QSens: QoS-aware Sensor Node Selection in Sensor-Cloud Architecture

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Abstract. In this paper, we propose a Quality-of-Service (QoS)-aware sensor node selection scheme, QSens, for sensor-cloud architecture. In this architecture, a Sensor-Cloud Service Provider (SCSP) provisions Sensors-as-a-Service (Se-aaS) to the registered end-users. On the other hand, the end-users pay the charges for their availed services. This work has twofold objectives – first, we define the Service-Level Agreements (SLAs) in sensor-cloud to bind sensor owners, SCSP, and end-users together with certain contracts, and second, with the help of these SLAs, the proposed scheme provisions to select a suitable set of sensor nodes, based on the QoS value, to serve an application. The SLA between sensor owner and SCSP enforces the former to share the detailed specifications of his/her sensor nodes to the SCSP. On the other hand, the SLA between SCSP and the end-users enforces the SCSP to determine the optimal QoS of different available sets of sensor nodes and share with the end-users. We formulate the QoS of a sensor node with its specifications shared by the sensor owner. Further, we apply *Karush-Kuhn-Tucker* (*KKT*) conditions to obtain an optimal sensor node, based on the QoS value. Extensive experimental results depict that the total payable service price varies in the range 77.69 – 86.97% with the increase in the service price of SCSP from 500 – 1000 units. On the other hand, with the change in the price of sensor nodes from 500–1000 units, the total payable service price varies from 35.79 – 54.6%.

Keywords: Service-Level Agreements (SLAs), sensor-cloud, Sensors-as-a-Service (Se-aaS), Quality-of-Service (QoS), Sensor Node Selection

1 Introduction

Sensor-cloud is based on the service-oriented architecture (SOA), which consists of multiple actors such as sensor owners, end-users, and SCSP [1,3]. This architecture provisions Sensors-as-a-Service (Se-aaS) for end-users using the concept of sensor *virtualization*. A sensor owner leases his/her sensor nodes and earns profit, depending upon the usage of the respective sensor nodes. On the other hand, an end-user pays rent to the SCSP for the services availed by him/her [2].

The SCSP acts as a centralized actor, who manages the sensor-cloud architecture along with the cash inflow and outflow in the system. As an end-user pays a significant amount of price for certain application, s/he expects for desirable Quality-of-Service (QoS). The proposed scheme, QSens, allows an end-user to select a sensor node for an application, based on its QoS. The Service-Level Agreement (SLA) plays a crucial role in sensor-cloud for selecting a sensor node, depending upon its QoS, by the end-users. In sensor-cloud, SLAs are in the form of a certain commitment of services among SCSP, end-users, and sensor owners. The proposed scheme, QSens, comprises two SLAs – SLA_{SS} and SLA_{SE}. The SLA between SCSP and sensor owner is termed as SLA_{SS}, while the SLA between SCSP and end-users is known as SLA_{SE}. However, these SLAs may contain other service agreement, as per their requirement. The primary aim of this work is to minimize the price charged from an end-user and maximize the QoS of the sensor nodes.

In the existing literature of sensor-cloud, there is no such scheme which facilitates the end-users to select the sensor nodes, as per their requirements. This motivate us to propose a scheme, QSens, for allowing the end-users to select a suitable set of sensor nodes for serving an application. The specific *contributions* of this work are:

– The authors in the existing literature do not propose any work on SLA for the sensor-cloud architecture. Therefore, in this work, we introduce two different SLAs – SLA_{SS} and SLA_{SE}, which are specifically designed for the sensor-cloud. These SLAs bind sensor owners, SCSP, and end-users, legally with certain contracts.
– QSens allows the end-users to know the optimal value of QoS of the sensor nodes. On the other hand, the end-users are capable of selecting a suitable set of sensor nodes within their financial budget, considering the optimal QoS. In this work, we derive a function for computing an optimal QoS of the sensor nodes with the help of SLAs.
– We solve the problem by optimization function and proving it as convex. Further, we apply the *Langragian Multiplier* [4] and the *Karush-Kuhn-Tucker* (KKT) [5] conditions to derive the optimal value of QoS. Additionally, we analyze QSens with rigorous simulation.

2 Related Work

Existing literature reveals different research works on SLA for the traditional cloud architecture. On the other hand, in the literature, the authors explored the concept of sensor-cloud architecture, which replace the traditional WSNs. Considering all these aspects, we categorized the related works in two parts – SLA and sensor-cloud architecture.

For a SOA-based system, SLA plays an important role to bind the service providers and consumers. In the existing literature, the authors proposed several SLA-enabled schemes for different technologies and applications. Gaillard

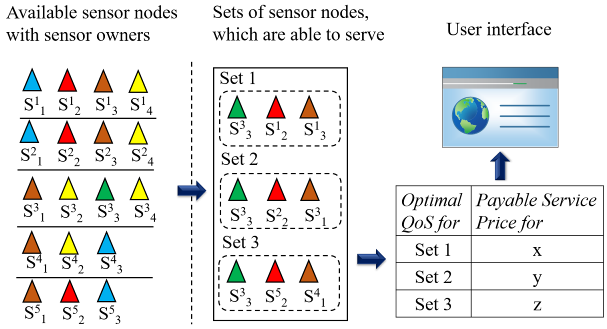


Fig. 1: Architecture of QSens

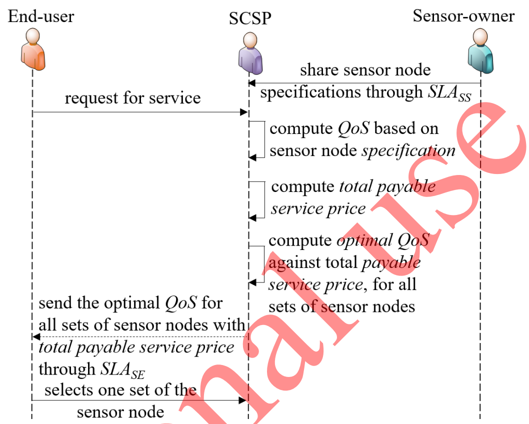


Fig. 2: Flow diagram of QSens

et al. [6] implemented SLA for WSNs. The authors discuss few important mechanisms – *SLA Observer*, *Service Registry*, *SLA Admitter*, *SLA Manager*, and *SLA Enforcer* – for ensuring QoS, in the context of WSNs. Similarly, Chieng *et al.* [7] proposed an SLA-driven scheme to facilitate the dynamic and flexible bandwidth reservation for a QoS-aware Internet. In order to discuss an SLA broker scenario, the authors used *Fujitsu's Phoenix Open Agent Mediator* (*OAM*). Garcia *et al.* [8] modeled an SLA with Linked Unified Service Description Language (USDL) agreement. The authors utilized the benefit of the Web principle for incorporating the technical and business aspects in the SLA. The proposed model offers the necessary facilities for capturing the semantics of the agreements. Typically, for a cloud service, the SLA is proactive and difficult to dynamically modify. Considering the dynamic modification of SLA, Paputungan *et al.* [9] proposed a scheme for enabling dynamic negotiation in SLA for cloud architecture.

In the existing literature, the authors explored different works in the domain of sensor-cloud architecture. Yuriyama *et al.* [1, 10] proposed the concept of virtualization of sensor nodes. Further, Madira *et al.* [11] presented the Sensing-as-a-Service (Se-aaS) paradigm to offer a common service platform for multiple end-user. In this work, the authors also discussed the formation of the virtual sensor (VS) considering the resource-constrained environment of traditional WSNs. A VS comprises multiple physical sensor nodes and provisions multiple end-users to receive services, simultaneously. However, the composition of VS changes with time and the types of applications. In order to form the dynamic VSs, Roy *et al.* [12] designed a scheme for the sensor-cloud architecture. Typically, a sensor-cloud architecture is based on pay-per-use model, in which different actors are involved to receive certain benefits. Therefore, Chakraborty *et al.* [3] proposed a pricing scheme to manage the financial transactions among the actors of sensor-cloud while enforcing the trust among SCSPs.

3 Problem Scenario

We consider a sensor-cloud architecture, where sensor owners procure multiple heterogeneous sensor nodes and rent them to serve the end-user applications. The rent of these sensor nodes varies with *application type* and *duration* of their usage. Additionally, the rent of a sensor node depends on its QoS. However, the specification of the sensor node decides the QoS. The SLA plays a crucial role to provide the QoS of the sensor nodes to the end-user. We define two SLAs, which legally bind the sensor-owners with SCSPs and SCSPs with end-users, respectively.

***Definition* 1** *The sensor owners are enforced, through a SLA, to share the detailed specifications of their respective sensor nodes to the SCSPs, such a SLA is known as* SLA_{SS}.

***Definition* 2** *The SCSPs are enforced, through a SLA, to share correct QoS of the sensor nodes with the total payable service price of the service to the end-users, such a SLA is known as* SLA_{SE}.

The QoS of the sensor nodes is computed with the sensor node specifications, shared by the sensor owners, whereas the total payable service price of the service is derived using the service cost of SCSP, sensor node, and their QoS. SLA_{SS} and SLA_{SE} are the key enablers for providing the specifications of sensor nodes in sensor-cloud architecture. In this work, we propose a mechanism to compute the QoS and derive the total payable service price for the end-users.

Let $SO = \{SO_1, SO_2, SO_3, \cdots, SO_p\}$ denote the set of sensor owners, where $SO_i \in SO$ represents any sensor owner and $1 \le i \le p$, such that p is maximum number of sensor owner present in the set. Any SO_i leases his/her respective sensor node to the sensor-cloud architecture and receives the rent as per the usage of the sensor nodes. The sensor node, j, owned by the i^{th} sensor owner is denoted as s_j^i. Further, we define the set of sensor nodes belonging to the i^{th} sensor owner as $S^i = \{s_1^i, s_2^i, s_3^i, \cdots, s_q^i\}$. The maximum number of sensor nodes belonging to SO_i is denoted as q. In a sensor-cloud architecture, multiple SCSPs are present to provision Se-aaS to multiple end-users. Let $\mathcal{S} = \{\mathcal{S}_1, \mathcal{S}_2, \mathcal{S}_3, \cdots, \mathcal{S}_r\}$ represent the set of available SCSPs in the system. The i^{th} sensor owner is legally binded to the k^{th} SCSP with a SLA, SLA_{ss}^{ik}. Also, we define the set of end-users as $EU = \{EU_1, EU_2, EU_3, \cdots, EU_s\}$. Any SCSP, k, is legally binded with an end-user EU_l using a SLA, SLA_{SE}^{kl}. Fig. 1 depicts the architecture of QSens. Additionally, we observe that Fig. 1 possesses a set of available sensor nodes with corresponding sensor owners. Among the available sensor nodes, a set of nodes are serves the end-user application. Using QSens, we facilitate the end user to choose the available set of nodes based on the QoS and its price. Fig. 2 depicts the process flow of the proposed architecture of QSens. It shows the communications between three entities – sensor owner, SCSP and the end-user – to offer the sensor node with an optimal QoS at a minimized price.

4 QSens: The Proposed Scheme

In this Section, we discuss the statistical variable used to categorize the various sensor nodes and formulation of QoS of these nodes.

4.1 Statistical Variables for Sensor Node Specifications

SLA_{SS} enables the SCSP to receive different specifications of the sensor nodes. We compute the QoS of the sensor nodes using their respective specifications. However, depending on the types of sensor node, the specifications vary from one another. Further, we draw an analogy of the statistical variables – *dichotomous*, *continuous interval*, and *discrete ratio* [13] and map the specifications of sensor nodes to these variables.

Justification for using the statistical variables: Let there be a sensor owner (SO_i), owning a sensor node, s_j^i. The node, s_j^i consists of a set of specifications such as technology support, sensor range, processing speed, energy consumption, temperature support, ADC resolution, interface support, debug support JTAG-SWD, Minimum Energy Performance Standard (MEPS), ISO security compliance. We denote *security* and *MEPS* as dichotomous variable. Dichotomous variables are binary, i.e., they attain a value of 0 or 1. In our context, *security* and *MEPS* are either compliant or non-compliant with the sensor node. Therefore, if the sensor node is compliant with *security* and *MEPS*, we map these to the dichotomous variable with value 1; otherwise, with value 0. Similarly, the temperature of a sensor node varying within a minimum and maximum range. The minimum and the maximum temperature values are considered as range set. This minimum and sets of maximum range are brought under a predefined range of [01]. These new sets obtained contribute towards the specification, which has an interval range. We map it as continuous interval variable. The specifications such as communication technology support, sensor range, processing speed, energy consumption, ADC Resolution, interface support, debug support

JTAG-SWD are provided with a sensor node. These technologies are provided corresponding to any sensor node, which are countable in nature and possess discrete countable values. Therefore, we categorize these specifications as discrete ratio variables.

4.2 QoS Formulation

Let the sets of dichotomous, continuous interval, and discrete ratio variables of a sensor node are denoted as $\mathbb{D} = \{d_1, d_2, d_3, \cdots, d_t\}$, $\mathbb{I} = \{i_1, i_2, i_3, \cdots, i_u\}$ and $\mathbb{R} = \{r_1, r_2, r_3, \cdots, d_v\}$, respectively. We compute the QoS, $\mathcal{Q}_j$, of the j^{th} sensor node with the help of these Statistical variables. Moreover, $\mathcal{Q}_j$, depends on the effective dichotomous variable, effective continuous interval variable, and effective discrete ratio variable of sensor node, j. Therefore,

$$d_j^i = \begin{cases} 1, & \text{if a particular specification is present} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Definition 3 *The effective dichotomous variable, $\mathcal{E}_j^{\mathbb{D}}$, of a sensor node, j, is the sum of all the dichotomous variables shared by its respective owner to the k^{th} SCSP, through SLA_{ss}^{ik}.*

We compute the effective dichotomous variable $\mathcal{E}_j^{\mathbb{D}}$, as:

$$\mathcal{E}_j^{\mathbb{D}} = \sum_{i=1}^{t} d_i \tag{2}$$

The value of continuous intervals and discrete ratio variables lies in a range minimum and maximum ranges. However, the ranges of these variables are different from one another. Therefore, for both interval and ratio variables, we use *min-max normalization* technique [14] and bring them between in the range of $\{\sigma_{min}, \sigma_{max}\}$. For simplicity, we consider $\sigma_{min} = 0$ and $\sigma_{max} = 1$. Then, any m^{th} element, i_m of the set of interval variables consist of its minimum value, i_m^{min} and maximum value, i_m^{max}, respectively. Therefore, the set of interval variables is represented as $\mathbb{I} = \{(i_1^{min}, i_1^{max}), (i_2^{min}, i_2^{max}), (i_3^{min}, i_3^{max}), \cdots, (i_u^{min}, i_u^{max})\}$

Let the minimum and maximum values in set $\mathbb{I}$ are denoted as ϵ_{min} and ϵ_{max}, respectively. Therefore, $\epsilon_{min} = Min(\mathbb{I})$ and $\epsilon_{max} = Max(\mathbb{I})$.

Also, ϵ denotes any values in set $\mathbb{I}$. The min-max normalization technique for the interval variable is represented as:

$$\mathcal{M} = \left(\left(\frac{\epsilon - \epsilon_{min}}{\epsilon_{max} - \epsilon_{min}} \right) \times (\sigma_{min} - \sigma_{max}) \right) + \sigma_{max} \tag{3}$$

where $\mathcal{M}$ is the normalized value of i_m, such that $\sigma_{min} \leq \mathcal{M} \leq \sigma_{max}$. Therefore, we define the set of minimum and the maximum normalized value of the interval variables, for node j as:

$$\mathcal{I}_j^{min} = \left\{ i_{(j,1)}^{min}, i_{(j,2)}^{min}, i_{(j,3)}^{min}, \cdots, i_{(j,u)}^{min} \right\} \tag{4a}$$

$$\mathcal{I}_j^{max} = \left\{ i_{(j,1)}^{max}, i_{(j,2)}^{max}, i_{(j,3)}^{max}, \cdots, i_{(j,u)}^{max} \right\} \tag{4b}$$

We use Equation (4) to define a parameter, *effective normalized interval variable* for deriving the QoS of any sensor node.

***Definition* 4** *The effective normalized interval variable, $\mathcal{E}_j^{\mathbb{I}}$ of a sensor node, j, is the total sum of all the elements in sets $\mathcal{I}_j^{min}$ and $\mathcal{I}_j^{max}$.*
We derive the effective interval variable $\mathcal{E}_j^{\mathbb{I}}$, as:

$$\mathcal{E}_j^{\mathbb{I}} = \sum_{m=1}^{u} i_{(j,m)}^{min} + \sum_{m=1}^{u} i_{(j,m)}^{max} \tag{5}$$

The set of discrete ratio variables is denoted as $\mathbb{R} = \{r_j^1, r_j^2, r_j^3, \cdots, r_j^v\}$, such that an element r_j^i represents the number of supporting technologies for a particular variable by a sensor node, j.

***Definition* 5** *The effective ratio variable, $\mathcal{E}_j^{\mathbb{R}}$ of a sensor node, j, is the total sum of all the elements in set $\mathbb{R}$.*
The effective ratio variable is derived $\mathcal{E}_j^{\mathbb{R}}$ as:

$$\mathcal{E}_j^{\mathbb{R}} = \sum_{p=1}^{v} r_j^p \tag{6}$$

We derive the QoS, $\mathcal{Q}_j$, of a sensor node, j using Equations (2), (5), and (6). On the other hand, energy consumption is a crucial factor for a sensor node. Let the maximum energy consumption of any sensor node, among the available ones, be E_{max}. Therefore the effective energy consumption, E_{eff}, of the j^{th} sensor node is computed as $E^{eff} = \frac{E_j}{E_{max}}$.

Also, we consider the effective energy, E_j, of the j^{th} sensor node for determining its $\mathcal{Q}_j$ as:

$$\mathcal{Q}_j = \frac{(\mathcal{E}_j^{\mathbb{D}} + \mathcal{E}_j^{\mathbb{I}} + \mathcal{E}_j^{\mathbb{R}})}{E^{eff}} \tag{7}$$

Similarly, we calculate the QoS of all the sensor nodes, available with the SCSP for certain application. The price of the j^{th} sensor node is denoted as, p_j, which depends on the QoS. Further, the effective energy, E^{eff} of a sensor node, j, influences the QoS, $\mathcal{Q}_j$. However, $\mathcal{Q}_j$ must not dominate the total price, $\mathcal{P}_j$. Therefore, the total service price of the j^{th} sensor node is mathematically represented as $\mathcal{P}_j^S = \{\mathcal{Q}_j\}^{1/\gamma} \times p_j$, where γ is a scaling factor with a positive constant value.

In Equation (7), we notice that the effective energy E^{eff} influences the QoS of the sensor node. Let a value of effective energy be denoted as $\mathcal{Y}$. The value of $\mathcal{Y}$ affects the QoS, $\mathcal{Q}_j$. We say that $\mathcal{Y}$ can affect the QoS as:

$$(\mathcal{Q}_j) > 1, \exists, \textit{if } \{E^{eff} > \mathcal{Y}\} \quad (\mathcal{Q}_j) \leq 1, \exists, \textit{if } \{E^{eff} < \mathcal{Y}\} \tag{8}$$

***Proposition* 1** *If n is the number of sensor nodes and the total effective energy of these nodes denoted as E_j^{eff}, then*

$$\sum_{j=1}^{n}(\mathcal{Q}_j) \geq \left\{\frac{n}{\sum_{j=1}^{n}\mathcal{Y}}\right\} \tag{9}$$

Justification: Let us assume that,

$$\sum_{j=1}^{n}\mathcal{Q}_j < \frac{n}{\sum_{j=1}^{n}E_j^{eff}} \tag{10}$$

Also, we observe that $0 < E_j^{eff} \leq 1$. On the other hand, from Equation (7) we get:

$$\sum_{j=1}^{n}\mathcal{Q}_j = \sum_{j=1}^{n}\frac{(\mathcal{E}_j^{\mathbb{D}} + \mathcal{E}_j^{\mathbb{I}} + \mathcal{E}_j^{\mathbb{R}})}{E_j^{eff}} \tag{11}$$

Therefore, from Equations (10) and (11), we obtain:

$$\sum_{j=1}^{n}\frac{(\mathcal{E}_j^{\mathbb{D}} + \mathcal{E}_j^{\mathbb{I}} + \mathcal{E}_j^{\mathbb{R}})}{E_j^{eff}} < \frac{n}{\sum_{j=1}^{n}E_j^{eff}} \tag{12}$$

The maximum possible effective energy, E_j^{eff} for all the nodes are 1. Therefore, the maximum value of R.H.S. in Equation (12) gives 1. On the other hand, the minimum value of L.H.S. is 1, which infer a contradiction to our assumption, as mentioned in Equation (10). This concludes the justification of the proposition.

Further, the SCSP charges a certain amount from the end-users, which includes the maintenance charges of the sensor-cloud infrastructure for offering the Se-aaS, considering per unit price of the sensor node and the price charged by the sensor owner. We denote the charge of SCSP as $\mathcal{P}^{SCSP}$. Price, p_j, of the j^{th} sensor node consists of a maximum value, p_j^{max}. Similarly, maximum service price of the j^{th} sensor node is, $P_j^{SCSPmax}$. Thus,

$$\forall j \in \{j = 1, \cdots, n\} \ \exists \ \mathcal{P}_j^{SCSP} \leq P_j^{SCSPmax} \tag{13a}$$

$$\forall j \in \{j = 1, \cdots, n\} \ \exists \ p_j \leq p_j^{max} \tag{13b}$$

Further, the total payable service price, $\mathbb{P}$, to an end-user for the j^{th} sensor node is represented as: $\mathbb{P} = \mathcal{P}_j^{SCSP} + \mathcal{P}_j^{S}$. We compute the total payable service price, $\mathbb{P}_{tot}$, for a set of sensor nodes, which are eligible to serve the application, as:

$$\mathbb{P}_{tot} = \sum_{j=1}^{n}\mathcal{P}_{SCSP_j} + \sum_{j=1}^{n}\left\{(\mathcal{Q}_j)^{1/\gamma} \times p_j\right\} \tag{14}$$

The main aim of QSens is to minimize $\mathbb{P}_{tot}$, while obtaining an optimal QoS. In order to achieve the minimum payable service price, we use $argmin\mathbb{P}_{tot}$, for an optimal value of total QoS, $\mathcal{Q}$. Therefore, we represent Equation (14) as:

$$\underset{\mathcal{Q}}{argmin}\left(\sum_{j=1}^{n}\mathcal{P}_{SCSP_j} + \sum_{j=1}^{n}\left\{(\mathcal{Q}_j)^{1/\gamma} \times p_j\right\}\right) \tag{15}$$

Theorem 1. *The proposed function in Equation (14) is convex, iff for each payable service price, $\mathbb{P}^1_{tot}$, $\mathbb{P}^2_{tot} \in Z$, where Z is a non-empty open convex set.*

Proof. Two service prices are denoted as $\mathbb{P}^1_{tot}$ and $\mathbb{P}^2_{tot}$, such that:

$$\mathbb{P}^1_{tot} = \sum_{j=1}^{n} \mathcal{P}^1_{SCSP_j} + \sum_{j=1}^{n} \{(\mathcal{Q}^1_j)^{1/\gamma} \times p^1_j\} \text{and} \mathbb{P}^2_{tot} = \sum_{j=1}^{n} \mathcal{P}^2_{SCSP_j} + \sum_{j=1}^{n} \{(\mathcal{Q}^2_j)^{1/\gamma} \times p^2_j\} \tag{16}$$

The respective first order partial derivatives of $\mathbb{P}^1_{tot}$ with respect to $\mathcal{Q}^{tot,1}$ is:

$$\frac{\partial \mathbb{P}^1_{tot}}{\partial(\mathcal{Q}^{tot,1})} = \{\frac{1}{\gamma}(\mathcal{Q}^{tot,1})^{\frac{1-\gamma}{\gamma}} \times \sum_{j=1}^{n} p^1_j\} \tag{17}$$

where, $\sum_{j=1}^{n} \mathcal{Q}^1_j = Q^{tot,1}$. Similarly, we obtain the first order partial derivative of $\mathbb{P}^2_{tot}$. From Equation (17), we obtain:

$$\left[\frac{\partial \mathbb{P}^1_{tot}}{\partial(\mathcal{Q}^{tot,1})} - \frac{\partial \mathbb{P}^2_{tot}}{\partial(\mathcal{Q}^{tot,2})}\right]\left(\mathcal{Q}^{tot,1} - \mathcal{Q}^{tot,2}\right) \geq 0 \tag{18}$$

Therefore, from Equation (17), we infer that Equation (14) is convex [5].

***Corollary* 1** *If the function for payable service price, in Equation (14), $\mathbb{P}_{tot}$, is convex, then the function attains a minimum value.*

Proof. In Theorem 1, we proved that the function derived in Equation (14) is convex. We apply the second order partial derivatives on Equations (17) to attain minimum $\mathbb{P}^1_{tot}$. Therefore, we obtain partial derivative of $\mathbb{P}^1_{tot}$, as:

$$\frac{\partial^2 \mathbb{P}^1_{tot}}{\partial^2(\mathcal{Q}^{tot})} = \left\{\frac{1}{\gamma} \times \frac{1-\gamma}{\gamma}(\mathcal{Q}^{tot})^{\frac{1-\gamma}{\gamma}-1} \times \sum_{j=1}^{n} p_j\right\} \tag{19}$$

Further, Equation (19) is equated to 0 and we get:

$$\frac{1}{\gamma} \times \frac{(1-\gamma)}{\gamma} \times ((Q^{tot})^{\frac{1}{\gamma}-1-1}) \times \sum_{j=1}^{n} p_j = 0 \tag{20}$$

As the value of γ is positive, $\mathcal{Q}^{tot} > 0$, and $p_j > 0$, Equation (20) gives us a positive value. Therefore, we conclude that $\mathbb{P}_{tot}$ attain a minimum value.

We apply the *Langragian multiplier* technique [4] on Equation (15), using Equations (9) and (13):

$$L_j = \left\{\sum_{j=1}^{n} \mathcal{P}^{SCSP}_j + \sum_{j=1}^{n}((\mathcal{Q}_j)^{1/\gamma}) \times \sum_{j=1}^{n} p_j - \mu_1(P^{SCSPmax}_j - P^{SCSP}_j) - \mu_2(p^{max}_j - p_j) \right.$$
$$\left. + \mu_3[\,(\frac{n}{\mathcal{Y}}) - (\sum_{j=1}^{n}(\mathcal{Q}_j)^{1/\gamma})]\right\} \tag{21}$$

Further, we apply the *Karush-Kuhn-Tucker* (*KKT*) [5] conditions to solve Equation (21). We obtain the *dual feasibility* and *complementary slackness* conditions as follows:

$$\mu_i \geq 0, \forall i = \{1,2,3\} \text{ and } \mu_i X_i = 0 \tag{22}$$

where X_i are the constraints as mentioned in Equations (9) and (13). To obtain the optimal value of Q^{tot}, we use partial derivative on Equation (21) with respect to Q^{tot} and equate to 0. Therefore,

$$\frac{\partial L_i}{\partial Q^{tot}} = \frac{1}{\gamma} \times ((Q^{tot})^{\frac{1}{\gamma}-1}) \times \sum_{j=1}^{n} p_j - \mu_3 \text{and} \frac{1}{\gamma} \times ((Q^{tot})^{\frac{1}{\gamma}-1}) \times \sum_{j=1}^{n} p_j - \mu_3 = 0 \tag{23}$$

Theorem 2. *The function proposed by in Equation (23) is convex and attains a minimum on domain Z.*

Proof. Let the variables of function, $f(x)$, be in domain Z, which are subset of real numbers R^n, and is twice differentiable over a domain, Z. We say that function f is convex, if its double differentiation, $f^{''}(x) > 0, \forall x \in Z$. Equation (23) represents *Langragian* function, the variable of the function are real numbers and are in domain Z. We apply double differentiation on Equation (23) and obtain:

$$\frac{\partial^2 L_i}{\partial^2 Q^{tot}} = \frac{1}{\gamma} \times \frac{(1-\gamma)}{\gamma} \times ((Q^{tot})^{\frac{1}{\gamma}-1-1}) \times \sum_{j=1}^{n} p_j \tag{24}$$

From, Equation (24) as we know that our domain Z conditions are γ is positive, $((Q^{tot})^{\frac{1}{\gamma}-1-1}) > 0$ and $\sum_{j=1}^{n} p_j > 0$. The double differentiation on the Langrangian function gives a positive value and therefore, the function is convex.

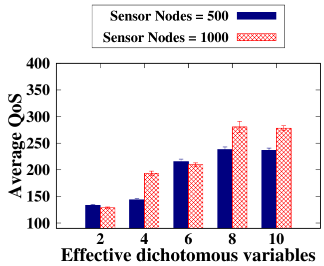
Finally, we obtained optimal $(Q^{tot})^*$, as:

$$(Q^{tot})^* = (\frac{\mu_3 \times \gamma}{\sum_{j=1}^{n} p_j})^{\frac{\gamma}{1-\gamma}} \tag{25}$$

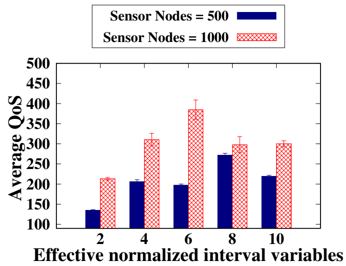
The multiple sets of sensor nodes are able to participate in serving an end-user application. However, the service charge depends on the quality of the sensor nodes. Therefore, the SCSP offers an optimal QoS for the sets of sensor node with the corresponding total payable service price to the end-users. Further, as per the requirement, the end-user selects one of the sets of sensor nodes, depending on the optimal QoS and total payable service price among the available ones.

5 Performance Analysis

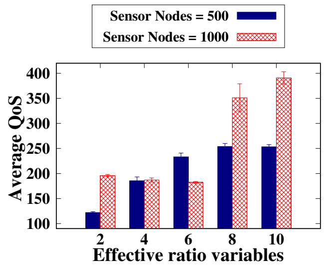
In this Section, we analyze the performance of our proposed scheme, QSens, with a detailed explanation of the results. In order to simulate the performance



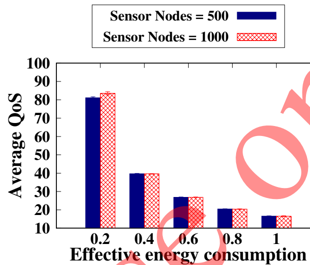
(a) Dichotomous variables



(b) Interval variables

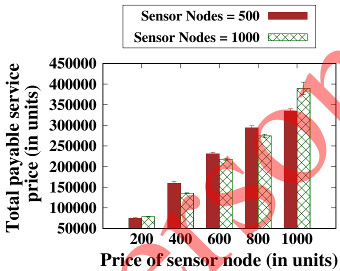


(c) Ratio variables

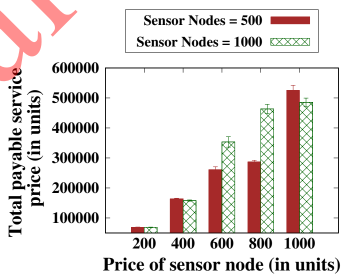


(d) Energy

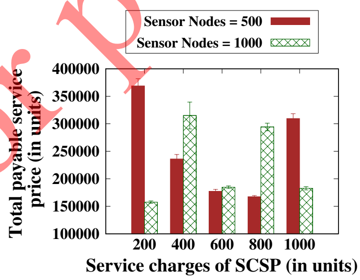
Fig. 3: Change in QoS



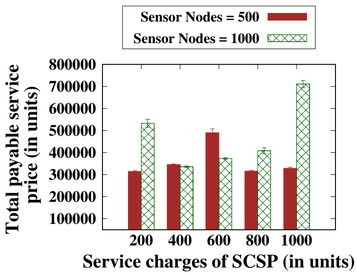
(a) Service price of SCSP = 500



(b) Service price of SCSP = 1000



(c) Price of sensor nodes = 500



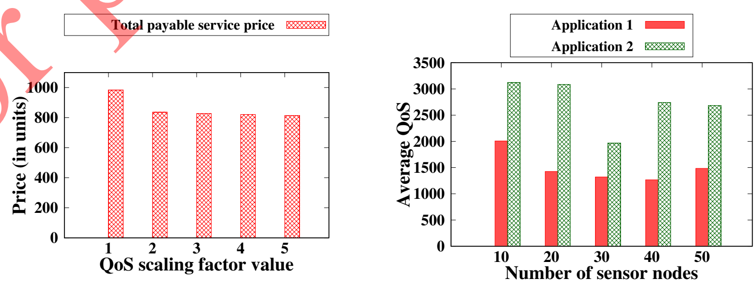
(d) Price of sensor nodes = 1000

Fig. 4: Change in total payable service price

Table 1: Simulation Parameters

Parameter	Value
Number of sensor nodes	100-1000
Deployment	Uniform random
Effective dichotomous variables ($\mathcal{E}^{\mathbb{D}}$)	0-10
Effective normalized interval variable ($\mathcal{E}^{\mathbb{I}}$)	0-10
Effective ratio variable ($\mathcal{E}^{\mathbb{R}}$)	1-10
Effective energy (E^{eff})	0-1
Scaling factor (γ)	1-5
Price for sensor nodes	200-1000
Service charges for SCSP	200-1000

of QSens, we consider the presence of $100-1000$ sensor nodes with a simulation area of $10 \times 10\ km^2$. The value of different simulation parameters are listed in Table 1. Fig. 3 represents the change in the value of QoS with the variations of different parameters such as $\mathcal{E}^{\mathbb{D}}$, $\mathcal{E}^{\mathbb{I}}$, $\mathcal{E}^{\mathbb{R}}$, and E^{eff}. Fig. 3(a) depicts the effect on QoS for increasing value of the dichotomous variables from 2 to 10. We observe that the general trend of the plot is increasing with the increase in the number of dichotomous variables. However, we also observe that the average QoS does not depend on the variation of the number of sensor nodes. Similarly, Fig. 3(b) depicts the variations in the QoS with a change in effective interval variables. Interestingly, we observe that the average QoS is lesser, when the total number of sensor nodes is 500, than that in the presence of 1000 nodes. We observe in Fig. 3(c) that with the increasing value of the effective ratio variables, the general trend of QoS is increasing. However, the presence of the number of nodes in the network does not affect the variations of QoS. We also evaluate the variations in the QoS with the change in effective energy consumption. In Fig. 3(d) we notice a smooth decreasing pattern in the QoS with increasing value of effective energy consumption. We also observed for all the values of effective energy consumption that the average QoS value is higher when the total number of nodes in the network is 1000 as compared to that of 500. We also examine



(a) Price with scaling factor value (b) QoS with number of nodes

Fig. 5: Change in pricing and average QoS

the total payable service price for an end-user in Fig. 4. Fig. 4(a) depicts the variations in the total payable service price with the price of the sensor nodes (p^j), considering the price of SCSP as 500 units. In this figure, we observe an increasing trend in the total payable service price with the increment in the price of the sensor nodes in the presence of 500 and 1000 sensor nodes. Similarly, in Fig. 4(b), we consider the price of the SCSP as 1000 and evaluate the effect on the total payable service price. In this figure, we notice an increasing trend in the total payable service price with the increment of price of the sensor node from 200-1000. From Figs. 4(a) and 4(b), we infer that the total payable service price increases with the increase of the price of the sensor nodes, irrespective of the number of sensor nodes present in the network. We also evaluate the effect on total payable service price with the variation in the service charges of SCSP as depicted in Figs. 4(c) and 4(c). In Fig. 4(c), we vary the service charges of the SCSP from 200-1000 units and the price of the sensor nodes is fixed at 500 units. Similarly, Fig. 4(d) depicts the variations in the total payable service price with the increasing value of service charges of the SCSP from 200-1000 and the price of the sensor nodes is fixed at 1000 units. However, in both the Figs. 4(c) and 4(d), we do not find any specific standard trend in the plots. Therefore, we infer that the price of the sensor nodes has the primary effects on the total payable service price.

In Equation (15), we use a variable γ as a scaling factor, which has significant effect on the total payable service price. Therefore, we analyze the variations in the total payable service price with change in the value of γ, as shown in Fig. 5(a). For this analysis, we consider the presence of 200 nodes in the network. We observe that when the value of γ is 1, the total payable service price attains the maximum value and decreases with the increasing value of γ. Fig. 5(b) depicts the change in average QoS with the number of nodes in the networks in the presence of two applications. For this evaluation, we fixed the number of nodes to be 4 and 6 for the applications 1 and 2, respectively. We observe the average QoS of application 2 is higher as compared application 1. Therefore, we infer that the average QoS also depends on the total number of nodes used in an application.

6 Conclusion

In this work, we introduced the concept of SLAs for the sensor-cloud architecture for selecting a set of sensor nodes by the end-users. These SLAs provision the end-users to access the QoS of all the available sets of sensor nodes, which are suitable to serve an end-user application. We also designed a scheme, QSens, which enables the end-users to select a suitable set of sensor nodes, based on the optimal QoS and the total payable service price, for serving their applications.

In future, we plan to extend the work by proposing a scheme for the QoS-based optimal resource allocation in sensor-cloud architecture and include as a component of SLA_{SS}. Further, we plan to design a data authentication scheme for the sensor-cloud architecture and include the same in SLA_{SE}.

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