efficient in terms of preserving efficacy in the utilization of the resources.

C. Organization of the paper

The rest of the work is organized as follows. Section II describes the background of the research and the work done so far. In Section III, we discuss the system model in which Section III-A, and III-B focus to solve the problem for two different scenarios. In Section IV, we present the theoretical analysis of the work. The performance evaluation of *CoV*s is illustrated in Section V. Finally, Section VI concludes the work.

II. Background

This Section studies and analyzes the work done so far on this aspect. Prior to the advent of sensor-cloud infrastructure, some works focussed on the integration of traditional WSNs to a cloud platform [9], [10]. Some of the works addressed the problem of dynamic channelization of the sensed data to the cloud gateways [11], [12]. In another work [13], Taleb and Ksentini proposed the integration of federation clouds and mobile networks. In [14], Mendes *et al.* addressed the issues associated with the differences in protocols (IEEE 802.15.3 and IEEE 802.15.4) during cloud-based communication of multimedia WSNs.

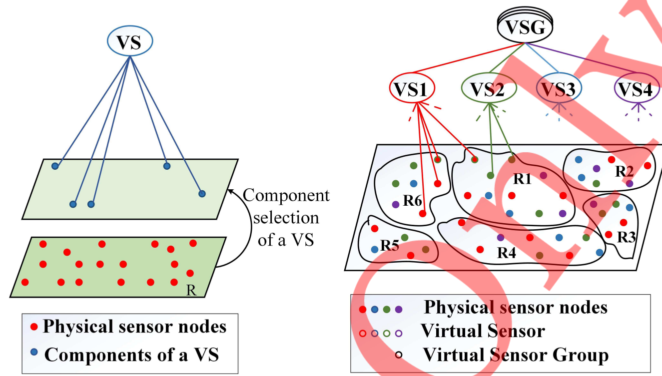
The original interpretation of sensor-cloud through virtualization of physical sensor nodes was presented by Yuriyama and Kushida [2], [3]. The dogma of the idea, the challenges, and the benefits are discussed in [4], [5]. Few application oriented works are also presented in [6], [15]. However, very few works addressed the technicalities concerning sensor-cloud infrastructure. Misra *et al.* theoretically modeled sensor-cloud infrastructure [7]. In [8], Bhunia *et al.* mentioned the event-driven gathering of data within sensor-cloud through fuzzification. Nguyen and Huh [15] presented some of the security aspects of sensor-cloud.

To the best of our knowledge, the above-mentioned works have not focused on the efficiency of virtualization, and the enhancement of resource utilization while doing so. As mentioned earlier, this paper focuses to compose a VS optimally, thereby ensuring the efficacy of resource utilization.

III. System Model

In this Section, we present the system model for the composition of the VS, and the VSG. The Section is subdivided into two distinct subsections. We consider two distinct scenarios as shown in Figure 1.

- *Case (a):*
  Initially, we focus on the methodology for the efficient composition of a VS, as shown in Figure 1(a). The Figure analyses the formation of a VS in which the underlying physical sensor nodes fall within the same geographic region, and are homogeneous with respect to the sensing hardware. Under such circumstances, the optimal formation of VS, *CoV-I*, is discussed in subsection III-A.
- *Case (b):*
  The other scenario considers the presence of heterogeneous sensor nodes spread across different geographic regions, as shown in Figure 1(b). Homogeneous sensor nodes from multiple regions (R_1, R_2, R_3, R_4, R_5, and R_6) together form a VS, whereas, multiple VSs (comprising of heterogeneous sensor nodes) combine to form a VSG that serve a particular application, as discussed in *CoV-II*, presented in subsection III-B.



(a) Formation of VS (b) Formation of VSG

Figure 1: Virtualization of the physical sensor nodes

Before we discuss the formation and optimality of a VS in a case by case manner, we define some of the preliminaries of our work. We assume a set of r non-overlapping finite regions, $\mathcal{R} = \{\mathcal{R}_1, \mathcal{R}_1, ..., \mathcal{R}_r\}, \mathcal{R}_i \bigcap \mathcal{R}_j = \Phi, \forall 1 \leq i, j \leq r, i \neq j$, within which the physical sensor nodes are deployed. Every sensor node s_i is characterized by the center of its deployment, (l_1, l_2), representing the latitude, and longitude of the absolute position of the node, respectively, and its sensing radius at time t, λ_t. Thus, the location specific nomination of sensor nodes, for a particular application *App* with $\mathcal{R}_{req}$ ($\mathcal{R}_{req} \subseteq \mathcal{R}$) as the region of interest is given by,

$$\mathcal{S} = \{s_i\} \mid (\varphi(l_1, l_2, \lambda_t^{s_i}) \subseteq \mathcal{R}_{req}) \wedge (s_i.type = App.type) \tag{1}$$

where $\varphi(\cdots)$ computes the region equivalent of the sensing area of a sensor node. The "*type*" attribute stores the type of the sensor nodes in terms of the sensing hardware, e.g. rainfall sensor, temperature sensor, and so on. For two sensor nodes, s_i, and s_j to be homogeneous, $s_i.type = s_2.type$.

A. CoV-I: Composition of VS within the same region

This subsection proposes the optimum *Composition of VS* (*CoV-I*) algorithm for the selection of homogeneous component nodes from the same geographic region, $\mathcal{S} = \{s_i\}$, where $s_i.type = s_j.type$, and Equation (1) holds. $\mathcal{S}$ is the largest set of compatible sensor nodes that can serve application *App*. In *CoV-I*, we assume K number of applications to be served by sensor-cloud. $\mathcal{P}_i$ is the priority of App_i, the lowest indicating the highest priority. The "*goodness*" of every physical node of $\mathcal{S}$ is initially quantified. The factors affecting the *goodness* of a node s_i are:

- *Normalized Residual Energy* (*NRE*): NRE is defined as the ratio of the current energy level to the initial energy level, expressed as, $\mathcal{Q}_{s_i}^t = \frac{E_{s_i}^{cur}}{E_{s_i}^{init}}$ where, E^{cur}, and E^{init} are the current and the initial battery level, respectively.
- *Expected Received Signal Strength Intensity* (*ERSSI*): The ERSSI, at time t, is defined as the expected value of the signal strength when perceived at the cloud end at t.

ERSSI is expressed as,

$$\upsilon^{s_i}(t) = \Psi_{s_i} \frac{P^{tr}_{s_i}(t)}{\xi(s_i, d_j)^a} \tag{2}$$

where ξ computes the Euclidean distance of the node with the Base Station (BS), d_j. $P^{tr}_{s_i}$ is the transmitted power, and Ψ is a constant that considers the other factors such as antenna gain and antenna height [16]. In our case, $a = 1$.

- *Proximity with BS*: The proximity of s_i with the BS is given by, $\chi_{s_i} = \sqrt{(s_i.x - BS.x)^2 + (s_i.y - BS.y)^2}^{-1}$, where x, and y represent the abscissa, and the ordinate, respectively.

$$\chi_{s_i} = \sqrt{(s_i.x - BS.x)^2 + (s_i.y - BS.y)^2}^{-1} \tag{3}$$

Definition 1. The goodness $\mathcal{G}$ of a node s_i, at time t, is defined in terms of the NRE, ERSSI, and its proximity with BS at t, and expressed as,

$$\mathcal{G}_{s_i}(t) = \mathcal{Q}^t_{s_i} + g \times \chi_{s_i} \upsilon^{s_i}(t) \tag{4}$$

where g is the normalization constant.

Motivated by the concept for quantifying the Quality of Information (QoI) in [17], we model the QoI of the sensor node s_i, based on a the confidence of data transmission, as defined below.

Definition 2. The transmission confidence of the data from s_i to the BS at time t, $f_{s_i}(t)$, is defined as a loss/gain factor governed by the difference of the transmitted, and received data. It is expressed as,

$$f_{s_i}(t) = \begin{cases} \frac{1}{N} f_{s_i}(t-1) e^{(\rho\delta)(t)}, & \rho = |D_{s_i} - D_{BS}| < \rho_{th} \\ \frac{1}{N} f_{s_i}(t-1) e^{-(\rho\delta)(t)}, & \text{otherwise} \end{cases} \tag{5}$$

ρ and N being the absolute deviation of the transmitted and received data, and the factor for normalization, respectively. D represents the data, and δ is the loss/gain factor [18].

We model the QoI of every component node of *CoV-I* as,

$$\Theta_{s_j}(t) = f_{s_j}(t)\Theta_{s_j}(t-1) + \mathcal{G}_{s_j}(t), \Theta_{s_j}(1) = 1 \tag{6}$$

Equation (6) can be simplified as,

$$\Theta_{s_j}(t) = \prod_{i=0}^{t-1} f_{s_j}(t-i) + \sum_{k=0}^{t-1} \prod_{j=0}^{k} f_{s_j}(t-j)\mathcal{G}(t-k-1) \tag{7}$$

$$= \mathcal{L}_{s_j}(\rho, \mathcal{Q}, \upsilon, \chi) \tag{8}$$

The total resources available is given by $\Omega = |\mathcal{S}|$, and $\Omega^{min}_{App_i}$ is the minimum resources (in terms of the sensor nodes) to be reserved for the VS of App_i. Thus, we design an optimization problem of *CoV-I* as,

$$\max \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi) \tag{9}$$

$$s.t \begin{cases} \sum_{i=1}^{K} \Omega_{App_i} \leq \Omega \\ \Omega_{App_i} \geq \Omega^{min}_{App_i}, i = 1, 2, ..., K \end{cases} \tag{10}$$

Therefore,

$$L_1(\Omega_{App}, \rho, \mathcal{Q}, \upsilon, \chi) = \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)$$
$$-\alpha_1 \left(\sum_{i=1}^{K} \Omega_{App_i} - \Omega \right) - \sum_{i=1}^{K} \beta_{1i} \left(\Omega_{App_i} - \Omega^{min}_{App_i} \right) \tag{11}$$

where α_1, and β_1 are the Lagrangian multipliers to the constraints. Using the gradients of L, we obtain,

$$\frac{\delta L_1}{\delta \Omega_{App_i}} = \sum_{i=1}^{K} \frac{\mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)}{\mathcal{P}_i \Omega^2_{App_i}} - \alpha_1 K - \sum_{i=1}^{K} \beta_{1i} \tag{12}$$

$$\frac{\delta L_1}{\delta \rho} = \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \frac{\delta \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)}{\delta \rho} \tag{13}$$

$$\frac{\delta L_1}{\delta \mathcal{Q}} = \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \frac{\delta \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)}{\delta \mathcal{Q}} \tag{14}$$

$$\frac{\delta L_1}{\delta \upsilon} = \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \frac{\delta \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)}{\delta \upsilon} \tag{15}$$

$$\frac{\delta L_1}{\delta \chi} = \sum_{i=1}^{K} \frac{1}{\mathcal{P}_i \Omega_{App_i}} \sum_{j=1}^{\Omega_{App_i}} \frac{\delta \mathcal{L}_j(\rho, \mathcal{Q}, \upsilon, \chi)}{\delta \chi} \tag{16}$$

Solving Equations (12) through (16), we obtain L_1^{max}, that maximizes the QoI of a VS, and optimizes the allocation of the component nodes for varied execution priorities of end-user applications. Having discussed the methodology to form a VS comprising of homogeneous components within the same region, we now present the second case of ours.

B. CoV-II: Composition of VS, and VSG across multiple regions

This Section proposes *Composition of VS* (*CoV-II*) algorithm that considers the set of compatible sensor nodes, $\mathcal{S} = \{s_i\}$, of heterogeneous types $T = \{t_1, , t_2, ..., t_F\}$, to span across multiple regions $\mathcal{R}$. Thus, in *CoV-II*, for a particular VS of type $t_f \in T$, $\forall s_j \mid s_j.type = t_f$, Equation (9) is modified as,

$$\max \sum_{i=1}^{K} \sum_{\forall \mathcal{R}_p \in \mathcal{R}} \frac{1}{\mathcal{P}_i \Omega_{App_i, \mathcal{R}_p}} \sum_{j=1}^{\Omega_{App_i, \mathcal{R}_p}} \mathcal{L}_{s_j}(\rho, \mathcal{Q}, \upsilon, \chi) \tag{17}$$

$$s.t \begin{cases} \sum_{i=1}^{K} \sum_{p=1}^{r} \Omega_{App_i, \mathcal{R}_p} \leq \Omega \\ \sum_{p=1}^{r} \Omega_{App_i, \mathcal{R}_p} \geq \Omega^{min}_{App_i}, i = 1, 2, ..., K \\ \Omega_{App_i, \cdot} > 0, i = 1, 2, ..., K \end{cases} \tag{18}$$

where $\Omega_{App_i,\mathcal{R}_p}$ indicates the physical nodes to be allocated for the VS of App_i at region $\mathcal{R}_p$. Therefore, using Equations ((17)), and (18), we obtain the primal of *CoV-II*,

$$L_2(\Omega_{App,\mathcal{R}},\rho,\mathcal{Q},\upsilon,\chi) = \sum_{i=1}^{K}\sum_{\forall\mathcal{R}_p\in\mathcal{R}}\frac{1}{\mathcal{P}_i\Omega_{App_i,\mathcal{R}_p}}\sum_{j=1}^{\Omega_{App_i,\mathcal{R}_p}}\mathcal{L}_{s_j}(\rho,\mathcal{Q},\upsilon,\chi) - \alpha_2\left\{\sum_{i=1}^{K}\sum_{p=1}^{r}\Omega_{App_i,\mathcal{R}_p}-\Omega\right\} - \sum_{i=1}^{K}\beta_{2i}\left\{\sum_{p=1}^{r}\Omega_{App_i,\mathcal{R}_p} - \Omega^{min}_{App_i}\right\} - \gamma_2\times\max\left(\Omega_{App_i,\cdot},0\right) \quad (19)$$

where α_2, β_2, and γ_2 are the Lagrangian multipliers. Hence, we have,

$$\frac{\delta L_2}{\delta\Omega_{App,\mathcal{R}}} = \sum_{i=1}^{K}\sum_{\forall\mathcal{R}_p\in\mathcal{R}}\frac{-\sum_{j=1}^{\Omega_{App_i,\mathcal{R}_p}}\mathcal{L}_{s_j}(\rho,\mathcal{Q},\upsilon,\chi)}{\mathcal{P}_i\Omega^2_{App_i,\mathcal{R}_p}} - \alpha_2 Kr - \sum_{i=1}^{K} r\beta_{2i} - \gamma_2\times sign(\Omega_{App_i,\cdot}) \quad (20)$$

where $sign()$ returns $+1$ or 0 based on the positive or negative magnitude of a quantity, respectively. Employing Equations similar to (12) - (16), and using Equation (20), L_2 is optimized, and thus, $\Omega^*_{App_i}$ is obtained. Using Equation (17), the formation of the set of VSGs $\mathcal{V}$ for $App_i, i=1,2,...,K$ is expressed as,

$$\mathcal{V} = \{\mathcal{V}_1,\mathcal{V}_2,...,\mathcal{V}_K\} = \{\Omega^*_{App_1},\Omega^*_{App_2},...,\Omega^*_{App_K}\} \quad (21)$$

$$\mathcal{V}_i = \{\Omega^*_{App_i,t_1},\Omega^*_{App_i,t_2},...,\Omega^*_{App_i,t_F}\} \quad (22)$$

such that, $\forall t_f\in T$,

$$\sum_{\forall\mathcal{R}_p\in\mathcal{R}}\frac{1}{\mathcal{P}_i\Omega^*_{App_i,\mathcal{R}_p}}\sum_{j=1}^{\Omega^*_{App_i,\mathcal{R}_p}}\mathcal{L}^{t_f}_{s_j}(\rho,\mathcal{Q},\upsilon,\chi)$$

is maximized where, $\{s_j\}\in\mathcal{S}^{t_f}$, and $\bigcup_{t_f\in T}\mathcal{S}^{t_f}=\mathcal{S}$. Also, $\Omega^*_{App_i,t_j}\subset\mathcal{S}^{t_j}$. Thus, the VSGs formed in *CoV-II* consist of VSs that are formed of the physical sensor nodes optimally in terms of the resource capacity of the nodes, and considering the priority of the applications. The theoretical analysis of the work is presented in Section IV.

IV. Theoretical Analysis

Theorem 1. *At a particular time t, the proposed algorithms — CoV-I, and CoV-II are loss less.*

Proof: To prove the loss less nature of the proposed *CoV-I*, and *CoV-II*, we define the metric of losslessness, as,

$$\sum s_i\in\mathcal{S}^{opt-}_{App_i}\mid\exists s_j\in\mathcal{S}_{opt},\mathcal{G}_{s_i}(t)>\mathcal{G}_{s_j}(t) \quad (23)$$

where $\mathcal{S}_{opt}$, and $\mathcal{S}^{-}_{opt}$ are the composition of VS_{App_i}, and the set of the remaining nodes of the maximal subset, respectively, $\mathcal{S}_{opt}\bigcup\mathcal{S}^{-}_{opt}=\mathcal{S}$. We prove the statement by the method of contradiction. We assume $\exists s_i,s_j$ for which Equation (23) holds true. Thus, $\mathcal{L}_{s_i}(\cdots)>\mathcal{L}_{s_j}(\cdots)$. Thus,

$$\sum_{j=1}^{\Omega_{App_i}-\{s_j\}+\{s_i\}}\mathcal{L}_j(\rho,\mathcal{Q},\upsilon,\chi) > \sum_{j=1}^{\Omega_{App_i}}\mathcal{L}_j(\rho,\mathcal{Q},\upsilon,\chi) \quad (24)$$

However, for *CoV-I*, $L_1(\Omega_{App},\rho,\mathcal{Q},\upsilon,\chi)$ is maximized. Thus, $\forall s_j\in\mathcal{S}_{opt,App_i}, s_i\in\mathcal{S}^{-}_{opt,App_i}$,

$$\sum_{k=1}^{K}\frac{\sum_{j=1}^{\Omega_{App_k}}\mathcal{L}_j(\rho,\mathcal{Q},\upsilon,\chi)}{\mathcal{P}_k\Omega_{App_k}} > \sum_{k=1}^{K}\frac{\sum_{i=1}^{\Omega^{-}_{App_k}}\mathcal{L}_i(\rho,\mathcal{Q},\upsilon,\chi)}{\mathcal{P}_k\Omega_{App_k}} \quad (25)$$

$$\Rightarrow\sum_{j=1}^{\Omega_{App_k}}\mathcal{L}_j(\rho,\mathcal{Q},\upsilon,\chi) > \sum_{i=1}^{\Omega^{-}_{App_k}}\mathcal{L}_i(\rho,\mathcal{Q},\upsilon,\chi)$$

$$\Rightarrow\sum_{j=1}^{\Omega_{App_k}}\Theta_{s_j} > \sum_{i=1}^{\Omega^{-}_{App_k}}\Theta_{s_i}\Rightarrow\sum_{j=1}^{\Omega_{App_k}}\mathcal{G}_{s_j} > \sum_{i=1}^{\Omega^{-}_{App_k}}\mathcal{G}_{s_i}$$

Thus, for App_i, $\nexists\mathcal{G}_{s_j}>\mathcal{G}_{s_i}$, $s_i\in\mathcal{S}^{opt-}_{App_i}, s_j\in\mathcal{S}^{opt}_{App_i}$ thereby disproving our assumption. Similarly, the same can be shown for *CoV-II*. This concludes the proof. ■

Proposition 1. *The asymptotic computational complexity of CoV-I, and CoV-II are* $O(\{\max_{i=1,2,...,K}N_i\}^2)$, *and* $O(\bigcup_{j=1}^{r}\mathcal{S}^2_{\mathcal{R}_i})$, *respectively for* K *applications.*

Proof: As *CoV-I* focuses on a particular region $\mathcal{R}$ for a particular application,, the computational complexity of *CoV-I* for K applications $C(K)$ is expressed as,

$$C(K) = C_1(\mathcal{R}_1)+C_2(\mathcal{R}_2)+...+C_K(\mathcal{R}_K) \quad (26)$$

where $C_i(\mathcal{R}_i)$ is the computational complexity involved for executing App_i over $\mathcal{R}_i$. The maximal compatible set is indicated by $\mathcal{S}_{App_i,\mathcal{R}_i}$. We have,

$$C_i(N_i) = C_i(N_i-1)+O(N_i), C_i(1)=O(k) \quad (27)$$

where $N_i=\mid\mathcal{S}_{App_i,\mathcal{R}_i}\mid$, and k is a constant. Therefore, $C_i(N_i)=O(N_i^2)$. Thus, using asymptotic algebra, Equation (26) is simplified as,

$$C(K) = \max_{i=1,2,...,K}\{C(\mathcal{R}_i)\}\simeq O(\{\max_{i=1,2,...,K}N_i\}^2) \quad (28)$$

For *CoV-II*,

$$C(K) = O(\sum_{i=1}^{K}C_i(\mathcal{R})) = O(\sum_{i=1}^{K}C_i(\bigcup_{j=1}^{r}\mathcal{R}_j)) \quad (29)$$

Thus using Master method, we have $C(K)=O(\bigcup_{j=1}^{r}\mathcal{S}^2_{\mathcal{R}_i})$. This concludes the proof. ■

V. Performance Evaluation

This Section presents the results of evaluation of the performance of *CoV-I*, and *CoV-II*. The details of experimental setup are illustrated in Table I.

Table I: Experimental Setup

Parameters	Values
Deployment Area	500 m × 500 m
Deployment type	Uniform, random
Number of nodes	100
Communication energy (E_{comm})	70 nJ/bit
Energy due to computation (E_c)	30 nJ
Sensing energy (E_s)	10 nJ/bit
Number of applications	3
Application priority ($\mathcal{P}$)	{1, 2, ..., 10}

For evaluation of the performance of *CoV-I*, and *CoV-II*, a comparative study is performed in terms of cumulative energy consumption, and network lifetime, as shown in Figure 2. The metric for cumulative energy consumption $\mathcal{E}$ is evaluated as,

$$\mathcal{E}(t) = h\mathcal{E}_{comm} + e\mathcal{E}_s + \mathcal{E}_c \quad (30)$$

where $\mathcal{E}_{comm}$, $\mathcal{E}_s$, and $\mathcal{E}_c$ are the energy expended due to communication (transmission, and reception), sensing, and computation, respectively. h and e are respectively the hop count and the total number of events at time t. Figure 2(a) indicates that by using *CoV-I*, and *CoV-II*, the expenditure of energy falls to respectively 34.9% and 68.4% of that while using the maximal set of compatible sensor nodes. Thus, *CoV*s perform better due to utilization of a reduced set of sensor nodes. Consequently, it enhances the network lifetime as well, as shown in Figure 2(b). The network lifetime $\mathcal{N}$ at t is evaluated as,

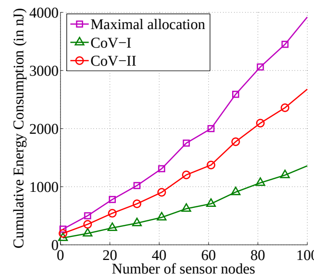
$$\mathcal{N}(t) = \frac{\mathcal{N}_{max} - \mathcal{E}(t)}{\mathcal{N}_{max}} \times 100\% \quad (31)$$

With the increase in the number of the physical nodes, the network lifetime falls steeply in case of the maximal formation of a VS, unlike *CoV*s in which the curve falls gradually. It is observed that *CoV-I*, and *CoV-II* increases the network lifetime by 61.04%, and 29.59%, respectively, in comparison to the case of utilizing the maximum set of compatible sensor nodes.

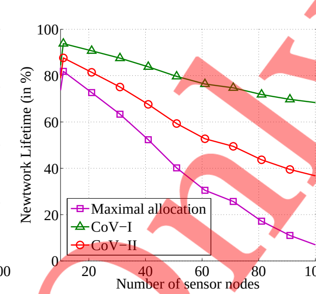
In order to examine the optimal composition of the VS for multiple applications, *CoV*s were executed with 3 running applications (App_A, App_B, App_C). The priorities of the applications are varied with time, and the change in Ω^{min}, and $\Omega_i, i = \{A, B, C\}$, are observed. The provisioned resource to the applications, as in Figure 3, is evaluated as,

$$S_{App_i} = \sum \mathcal{G}_{s_i} \mid s_i \in \Omega_{App_i} \quad (32)$$

At t_1 (indicated by Figure 3(a)), with the decrease in the application priorities (the lowest indicating the highest priority), the allocated resources, and the minimum threshold increases,



(a) Study of cumulative energy consumption



(b) Study of network lifetime

Figure 2: Comparative study of the network parameters

as shown in Figure 3(a). At t_2 (indicated by Figure 3(b)), with the change in $\mathcal{P}$, Ω^{min} and Ω changes accordingly. At t_3 (indicated by Figure 3(c)), the priorities and Ω^{min} of the applications change. However, the optimality in resource allocation is preserved. Figure 4 illustrates the optimal composition of VS for applications App_A, App_B, and App_C under several circumstances in terms of the resource range ϑ_i^{max}, of each application where,

$$\Omega_{App_i} = \vartheta_i^{max} - \vartheta_i^{min} \quad (33)$$

ϑ_A^{min} and ϑ_i^{max} denote the lower and the upper limit of the composition of VS, respectively, and are required to evaluate the exact composition of the VS. In case 1, as shown in Figure 4(a), all the applications have high priorities, and hence, the optimal utilization of the physical nodes is quite high. As the priorities of App_B, and App_C fall in Figure 4(b), the total consumption of the physical nodes is dominated by the demand of App_A. For a situation in which all the applications have a low priority, the resource utilization falls appreciably by a good extent, as depicted in Figure 4(c).

VI. Conclusion

This work focuses on resource efficient virtualization within sensor-cloud infrastructure. The work addresses the problem of optimum composition of VSs both within the same geographic region, as well as across multiple regions by proposing *CoV-I*, and *CoV-II*, respectively. Results show that *CoV*s enhance the resource utilization to a good extent, compared to the existing techniques of maximal allocation of the physical sensor nodes.

Future scope of research will focus on extension of this problem from an Service Level Agreement (SLA)-based perspective with a view to strength the Quality of Service (QoS) of Se-aaS. An analysis of bandwidth exhaustion of this problem may also induce research interest.

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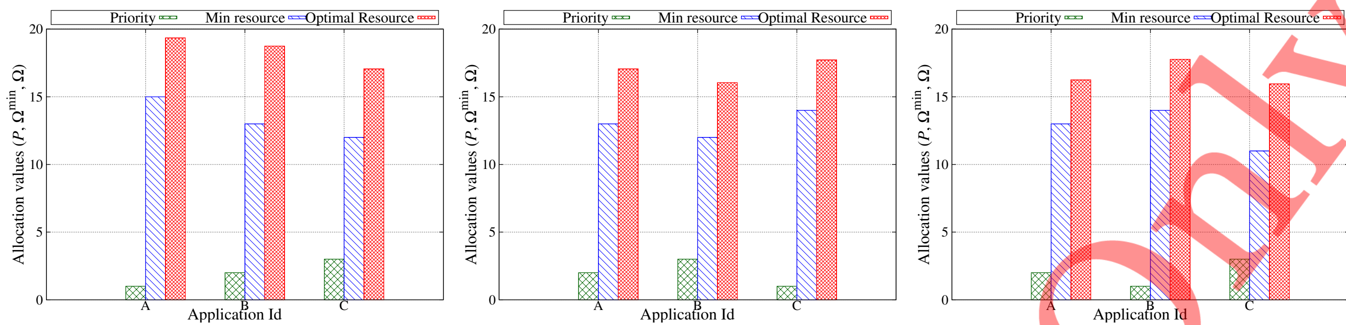
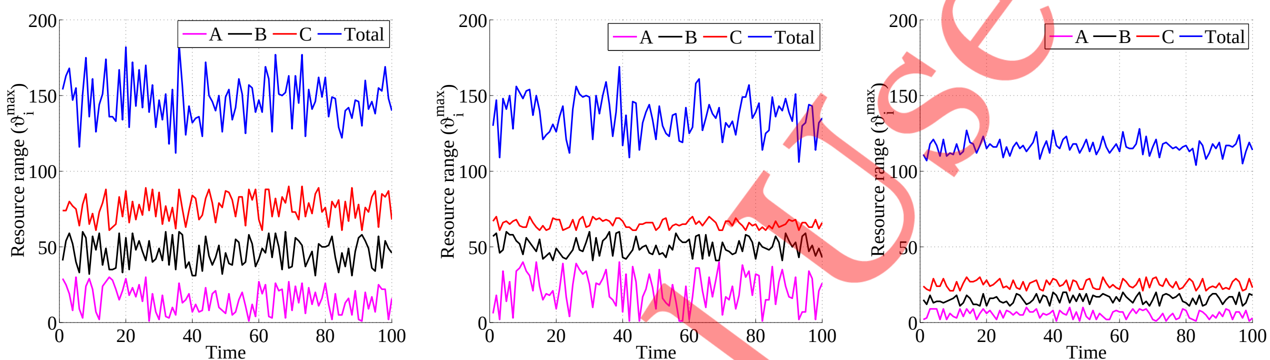


(a) $t_1 : \mathcal{P}_A < \mathcal{P}_B < \mathcal{P}_C$, $\Omega^{min} = \{15, 13, 12\}$ (b) $t_2 : \mathcal{P}_C < \mathcal{P}_A < \mathcal{P}_B$, $\Omega^{min} = \{13, 12, 14\}$ (c) $t_3 : \mathcal{P}_B < \mathcal{P}_A < \mathcal{P}_C$, $\Omega^{min} = \{13, 14, 11\}$

Figure 3: Optimality of resource allocation based on application priority and minimum resource requirement



(a) Case 1: $\vartheta_A^{min} = 0, \vartheta_B^{min} = 30, \vartheta_C^{min} = 60$ (b) Case 2: $\vartheta_A^{min} = 0, \vartheta_B^{min} = 40, \vartheta_C^{min} = 60$ (c) Case 3: $\vartheta_A^{min} = 0, \vartheta_B^{min} = 10, \vartheta_C^{min} = 20$

Figure 4: Study of resource allocation under varied application demand and priorities

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