Bounding A Statistical Measure Of Network Lifetime For Wireless Sensor Networks

Muhammad U. Ilyas, and Hayder Radha

Abstract—**The inherent many-to-one flow of traffic in Wireless Sensor Networks produces a skewed distribution of energy consumption rates leading to the early demise of those sensors that are critical to the ability of surviving nodes to communicate their readings to the data collection center. Numerous previous approaches aimed at balancing the consumption of energy in wireless networks are based on a linear programming-based minmax formulation that seeks to maximize the minimum lifetime of sensors in a network. However, this approach fails to provide a clear picture of the cost at which this optimization is achieved and focuses attention on a single sensor, the minimum lifetime sensor. This paper makes two contributions; 1) it puts forward a new understanding of sensor network lifetime based on statistical measures, mean and variance, of node power consumption rates that provides a more inclusive view of the consumption rates, and 2) it provides an optimal quadratic programming (QP) formulation that provides an upper bound on the lifetime under a given set of topological and energy budgetary constraints. Our results demonstrate that the QP formulation has the ability to provide a soft trade-off between the mean and variance of power consumption rates.**

***Index Terms*—Quadratic Programming, Network Lifetime, Wireless Sensor Networks.**

I. INTRODUCTION

WIRELESS Sensor Networks (WSNs) [1] are set to become an integral part of the networked computing landscape we live in. In recent months the world has witnessed numerous natural disasters such as the inundation of New Orleans, the South-East Asian tsunami, the massive earthquake in Kashmir and wildfires in California. In each of these instances, losses could have been dramatically reduced or prevented by appropriate action based on the availability of accurate and timely information. The large loss of life and property and the promise of sensor networks to provide necessary timely information to decision makers in some instances spurned governments into action and accelerated the development and deployment of large early warning systems based on sensor network systems.

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One of the most fundamental challenges in WSNs is the short and often limited supply of energy. Due to the disposable nature of WSN nodes power sources are often non-replenishable or replenishable very slowly at best. In either case this forces prudent use of battery power for all operations. Since WSNs can be spread over large geographical areas multi-hop communication is employed in transmitting sensor measurements to the data collection point, also known as the base station. The problem is further compounded by the many-to-one traffic flow pattern that is imposed by the data collection process. It produces a traffic hot-spot or bottleneck around the base station and, depending on the positioning of nodes, in other regions of the network as well. This phenomenon is called the *reachback* and was investigated by Servetto in [2]. If the same Shortest-Path-First (SPF) routes [3] are maintained, as in the case of most present day Mobile Ad-Hoc Networks (MANET) and WSN routing algorithms, nodes start running out of energy. Nodes gradually start disappearing from the sensor network beginning with those handling the highest traffic volume, the ones communicating directly with the base station. Such nodes are referred to as critical nodes. Each node going offline will reduce coverage provided by the WSN. Eventually all nodes in communication range of the base station will run out of power and the base station will stand disconnected from all surviving nodes, effectively dropping situational awareness at the base station to zero. While the nature of the traffic flow makes the degradation of system capabilities over time inevitable, it is desirable to make it as graceful as possible. This leads us to consider a solution that will redistribute the volume of traffic handled by critical nodes more evenly. It is noted here that any deviation from routes selected using a routing algorithm based on SPF means selecting a route that is suboptimal in the traditional, greedy sense (of which there are many even for small sets of critical nodes).

The above discussion provides us with two objectives; 1) reducing the differences between energy consumption rates of nodes, 2) but at the same time keeping the average energy consumption rate low. This requires the joint minimization of both objectives. Since these two objectives run counter to each other the selection of an operating point is a trade-off between mean and variance of power consumption rates.

The rest of the paper is organized as follows. Section II reviews some recent efforts that attempt to increase longevity of WSNs and positions our work. Section III describes our interpretation of network lifetime and how the advantages of its use as an objective over previous definitions. Section IV describes our network model and introduces terminology. Section V formulates the problem as a quadratic program. Section VI describes some results for small scale examples and section VII concludes the paper.

II. Prior Work

The volume of works spanning energy efficient routing protocols for WSN is extensive. Early WSNs borrowed routing protocols from ad-hoc wireless networks and MANETs. The routes selected by Dynamic Destination-Sequenced Distance-Vector (DSDV) [4], Dynamic Source Routing (DSR) [5], Ad-hoc On-Demand Distance Vector (AODV) [6] and Directed Diffusion [7] protocols are "optimal" only in a greedy, SPF sense which worked well enough for networks without power constraints. The performance of a system using these protocols is as much subject to the reachback problem as one making use of naïve SPF routing.

In [8] Chang and Tassiulas formulate the lifetime problem as a minmax linear program (LP) that seeks to maximize the minimum sensor lifetime. However, while the approach is theoretically sound and provides a bound for any attempt at maximizing that particular notion of network lifetime, there are scalability problems which are exacerbated by the very large number of optimization variables for which the LP is solved. This was followed by several other LP formulations of the lifetime problem [9],[10],[11],[12], all based on the same or similar meaning of network lifetime, of varying degrees of usability. In [13] Baek and de Veciana proposed a proactive multi-path routing scheme by introducing joint minimization of the "spreading factor" w, and the probability of battery depletion of a sensor which is very similar to Ilyas and Radha's parallel work in [14] that uses average and variance of power consumption rates in sensors. However, Baek and de Veciana's mechanism used for path discovery does not take into account several other available communication links. While the authors demonstrate the improvements offered by their energy balancing algorithm in networks with any-to-any data flow the proposed solution does not seem to offer an improvement when the traffic flow is many-to-one/ all-to-one. More recently Khanna, Liu and Chen [15] took an evolutionary approach. However, this was marked by a high complexity due to the inherent nature of Genetic algorithms and poses challenges to scalability.

III. Novelty Of Approach

The bulk of previous work on the lifetime problem defines network lifetime as the time until the first sensor runs out of power. The rigidity of this definition is of advantage because it provides a clear objective function for optimization. However, any set of routes that deviate from greedy SPF routes produce an increase in the power consumption rates of some nodes, decreasing their individual lifetimes. The prior LP approaches that maximize the minimum sensor lifetime are no exception. However, by solely focusing on one sensor's lifetime (the minimum lifetime sensor), it ignores the cost, the decrease in other sensors' lifetimes at which this maximization is achieved. This also implies a higher rate of failure of sensors as a network approaches the end of its life, as defined under LP minmax problem formulations. This definition disregards the inherent redundancy in WSNs and their ability to cope with a limited device failure rate. In this paper we use a notion of lifetime that takes these "shortcomings" into account. We propose the joint use of two statistics of P, the random variable modeling the energy consumption rates of sensors in a WSN, namely;

1. $E[P]$: the mean of P.
2. $Var[P]$: the variance of P.

The problem then becomes a joint-minimization problem. This notion of lifetime takes into account the lifetimes of the entire population of sensors making up the network. Some previous solutions such as Singh, Woo and Raghavendra [19] describe the independent minimization of only the variance of node power levels to extend the lifetime of a network. Minimization of $E[P]$ alone is achieved by SPF routing protocols based on energy as a cost metric. However, selecting routes based solely on the minimization of $E[P]$ will inevitably lead to the aforementioned reachback problem where sensor nodes closer to the base station transmit packets at significantly higher frequency compared to sensor nodes farther away. This problem can be formulated as a budget constrained allocation problem: The minimization of $Var[P]$ defined as (2) is subject to the constraint (1) that $E[P]$ be less than some maximum budget value $E[P]^*$, where P_i is the energy consumption rate of node $n_i, \forall 1 \le i \le N$, and N is the number of nodes.

$$\min Var[P] = \frac{\sum_{i=1}^{N} \left(P_i - E[P]\right)^2}{N} \tag{1}$$

Subject to,

$$E[P] = \frac{\sum_{i=1}^{N} P_i}{N} \le E[P]^* \tag{2}$$

Using the constraint formulation highlighted above, we can summarize our optimization framework as identifying the set of routes throughout a given WSN such that the following is satisfied: $\min_{E[P] \le E[P]^*} \{Var[P]\}$.

IV. Network Model

To model devices we are adhering to the IEEE 802.15.4 *Low-Rate Wireless Personal Area Network* (LR-WPAN) draft standard [16]. The standard defines two device classes, *Reduced-Function Devices* (RFDs) and *Full-Function Devices*

(FFDs). Since RFDs are incapable of performing routing functions and since we are investigating a routing solution we use the term node to refer to FFDs only.

A WSN consists of $N_{FFD} + N_{RFD}$ sensors and one base station. Since we will only be dealing with FFDs in a routing solution we abbreviate N_{FFD} by N. FFD routers are numbered 1 through N and denoted by n_1 through n_N The base station is assigned FFD ID 0 and denoted by n_0. Furthermore we are assuming the nodes participating in the WSN to be capable of measuring Received Signal Strength Indication (RSSI) and Link Quality Indication (LQI) for received packets and adjusting their transmission power as laid down in the standard. Nodes are capable of varying transmission power at run-time on a packet-by-packet basis. Transmission power is chosen as a function of the spatial separation between transmitter and receiver.

For the channel model we adhere to the model of the 802.15.4 Physical Channel Modeling Subgroup [17]. Early exploratory work by Ilyas and Radha [14] assumed the simple disk model for a node's communication range. A consequence of this model was that it made all links bidirectional which is not necessarily true in real wireless networks. We are modeling the communication range of a sensor in each direction by a Gaussian random variable Z with mean μ_Z and variance σ_Z^2. As a result, some links in the network are unidirectional. Each link from a node n_i to another node n_j is assigned a link cost C_{ij} obtained by,

$$c_{ij} = \frac{d^{\alpha}\left(n_i, n_j\right) + Z\left(\mu_Z, \sigma_Z^2\right)}{B_i} \geq 0 \, . \tag{3}$$

Here α is an exponential decay factor which varies for wireless communication from 2 to 4, depending on the type of environment. An assignment of $c_{ij} = 0$ denotes the absence of a direct link from n_i to n_j. Here $d(a,b)$ is a function that returns the Euclidean distance between the nodes provided in the argument, and B_i denotes the battery reserve of n_i. The cost c_{ij} is the cost of transmitting the packet from n_i at a power that ensures reception at n_j with a minimum Signal-to-Noise Ratio (SNR) [18] of $SNR_{\min}$ with required certainty.

For the MAC model we refer to the 802.15.4 LR-WPAN standard [16]. The standard is geared towards energy-conservation. Since the protocol supports a slotted Collision Sense/Multiple Access (sCSMA) mode based on Time Division Multiple Access (TDMA) we can make the reasonable assumption that there is little interference as long as link utilization remains under the maximum possible data throughput rate.

V. Quadratic Program Formulation

In view of the new understanding of network lifetime and the associated objective function we formulate the lifetime maximization program as a Quadratic Program (QP). Let Q_i denote the data produced by n_i for transmission to n_0. This value can depend on the spatial distribution of the entropy [20] of the underlying event being sensed by the WSN. Let q_{ij} denote the flow from n_i to its neighbor n_j with which it communicates directly. Also, $q_{ij} \geq 0$. If c_{ij} denotes the cost of communicating a unit of information directly from n_i to n_j, then the cost incurred by n_i in communicating q_{ij} to n_j is $c_{ij} q_{ij}$. We are not assuming the use of any in-network processing that might violate the conservation of flow in the network. This condition is illustrated in Fig. 1. Then, if S_i denotes the set of nodes n_i can relay its flow to, the condition of flow conservation for any single node n_i can be expressed as,

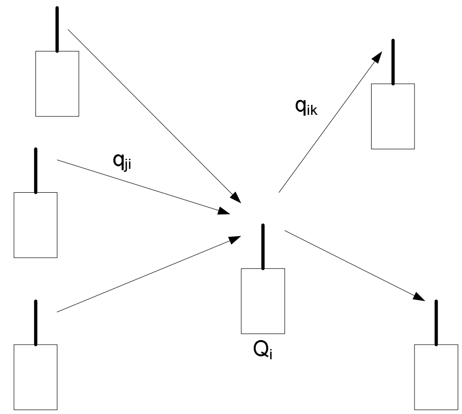

Fig. 1. The law of conservation of flow requires that the sum of incoming flows q_{ji} and data Q_i generated at node n_i must equal the sum of all outgoing flows q_{ik}.

$$Q_i + \sum_{i \in S_j} q_{ji} = \sum_{j \in S_i} q_{ij}, \; \forall 1 \leq i \leq N \, . \tag{4}$$

Note that the base station n_0 has been deliberately excluded from the condition of flow conservation in equation (4) since it is a consumer of flow. Since links between nodes are not necessarily bi-directional, hence generally $c_{ij} \neq c_{ji}$. If m_i denotes the cardinality of S_i, then individual elements of S_i are referred to by $S_i(j)$ where $1 \leq j \leq m_i$. For the purpose of simplified notation elements within S_i are assumed to be sorted in ascending order of their node IDs. The total number of links in the network is denoted by $M = \sum_{i=1}^{N} m_i$.

We now proceed to formulate the problem as a quadratic program in matrix form. Let $\underline{q}$ denote the *flow vector* that is to be optimized and $\underline{Q}$ the flow generation vector as in.

$$\underline{q} = \begin{bmatrix} q_{1,S_1(1)} \\ \vdots \\ q_{1,S_1(m_1)} \\ q_{2,S_2(1)} \\ \vdots \\ q_{2,S_2(m_2)} \\ \vdots \\ q_{N,S_N(1)} \\ \vdots \\ q_{N,S_N(m_N)} \end{bmatrix}, \underline{\mathrm{Q}} = \begin{bmatrix} \mathrm{Q}_1 \\ \mathrm{Q}_2 \\ \vdots \\ \mathrm{Q}_\mathrm{N} \end{bmatrix}$$

Let the separable cost matrix C be defined as,

$$C = \begin{bmatrix} c_{1,S_1(1)} & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ c_{1,S_1(m_1)} & 0 & \cdots & 0 \\ 0 & c_{2,S_2(1)} & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & c_{2,S_2(m_2)} & \cdots & 0 \\ 0 & 0 & \cdots & c_{N,S_N(1)} \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \cdots & c_{N,S_N(m_N)} \end{bmatrix}^T$$

C contains the same information as the adjacency matrix of the network, but is organized in a sparser and separable fashion more suitable for later use. Since the bulk of power consumed in sensors is due to data transmission we are associating a cost only to the data transmission process. Power consumption for reception is usually constant and significantly less than transmission power. Since $P_i = \sum_{j \in S_i} c_{ij} q_{ij}$ the objective function of minimizing the variance of power consumption in equation (1) can be expressed in the terms defined above as,

$$\min \frac{1}{N} \sum_{i=1}^{N} \left[\sum_{j \in S_i} c_{ij} q_{ij} - \frac{1}{N} \sum_{i=1}^{N} \sum_{j \in S_i} c_{ij} q_{ij} \right]^2$$

$$\min \sum_{i=1}^{N} \left[\begin{array}{l} \left(\sum_{j \in S_i} c_{ij} q_{ij} \right)^2 + \left(\frac{1}{N} \sum_{i=1}^{N} \sum_{j \in S_i} c_{ij} q_{ij} \right)^2 \\ - \frac{2}{N} \left(\sum_{j \in S_i} c_{ij} q_{ij} \right) \left(\sum_{i=1}^{N} \sum_{j \in S_i} c_{ij} q_{ij} \right) \end{array} \right] \quad (5)$$

Note that we dropped the $1/N$ term. Equation (5) can be rewritten in matrix form as,

$$\min \left(C\underline{q} \right)^T C\underline{q} + \frac{1}{N^2} \left(\underline{1}^T C\underline{q} \right)^2 - \frac{2}{N} \underline{1}^T \left(C\underline{q} \left(\underline{1}^T C\underline{q} \right) \right)$$

$$\min \underline{q}^T C^T C\underline{q} + \left(\frac{1-2N}{N^2} \right) \left(\underline{1}^T C\underline{q} \right) \left(\underline{1}^T C\underline{q} \right)$$

$$\min \underline{q}^T C^T C\underline{q} + \left(\frac{1-2N}{N^2} \right) \left(\left(C\underline{q} \right)^T \underline{1} \right) \left(\underline{1}^T C\underline{q} \right)$$

$$\min \underline{q}^T \left(C^T C + \left(\frac{1-2N}{N^2} \right) C^T 1_{N \times N} C \right) \underline{q} \quad (6)$$

Here $\underline{1}$ denotes a vector of 1s. Since the second order coefficient matrix in equation (6) is symmetric this QP has a solution, provided that the constraints are well defined. The budget constraint in (2) can be expressed in matrix form as,

$$\frac{\underline{1}^T C\underline{q}}{N} \le E[P]^* \quad (7)$$

$$\underline{q} \succeq 0 \quad (8)$$

Finally we need to define the constraint based on the conservation of flow. We define a *flow matrix* F of size $N \times M$ as below.

$$F = \begin{bmatrix} f_{1,S_1(1)}(1,1) & f_{1,S_1(1)}(2,1) & \cdots & f_{1,S_1(1)}(N,1) \\ \vdots & \vdots & & \vdots \\ f_{1,S_1(m_1)}(1,m_1) & f_{1,S_1(m_1)}(2,m_1) & \cdots & f_{1,S_1(m_1)}(N,m_1) \\ f_{2,S_2(1)}(1,m_1+1) & f_{2,S_2(1)}(2,m_1+1) & \cdots & f_{2,S_2(1)}(N,m_1+1) \\ \vdots & \vdots & & \vdots \\ f_{2,S_2(m_2)}\left(1,\sum_{i=1}^{2} m_i\right) & f_{2,S_2(m_2)}\left(2,\sum_{i=1}^{2} m_i\right) & \cdots & f_{2,S_2(m_2)}\left(N,\sum_{i=1}^{2} m_i\right) \\ \vdots & \vdots & & \vdots \\ f_{N,S_N(1)}\left(1,\sum_{i=1}^{N-1} m_i + 1\right) & f_{N,S_N(1)}\left(2,\sum_{i=1}^{N-1} m_i + 1\right) & \cdots & f_{N,S_N(1)}\left(N,\sum_{i=1}^{N-1} m_i + 1\right) \\ \vdots & \vdots & & \vdots \\ f_{N,S_N(m_N)}\left(1,\sum_{i=1}^{N} m_i\right) & f_{N,S_N(m_N)}\left(2,\sum_{i=1}^{N} m_i\right) & \cdots & f_{N,S_N(m_N)}\left(N,\sum_{i=1}^{N} m_i\right) \end{bmatrix}^T$$

Elements $f_{a,S_b(c)}(d,e)$ for which $d = b$ are set to 1. All elements for which $d \in S_a$ are set to -1. All remaining elements are set to 0. That allows us to express the condition for the conservation of flow like in equation (9).

$$F\underline{q} = \underline{Q} \quad (9)$$

Thus equations (6) through (9) constitute the QP formulation. Note that the base station or data collection point n_0 is exempted from the condition of conservation of flow. The nature of this formulation is such that the solution $\underline{q}^*$ provides the optimal distribution of traffic with which outgoing links should be utilized.

Any routing strategy that seeks to redistribute the traffic load deviates from the SPF routing strategy that provides minimum global energy consumption, thereby raising $E[P]$. The increase in Chang and Tassiulas' [8] defined network lifetime comes at the cost of decreased individual lifetimes of some other nodes in the network. However, the LP formulation is such that there is no control over the cost at which this increase in lifetime is achieved. A benefit of the QP formulation over previous LP formulations is that the objective function provides a global view of node consumption rates.

Unfortunately, the complexity of solving this QP even for moderate values of M and N is too high to be of interest for practical use. Nevertheless it provides us with a bound on the best possible solution given a set of constraints.

VI. RESULTS

We applied the QP formulation to some example networks of varying, yet manageable sizes of 10, 15 and 20 nodes. The nodes are randomly scattered in a square region of 10×10 dimensions. All nodes are assumed to have equal initial battery reserves $B_1(0) = B_2(0) = \ldots = B_N(0) = 1$ with maximum transmission range $r = 10$. The Gaussian noise source producing irregular link costs is set to $Z(10,2)$. The decay factor is taken $\alpha = 3$, typical of omni-directional antennas in open spaces. The spatial distribution of the sensed event's entropy is assumed to be uniform. Hence, all sensors are generating data at a uniform rate as well, i.e. $Q_1 = Q_2 = \ldots = Q_N$.

To illustrate the QPs ability to offer a gradual tradeoffs of $Var[P]$ for $E[P]$. Each operating point in Fig. 2, Fig. 4. and Fig. 3 is obtained by successively relaxing the constraint in equation (7) by incrementally raising $E[P]^*$ and solving each resulting QP. As expected, each successive solution offers decreasing $Var[P]$. However, after a certain point $Var[P]$ starts increasing again. Ilyas and Radha reported similar behavior in their Dynamic Programming based approach in [14].

VII. Conclusions

We propose a new definition of network lifetime consisting of $E[P]$ and $Var[P]$. This notion of network lifetime provides a more inclusive view of the power consumption of sensors across the network. The objective function offers an alternative view of network lifetime. We went on to formulate the optimization problem for the new objective function in the form of a QP and showed that a solution exists.

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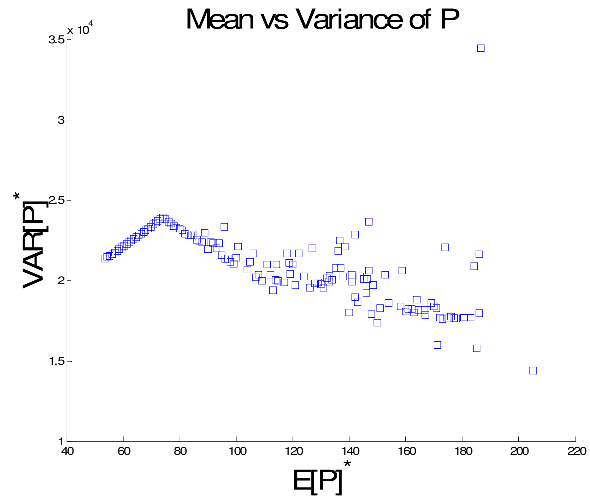

Fig. 4. Tradeoff of $Var[P]$ versus $E[P]$ for a network with $N = 10$.

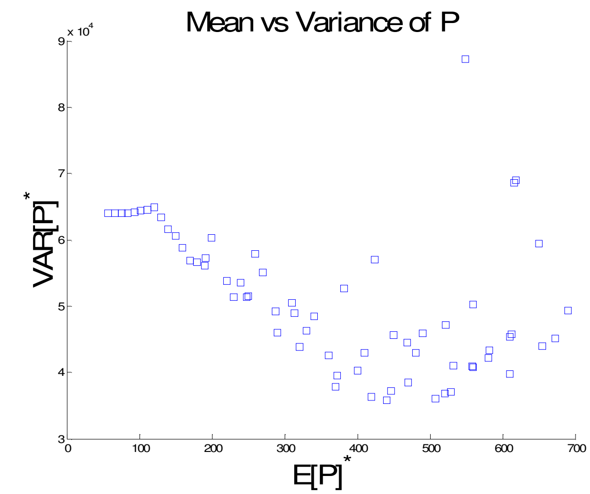

Fig. 2. Tradeoff of $Var[P]$ versus $E[P]$ for a network with $N = 15$.

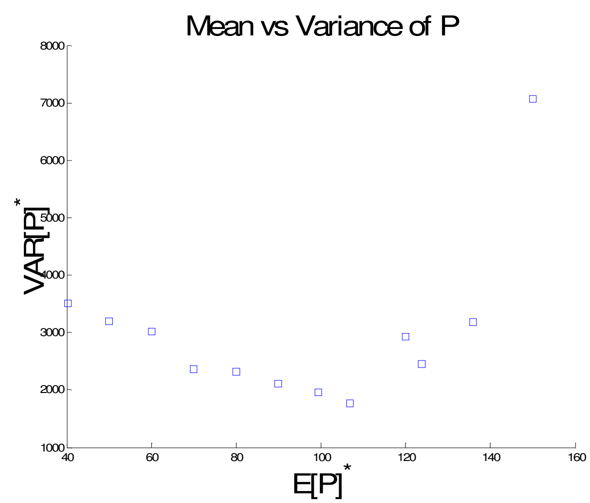

Fig. 3. Tradeoff of $Var[P]$ versus $E[P]$ for a network with $N = 20$.

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