A novel protocol for adaptive broadcasting of sensor data in urban scenarios

Jinseok Yang
ECE, UCSD
La Jolla, USA
jty011@ucsd.edu

Sameer Tilak
Calit2
La Jolla, USA
stilak@ucsd.edu

Tajana S. Rosing
CSE, UCSD
La Jolla, USA
tajana@ucsd.edu

Abstract—In a number of sensing applications users are only interested in the data relevant to their present location and current type. This paper presents a novel distributed and low-power protocol that allows mobile users, while moving around the deployed stationary sensor networks, access data from the sensors in their vicinity. As users acknowledge the data, sensors use these acknowledgements as a statistical basis to estimate users’ mobility. Sensors dynamically adjust their broadcast rate based on estimated users’ mobility pattern. To evaluate the performance of our protocol, we use a well-grounded and realistic pedestrian mobility models to generate the user movement patterns and a realistic radio model. Our approach does not require any additional hardware or does not assume any control over user’s mobility. We analyzed the performance of the proposed protocol for a single sensor and network consisting of 10 sensors. The results show a decrease in power consumption by a factor of 2 to 8x (single sensor) and 2x to 16x (10 node sensor network) when compared to the existing protocols.

I. INTRODUCTION

The proliferation of smart portable devices (tablets and smart phones) is enabling mobile users to dynamically discover the sensors and interact with them in real-time. In this paper, we focus on an important class of applications in which mobile users require only the data within a specific context (e.g., present location and current time), of interest. Consider a sensor network deployed for air-quality monitoring. The deployed sensors can alert nearby users upon detecting high allergen levels. In this application, instead of continually streaming all the data to backend servers, and having users access a small fraction of the data via long-haul networks, it is more efficient to enable users to access the sensed data within their context of interest. To that end, we propose a novel distributed technique that lets users, while moving around the deployed sensor network, collect information from the sensors in their vicinity.

A key component of our technique is the sensor node’s ability to adjust their broadcasting rate as a function of the travel time of users in their transmission range (broadcast area). To achieve this goal, each sensor node independently estimates users’ mobility at low cost. Most of the existing travel time estimation techniques normally rely on additional power hungry devices, such as cameras [4]. Such techniques are accurate at the expense of high power consumption and additional hardware, which makes them inappropriate for low-power, low-cost, ubiquitous sensor networks. In contrast, we use the number of acknowledgment (ACK) messages received from users as the statistical basis for estimating users’ mobility. As the users acknowledge the data, each sensor node selects the smallest sampling rate based on estimated users’ mobility thereby saving a significant amount of energy. Our technique is completely distributed and does not require any communication among sensor nodes. If the data is needed also at a later time, it can be forwarded by a user’s phone to a backend server. An application running on the server may provide improved interfaces, statistics and services based on the data collected. However, this has been addressed by other work [5] and is not the topic of this paper.

This paper is organized as follows: In Section II, we present the related work and in Section III and IV, we describe the proposed low-cost distributed approach and the simulation setup. In Section V we evaluate the performance of the proposed approach with the state-of-the-art approaches. The results show a decrease of between in power consumption 2x to 8x (single sensor) 2x to 16x (network-wide) when compared to the existing protocols.

II. RELATED WORK

The mobile sink approaches [1][2] typically assume that the system has control over the sink mobility to ensure that it collects data from all the sensors. We instead assume that users carry their mobile phones while moving freely throughout the area where sensors are deployed. In the proposed approach we assume that the sensor nodes do not have any control over users’ mobility (e.g., user speed, direction, etc.). While Xu et al. [15] does not require any control over the sink mobility, the data is forwarded to mobile sink by acquiring trajectory of mobile sink and establishing energy-efficient routing protocol, which does not scale well with number of mobile users. Recent work proposed a technique where a sensor node wakes up when it receives a RFID impulse from a user and then it unicast the data [3]. However, this mechanism requires users to carry an RFID reader that is expensive and cumbersome. We next discuss the design of our adaptive broadcast mechanism.

III. ADAPTIVE INFORMATION DISSEMINATION PROTOCOL

Our system consists of a network of stationary wireless sensor nodes deployed in an area of interest. Each stationary sensor node has a low power microcontroller, one or more sensors, and a radio. We assume that each node uses a low power MAC protocol capable of sending broadcast packets and capable of minimizing channel contention and collisions. As shown in Figure 1, sensor nodes divide the time in a day in slots of variable length (Slot, s [1,d]). In addition, each time slot is divided into two components: (a) Traffic estimation slot and (b) Adjustment slot. During the traffic estimation slot, sensors broadcast messages at a fixed rate and gather data needed for estimating the user’s mobility. During the adjustment slot, sensors dynamically adjust their (1) broadcast rate and (2) the
length of the adjustment slot to match the estimated user’s mobility pattern.

![Traffic estimation slot](image)

Figure 1. A day is divided into d time slots (Slot).

### A. Traffic estimation slot

Ideally, the best way to estimate real user travel time is by using measured values of user’s speed and direction as shown in Equation (1). Here user i’s travel time, $T_i$, is a function of the user’s speed ($v_{real,i}$) and length of the user’s trajectory within the transmission range, where $l_i$ denotes the distance from the sensor node, $S$ with transmission radius $r$. Figure 2 shows that the distance between a user and a sensor node $S$, and $l_i$ can be described with user’s angle of arrival, $\theta$.

$$T_i = \frac{2(l_i^2 - r^2)}{v_{real,i}} - \frac{2r \cos \theta}{v_{real,i}}$$  \hspace{1cm} (1)

![Example of distance and arrival angle of user](image)

However, in reality, when a sensor node measures user’s travel time, user’s angle of arrival and speed are not measurable without special equipment. Thus, we propose a novel low-power ACK-based mechanism for estimating the users’ travel time which does not require above information.

During the traffic estimation slot, sensors broadcast messages at a fixed rate with the goal of estimating the user’s mobility (i.e. travel time). Each time a mobile user receives a message from a sensor, it acknowledges it by unicasting an acknowledgement (ACK) message, which includes its unique ID. After every broadcast, a sensor node keeps its radio on for a fixed amount of time to ensure that it can receive the ACK messages from mobile users. A sensor node then uses the number of ACKs received from the users as the statistical basis for estimating users’ mobility. Each sensor node maintains a two-column table. The first column stores the user’s IDs and the second column has the number of ACKs received from that user during the traffic estimation slot. This allows sensor nodes to detect if a new user has moved into the transmission range, and to estimate the user travel time using sequences of ACKs from the same user.

The estimated user’s travel time ($\hat{T}_i$) is a function of the amount of time between broadcasts ($B_{TE}$) and the number of received ACKs ($K_i$) as shown in Equations (2) and (3). When a user’s actual travel time is larger than $B_{TE}$, depending upon the user’s arrival time a sensor can receive either case 1: $ceil(T_i/B_{TE})$, or case 2: $floor(T_i/B_{TE})$ number of ACK messages. For example, when the user’s travel time is smaller than the $B_{TE}$ in case 1, the user arrives within the sensor’s transmission range just before the broadcast and receives one message from the sensor node. In case 2, the user arrives and leaves the region between two successive broadcasts and cannot receive any messages from the sensor node.

$$\hat{T}_i = K_i \cdot B_{TE}$$  \hspace{1cm} (2)

$$K_i = \begin{cases} ceil(T_i/B_{TE}) & \text{case 1} \\ floor(T_i/B_{TE}) & \text{case 2} \end{cases}$$  \hspace{1cm} (3)

The upper bound of estimation error between actual travel time ($T_i$) and ACK-based estimated travel time ($\hat{T}_i$) is described in Equation (4).

$$\text{est}. \text{Error}_i = \left| \frac{T_i - \hat{T}_i}{T_i} \right| = \frac{K_i \cdot B_{TE} - T_i}{T_i}$$  \hspace{1cm} (4)

We now describe how a sensor determines when to terminate its current traffic estimation slot. When $\delta$ percent of users ($\delta$ is 90% in our experiments) leave the transmission range, a sensor node generates a set of users’ travel times, $T_{set}$. It next sets the upper bound on the length of the traffic estimation slot, $L_{TE}$, based on the largest estimated user’s travel time, $max(T_{set})$, and $B_{TE}$, as shown in Equation (5).

$$L_{TE} = \text{ceil}\left( \frac{\text{max}(T_{set})}{B_{TE}} \right) \cdot B_{TE}$$  \hspace{1cm} (5)

The time interval between the two successive broadcasts during the traffic estimation slot, $B_{TE}$, is updated for next traffic estimation slot using exponential moving average as described in Equation (6). This allows a sensor node to further save its energy during the traffic estimation slot.

$$B_{TE}(n) = (1 - \alpha) \cdot B_{TE}(n-1) + \alpha \cdot \text{mean}(T_{set}), \alpha \in [0,1]$$  \hspace{1cm} (6)

In Equation (6), $\alpha$ denotes an application’s sensitivity to current traffic conditions. When $\alpha$ is 0, then $B_{TE}$ is not updated with current traffic condition, whereas, when $\alpha$ approaches 1, the current traffic condition is the dominant factor and the $B_{TE}$ is updated based sample mean of $(T_{set})$. The benefit of this can be seen as follows. When the current traffic condition is slower than past traffic conditions, mean $(T_{set})$ decreases, which in turn increases $B_{TE}$. This optimization allows sensors to broadcast at a lower rate during the estimation slot and save energy. Parameter $\alpha$ is set in an application-specific manner. Existing research [15] shows that the average speed of all different races such as European, American, Austrian, and Asian is 1.34 m/s with a standard deviation of 0.26 m/s. We set the initial value of $B_{TE}$ as $(2 \cdot \text{Transmission range}) / 1.34$. Transmission range is determined from the transmission power specifications [10].

### B. Adjustment slot

At the beginning of each adjustment slot, sensor nodes determine the length of time between broadcasts ($B_{adj}$) and the length of adjustment slot ($L_{adj}$) based on $T_{set}$, obtained during the traffic estimation slot. During the adjustment slot, sensor nodes broadcast messages every $B_{adj}$ interval while successfully meeting application requirement. After every broadcast, sensor nodes turn off their radio to save power.

To determine the value of optimal $B_{adj}$, we first define $N_i$ as the expected number of packets received by each user $i$ during the adjustment slot over $B_{adj}$, given the estimated travel time of user $i$, $K_i \cdot B_{TE}$, is obtained during the traffic estimation slot.
Then, the packet reception reliability is calculated by counting the number of users who receive at least one packet during their travel time as shown in Equation (8). The $I(x)$ is an indicator function of $x$ which returns 1 when $x$ is positive, and 0 otherwise. (9). Here $|T_{est}|$ is the size of $T_{est}$. 

$$P_{\text{pkt}_{est}}(i) = E[I(N_i)] = \frac{\sum I(N_i) / |T_{est}|}{|T_{est}|}$$

The average number of packets received by every user when sensor nodes broadcast every $B_{ad}$ seconds, $P_{\text{pkt}_{ad}}(i)$, is described in Equation (9).

$$P_{\text{pkt}_{ad}}(i) = E[N_i] = \frac{\sum N_i / |T_{est}|}{|T_{est}|}$$

If we increase $B_{ad}$, then both $P_{\text{pkt}_{ad}}$ and $P_{\text{pkt}_{est}}$ decrease as shown in Equations (9) and (8). Thus, the optimal $B_{ad}$, $B_{ad}^*$, is the largest $B_{ad}$ that guarantees $P_{\text{pkt}_{est}}$ satisfies application defined quality of service (e.g. 90% of users receiving at least one packet while travelling through a sensor’s transmission range), while minimizing $P_{\text{pkt}_{ad}}$ as described in Equation (10). The selected $B_{ad}^*$ is derived at the beginning of the adjustment slot, and $B_{ad}^*$, in equation (10), is any set of positive numbers.

$$B_{ad}^* = \arg \min_{B_{ad}} P_{\text{ pkt}_{ad}}$$

$$s.t. \ P_{\text{ pkt}_{ad}} \geq QoS, \ QoS \geq 0$$

The length of the adjustment slot determines the system reliability because a mismatch between the estimated and the ongoing traffic conditions degrades the system performance in terms of data collection reliability (when user’s speed increases) or energy efficiency (when the user slows down). We initially set the $L_{adj}$ using $T_{est}$ as shown in Equation (11). Then, the length is adjusted based on traffic condition similarity.

$$L_{adj} = \text{mean}(T_{adj}) + 2 \cdot \text{std}(T_{adj})$$

To check for the similarity, we use the concept of Prediction Interval (PI), as shown in Equation (12), where the $\mu_{\text{prev}}$ and $\sigma_{\text{prev}}$ are mean and standard deviation from the previous traffic estimation slot. The $t^*$ in Equation (12) follows student’s t-test and is determined by the application defined success rate. For example, if a sensor node wants 99% of the mean ($T_{adj}$) to fall into prediction interval, the node can set $t^*$ as 2.58 (most standard statistical textbooks list $t^*$ values [12]).

$$PI = [\mu_{\text{prev}} - t^* \sigma_{\text{prev}}, \ \mu_{\text{prev}} + t^* \sigma_{\text{prev}}]$$

Current users’ mobility metrics are considered to be similar to the previous ones if the current mean ($T_{adj}$) lies within PI. However, the duration of the current traffic distribution has random nature, so when conditions are similar, the sensor node increments $L_{adj}$ by using the binary exponential backoff algorithm mention Equation (13).

$\begin{cases} L_{adj} = L_{adj} \cdot \text{sim} = \text{FALSE} \\
L_{adj} + \text{rand}(0.2 \text{success}) \cdot L_{adj} \ , \ \text{sim} = \text{TRUE} \end{cases}$

Parameter ($\#success$) is initialized to 1 and is incremented by one until it reaches the system defined parameter, $S_{\text{max}}$. If the current mobility estimates are not similar to the previous, the sensor node does not increment $L_{adj}$ and set $\#success$ to 1. The above optimization allows sensor nodes to increase the length of the adjustment slot when the traffic conditions do not vary much and save more energy. When $T_{est}$ is empty, a maximum value of travel time ($T_{max}$) is set to $B_{ad}$ to save energy. After the adjustment slot ends, the sensor nodes start a new traffic estimation slot.

During the adjustment slot a sensor simply broadcasts data at $B_{ad}$ interval and does not require ACKs. Thus, when $B_{ad}$ is always larger than or equal to $B_{TE}$ (which we now prove), we prove that adjustment slot always spend less energy than traffic estimation slot.

**Lemma 1.** If all $K_i=1$ where $K_i B_{TE} \subseteq T_{est}$ the $B_{ad}^*$ that satisfies Equation (10) is $B_{ad}^* = B_{TE}$.

**Proof:** 

a) If $B_{ad}^* > B_{TE}$, then all $N_i$ are 0 (ref. Equation (7)) and $P_{\text{pkt}_{ad}}(i)$ is also 0 for all $i$. This violates the constraints of Equation (10), so $B_{ad}^* \leq B_{TE}$. 
b) $P_{\text{pkt}_{ad}}$ is a non-decreasing function of $N_i$ (ref. Equation (9)). Since $N_i$ is inversely proportional to $B_{ad}^*$, $P_{\text{pkt}_{ad}}$ is also inversely proportional to $B_{ad}^*$.

Thus, the min. $P_{\text{pkt}_{ad}}$ is achieved when $B_{ad}^* = B_{TE}$.

**Theorem 1.** If all $K_i \geq 1$ where $K_i B_{TE} \subseteq T_{est}$ the optimal $B_{ad}^*$ that satisfies Equation (10) is greater than equal to $B_{TE}$.

**Proof:** 

a) If $K_i \geq 1$ and $B_{ad}^* < B_{TE}$, then $N_i \geq 1$ (ref. Equation (7)) and $P_{\text{pkt}_{ad}}(i)$ becomes 1 (ref. Equation (9)). If $K_i B_{ad}^* \geq B_{TE}$ and $N_i \geq 1$, then there exists some $B_{ad}^*$ such that $B_{ad}^* \geq B_{TE}$ (i.e. $K_i B_{ad}^* \geq B_{TE}$). 
b) Since both $N_i$ and $P_{\text{pkt}_{ad}}$ are inversely proportional to $B_{ad}^*$, the largest $B_{ad}^*$ that satisfies reliability constraint is always $B_{ad}^* = B_{TE}$.

**IV. SIMULATION SETUP**

Radio specifications and accurate user mobility modeling are critical for evaluating our proposed approach.

**Radio specification:** We use Chipcon CC2420 IEEE 802.15.4 radio specifications [10] in our simulations. We vary the transmission range as 10, 30, and 55 meters. These ranges are derived using Friis transmission equation. The corresponding power consumption values are shown in Table 1. With the maximum packet size of 123 bytes transmitted at 250kbps, the packet transmission takes 4ms, and average ACK reception time is 0.5ms [10]. In order to calculate the distance between receiver and sender, we use the Friis transmission equation, and set receiver and transmitter gain as 2. We also assume the frequency is 2.4MHz.

<table>
<thead>
<tr>
<th>Power (mA)</th>
<th>Transmit (10m)</th>
<th>Transmit (30m)</th>
<th>Transmit (55m)</th>
<th>Receive</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.712</td>
<td>8.41</td>
<td>9.71</td>
<td>10.9</td>
<td>18.8</td>
</tr>
</tbody>
</table>

As shown in Equation (14), in order to model transmission range in a realistic manner, we use log-normal shadowing radio propagation model [1]. In this equation $X$ is the shadowing deviation, which determines the radio irregularity.

$$P_n = P_n \cdot (C)^{X} \cdot 10^{Ki/10}$$

**User mobility modeling:** User mobility pattern has a significant impact on design, development, and performance of network protocols [13]. Existing research has shown that simple user mobility models do not generate realistic movement patterns.
Existing research [7] shows that the behavior of masses of people can be modeled similar to gases or fluids [8]. Thus, we use the model that characterizes user’s mobility with three parameters: density (user/m²), flow level (user/s/m), speed (m/s). The density is represented by the number of users in a confined space (e.g. street), and the flow level is the number of arrivals per second in a given area [16]. The relationships between those parameters are described in Equation (15).

\[
\text{Density}(\text{ped} / \text{m}^2) = \frac{\text{Flow level} (\text{ped} / \text{s} - \text{m})}{\text{Mean of flow speed} (\text{m} / \text{s})}
\]

Table 2. Simulation parameters for steady traffic flow conditions: congested and non-congested [9]

<table>
<thead>
<tr>
<th>Traffic type</th>
<th>Mean(m/s)</th>
<th>Stdv(m/s)</th>
<th>Density (ped/m²)</th>
<th>Flow level (ped/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-congested</td>
<td>1.46</td>
<td>0.15</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Congested</td>
<td>0.96</td>
<td>0.26</td>
<td>0.8</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Winnie [9] shows that the street width and the number of users in a confined area determine the mean and the variance of the flow speed. When there are few users in confined space, the user density is proportional to the flow level. However, when there are a lot of users in a confined space, density and flow level have inversely proportional relationship [1][6] and the mean of flow speed decreases because the users adjust their walking speed to avoid physical interaction with other users, which increases variation flow speed (ref. Table 2).

We evaluate the performance of the proposed protocol against the following three state of the art protocols: periodic information broadcast, non-uniform information dissemination, and RFID impulse protocol.

**Periodic information broadcast protocol:** In this protocol, the sensor nodes broadcast data at fixed rate. This protocol is simple to implement, however since it cannot adapt to user mobility it results in either high overhead (when the user’s speed is low) or low reliability (when the user’s speed is high). The broadcast interval is calculated as function of the transmission range and mean users’ speed.

**Non-uniform information dissemination protocols** [14]: Tilak et al. [14] proposed a suite of non-uniform information dissemination protocols, where the packet forwarding probability is inversely proportional to the distance the packet has traveled. In other words, if a sensor receives a packet from a close neighbor, it is more likely to forward this than a packet received from a neighbor much farther away. Our approach is a special case of non-uniform protocol where only the one-hop information is relevant to a given user.

**RFIDImpulse protocol** [3]: This protocol assumes that all sensor nodes turn off their radios as long as they have no packets to send or receive. When a sensor has a packet to send, it triggers RFID tag of a user. Then the user generates interrupt to wake up radios, and send ACK to the sensor when radios become fully active. The ACK represents the successfully wake-up of the user, so the sensor starts transmit packet. However, their approach is not suitable if the goal is provide information to all users who pass through the sensor node’s transmission region. Thus, we reversed the role between user and sensor in order to the protocol can serve multiple users request such that when a sensor node receives a RFID impulse from the user it wakes up and sends (unicasts) its data. Later, we use term RFIDImpulse to denote the revised RFIDImpulse protocol. The updated protocol is more suitable for the studied application than the original protocol.

**V. RESULTS**

We evaluate the performance of the proposed protocol in terms of power consumption and data collection reliability under two different cases: (1) single sensor and (2) multiple sensors nodes. We assume 100 users traverse the transmission range. The weighting factor α (ref. Equation (6)) is set to 0.5. Since we consider pedestrian mobility, \( T_{max} \) is set as \( n \cdot 2r \) where \( n \) is the reciprocal of the slowest user’s speed. We set \( n \) to 0.91m/s–walking speed of an elderly person [16].

**Energy-efficiency and reliability comparison study:** In this study we evaluated the energy-efficiency of all the protocols. We vary the transmission range as 10, 30, and 55 meters. As described in Table 2 users arrive at a fixed flow level.

Table 3: Factor reduction in energy consumption for all the protocols (and number of messages transmitted by all the protocols in bracket) under steady state flow (non-congested traffic condition) for different transmission ranges

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>10m</td>
<td>10.83 [21]</td>
<td>6.31 [41]</td>
<td>6.31 [41]</td>
<td>1.29 [100]</td>
</tr>
</tbody>
</table>

Table 3 shows the factor reduction in energy consumption and number of messages transmitted (in bracket) for various protocols. Since we do not consider forwarding overhead in case of the non-uniform protocol, its performance is identical to the periodic protocol’s performance. In the case of non-uniform and periodic broadcast protocols, once the broadcast interval selected at onset and then it does not change. However, in case of the adaptive protocol, a sensor node broadcasts at a fixed rate only during the traffic estimation slot whereas the broadcast interval during the adjustment slot is adapted based on user mobility estimated during the traffic estimation slot. Therefore the adaptive protocol transmits the least number of messages and significantly outperforms all other protocols (ref. Table 3). Since the adaptive protocol transmits significantly lower messages, and turn off radio after transmit packet, the factor reduction in energy consumptions varies from 10.83-33.65 (Adaptive), 0.06-0.05 (Non-uniform), and 1.29-1 (RFIDImpulse). The overall power consumption depends on both the transmission power/packet and the number of transmissions, but as shown in Table 3, as the transmission range increases the overall energy consumption goes down. This is counter-intuitive; however, this happens for the following reason. During the traffic estimation slot, \( B_{TE} \) is calculated as \( (2 \cdot r / \text{Average user speed}) \), so \( B_{TE} \) increases as a function of \( r \). This implies that the number of messages transmitted is inversely proportional to the transmission range, \( r \) (ref. Table 3). For example, following tuples denote (transmission range in meters, average broadcast interval in seconds): (10, 15), (30, 45), and (55, 82). Therefore, the increase in power/packet due to higher transmission range is overcompensated by the decrease in number of transmissions.

We now compare the reliability of all the protocols. From Figure 3, the reliability of the adaptive protocol is comparable to other protocols. In fact, at least 92% of users receive at least
one packet while passing through the sensor’s transmission range, and the non-uniform/periodic protocols have 93% reliability. The RFIDImpulse protocol has the highest reliability since each sensor node wakes up and sends sensed data when it receives a RFID impulse from the user, but it requires the highest number of packet transmission as shown in Table 3 (in bracket). To sum up, reliability of adaptive protocol is slightly less than the non-uniform/periodic protocols by 1%, but it has significant energy savings at least 2x than others.

Figure 3: Comparison of reliability for all the protocols under steady state flow type (non-congested traffic condition) for different transmission ranges

**Effect of variation of δ**: A sensor node generates a set of users’ travel times, $T_{set}$ after the δ percent of users leaving the transmission range. Therefore, δ is a critical factor in evaluating the performance of the proposed protocol. To study its impact, we fixed $B_{TE}$ and traffic condition, and varied δ from 10% to 100%, which in turn varied $L_{TE}$. We observed the following “phase transition” phenomenon. When δ is less than 80%, the reliability is less than 20% (less than 20% of users receive at least one packet). However, when δ becomes larger than 80%, the system reliability becomes more than 95%.

**Effect of $L_{adj}$ adaptation**: We initially set the length of the adjustment slot using the average measured travel time of $T_{set}$ as shown in Equation (11). However, as shown in Equations (12) and (13), sensor nodes vary $L_{adj}$. The intuition behind this is that a sensor node can increase the length of the adjustment slot when the traffic conditions are do not vary much and save more energy.

To quantify this benefit, we varied the transmission range as 10, 30, and 55 meters. We observed that when the traffic condition did not vary significantly over time, incrementing $L_{adj}$ results in 20% decrease in sensor’s power consumption.

**Impact of transmission range variation and shadowing on energy-efficiency**: In this study we use log-normal shadowing propagation model [29] to explore the impact of radio irregularities on the energy efficiency and reliability of various protocols. As the shadowing deviation increases, the transmission range turns into a more irregular shape, which in turn increases the transmission range (users’ travel time). As shown in Figure 4 and Figure 5, this has two implications: (a) As the shadowing deviation increases, the ratio of energy spent in adjustment slot over estimation slot decreases. Therefore, a sensor node spends more time and energy in the estimation slot and less during the adjustment slot. (b) In case of congested traffic condition (ref. Figure 5), a sensor spends higher energy during estimation slot than in the case of non-congested traffic (ref. Figure 4). On the other hand, in case of congested traffic condition (ref. Figure 5), a sensor spends less energy during the adjustment slot as compared to the energy spend in non-congested traffic condition (ref. Figure 4). This happens because in the congested case since the user speed is lower than the non-congested traffic (ref. Table 2), both the mean($T_{adj}$) and max($T_{set}$) values are higher, which in turn results in higher $B_{TE}$ and $L_{TE}$ (ref. Equations (5) and (6)).

Figure 4: Impact of transmission range variation and shadowing on energy-efficiency of protocols non-congested traffic condition

Figure 5: Impact of transmission range variation and shadowing on energy-efficiency of protocols congested traffic condition

**Sensor network-wide Power consumption**: Till this point, we only considered power consumption for an individual sensor node. We now evaluate the power consumption at the network level. We assume that K sensors are placed in a field. Equation (16) denotes the energy consumption of non-uniform protocol for $K \geq 2$ sensor nodes, where $E_{on}$, $E_{off}$ transmission and reception energies, $N_{s}$ is the number of packet transmissions. A sensor node placed $i$ hops away from the sink has $1/i+1$ as its forwarding probability [14].

$$E_{i} = \begin{cases} N_{s} \cdot E_{tx} + N_{s} \cdot E_{rx} & \text{if } i = K \\ N_{s} \cdot E_{tx} + \frac{1}{i+1} \cdot E_{rx} & \text{otherwise} \end{cases}$$

Equation (17) derives $K \cdot N_{s} \cdot E_{on} + E_{off} + 0.5 \cdot E_{on}$ is the lower bound of energy consumption of the non-uniform protocol. The energy consumption of adaptive protocol is affected by both the number of messages transmitted, $N'$, and the number of sensor nodes, so its lower bound is $K \cdot N' \cdot (P_{on} + P_{off})$. Since $N_{s}$ is larger than $N'$ as shown in Table 3 (in bracket) and the Non-uniform has an additional term, the adaptive protocol is more energy-efficient than the non-uniform protocol.

Table 4: Sensor network-wide Power consumption bound for all the protocols

<table>
<thead>
<tr>
<th>Adaptive</th>
<th>Non uniform</th>
<th>Periodic</th>
<th>RFID-Impulse</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K \cdot N \cdot (E_{on} + E_{off})$</td>
<td>$&gt;K \cdot N \cdot (E_{on} + E_{off})$</td>
<td>$=K \cdot N \cdot (E_{on} + E_{off})$</td>
<td>$N_{s} \cdot E_{on}$</td>
</tr>
</tbody>
</table>

$$\sum_{i=1}^{K} E_{i} = \sum_{i=1}^{K} \left[ N_{s} \cdot E_{tx} + N_{s} \cdot E_{rx} \left( \frac{1}{i+1} \cdot E_{rx} \right) \right] + N_{s} \cdot E_{rx}$$

$$= K \cdot N_{s} \cdot E_{tx} + E_{rx} \sum_{i=1}^{K} N_{s} \cdot E_{rx} \sum_{i=1}^{K} \frac{1}{i+1}$$

$$> K \cdot N_{s} \cdot E_{tx} + \left( K \cdot \frac{1}{2} \right) \cdot N_{s} \cdot E_{rx} = K \cdot N_{s} \cdot \left( E_{on} + E_{off} \right) + \left( K \cdot \frac{3}{2} \right) \cdot E_{rx}$$

$$\geq K \cdot N_{s} \cdot \left( E_{on} + E_{off} \right) + 0.5 \cdot E_{on}, \text{ where } K \geq 2$$

Table 3 (in bracket) shows the number of messages transmitted by all the protocols by a single sensor. Using Table
3 and Equation (17), as shown in Table 5, we can estimate the energy consumption (in mJ) of each protocol for a sensor network consisting of 10. Table 5 shows that the Adaptive protocol decreases energy consumption from 6x to 16x in comparison with the RFIDImpulse protocol, and 2.4x and 1.95x in comparison with Non-uniform and Periodic protocols respectively.

Table 5: Factor reduction in energy consumption for a 10-node sensor network

<table>
<thead>
<tr>
<th></th>
<th>Adaptive</th>
<th>Non uniform</th>
<th>Periodic</th>
<th>RFIDImpulse</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 m</td>
<td>6.16</td>
<td>2.54</td>
<td>3.15</td>
<td>1.29</td>
</tr>
<tr>
<td>30 m</td>
<td>10.2</td>
<td>3.31</td>
<td>3.59</td>
<td>1.12</td>
</tr>
<tr>
<td>55 m</td>
<td>16.31</td>
<td>6.71</td>
<td>8.33</td>
<td>1</td>
</tr>
</tbody>
</table>

Study of data collection resilience for all protocols: The percentage of users who receive at least one packet while traversing sensor’s transmission range is defined as data collection reliability. We now extend this to the network wide reliability, that we call data collection resilience, as the percentage of users who receive at least one packet from every sensor node. RFIDImpulse protocol has the highest resilience because a sensor wakes up and unicasts data when it receives RFID signal from a user. Suppose \( K \) is the number of sensor nodes and \( r_p, r_w, r_f \) and \( r_p \) denote average resilience of adaptive, non-uniform, and periodic protocols respectively and \( C \) is the sum of forwarding probabilities over \( K \) sensor nodes (ref. Equation (18)). \( K_1 \) and \( K_2 \) represent the distance between the sink node and the farthest node on the left and farthest node on the right respectively (\( K_1 + K_2 = K \)). Since \( C \) is always less than \( K \), the data collection resilience of adaptive protocol is always larger than the non-uniform protocol. Then, we can estimate the data collection resilience of all the protocols as shown in Table 6.

\[
C = \sum_{i=1}^{K_1} \frac{1}{i} + \sum_{j=1}^{K_2} \frac{1}{j} 
\]

\( d \) is the distance between the static sink, \( K_1 + K_2 = K \).

We define parameter, \( \psi \), as the product of factor reduction in energy consumption and data collection resilience. The higher value of \( \psi \), better the performance of the protocol. Figure 6 shows that \( \psi \) of the proposed protocol is 2x and 5x in comparison with Periodic and Non-uniform protocols respectively.

Table 6: Data collection resilience comparison across all the protocols

<table>
<thead>
<tr>
<th></th>
<th>Adaptive</th>
<th>Non uniform</th>
<th>Periodic</th>
<th>RFIDImpulse</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( r_c )</td>
<td>(( r_c ), ( C/K ))</td>
<td>( r_p )</td>
<td>100</td>
</tr>
<tr>
<td>10 m</td>
<td>1600</td>
<td>3030</td>
<td>1600</td>
<td>1000</td>
</tr>
<tr>
<td>30 m</td>
<td>1300</td>
<td>2500</td>
<td>1300</td>
<td>2500</td>
</tr>
<tr>
<td>55 m</td>
<td>1000</td>
<td>1500</td>
<td>1000</td>
<td>1500</td>
</tr>
</tbody>
</table>

Figure 6. \( \psi \) comparison across all the protocols

VI. CONCLUSION

In this paper we present a novel distributed low-power protocol that lets users, while moving around the deployed sensor network, collect information from the sensors in their vicinity. As users mobile acknowledge the data, the sensors estimated user travel time and use it as a statistical basis for dynamically adjust their data broadcast rate. We compared our approach with state-of-the-art protocols using realistic mobility models and radio propagation model. The results show a decrease of between in power consumption 2x to 8x (single sensor) 2x to 16x (network-wide) when compared to the existing protocols while its reliability is only 1% less than other protocols for three different transmission ranges.

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