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Energy-Efficient Data Transmission in Sensor-Cloud

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***Abstract*—Sensor-cloud has been perceived as a potential paradigm for executing wireless sensor based applications. In sensor-cloud, the underlying sensor network is highly heterogeneous in terms of the hardware, sensing and communication ability, and other configuration issues. Thus, the transmission from the underlying networks to the cloud is challenging and induces research interest. The underlying physical sensor nodes for a virtual sensor network (VSN) that transmit the data through a set of intermediate nodes, namely, the bridge nodes to the cloud. This work focuses on obtaining an optimal decision rule to select a bridge node on behalf of a VSN. The work achieves the reduce energy consumption of every node which, in turn, improves the energy expenditure of the entire VSN.**

***Index Terms*—Sensor-cloud, Wireless Sensor Network (WSN), Energy efficiency, Virtual Sensor Network (VSN)**

I. Background

Recent research has exposed the limitations of traditional Wireless Sensor Networks (WSNs) [1]–[3]. So far WSN-centric research has explored issues related to sensor data management namely, routing [4], localization [5], power management [6], synchronization [7], [8], and many more. However, none of the works address the issues of sensor system management. Of late, *sensor-cloud infrastructure* is being viewed as a potential substitute of traditional WSNs [9], [10]. Sensor-cloud infrastructure is primarily a sensor-management platform that functions as an interface between the physical and cyber world [9]. Such infrastructure virtualizes the physical resources (the physical sensor nodes) within the cloud platform and renders *Sensor-as-a-Serice (Se-aaS)* to the end-users. Thus, this new technology allows the end-users to envision the sensor nodes as a service, rather than as a typical hardware. Hence, the present-day research suggests a shift of technology from the traditional WSNs to sensor-cloud [11]–[13].

All of the very few works, as of now, that focus on sensor-cloud, primarily emphasizes on the dogma and challenges of sensor-cloud. The existing works illustrate the possible working model of sensor-cloud and enlist the opportunities and challenges that are involved in implementing the infrastructure. However, the technical establishments and developments in this domain is still unexplored from an implementation point of view. In this paper, we primarily focus on the physical topology and the data transmission aspects of sensor-cloud from the physical sensor nodes. In a nutshell, the goal of our work is as follows:

(i) To introduce a hierarchy of physical sensor nodes serving as intermediate hops during data transmission.
(ii) To ensure efficiency in the process of data transmission, in terms of energy, and cost-effectiveness.

A. Motivation

As previously mentioned, research has not been initiated in the networking aspects of sensor-cloud infrastructure. The underlying physical networks of sensor-cloud are absolutely heterogeneous in their features and functionalities. Unlike traditional WSNs that primarily exhibit heterogeneity in sensing, and communication abilities, or battery life of the physical sensor nodes [14]–[16], the nodes within sensor-cloud also differ in terms of hardware types and configurations. Thus, data transmission, and routing under this acute heterogeneity is highly challenging. Also traditional WSNs generally assume each sensor node to be directly within the communication range of another sensor node (of the same type) i.e., atleast one of the adjacent nodes of a particular node can serve the same application. However, the underlying physical sensor nodes, serving a particular application in a sensor-cloud platform, may not be within direct reach of each other, leading to the formation of virtual sensor networks (VSNs) [17]. However, data transmission and routing aspects of VSNs are also unexplored in current research.

From the goal of the proposed work, apparently, it might appear that the problem of intermediate hop selection is already explored for the traditional WSNs. Such prior work mostly assume the nodes to be "infallible" in nature, i.e., the nodes do not have the tendency to be erroneous. Thus, if one or more nodes report the sensed data, wrongly, these work may wrongly select the hop nodes. The proposed work is sensitive to software, or hardware "fallibility" of nodes. In VSNs, when some decisions are taken involving the member nodes of the network, every member node expresses its opinion in the form of data packets, which are aggregated to infer the decision of the network. As the opinions of the individual nodes vary, the overall decision of the network is also affected. In practical scenarios, the physical sensor nodes are programmed to obey certain algorithms. However, due to external factors associated with the physical environment, a node may function erroneously while sensing, or processing. This "fallible" nature of a node can significantly create an impact on the overall decision of the network. This work is highly motivated by this intrinsic property of physical nodes.

B. Contribution

The primary contribution of this work is that, it is one of the earliest in this domain. The work contributes to design a multi-hop data transmission scheme from the physical sensor networks to the sensor-cloud. The main contributions of the work are hereby enlisted.

i) This work addresses the problem of multi-hop data transmission in from VSNs to sensor-cloud. The work proposes a solution that complies with the overall network heterogeneity.
ii) The proposed solution is energy efficient as it optimizes the cumulative energy consumption of a VSN while selection or deselection of a bridge node.
iii) The work obtains the optimal decision rule that eventually maximizes the expected payoff of a VSN in terms of energy consumption thereby, selecting the optimal bridge node.
iii) The work considers a realistic nature of a physical node - fallibility in decision making. The decision making skill of a node is probabilistically quantified in this paper to account for the inaccuracy or the error in the computing ability of the node.

II. System Architecture

This Section highlights the overall network architecture of sensor-cloud infrastructure. As shown in Fig. 1, the underlying physical network consists of heterogeneous sensor nodes owned by different sensor-owners [10], As per the end-user demand, the appropriate physical sensor nodes are scheduled for data sensing and transmission. The set of physical sensor nodes that are involved in data provisioning for a particular application at a particular time, together constitute a virtual sensor. The aggregated sensed information from different virtual sensors are directly transmitted to the respective end-users, over the Internet.

The physical network of sensor-cloud consists of subsets of homogeneous types of sensor nodes serving different applications (e.g., rainfall monitoring, temperature monitoring, target tracking, and so on), thereby forming a heterogeneous network. In such heterogeneous platform, several network issues arises during the process of data transmission, from the physical networks to the cloud. The sensor nodes serving an application may not be always adjacent to each other. Thus, data from one node of an application is transmitted with the help of another node of another application, thereby forming a VSN [18], [19].

This work focuses on a problem scenario in which multiple heterogeneous VSNs are formed within the underlying physical layer of sensor-cloud. In such a scenario, the data from every sensor node is routed separately in a multi-hop manner to reach the cloud end [19], [20]. However, this incurs significant consumption of network resources (in terms of power consumption, node lifetime, and network lifetime), and causes overhead. With a view to improve the network performance, we propose to select a subset of these nodes instead, that collect the data from the individual VSNs, and route it to the sensor-cloud. We call these nodes as "bridge" nodes, as they essentially function as a bridge by connecting the physical nodes to the cloud. To improve the network performance, there can be a hierarchical selection of bridge nodes to form a smaller subset of bridge nodes. Fig. 2 illustrates the projected view of the proposed data transmission procedure from VSNs to sensor-cloud, for a two-hop scenario.

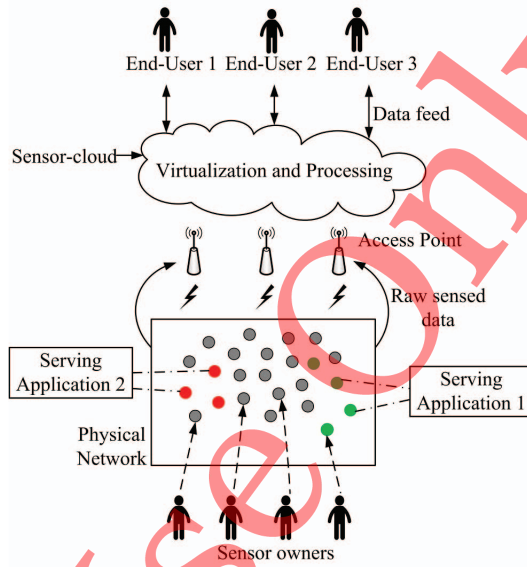

Fig. 1: Network architecture of Sensor-cloud

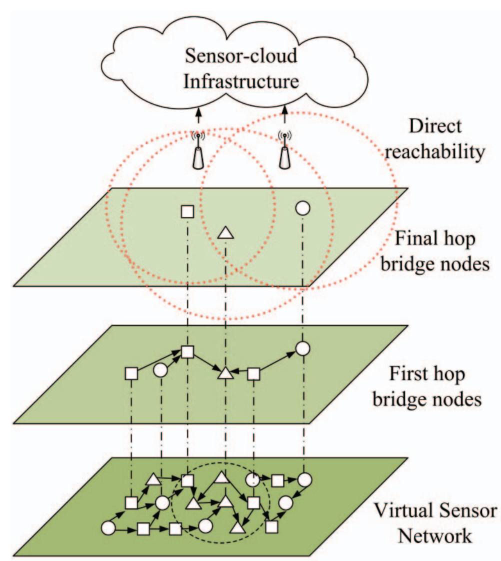

Fig. 2: Projection of a two-hop scenario for data transmission from multiple VSNs

III. Formal Definition of the Problem

We consider n number of physical sensor nodes, registered within the sensor-cloud infrastructure. We form a VSN by grouping a subset of these nodes that represent a virtual sensor, serving a particular application, for a particular end-user. We formally define the components of our system as,

- $S = \{s_1, s_2, ..., s_n\}$, represents the set of available physical sensor nodes.
- $V = \{\nu_{k,u_j}\}, 1 \leq k \leq 2^n$, where V represents the set of VSNs. ν_{k,u_j} represents the k^{th} VSN of end-user u_j.
- ξ_{ij} is the Euclidean distance between s_i and s_j.
- E_{elect} represents the energy dissipated due to transmitter or receiver circuitry.
- ϵ_{amp} represents the energy dissipated due to transmission of amplifier.
- m_i is the message transmission rate of s_i.
- r_i is the duration of the i^{th} round.
- E_{ij} is the energy loss of s_i for the j^{th} round.

The objective of this work is to select or choose the sensor node that will function as the intermediate hop for a VSN at a particular round. Such a node is denoted as *Bridge Node*, hereafter. We initially create a set, $BN = \{b_1, b_2, ..., b_m\}, m \ll n$, comprising of potential bridge nodes. A member of BN finally emerges as the Winner Bridge Node (WBN). Thus, mathematically, we define the objective as a mapping function $f : V \rightarrow BN$, that maps each virtual sensor network to a bridge node. f minimizes the total power consumption of the VSN. For a particular $\nu_k \in V$, f belongs to the solution set of the minimization function,

$$\arg\min \sum_{\forall s_i \in \nu_k} E_{ij} \tag{1}$$

$$\text{where, } E_{ij} = m_i r_j E_{i,elect} + m_i \xi_{ij}^2 \epsilon_{i,amp} \tag{2}$$

IV. System Model

Motivated by the *Optimal Decision Rule*, as illustrated in [21], we consider the "general pairwise choice framework" implemented over a VSN, ν. Every member of ν select or deselect each bridge node $b_i, 1 \leq i \leq m$, to be the WBN at the next time instant. Considering the *Optimal Decision Rule*, every bridge node can be within two possible states of nature – good (+1) and bad (–1). The payoff obtained from the approval (or disapproval) of a good (or bad) bridge node is denoted by $\mathcal{P}(1 : -1)$ (or $\mathcal{P}(-1 : 1)$).

Let us assume that the VSN ν consists of n' number of physical nodes, out of which m' nodes are eligible as bridge nodes, $m \ll n$. As per the *Optimal Decision Rule*, each of the $s_i, 1 \leq i \leq n'$, prepares a decision for approval or disapproval of every $b_j, 1 \leq j \leq m'$. The approval for a nominated bridge node b_j is based on the average distance ($\xi_{avg}^{b_j}$) of the node from the other nodes of the VSN. Thus, for all b_j, we have,

$$\xi_{avg}^{b_j} = \frac{\sum_{\forall s_i \in \nu} \xi_{ij}}{n' - m'}, s_i \notin BN, b_j \in \nu \tag{3}$$

Now, $X_{ij}(t) = \{1, -1\}$ is the decision outcome of node i, for a bridge node j, at time t. $X_{ij}(t)$ is modeled as,

$$X_{ij}(t) = \begin{cases} 1, & \xi(ij) \leq \xi_{norm}, \forall s_i \in \nu, b_j \in (BN \cap \nu) \\ -1, & \text{otherwise} \end{cases} \tag{4}$$

$$\text{where } \xi_{norm} = \frac{\sum_{1 \leq j \leq m'} \xi_{avg}^{b_j}}{m'} \tag{5}$$

Thus the decision profile of a ν, at time t, is indicated by $X_\nu(t)$. Since we are currently dealing with a single VSN, $X_\nu(t)$ will be called by $X(t)$ for the sake of simplicity. Thus, every physical sensor node of ν approves or disapproves a "good" or "bad" bridge node.

Definition 1. The *events* of our model are:

(i) $W_1^i = \{1, -1\}$: Approving or disapproving a bridge node by a physical node s_i.
(i) $W_2^j = \{1, -1\}$: A bridge node, b_j, appearing as a "good" or "bad".

The *correct* decision making ability of a physical sensor node s_i, is denoted by $P(1 : 1)$, and is expressed as,

$$P(1 : 1) = P(W_1^i = 1 \mid W_2^j = 1) \tag{6}$$

$$P(-1 : -1) = P(W_1^i = -1 \mid W_2^j = -1) \tag{7}$$

Now, we formally define a "good" and a "bad" bridge node.

Definition 2. A bridge node b_j is "good" if the total number of positive votes for the node exceeds a pre-negotiated threshold ($X_{threshold}$). The "goodness" of b_j is proportional to the residual energy of the node and is cumulatively evaluated over k instants of time, and holds true (at time t), if,

$$\left(\sum_{k \leq t' \leq t} \sum_{\forall s_i \in (\nu - BN_\nu^{t'})} X_{ij}^{t'} = 1 \right) \geq X_{threshold}, k \geq 1 \tag{8}$$

Thus, "goodness" of a node is expressed as,

$$\mathcal{G}(b_j) = \frac{E_{b_j}^{t'}}{E_{b_j}^{t_0}} (X_c - X_{threshold}) \tag{9}$$

X_c is substituted for $\left(\sum_{k \leq t' \leq t} \sum_{\forall s_i \in (\nu - BN_\nu^{t'})} X_{ij}^{t'} = 1 \right)$, and $E_{b_j}^t$ is the energy level of b_j, at time t. k is also system-modeled pre-negotiated value, and $BN_\nu^{t'}$ is the set of nominated bridge nodes of VSN ν at time t'. As every bridge node has two possible states of nature, a bridge node is "bad", if it is not "good" i.e., when $X_c = \left(\sum_{k \leq t' \leq t} \sum_{\forall s_i \in (\nu - BN_\nu^{t'})} X_{ij}^{t'} = 1 \right) < X_{threshold}$. "Badness" is expressed as,

$$\bar{\mathcal{G}}(b_j) = \frac{E_{b_j}^{t'}}{E_{b_j}^{t_0}} (X_c - X_{threshold}) \tag{10}$$

Evidently, $\bar{\mathcal{G}}(b_j)$ is a negative quantity. We now model the heterogeneous decision making ability of a sensor node s_i ($P(1, 1)$, and $P(-1, -1)$). For this purpose, it is necessary to model the apriori proportion of "good" bridge nodes, α_t. This is calculated from the previous values of α for the last k instants of time. However, when $1 \leq t \leq k$, the value of α depends on the ratio of the number of bridge nodes that were positively voted to the total number of bridge nodes. The value is calculated from the current tine instant till t_0, to enforce the effect of learning the proportion of "good" bridge nodes, with time. Thus, for the first k instants of time, we follow a learning mechanism to estimate α_t, also represented by $\mathcal{L}_t$ or $\hat{\alpha}_t$. Thus, we have,

$$\mathcal{L}_t = \hat{\alpha}_t = \frac{\left|\sum_{k \le t' \le t} \sum_{\forall s_i \in (\nu - BN_\nu^{t'})} X_{ij}^{t'} = 1 \ge X_{threshold}\right|}{|BN_\nu^{t_0}| + |BN_\nu^{t_1}| + ... + |BN_\nu^{t}|} \tag{11}$$

The value of $(X_{ij}+1)! - 1$ simply turns out to be 1 for a positive vote of s_i for b_j, and turns out to be 0 for a negative vote. Thus the numerator of Equation (11) returns the total number of positively voted bridge nodes by every member of ν, at different instants of time. The reliability of computation of α can be increased with the increase in the value of k. Therefore, we have,

$$\hat{\alpha}_t = \begin{cases} \frac{\left|\sum_{k \le t' \le t} \sum_{\forall s_i \in (\nu - BN_\nu^{t'})} X_{ij}^{t'} = 1 \ge X_{threshold}\right|}{|BN_\nu^{t-1}| + |BN_\nu^{t-2}| + ... + |BN_\nu^{k}|}, & t > k \\ \mathcal{L}_t, & 1 \le t \le k \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

Now, the estimated probability of approving any bridge node irrespective of its being "good" or "bad", by node i, at time t, is expressed as the mean of the number of positively voted bridge nodes by node i, over the last k instants of time. However, at time $t = 0$, the node is yet to build it decision ability, and therefore we assume a 50% chance of the node to make a correct decision. Thus, we obtain,

$$\hat{P}(W_1^i = 1) = \begin{cases} \frac{\sum_{k \le t' \le t} \sum_{j \in BN_\nu^{t'}} (X_{ij}=1)}{|BN_\nu^{t-1}| + |BN_\nu^{t-2}| + ... + |BN_\nu^{k}|}, & t > k \\ \frac{\sum_{1 \le t' \le t} \sum_{j \in BN \cap \nu} (X_{ij}=1)}{|BN_\nu^{t_1}| + |BN_\nu^{t_2}| + ... + |BN_\nu^{t}|}, & 1 \le t \le k \\ 0.5, & \text{otherwise} \end{cases} \tag{13}$$

$$\hat{P}(W_1^i = -1) = \begin{cases} \frac{\sum_{k \le t' \le t} \sum_{j \in BN_\nu^{t'}} (X_{ij}=-1)}{|BN_\nu^{t-1}| + |BN_\nu^{t-2}| + ... + |BN_\nu^{k}|}, & t > k \\ \frac{\sum_{1 \le t' \le t} \sum_{j \in BN \cap \nu} (X_{ij}=-1)}{|BN_\nu^{t_1}| + |BN_\nu^{t_2}| + ... + |BN_\nu^{t}|}, & 1 \le t \le k \\ 0.5, & \text{otherwise} \end{cases} \tag{14}$$

Having estimated α_t, $P(W_1^i = 1)$, and $P(W_1^i = -1)$, $P(1,1)$, and $P(-1,-1)$ can be simply obtained using Bayesian classification [22], [23]. $P(-1,1)$, and $P(1,-1)$ are computed as the compliments of $P(1,1)$, and $P(-1,-1)$, respectively.

Definition 3. The decision profile of the VSN, for a particular bridge node b_j, is defined as,

$$\mathcal{D}_{b_j} = \{X_{ij}\}, \forall s_i \in S \tag{15}$$

$$\mathcal{D}_{b_j} \in D = \{1, -1\}^{n'} \tag{16}$$

The decision of the VSN for b_j is the outcome of the aggregation rule $f : \mathcal{D}_{b_j} \to \{1, -1\}$. Thus, every decision profile can be partitioned into $A^+(\mathcal{D}_{b_j})$ and $A^-(\mathcal{D}_{b_j})$, where $A^+(\mathcal{D}_{b_j}) = \{s_i \mid X_{ij} = 1\}$, and $A^-(\mathcal{D}_{b_j}) = \{s_i \mid X_{ij} = -1\}$. $A^+(\mathcal{D}_{b_j}) \bigcup A^-(\mathcal{D}_{b_j}) = \mathcal{D}_{b_j}$. Under a particular decision rule f, we also partition the set of all possible decision profiles into two disjoint sets $\mathcal{D}_{b_j}^{f+}$ and $\mathcal{D}_{b_j}^{f-}$, such that,

$$\mathcal{D}_{b_j}^{f+} = \{\mathcal{D}_{b_k}, f(\mathcal{D}_{b_k}) = 1\} \tag{17}$$

$$\mathcal{D}_{b_j}^{f-} = \{\mathcal{D}_{b_k}, f(\mathcal{D}_{b_k}) = -1\} \tag{18}$$

$\mathcal{D}_{b_j}^{f+} + \mathcal{D}_{b_j}^{f-} = D$. Now, given a bridge node is good or bad, the VSN approves or disapproves the node, for a particular decision profile, with probability $h(1:1)$, and $h(-1:-1)$, respectively. Thus we have,

$$h(1:1) = \prod_{s_i \in A^+(\mathcal{D}_{b_j})} P(1,1) \prod_{s_i \in A^-(\mathcal{D}_{b_j})} (1 - P(1,1)) \tag{19}$$

$$h(-1:-1) = \prod_{s_i \in A^-(\mathcal{D}_{b_j})} P(-1,-1) \prod_{s_i \in A^+(\mathcal{D}_{b_j})} (1 - P(-1,-1)) \tag{20}$$

Now, for a given decision rule f, the VSN approves a good bridge node and disapproves a bad bridge node with probabilities $\Omega_j(1:1) = P(\mathcal{D}_{b_j} \in \mathcal{D}_{b_j}^{f+} : 1)$, and $\Omega_j(-1:-1) = P(\mathcal{D}_{b_j} \in \mathcal{D}_{b_j}^{f-} : -1)$, respectively. However, for Type I and Type II errors in decision making, by the nodes of the VSN itself, we also have,

$$\Omega_j(-1:1) = P(\mathcal{D}_{b_j} \in \mathcal{D}_{b_j}^{f-}, W_1^i = 1) = 1 - \Omega_j(1:1) \tag{21}$$

$$\Omega_j(1:-1) = P(\mathcal{D}_{b_j} \in \mathcal{D}_{b_j}^{f+}, W_1^i = -1) = 1 - \Omega_j(-1:-1) \tag{22}$$

From Equations (19) and (20), it follows,

$$\Omega(1:1) = \sum_{\mathcal{D}_{b_k} \in \mathcal{D}_{b_j}^{f+}} h(1:1) \tag{23}$$

$$\Omega(-1:-1) = \sum_{\mathcal{D}_{b_k} \in \mathcal{D}_{b_j}^{f-}} h(-1:-1) \tag{24}$$

The goal of our problem is to maximize the expected payoff $\mathcal{E}_{b_j}^t$, at a time t, for a particular b_j, for the set of all possible aggregation rules F. Now, from Equations (1) and (2), it directly follows that,

$$\mathcal{P}(\zeta : \zeta) \propto \frac{1}{\sum_{\forall s_i \in \nu} m_i r_j E_{i,elect} + m_i \xi_{ij}^2 \epsilon_{i,amp}} \tag{25}$$

where $\zeta = \{1, -1\}$. Thus, the profit/loss incurred with the approval/disapproval of a bridge node is proportional to the cumulative energy expenditure of the VSN.

$$\mathcal{P}(\zeta : \zeta) = \kappa \times \frac{1}{\sum_{\forall s_i \in \nu} m_i r_j E_{i,elect} + m_i \xi_{ij}^2 \epsilon_{i,amp}} \tag{26}$$

where, κ is the profit-loss factor, evaluated as per the "goodness" or "badness" of the node.

Thus, following the Optimal Decision Rule [21], the goal is formulated as,

$$\max_{f \in F} \mathcal{E}^t_{b_j} \tag{27}$$

where, $\mathcal{E}^t_{b_j}$ is expressed as,

$$\begin{aligned}\mathcal{E}^t_{b_j} = \alpha_t \Big[\mathcal{P}(1:1)\Omega_j(1:1) + \mathcal{P}(-1:1)(1-\Omega_j(1:1)) \Big] \\ +(1-\alpha_t)\Big[\mathcal{P}(-1:-1)\Omega_j(-1:-1) \\ +\mathcal{P}(1:-1)(1-\Omega_j(-1:-1)) \Big]\end{aligned} \tag{28}$$

Thus, the goal function can be rewritten as,

$$\max_{f \in F} \mathcal{E}^t_{b_j} \tag{29}$$

From the outcome of Equation (29), we obtain the optimal decision rule $\hat{f} \in F$ that satisfies Equation (27) thereby, minimizing the overall energy consumption of the VSN.

V. Simulations and Results

This Section presents the simulation results which, in a nutshell, dictates about the performance of the proposed algorithm. Additionally, we compare the performance of the system using the optimal decision rule against the random bridge node selection algorithm and the centralized bridge node system to prove its efficiency. The simulation results are depicted in Table I, followed by the details of the simulation and performance evaluation.

TABLE I: Simulation Setup

Parameters	Values
Deployment Area	100 m $\times$ 100 m
Deployment	Uniform, random
Number of nodes	100
Channel overhead	[1, 5]%
E_{elect}	50 nJ/bit [24]
E_{amp}	100 pJ/bit/m^2 [24]
Packet size	2358 Bytes

Firstly, we plot the energy consumption by the all the nodes within a VSN under all three schemes, as shown in Fig. 3. It is observed that the cumulative energy consumption is highest for the system with random bridge node selection scheme as the nodes are allowed to choose any of the bridge nodes present in the system without considering the distance factor into account. For the centralized bridge node scheme all nodes transmit to a single centralized sink which transmits the data to the sensor-cloud infrastructure the energy consumption is found to be moderately high. However, using the optimal decision rule, where the bridged nodes are chosen dynamically based on the preference profile, minimum energy is consumed.

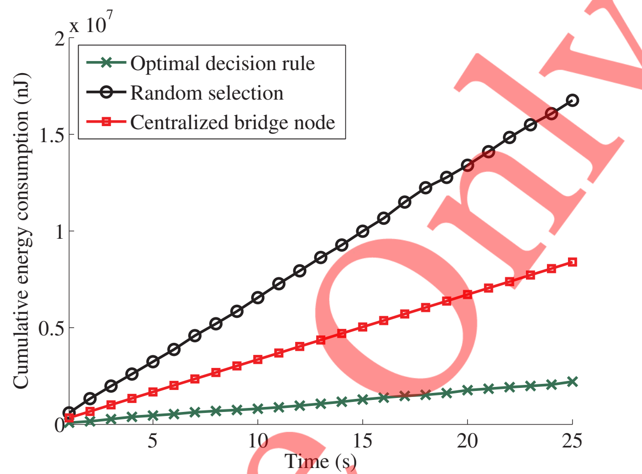

Fig. 3: Cumulative energy consumption of a VSN vs. time

In Fig. 4, the variation of the energy consumed by a (non-bridge) node with the change in the rate of transmission is projected. A similar comparative pattern for the three graphs is observed in this case, as well. Clearly, with the increase in the data transmission rate of a node, its energy consumption is noticed to increase.

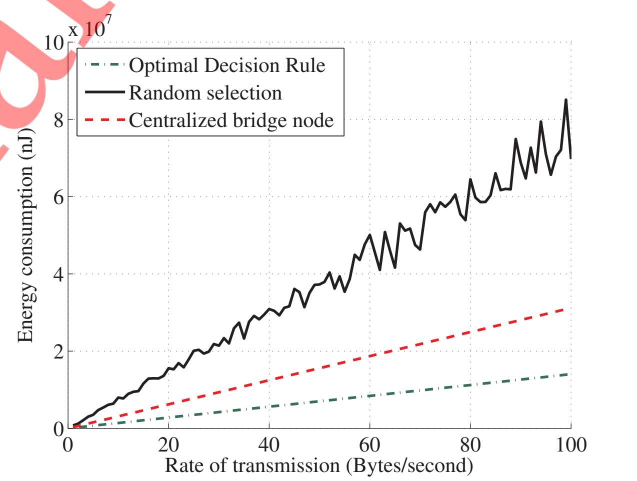

Fig. 4: Energy consumption for a node vs. rate of data transmission

The variation of the lifetime (in percentage) of the network against the number of non-bridge nodes present in the system is plotted in Fig. 5. We observe that as the number of nodes in the system increases the lifetime of the network gradually decreases. Also, it is notices that the network life is significantly higher for the system using the optimal decision rule than the remaining two schemes.

Finally, in Fig. 6, we plot the cumulative energy consumption for the nodes within a VSN against time for different hop-count. As the number of hops increases, the total energy consumed due to the transmission is noted to increase as well. This is due to the additional transmission overhead introduced with the increase in the transmission iteration.

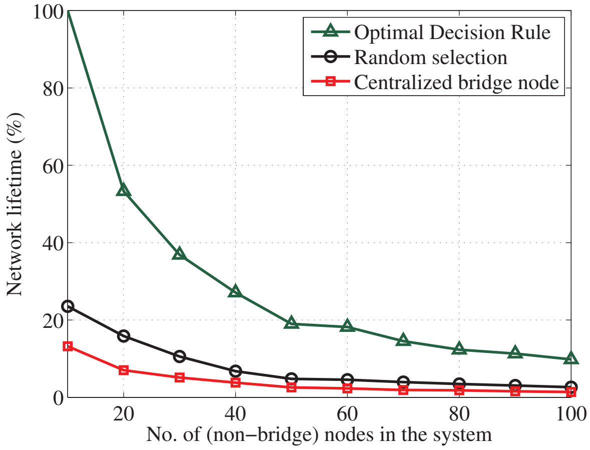

Fig. 5: Network lifetime vs. number of non-bridge nodes in the system

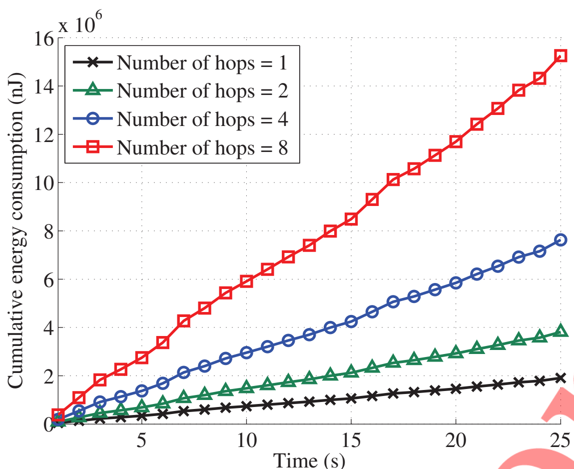

Fig. 6: Cumulative energy consumption vs. hop count of bridge nodes

VI. Conclusion

In this work, we consider a general pairwise choice framework over a VSN. The members of a VSN choose a particular bridge node in order to minimize its energy consumption in the process of data transmission from the sensor network to the sensor-cloud. The goal of the work is to obtain an optimal decision rule that maximizes the payoff by selection the best bridge node in terms of reduced energy consumption. Future research directions will include node heterogeneity, node mobility and other network parameters.

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