Architecture of Wireless Sensor Networks with Mobile Sinks: Sparsely Deployed Sensors

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Abstract

We propose to develop wireless Sensor Networks with Mobile Sinks (MSSN). The proposed MSSN is highly energy-efficient because the multi-hop transmissions of high volume data over the network are converted into single-hop transmissions. We focus our investigation on sparsely deployed networks, where single node to sink transmission is considered. The Transmission Scheduling Algorithm (TSA-MSSN) is proposed, where a parameter $\lambda$ is employed to control the tradeoff between the maximization of the probability of successful information retrieval and the minimization of the energy consumption cost. It is shown that the proposed implementation of the TSA-MSSN has a complexity of $O(1)$. Our study serves as the foundation for understanding fundamental laws behind the above mentioned tradeoff with useful implications for the design of more complex sensor networks with mobile sinks.

Index Terms


I. INTRODUCTION

Recent developments in digital circuitry, wireless communication, and Micro Electro-mechanical Systems (MEM), have made possible the integration of sensing, communication, and power...
supply into an inch scale sensor devices. Thus, the investigation for development of robust, easy deploying, micro-sensor networks has attracted a great deal of attention [1].

Wireless sensor networks are energy-limited and application-specific. These two characteristics pose new challenges in the network design. Inch scale sensor devices are expected to operate over years with limited power supply. Thus, the energy consumption becomes the foremost design consideration, while other constraints, such as throughput, latency, and fairness, become relatively less important. On the other hand, sensor networks are considered for a diverse range of civil and military applications, such as environmental monitoring, home networking, medical vital signs monitoring and smart battlefield, among others. These requirements suggest that the classical Open System Interconnect (OSI) paradigm may not be suitable for sensor networks, but rather a methodology of cross layer communications network design may be more appropriate. [2].

In this paper, we propose to develop Sensor Networks with Mobile Sinks (MSSN). We believe that such networks are appropriate either for environmental applications or intelligent space applications with large latency tolerance. In such applications, multi-hop wireless transmission along the network to a fixed sink is not cost-efficient, [2], [3]. Also, it is not efficient and safe to install densely located fixed sinks for mediating the multi-hopping cost. Furthermore, fixed-sink sensor networks suffer from a severe problem of high duty-load in the nodes around sinks [4]. On the other hand, with a mobile sink, expensive multi-hop transmission can be avoided since it is realistic to assume that a node transmits to the sink only when they are physically near to each other. In a more general scenario, mobile users subscribed to some information service, such as “navigation”, may act as mobile sinks. A mobile user can be a laptop, PDA or cellular phone. Also, by considering MSSN, the difficult problem of self-positioning [5] of sensor nodes becomes intuitively simple. The sink can broadcast its location when passing through the sensor-deployed region. Then, assuming that ranging capability is available [5], [6], every sensor node picks up three such locations for position-triangulation [7].

An interesting example is that of traffic surveillance applications (Fig. 1), where a sensor network is deployed along a highway. A homogeneous sensor network can operate collaboratively in deciding who is speeding and store data, such as the picture of the speeding car, locally. A mobile sink is installed in a police car driven along the highway once a day for collecting
the acquisition data, e.g. pictures. The one-hop transmission guarantees a long life-time for the wireless sensor nodes. The police car itself provides a high sink security level for the entire sensor network. Moreover, due to the homogeneous nature of the network, sensor nodes can be deployed with low cost.

In this paper, we consider scheduling problems in node-to-sink transmission. Specifically, the tradeoff between the probability of successful information retrieval and node energy consumption cost, is studied. Our investigation is focused on sparsely deployed networks, where the simplified model of single node to sink transmission is considered. This simplified model facilitates the analysis and helps us to understand the fundamental rules behind the above mentioned tradeoff. The model does have practical value. While it may not always be true that only one sensor is within the communication range to the sink, it may be reasonably assumed that only one sensor in that range has packets of interest to the sink. Or assuming there are multiple wireless channels available, only one node will transmit in a specific channel. The sparsely deployed network model is particularly useful for the previously mentioned traffic surveillance application. The results in the paper serve as the foundation for the study of more sophisticated multiple nodes to sink transmission scheduling problems that rise in densely deployed networks [8].

In Section II, literature review is provided. In Section III, the Transmission Scheduling Algorithm for MSSN (TSA-MSSN) in sparsely deployed networks is formulated. In Section IV, the optimization methodology used in the TSA-MSSN is described. In Section V, design and implementation issues of TSA-MSSN are discussed, under different application requirements. In Section VI, simulation results are provided. Concluding remarks are presented in Section VII. Finally, easy reference to the notation used in the paper is provided by Table 1.

II. RELATED WORK

For fixed sink sensor networks, a clustered network structure has been widely studied, since data aggregation is an important way to reduce energy consumption [9]. The optimal clustering problem was shown to be NP-hard [10], and various heuristic solutions were proposed, e.g. with respect to node addresses [11], or geographical zones [12]. In cluster-head election algorithms, such as WCA [13] and DCA [14], a combination of node degree, residual energy, transmission
power, mobility, etc., have been considered to heuristically decide the cluster leader. Cluster-heads can be used for routing, for resource allocation among nodes in their cluster and network management. For example, LEACH, [15], is an energy-aware cluster head selection algorithm for sensor networks, which assumes that sensor nodes always have data for transmission.

From the perspective of physical layer, another interesting area is the power sensitive network design, which is studied under a general wireless communication scenario. Opportunistic radio resource management [16]–[18], which reduces energy expenditure (or increases the network throughput) by exploiting the system dynamics, is shown to be efficient in the wireless transmission of non-voice data. Such studies are intuitively similar to the TSA-MSSN, however, their application objectives are different.

In [19], SENMA (Sensor Networks with Mobile Agents) was studied under a sensor network topology similar to the MSSN. Distributed random access algorithms were proposed. However, SENMA assumes a simple reachback network, where acquisition data is assumed with high redundancy. This differentiates it from MSSN, in which much higher application flexibility is provided. SENMA provides design simplicity for both sensor nodes and mobile agents. As it will be demonstrated later, the MSSN achieves simplicity in sensor nodes design, while at the same time utilizes the higher storage/computing/communication capabilities of the sink.

III. Problem Formulation

In designing the single node to sink transmission scheduling algorithm, we assume that both the sink and sensor nodes are aware of their own position. In addition, we assume that the sink has an estimate of its current velocity and direction of mobility, by means of a global positioning system (GPS). Also, the sink is equipped with a rechargeable battery and has much higher computation and communication capabilities compared to a node. The individual sensor node is not mobile and has storage capability for a number of information packets to be transmitted to the sink.

The TSA-MSSN problem is conceptually formulated by the following question: how can a sensor node complete transmission of all the information packets with minimum energy consumption? The approach we take is: find the best time slots for packets transmission and use
minimum transmission power for those slots. Thus, at a given time slot $i_0$, we should decide whether to force the sensor to sleep or transmit, and if the sensor is transmitting what would be the transmitting power. As a simple illustration, consider the condition that the sensor has only one packet to send. The sensor then should wait until the sink gets as close as it would, and then send the single packet at the lowest power.

Although the solution seems to be correlated with the future mobility pattern of the sink, we do not assume that mobility information is known at the sink in advance. On the other hand, at the current time slot $i_0$, TSA-MSSN makes the assumption that the sink mobility (velocity and direction) would remain constant in the future. Provided that the mobility information is updated at every time slot, this is a good approximation.

Since the sink has much higher storage/computing/communication capabilities than a sensor node, the TSA-MSSN is a highly centralized algorithm. The sink runs TSA-MSSN and assigns the transmission power level to the node at the beginning of every time slot. The sink can piggyback the assigned transmission power level in the Acknowledge (ACK) packets which serve to acknowledge successful or failed data transmission during the previous time slot.

IV. System State Model

Let $Range$ denote the communication range of the sensor node. Assume that at the current time slot $i_0$, the location, mobility direction and velocity of the sink are $L_s(i_0), \theta_s(i_0), v_s(i_0)$, respectively. Let $L_n$ and $K(i_0)$ denote the location of the sensor and the number of packets awaiting for transmission, respectively. Then, the system state, $E(i_0)$, is composed of these five parameters,

$$E(i_0) = \{L_s(i_0), \theta_s(i_0), v_s(i_0), L_n, K(i_0)\}.$$  \hspace{1cm} (1)

Let $D(i_0)$ denote the distance between the sink and the sensor node,

$$D(i_0) = \|L_s(i_0) - L_n\|,$$  \hspace{1cm} (2)

The communication channel gain (in $dB$) between the sink and the sensor node can be modelled as [20],

$$G(i_0) = 10 \cdot \log(A) - 10n \cdot \log(D(i_0)) + \xi \quad (dB),$$  \hspace{1cm} (3)
where $A$ is a constant, $n$ is the path loss exponent, and $\xi \simeq N(0, \sigma^2_{\xi})$ is a normal random variable modeling the shadowing effects.

It is assumed that the sink mobility remains constant when the sink is passing through the circular region centered at $L_n$ with the radius $\text{Range}$, as depicted in (Fig. 2). Let $T(i_0)$ denote the estimated number of transmission time slots available before the sink moves out of the sensor communication range. We have,

$$T(i_0) = \left\lfloor \frac{\|L_s(i_0) - L_{s\text{out}}\|}{v_s(i_0) \cdot \Delta t} \right\rfloor,$$

where

$$\Delta t = \frac{F_d + F_b}{R},$$

is the time duration for one slot. $F_d$ and $F_b$ are the size of the data and ACK packets, respectively. $R$ is the transmission data rate. $L_{s\text{out}}$ is defined as the point at which the sink goes out of the communication range of the sensor node, as illustrated in Fig. 1. The mathematical formula of $L_{s\text{out}}$ is derived in Appendix I.

Then, at current time slot $i_0$, the series of estimated states can be defined as,

$$\hat{E}(i_0) = \{\hat{E}(i_0), \hat{E}(i_0 + 1), \ldots, \hat{E}(i_0 + T(i_0) + 1)\},$$

where $\hat{E}(i_0)$ is known as,

$$\hat{E}(i_0) = E(i_0),$$

and,

$$\begin{cases}
\hat{L}_s(i_0 + j) = L_s(i_0) + j \cdot v_s \cdot \Delta t \cdot [\cos(\theta_s(i_0)), \sin(\theta_s(i_0))] \\
\hat{\theta}_s(i_0 + j) = \theta_s(i_0) = \theta_s \\
\hat{v}_s(i_0 + j) = v_s(i_0) = v_s \\
j = 0 \ldots T(i_0) + 1
\end{cases}.$$

Thus, the only variable parameter in $\hat{E}(i)$, $i_0 < i \leq i_0 + T(i_0) + 1$ is $\hat{K}(i)$, which takes values between 0 and $K(i_0)$. The size of $\hat{E}(i)$ is then decided by $K(i_0) + 1$.

For every future time slot $i$, $i_0 \leq i \leq i_0 + T(i_0)$, the transmission strategy is decided by $P_t(i)$, which is the transmission power at the sensor node (and could be 0 if the strategy is to sleep during that slot). We consider that the transmission power is of discrete levels, and the number
of optional levels is \textit{Sizeof} \{\textit{P}_i\}. Given \(\hat{E}(i)\) and \(P_t(i), \hat{E}(i+1)\) is not related to any previous states before \(i\). Thus, \(\{\hat{E}(i)\}\) can be modelled as a Markov chain in time domain, that is,
\[
\begin{align*}
\text{Prob} \left( \hat{E}(i+1) | \hat{E}(i_0), \ldots, \hat{E}(i), P_t(i_0), \ldots, P_t(i) \right) &= \text{Prob} \left( \hat{E}(i+1) | \hat{E}(i), P_t(i) \right). 
\end{align*}
\]
(9)

We assume that only one packet can be transmitted in one time slot, and every lost packet will be retransmitted in the next assigned slot. The state transferring probability function can be given by,
\[
\begin{align*}
\text{Prob} \left( \hat{E}(i+1) | \hat{E}(i), P_t(i) \right) &= \\
&= \begin{cases} 
\hat{\text{PER}}(i), & \hat{K}(i+1) = \hat{K}(i) \\
1 - \hat{\text{PER}}(i), & \hat{K}(i+1) = \hat{K}(i) - 1 \\
0, & \text{others}
\end{cases} \\
&= i = i_0 \ldots i_0 + T(i_0),
\end{align*}
\]
(10)

where \(\hat{\text{PER}}(i)\) is the estimated packet error rate of the transmission time slot \(i\). \(\hat{K}(i+1) = \hat{K}(i)\) suggests that the packet is lost (or not transmitted), while \(\hat{K}(i+1) = \hat{K}(i) - 1\) suggests the packet is successfully retrieved by the sink, at slot \(i\). If we use BPSK without channel coding, the \(\hat{\text{PER}}(i)\) can be written as [21],
\[
\hat{\text{PER}}(i) = 1 - \left( 1 - Q \left( \sqrt{\frac{2P_t(i) \cdot \hat{G}(i)}{\sigma_n^2}} \right) \right)^{F_d},
\]
(11)

where \(\sigma_n^2\) is the noise power, \(Q(x) = \frac{1}{\sqrt{\pi}} \cdot \int_{\sqrt{x}}^{\infty} e^{-t^2} dt\), and
\[
\hat{G}(i) = A \cdot \hat{D}(i)^{-n}.
\]
(12)

V. TSA-MSSN Algorithm and Implementation

At current time slot \(i_0\), with system state \(E(i_0)\), the objective of TSA-MSSN is to decide the optimal strategy \(P_t^* (E(i_0))\) that maximizes the probability of successful transmission and at the same time minimizes the energy consumption. However, these two objectives can not be achieved simultaneously, since both the rate of successful transmission and the energy consumption increase monotonically with \(P_t(i_0)\). Thus, we search for the optimal strategy \(P_t^* (E(i_0))\) by maximizing a utility function \(J \left( P_t(i_0), \hat{E}(i_0) \right)\), that is,
\[
P_t^* (E(i_0)) = \arg \max_{P_t(i_0)} \left\{ J \left( P_t(i_0), \hat{E}(i_0) \right) \right\}.
\]
(13)
The design of the utility function is discussed next.

A. Recursive Design of Utility Functions

A recursive design makes the assumption that during the time slot \( i, i_0 \leq i \leq i_0 + T(i_0) \), the algorithm has complete knowledge of \( J\left(P_t(i+1), \hat{E}(i+1)\right) \). Thus, the TSA-MSSN problem is formulated mathematically as the design of the utility function \( J\left(P_t(i), \hat{E}(i)\right) \) given \( J\left(P_t(i+1), \hat{E}(i+1)\right) \). We also define \( U\left(\hat{E}(i)\right) \) as the maximum value of utility associated with \( \hat{E}(i) \), that is,

\[
U\left(\hat{E}(i)\right) = \max_{P_t(i)} \left\{ J\left(P_t(i), \hat{E}(i)\right) \right\} .
\]  

(14)

The utility function \( J\left(P_t(i), \hat{E}(i)\right) \) is formed by two components, which are \( J_m\left(P_t(i), \hat{E}(i)\right) \) and \( J_c\left(P_t(i)\right) \) respectively. Conceptually, the \( J_m\left(P_t(i), \hat{E}(i)\right) \) is the figure of credit which denotes the expected achievable utility credit by adopting strategy \( P_t(i) \) at state \( \hat{E}(i) \). The \( J_c\left(P_t(i)\right) \), on the other hand, is the figure of cost, which is determined by the energy consumption associated with \( P_t(i) \). Thus, we have the following intuitive formulation,

\[
J\left(P_t(i), \hat{E}(i)\right) = J_m\left(P_t(i), \hat{E}(i)\right) - J_c\left(P_t(i)\right) .
\]  

(15)

Since \( \left\{ \hat{E}(i) \right\} \) is modelled as a Markov chain, the expected achievable credit \( J_m\left(P_t(i), \hat{E}(i)\right) \) can be written as,

\[
J_m\left(P_t(i), \hat{E}(i)\right) = \sum_{\hat{E}(i+1)} U\left(\hat{E}(i+1)\right) \cdot \text{Prob}\left(\hat{E}(i+1)|P_t(i), \hat{E}(i)\right) .
\]  

(16)

\( J_c\left(P_t(i)\right) \) is only a function of \( P_t(i) \), and can be written as,

\[
J_c\left(P_t(i)\right) = \frac{\lambda}{\max\{P_i\}} \cdot P_t(i) ,
\]  

(17)

where \( \lambda \) is a weight coefficient indicating the tradeoff between energy consumption cost and successful transmission credit. The \( \max\{P_t\} \) is the maximum transmission power level, which acts as a normalization factor.

Thus, by combining Eqs.(14,15,16,17), we get,

\[
J\left(P_t(i), \hat{E}(i)\right) = \sum_{\hat{E}(i+1)} \max_{P_t(i+1)} \left\{ J\left(P_t(i+1), \hat{E}(i+1)\right) \right\} \cdot \text{Prob}\left(\hat{E}(i+1)|P_t(i), \hat{E}(i)\right) - \frac{\lambda}{\max\{P_t\}} \cdot P_t(i) ,
\]  

(18)

\( i = i_0, \ldots, i_0 + T(i_0) \).
Since the power level $P_t(i)$ takes values from a discrete set with the size $\text{Sizeof} \{P_t\}$, the calculation in Eq.(18) should be executed $(K(i_0) + 1) \cdot \text{Sizeof} \{P_t\}$ times during any iteration. Although searching over all the discrete values of $P_t(i)$ seems to be cumbersome, it is only used here to illustrate the concept. A careful inspection on Eq.(18) reveals that, given $\hat{E}(i)$, the optimization problem over $P_t(i)$ is one dimensional. For every system state $\hat{E}(i)$, both $J_m$ and $J_c$ are monotonically increasing functions of $P_t(i)$. Moreover, it is shown that $J_m$ is concave over a certain region (see Appendix III). Due to the linearity of $J_c$, (Eq.(17)), given $\hat{E}(i)$, the $J = J_m - J_c$ is also a concave function of $P_t(i)$ over the same region. Also, it is shown that: if $P_t^*(\hat{E}(i)) > 0$, then, the $P_t^*(\hat{E}(i))$ must be within that region where the concavity actually makes the desired optimization problem mathematically simple.

The design of the utility function $J = J_m - J_c$ is not only intuitive. It also implies that the cost of energy consumption is additive and should be additively accumulated over the iterations. To achieve this, both $J_m$ and $J_c$ have to be linear components of $J$. This requirement excludes other possible formulas, such as $J = \frac{J_m}{J_c}$. For example, assuming that $J = \frac{J_m}{J_c}$, then the overall cost will be the product of the costs over iterations, which is physically wrong.

B. Final-State Configuration

At the final state, that is when $i = i_0 + T(i_0) + 1$, the $J_c$ is zero for all system states, since there will be no active transmission and therefore $P_t(i_0 + T(i_0) + 1) = 0$. Thus, we can write:

$$
J \left( P_t(i_0 + T(i_0) + 1), \hat{E}(i_0 + T(i_0) + 1) \right) \\
= J_m \left( P_t(i_0 + T(i_0) + 1), \hat{E}(i_0 + T(i_0) + 1) \right) \\
= J_m \left( \hat{E}(i_0 + T(i_0) + 1) \right).
$$

(19)

Note however, that the design of $J_m$ is application-specific. Next, without loss of generality, we consider two different application scenarios.

1) Application Scenario I: we assume that every $K(i_0)$ packet is of the same credit, say “1”. Thus, $J_m \left( \hat{E}(i_0 + T(i_0) + 1) \right)$ is defined by,

$$
J_m \left( \hat{E}(i_0 + T(i_0) + 1) \right) = K(i_0) - \hat{K}(i_0 + T(i_0) + 1),
$$

(20)

which is the number of successfully transmitted packets.
When $\lambda = 1$, according to Eq. (17), the cost of a maximum-power transmission time slot equals to the credit of successfully transmitting one packet. The parameter $\lambda$ can be adjusted according to different energy consumption requirements, for example, if we decide to set the cost of transmission power $J_c(\alpha \cdot \max\{P_t\}) = 1$, then, $\lambda$ takes the form:,

$$\lambda(\alpha) = \arg\{J_c(\alpha \cdot \max\{P_t\}) = 1\} = \frac{1}{\alpha}, \quad (21)$$

where $\alpha$ is a variable coefficient.

2) Application Scenario II: we assume that the integrity of all $K(i_0)$ packets is essential. Then, $J_m(\hat{E}(i_0 + T(i_0) + 1))$ can be written as,

$$J_m(\hat{E}(i_0 + T(i_0) + 1)) = \begin{cases} 1, & \hat{K}(i_0 + T(i_0) + 1) = 0 \\ 0, & \hat{K}(i_0 + T(i_0) + 1) \neq 0 \end{cases}. \quad (22)$$

Eq.(22) indicates that the credit of successfully transmitting all $K(i_0)$ packets is 1, and therefore, by missing any one of them will decrease the credit to 0.

According to Eq.(17), placing $\lambda = \frac{1}{T(i_0)+1}$ implies that the credit of successful transmission equals the cost of the average transmission power $P_{avg}(i_0) = \max\{P_t\}$, where,

$$P_{avg}(i_0) = \frac{1}{T(i_0)+1} \cdot \sum_{i=i_0}^{i_0+T(i_0)} P_t^*(\hat{E}(i)). \quad (23)$$

On the other hand, if we want to have the cost of average transmission power $P_{avg}(i_0) = \alpha \cdot \max\{P_t\}$ to be 1, we should set $\lambda$ to

$$\lambda(\alpha) = \arg\{(T(i_0) + 1) \cdot J_c(\alpha \cdot \max\{P_t\}) = 1\} = \frac{1}{\alpha \cdot (T(i_0)+1)}. \quad (24)$$

According to the above treatment of the problem, the problem of the utility function design has been reduced to the determination of the final-state configuration function $J_m(\hat{E}(i_0 + T(i_0) + 1))$ and the coefficient $\lambda$. From Eqs. (21,24), it may seem that the variable coefficient $\alpha$ should be within the range $0 < \alpha < 1$ in both application scenarios, nevertheless, we emphasize here that 1 is not an upper-bound for $\alpha$. In general, if the system places an upper bound, $\alpha_1 \cdot \max\{P_t\}$, on $P_t$ (or $P_{avg}$ in application II) and a lower bound, $\alpha_2$, on the probability of successful packet transmission (all $K(i_0)$ packets in application II), then $\alpha$ should be within $0 < \alpha < \frac{\alpha_1}{\alpha_2}$. The proof is given in Appendix II.
C. Summary and Implementation Complexity

The algorithm is summarized in Table 2. Basically, Eq. (18) searches for values of \( J(P_t(i), \hat{E}(i)) \), from which the optimal strategy \( P_t^*(E(i_0)) \) is obtained by means of Eq. (13). Considering the underlying Markov chain model of the system states, the search space is limited to the power space. Thus, this process is somewhat analogous to the well-known Viterbi decoding [21].

In the implementation, since Eq. (18) is executed \((K(i_0)+1) \cdot \text{Sizeof } \{P_t\} \) times per iteration and there are \( T(i_0) \) iterations in total, the complexity of the TSA-MSSN algorithm is of the order \( O(T(i_0) \cdot (K(i_0) + 1) \cdot \text{Sizeof } \{P_t\}) \). However, a more efficient implementation with reduced complexity can be obtained as follows: By fixing the values of \( \theta(i_0) \) and \( L_s(i_0) \) at 0 and \([0, 0]\) respectively, we divide the circular region (with the radius \( \text{Range} \)) centered at \( L_s(i_0) \) into grids. Then, the optimal transmission power \( P_t^*(E(i_0)) \) can be pre-computed for all the grids of \( L_n \), and for all the possible discrete values of \( K(i_0) \) and \( v_s(i_0) \). The precomputed values can be stored in the sink in table form. During the execution of the algorithm, every encountered state \( E(i_0) \) can be projected to a corresponding entry in the table by properly mapping the absolute coordinates \( L_n \). This table look-up operation reduces the implementation complexity to the order of \( O(1) \).

The reduction in the implementation complexity of the algorithm is achieved at the expense of increased storage requirements at the sink. To be more specific, assume that the grid size is \( \Delta S \), and that the velocity resolution is \( \Delta v \). Then, the number of grids for \( L_n \) is approximately \( \lceil \frac{\pi \cdot \text{Range}^2}{\Delta S} \rceil \). The number of discrete values for \( v_s(i_0) \) is \( N_v = \lceil \frac{v_{max}}{\Delta v} \rceil \), where \( v_{max} \) denotes the maximum speed of the sink under consideration. Since the maximum number of packets that could be transmitted under \( v_s(i_0) \) is \( \lceil \frac{2 \cdot \text{Range}}{v_s(i_0) \cdot \Delta t} \rceil \), the range of \( K(i_0) \) in calculating the table entries is from 1 to \( \lceil \frac{2 \cdot \text{Range}}{v_s(i_0) \cdot \Delta t} \rceil \). Thus, an upper bound to the number of table entries \( N_t \) is:

\[
N_t < \sum_{k=1}^{N_v} \left\lfloor \frac{2 \cdot \text{Range}}{k \cdot \Delta v \Delta t} \right\rfloor \cdot \left\lfloor \frac{\pi \cdot \text{Range}^2}{\Delta S} \right\rfloor.
\] (25)

As an example, consider a practical setting where \( \text{Range} = 50\ m \), \( v_{max} = 30\ m/s \), \( \Delta v = 1\ m/sec \), \( \Delta S = 1\ m^2 \). We set \( F_d, F_b, R \), as \( 128 \times 8\ bits, 20 \times 8\ bits, \) and \( 20k\ bits/sec \), respectively. Then, \( \Delta t \) is computed by using Eq.(5) and by substituting these values in Eq.(25) we get \( N_t < 53 \times 10^6 \). By allocating one byte of storage per entry the total required storage for
the table in the sink is at most $53M$ bytes, something that is practically feasible. Note that one table is sufficient for all the sensor nodes in the network.

VI. SIMULATIONS

For the simulations, we assume that the sink is installed in a car which is driven along the highway, while the sensor nodes are deployed along the highway. The setup for communication parameters generally applies to IEEE 802.15.4 [22], and is listed in Table 3. The number of transmission power levels is set to 15, and the set of discrete levels is,

$$P_t(i) \in \{ -\infty, -32, -28, -24, -20, -18, -16, -14, -12, -10, -8, -6, -4, -2, 0 \} (dBm).$$

(26)

A. Transmission Scheduling in TSA-MSSN

1) Application Scenario I: The final-state configuration function $J_m \left( \hat{E}(i_0 + T(i_0) + 1) \right)$ is given by Eq.(20). First, we fix $L_n = [0, 0], \theta_s(i_0) = 0, L_s(i_0) = [-20, 10]$. The coefficient $\lambda$ is set to 1. The optimal strategy $P^*_t$ varies with $K(i_0)$, and is plotted in Fig. 3. Then, we move the location of the sink $L_s(i_0)$ along the map from $[-97, 5]$ to $[97, 5]$, and fix $K(i_0) = 50$. Fig. 4 shows the corresponding curve of $P^*_t(E(i_0))$.

Fig. 3 and Fig. 4 demonstrate the general concept of the transmission strategy. In Fig. 3, the node transceiver sleeps when $K(i_0)$ is less than 30. When $K(i_0) \geq 40$, it starts transmission, because there are not enough better slots available for $K(i_0)$ packets. Moreover, when $K(i_0) \geq 90$, it sets the transmission power level even higher to continue successful transmission. In Fig. 4, there is no transmission when $L_s(i_0)$ is less than $[-37, 5]$, because there are enough “better” slots ahead. When $L_s(i_0)$ is greater than $[-37, 5]$, transmission starts and the power level changes with the distance between the sink and the node.

2) Application Scenario II: The final-state configuration function is given by Eq.(22). we set $\alpha = 1$ in Eq. (24). Fig. 5 and Fig. 6 are obtained in the same way as Fig. 3 and Fig. 4, respectively. By comparing the corresponding results in the two application scenarios, we observe that Fig. 5 is generally similar to Fig. 3, however, Fig. 6 is different than Fig. 4. In particular, we observe in Fig. 6 that transmission stops when $L_s(i_0)$ becomes greater than approximately $[40, 5]$. The reason is that the number of available slots, $T(i_0) + 1$, is less than the total number
of packets, $K(i_0)$, and therefore transmission of $K(i_0)$ packets will fail with probability one. Thus, the transmitter is forced to sleep instead of wasting energy.

**B. Real-world Simulations**

In this section, real-world simulations are performed with variable $\lambda$ to evaluate the behaviour of the TSA-MSSN. As before, we assume that $L_n = [0,0]$, and $\theta_s(i) = 0$. Set $K(i_0) = 18$. With $L_n(i_0) = [75,10]$, the sink passes through the circular communication region of the node. All the results are have been averaged over 200 Monte-Carlo runs.

1) **Application Scenario I:** The final-state configuration function $J_m\left(\hat{E}(i_0 + T(i_0) + 1)\right)$ is given by Eq.(20). For different $\lambda$, Fig. 7 and Fig. 8 depict the total energy consumption $E_{all}$ and the number of successfully transmitted packets $P_{all}$ respectively, where

$$E_{all} = \sum_{i=i_0}^{i_0+T(i_0)} P^\ast_i(E(i)) \cdot \frac{F_d}{R},$$

$$P_{all} = K(i_0) - K(i_0 + T(i_0) + 1).$$

as a function of $\sigma_\xi$. By definition, a higher value of $\lambda$, implies that the TSA-MSSN puts more weight on the energy consumption. Hence, we get lower energy consumption per transmission that corresponds to higher probability of packets loss. On the other hand, higher probability of packet loss, which is forcing the re-transmission of lost packets, is also expected by higher values of $\sigma_\xi$. Too many re-transmissions will increase the total energy consumption $E_{all}$, eventually. It is observed in the figures, that the $E_{all}$ generally decreases as $\lambda$ increases while it increases as $\sigma_\xi$ increases. The $P_{all}$, however, decreases as both $\lambda$ and $\sigma_\xi$ increase. It is interesting to note that for $\sigma_\xi = 0.6$, the cases $\lambda = 1.2$ and $\lambda = 0.9$ have similar $P_{all}$, however, different $E_{all}$. This is due to the re-transmission mechanism. In the figures, we observe that a practical value for $\lambda$ for this application scenario is around 1 with increasingly higher or lower values of $E_{all}$ and $P_{all}$ as $\lambda$ deviates from 1.

2) **Application Scenario II:** The final-state configuration function is given by Eq.(22). Let $\lambda$ take the form of Eq.(24). For different values of $\alpha$, Fig. 9 and Fig. 10 depict $E_{all}$ and the ratio of successful transmission $P_{success}$, respectively, where

$$P_{success} = \begin{cases} 
1, & K(i_0 + T(i_0) + 1) = 0, \\
0, & K(i_0 + T(i_0) + 1) > 0
\end{cases}.$$
as a function of $\sigma_\xi$. We use $\alpha$ instead of $\lambda$ in Fig. 9 and 10, because it shows more clearly the tradeoff between the credit of successful transmission vs the cost of average transmission power, which has been discussed previously in Section V-B.2.

According to the relationship between $\alpha$ and $\lambda$, a lower $\alpha$ suggests that the algorithm places more weight on energy consumption. Hence, $E_{all}$ should increase with $\alpha$, as it is verified by the results of Fig. 9. $P_{success}$ should also increase with $\alpha$, as it is observed in Fig. 10. However, the impact of $\sigma_\xi$ is more complicated. Generally speaking, by increasing $\sigma_\xi$ we expect a higher packet loss probability. Accordingly, in Fig. 10, we observe that $P_{success}$ decreases as $\sigma_\xi$ increases. With respect to $E_{all}$, a higher packet loss probability will force the re-transmission of packets, and therefore, the $E_{all}$ should increase. However, if the packet error rate is too high, the algorithm will terminate the transmission since then, the probability of successfully transmitting $K(i_0)$ packets is slim. Thus, as we observe in Fig. 9, the $E_{all}$ initially increases with $\sigma_\xi$ and starts decreasing again when $\sigma_\xi$ reaches a certain threshold. This threshold is obviously a function of $\alpha$ and decreases as alpha decreases as we observe in the obtained results. According to the obtained results, a practical choice of $\alpha$ in this application scenario should also be around 1. By comparing the $P_{success}$ curves for different values of $\alpha$ we observe a significant and increasing degradation as $\alpha$ deviates from 1.

**VII. Conclusion**

We have proposed an architecture of Wireless Sensor Networks with Mobile Sinks (MSSN). We have analyzed the case of sparsely deployed sensor networks and proposed the node-to-sink transmission scheduling algorithm TSA-MSSN. In the design of the TSA-MSSN, a coefficient $\lambda$ has been employed to control the tradeoff between the credit of successful transmission retrieval and the cost of energy consumption. The major contribution of the paper comes from the understanding of the fundamental transmission scheduling laws in MSSN, by analyzing the particular tradeoff. The results can possibly lead to a MSSN network deployment for highway traffic surveillance applications.
APPENDIX I

COMPUTATION OF $L_{s\_out}$

The coordinates vector $L_{s\_out}$ is shown geometrically in Fig. 2. It can be computed as follows:

$$L_{s\_out} = \left[ \sqrt{\text{Range}^2 - L[y]^2}, L[y] \right] \cdot \begin{bmatrix} \cos \theta_s & \sin \theta_s \\ -\sin \theta_s & \cos \theta_s \end{bmatrix} + L_n,$$

(30)

where,

$$L = (L_s(i_0) - L_n) \cdot \begin{bmatrix} \cos \theta_s & -\sin \theta_s \\ \sin \theta_s & \cos \theta_s \end{bmatrix}.$$  

(31)

APPENDIX II

ON THE RANGE OF $\lambda$

In Section V-B, we have defined $\lambda$ by a variable coefficient $\alpha$. The corresponding relationship is given by Eq.(21) and Eq.(24 under application scenario I & II, respectively. In this appendix, we derive the range of $\alpha$ under the following assumptions: i) the system enforces $\alpha_1 \cdot \max\{P_t\}$ as an upper bound on $P_1(i_0)$ in application I or on $P_{avg}(i_0)$ in application II; ii) the system enforces $\alpha_2$ as a lower bound on the probability of successfully transmitting one packet in application I or all $K(i_0)$ packets in application II. Both $\alpha_1$ and $\alpha_2$ are within the range $0 < \alpha_1, \alpha_2 \leq 1$.

A. Application Scenario I

The credit of successfully transmitting one packet is defined as “1”. The cost of transmitting at a power level $\alpha \cdot \max\{P_t\}$ in one time slot equals also “1”, that is,

$$J_c(\alpha \cdot \max\{P_t\}) = 1.$$  

(32)

To obtain the lower bound on the probability of successfully transmitting one packet, we assume that the cost of transmitting at the maximum power is greater than $\alpha_2$, that is

$$J_c(\alpha_1 \cdot \max\{P_t\}) \geq \alpha_2.$$  

(33)

Since $J_c$ is a linear function of $P_t(i)$ (refer to Eq.(17)), by combining Eq. (32) and Eq. (33), we find,

$$0 < \alpha \leq \frac{\alpha_1}{\alpha_2}.$$  

(34)
B. Application Scenario II

In this scenario, the credit of successfully transmitting all $K(i_0)$ packets is defined as “1”. The cost of average transmission power level, $P_{avg}(i_0) = \alpha \cdot \max\{P_i\}$, equals

$$J_c(\alpha \cdot \max\{P_i\}) = \frac{1}{T(i_0) + 1}.$$  \hspace{1cm} (35)

Furthermore, to obtain the lower bound on the probability of successful transmission, we assume that the cost of transmitting at the maximum average power is greater than $\alpha_2$, that is

$$J_c(\alpha_1 \cdot \max\{P_i\}) \geq \frac{\alpha_2}{T(i_0) + 1}.$$ \hspace{1cm} (36)

From Eq. (35) and Eq. (36), we get $0 < \alpha \leq \frac{\alpha_1}{\alpha_2}$, which is the same as in Eq.(34). Note, however, that the definitions of $\alpha$ are different in the two cases.

APPENDIX III

ON THE CONCAVITY OF THE UTILITY FUNCTION $J\left( P_t(i), \hat{E}(i) \right)$

Throughout the paper, we have assumed a discrete set of transmission power levels which is the state of art in wireless transceiver hardware design. In this appendix, we show that the optimization $J\left( P_t(i), \hat{E}(i) \right)$ of is computationally simple even if $P_t(i)$ is continuous. Throughout this section, $i_0 \leq i \leq i_0 + T(i_0)$. Also, given the $\hat{E}(i)$, we simplify the notation of $J\left( P_t(i), \hat{E}(i) \right)$ and $J_m\left( P_t(i), \hat{E}(i) \right)$ into $J(P_t(i))$ and $J_m(P_t(i))$, respectively.

**Lemma:** Given $\hat{E}(i)$, there exists a threshold $P_{th}$ satisfying the following conditions: $J\left( P_t(i) \right)$ is a convex function of $P_t(i)$ for $0 \leq P_t(i) \leq P_{th}$ and a concave function of $P_t(i)$ for $P_t(i) \geq P_{th}$.

**Proof:** Let $E_1$ and $E_2$ denote the two possible values of the state $\hat{E}(i + 1)$, where

$$
\begin{align*}
\hat{K}(i + 1)|E_1 &= \hat{K}(i) \\
\hat{K}(i + 1)|E_2 &= \hat{K}(i) - 1.
\end{align*}
$$ \hspace{1cm} (37)

In general,

$$U\left( \hat{E}(i + 1) = E_1 \right) < U\left( \hat{E}(i + 1) = E_2 \right),$$ \hspace{1cm} (38)

which is rewritten as,

$$U( E_1 ) < U( E_2 ).$$ \hspace{1cm} (39)
By means of Eq. (10), the Eq.(16) can be simplified as,

\[
J_m(P_t(i)) = U(E_1) \cdot \hat{P}\hat{E}R(i) + U(E_2) \cdot (1 - \hat{P}\hat{E}R(i)) \\
= U(E_2) - (U(E_2) - U(E_1)) \cdot \hat{P}\hat{E}R(i),
\]

(40)

where \(U(E_1)\) and \(U(E_2)\) are known from the previous iteration and satisfy Eq.(39).

Moreover, it can be shown that there exists a threshold \(P_{th}\). Under the condition that \(P_t(i) \geq P_{th}\), the \(\hat{P}\hat{E}R(i)\), given by Eq.(11), is a convex function of \(P_t(i)\). When \(0 \leq P_t(i) \leq P_{th}\), \(\hat{P}\hat{E}R(i)\) is a concave function of \(P_t(i)\). Note that, \(P_{th} = 0\) for \(F_d = 1\), and \(P_{th} > 0\) for \(F_d > 1\). (The details can be shown by taken the second order derivative on \(\hat{P}\hat{E}R(i)\), which is mathematically tedious and omitted here for space saving.)

Hence, by Eq. (40), such a threshold \(P_{th}\), determined by \(\hat{P}\hat{E}R(i)\), also decides the concavity/convexity of \(J_m\), that is, \(J_m\) is a convex function for \(0 \leq P_t(i) \leq P_{th}\), while it is concave function for \(P_t(i) \geq P_{th}\). In Eq.(17) \(J_c\) is a linear function of \(P_t(i)\). Thus, according to the Eq.(15), given \(\hat{E}(i)\), the concavity/convexity of \(J\) depends only on \(J_m\). This proves the lemma.

**Theorem:** Given \(P_{th}\) as by the Lemma, under the condition \(P_t^*(\hat{E}(i)) > 0\) there is: \(P_t^*(\hat{E}(i)) \geq P_{th}\) for \(P_{th} \leq \max\{P_t\}\) and \(P_t^*(\hat{E}(i)) = \max\{P_t\}\), for \(P_{th} > \max\{P_t\}\).

**Proof:** By definition,

\[
P_t^*(\hat{E}(i)) = \arg\max_{P_t(i)} J \left( P_t(i), \hat{E}(i) \right).
\]

(41)

For \(P_{th} \leq \max\{P_t\}\), we prove the first claim of the theorem by showing that if there exists \(P_1 < P_{th}\) satisfying \(J(P_1) > J(0)\), then it must be \(J(P_{th}) > J(P_1)\). This is a result of the convexity of \(J\) in the region \(0 \leq P_t(i) \leq P_{th}\). For \(P_{th} > \max\{P_t\}\), we prove the second claim of the theorem by showing that if there exists \(P_1 < \max\{P_t\}\) satisfying \(J(P_1) > J(0)\), then it is \(J(\max\{P_t\}) > J(P_1)\). This is again a result of the convexity of \(J\) in the region \(0 \leq P_t(i) \leq \max\{P_t\}\).

Furthermore, we argue that the value of \(P_{th}\) is decided by \(\hat{P}\hat{E}R(i)\) and depends on \(\hat{G}(i)\). In general it is \(P_{th} = \frac{C}{\hat{G}(i)}\), where \(C\) is a positive constant. For example, according to the Eq. (11), by adopting the parameters of Table 3, \(C\) can be numerically computed as \(C = 1.7 \times 10^{-9}\) mW. Note that \(C\) is determined by the system model parameters and is computed only once.

The above Theorem permits us to construct a computationally simple way of searching for the maximum of \(J\). If \(P_{th} < \max\{P_t\}\), we search for the maximal value of \(J\) in the concave
region $P_{th} \leq P_t(i) \leq \max\{P_t\}$ and compare it to $J(0)$. The larger one of the two is taken as the $J$ maximum. Due to the concavity of $J(P_t(i))$ in $P_{th} \leq P_t(i) \leq \max\{P_t\}$ the search is computationally simple. On the other hand, if $P_{th} > \max\{P_t\}$, the larger number between $J(0)$ and $J(\max\{P_t\})$ is simply selected as the maximum.

REFERENCES


Table 1. Notation Description

<table>
<thead>
<tr>
<th>Notation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i_0)</td>
<td>the current time slot</td>
</tr>
<tr>
<td>(D(i_0)) and (\hat{D}(i))</td>
<td>current and estimated future (slot (i \geq i_0)) distance from the sensor node to the sink</td>
</tr>
<tr>
<td>(E(i_0)) and (\hat{E}(i))</td>
<td>current and estimated future (slot (i \geq i_0)) system state</td>
</tr>
<tr>
<td>(\hat{E}(i_0))</td>
<td>the series of estimated system states</td>
</tr>
<tr>
<td>(F_d) and (F_b)</td>
<td>length of the data and ACK packets in bit</td>
</tr>
<tr>
<td>(G(i_0))</td>
<td>current wireless channel gain</td>
</tr>
<tr>
<td>(\hat{G}(i))</td>
<td>estimated wireless channel gain, (i \geq i_0)</td>
</tr>
<tr>
<td>(J\left(P_t(i), E(i)\right))</td>
<td>estimated utility function, (i \geq i_0)</td>
</tr>
<tr>
<td>(J_m\left(P_t(i), E(i)\right))</td>
<td>estimated credit function, (i \geq i_0)</td>
</tr>
<tr>
<td>(J_c\left(P_t(i)\right))</td>
<td>estimated cost function, (i \geq i_0)</td>
</tr>
<tr>
<td>(K(i_0)) and (\hat{K}(i))</td>
<td>current and estimated future (slot (i \geq i_0)) number of packets await for transmission</td>
</tr>
<tr>
<td>(L[x]) and (L[y])</td>
<td>(L = [L[x], L[y]]) for all the 2-D location coordinates vector (L)</td>
</tr>
<tr>
<td>(L_s(i_0)) and (\hat{L}_s(i))</td>
<td>current and estimated future (slot (i \geq i_0)) location coordinates of the sink</td>
</tr>
<tr>
<td>(\hat{L}_n)</td>
<td>location coordinates of the sensor node</td>
</tr>
<tr>
<td>(L_{s, out})</td>
<td>the point coordinates where the sink leaves the communication range of the sensor</td>
</tr>
<tr>
<td>(\text{max}{P_t})</td>
<td>the maximum transmission power level</td>
</tr>
<tr>
<td>(n)</td>
<td>wireless channel path loss component</td>
</tr>
<tr>
<td>(P_t(i))</td>
<td>supposed transmission strategy (transmission power), (i \geq i_0)</td>
</tr>
<tr>
<td>(\text{Sizeof}{P_t})</td>
<td>number of discrete transmitting power levels (size of strategy space)</td>
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<tr>
<td>(P^*_t(E(i_0)))</td>
<td>optimal TSA-MSSN strategy decision at current slot (i_0)</td>
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<tr>
<td>(P^*_t(E(i_0)))</td>
<td>optimal TSA-MSSN strategy decision at slot (i_0 = i)</td>
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<td>(P^*_t(\hat{E}(i)))</td>
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<td>(PER(i))</td>
<td>estimated packet error rate, (i \geq i_0)</td>
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<tr>
<td>(R)</td>
<td>communication data rate</td>
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<tr>
<td>(T(i_0))</td>
<td>current estimated number of time slots available for packets transmission</td>
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<tr>
<td>(U(\hat{E}(i)))</td>
<td>the maximum achievable utility value associated with (\hat{E}(i))</td>
</tr>
<tr>
<td>(\Delta t)</td>
<td>duration of one time slot</td>
</tr>
<tr>
<td>(v_s(i_0)) and (\hat{v}_s(i))</td>
<td>current and estimated future (slot (i \geq i_0)) mobility velocity of the sink</td>
</tr>
<tr>
<td>(\theta_s(i_0)) and (\hat{\theta}_s(i))</td>
<td>current and estimated future (slot (i \geq i_0)) mobility direction of the sink</td>
</tr>
<tr>
<td>(\xi)</td>
<td>wireless shadowing effect component with a normal distribution (N(0, \sigma^2_\xi)) (dB)</td>
</tr>
</tbody>
</table>
Table 2. Summary of the TSA-MSSN Algorithm

Given $E(i_0)$;

Get $T(i_0)$ by Eq.(4);

Initialize final-state utility function

$$ J \left( P_t(i_0 + T(i_0) + 1), \hat{E}(i_0 + T(i_0) + 1) \right) $$

by Eq.(19);

For $i$ equals $i_0 + T(i_0)$ down to $i_0$,

For all $\hat{E}(i)$,

Calculate $J \left( P_t(i), \hat{E}(i) \right)$ by Eq.(18);

Decide the optimal transmission strategy $P_t^* \left( E(i_0) \right)$

by Eq.(13).

Table 3. Communication Parameters Setup

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>Value</th>
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<tr>
<td>$F_d$</td>
<td>bit</td>
<td>$128 \times 8$</td>
</tr>
<tr>
<td>$F_b$</td>
<td>bit</td>
<td>$20 \times 8$</td>
</tr>
<tr>
<td>$R$</td>
<td>bits/sec</td>
<td>20000</td>
</tr>
<tr>
<td>$n$</td>
<td></td>
<td>2.5</td>
</tr>
<tr>
<td>$A$</td>
<td>dB</td>
<td>$-31$</td>
</tr>
<tr>
<td>$\xi$</td>
<td>dB</td>
<td>$N \left( 0, \sigma^2_\xi \right)$</td>
</tr>
<tr>
<td>Range</td>
<td>m</td>
<td>100</td>
</tr>
<tr>
<td>$\sigma^2_n$</td>
<td>dBm</td>
<td>$-92$</td>
</tr>
<tr>
<td>$v_s(i)$</td>
<td>m/sec</td>
<td>20</td>
</tr>
</tbody>
</table>
Fig. 1. MSSN for Traffic Surveillance
Fig. 2. The mobile sink passes through the circular region centered on $L_n$. 
Fig. 3. Application I: optimal transmission power $P_t^*(E(i_0))$ vs. $K(i_0)$
Fig. 4. Application I: optimal transmission power $P^*_t(E(i_0))$ vs. $L_s(i_0)[x]$ (m)
Fig. 5. Application II: optimal transmission power $P^*_t(E(i_0))$ vs. $K(i_0)$
Fig. 6. Application II: optimal transmission power $P_t^* (E(i_0))$ vs. $L_{s(i_0)}$
Fig. 7. Application I: total energy consumption $E_{all}$ vs. $\sigma_\xi$
Fig. 8. Application I: successfully transmitted packets $P_{all}$ vs. $\sigma_\xi$
Fig. 9. Application II: total energy consumption $E_{\text{all}}$ vs. $\sigma_\xi$
Fig. 10. Application II: ratio of successful transmission $P_{\text{success}}$ vs. $\sigma_\xi$