Neural Network-Based Approach to for Adaptive Density Control and Reliability in Wireless Sensor Networks

Renita Machado, Sirin Tekinay

ECE Department,

New Jersey Institute of Technology,

University Heights, Newark, NJ 07102

{rmm23, sirin.tekinay}@njit.edu

***Abstract*- A primary constraint in wireless sensor networks (WSNs) is obtaining reliable and prolonged network operation with power-limited sensor nodes. Most of the approaches to the energy constraint problem focus mainly on the WSN and its architecture without analyzing the underlying process for the depletion of battery levels of individual nodes and consequent reduction in network lifetime: the variation of sensing environment in the deployment region. We study the energy model of a WSN as interdependence between the environmental variation and its impact on the energy consumption at individual nodes. This paper motivates the need for modeling energy variation in WSNs along with the environment in the deployment region. Defining network energy as the sum of residual battery energy at nodes, we provide an analytical framework for the dependence of node energy and sensitivity of network energy as a function of environmental variation and reliability parameters. Using a neural network based approach, we perform adaptive density control and show how reliability requirements and environment variation influences the rate of change of network energy.**

I. INTRODUCTION

A key challenge in energy optimization for densely deployed WSNs is selecting the set of sensors that remain 'awake' for a given cycle. Some of the criteria developed for choosing the set of active nodes are environment probing [1] to determine active neighbors, k-coverage [2] and connectivity-based participation in multi-hop network [3]. While these approaches target the WSN architecture and individual node lifetimes, they overlook the dependence of the battery variation on the variation in the sensed environment. Since nodes typically report data to the base station when the sensed data exhibits large variance, a rapidly changing environment influences the energy consumption at nodes due to higher number of transmissions from nodes to base station/other nodes. Hence, it is essential to model the WSN system with interdependence between the WSN and the environment. This kind of a system modeling approach reflects the sensitivity of network lifetime to the pattern of variation in the environment with the help of bifurcation parameters of the environment model.

In this paper, we describe a neural-network approach for density control based on the interdependence between environment variation and node energy. Our first objective is to develop an approach that takes into account reliability of the sensing operation. The goal is to vary the density of 'awake' nodes according to a user-defined reliability requirement. For instance, a higher reliability requirement requires a higher density of nodes in the deployment region that are continuously sensing and transmitting to a central base station (BS) that acts as a sink. The second objective is to account for variation of environment in parts of the deployment region. Since some areas of the deployment region may exhibit different environment variations, the rate of reporting data from nodes to BS should allow for adaptive density control in different areas of the deployment region. Specifically, we use the Boltzmann learning rule to choose the set of active sensors for a given sensing cycle. Our scheme incorporates features of reliability by providing means to increase the density of active sensors and/or increasing the rate of reporting sensed data to the base station (BS).

Approaches from neural networks (NN) have been widely used in WSNs for routing, fault recognition and modeling [4-7]. Recent research on specific WSN applications has exposed the impact of environment modeling on the WSN performance parameters [8]. In [8], the authors study the data gathering problem, in which they model the physical phenomena being sensed as a system of partial differential equations and have sensors transmit estimates of data rather than the raw data. Our work differs in that we develop the WSN energy model by taking into account the environment variation and the dependence of node energy change on this variation. We then use the Boltzmann rule to train the BS about the environment variation, so that it can predict the sensed data values and reduce the energy consumption involved in transmission of data from nodes to BS. It does this by taking into account the desired reliability constraints of the sensing operation and then performs adaptive density control.

The rest of this paper is organized as follows: Section 2 describes the adaptation of the Boltzmann learning algorithm for WSNs by taking into account reliability requirements of the sensing operation. In section 3, we develop an analytical model for the environment variation and its influence on node energy. Section 4 describes the use of the Boltzmann rule in this framework to determine the density of nodes for the given reliability requirements. Section 5 presents the results of numerical simulation of the proposed energy model. Section 6 concludes the paper and presents directions for future work.

II. Adaptation Of The Boltzmann Learning Rule For Adaptive Density Control

Preliminaries: We assume a dense WSN of stationary, homogenous and power-limited nodes, deployed for continuous sensing. The nodes report sensed data to the BS with the help of direct communication links between nodes and the BS. The approach we take to integrate the Boltzmann machine [9] with a WSN can be detailed as follows.

We assume that the nodes in the WSN are in one of the following two states: *visible* or *hidden*. The *visible/hidden* state indicates the state of the transceiver in individual nodes, and thereby whether the node is 'visible' to the BS in terms of its ability to transmit/receive data to/from the BS. Studies of energy consumption in wireless sensor nodes indicate that the transceiver energy consumption is an order of magnitude higher than that of other components at a node. To facilitate further energy savings, within each of the visible/hidden states, a node can be either in the '0' or '1' modes which signifies the on/off states of the various components that make up the wireless sensor node. Thus at any given instant during the network operation, a node can be in one of the following energy-saving states: visible-0 (V0), visible-1(V1), hidden-0 (H0), hidden-1 (H1). The description of each of these states is as follows:

V1 (visible transmit): transceiver, sensors and data processor on.

V0 (visible receive): transceiver and data processor on

H1 (hidden sense): only transducer/sensor on

H0 (hidden sleep): all components off

We use the energy model developed in [10] to calculate the energy consumption of nodes in each of these states.

Boltzmann learning rule: The aim of the Boltzmann learning rule-based network density control is to obtain reliable operation while prolonging network lifetime. We do this by adaptively learning the variation of the environment and minimizing the amount of transmission-related energy expenditure at the nodes.

The network goes through two distinct phases: training/clamped phase and the trained/free-running phase. The nodes enter V1, V0, H1 or H0 states in the training and trained phase as follows:

Training phase:

V1: Initially, all nodes are in the V1 state. Nodes continuously gather and transmit data to the BS. Most real-world systems such as temperature variations, humidity and light variations follow an oscillatory pattern with diurnal, seasonal or daily variations. WSNs deployed to sense such parameters can exploit this pattern of variation with external and parametric noise and the bifurcation parameters. The BS learns the pattern of environment variation from this data. Since the data collected follows an oscillatory nature of variation, the BS decides to stop data collection from nodes in the training phase when it begins to observe the identical patterns of data collected, for e.g., photodetectors measuring the amount of light incident on an area at certain times of the day on consecutive days. The BS then instructs the nodes to enter the trained/free-running phase.

Trained/free-running phase:

V0: In order to reduce the number of transmissions from the nodes to the BS and thereby conserve battery energy, the nodes report data only when the difference between the data sensed in the current cycle differs from that in the previous cycle by a value that exceeds a certain threshold. This threshold is determined by the user demand for reliability, and is known as the reliability factor γ. The BS instructs γ % of nodes to enter the visible-receive (V0) mode, while the other nodes enter the hidden mode such that the density of 'awake' nodes satisfies the user requirements of reliability. The highest reliability is obtained when all nodes are in the V1 state and continuously reporting data to the BS. The data obtained by the BS in the V1 training phase is retrieved for analysis and prediction in the trained phase. To this end, the BS then uses prediction functions to evaluate the data values sensed by the nodes across the network and broadcasts these values to the nodes. Nodes compare the predicted values received in the BS broadcast message with the sensed value obtained in the previous cycle. If the difference fails the reliability requirement i.e. exceeds the threshold, the nodes enter the V1 mode and transmit the sensed value to the BS. The BS can thus fine tune its prediction algorithm to better reflect the changes in the sensed environment in the whole or part of the deployment region depending upon the number of nodes who enter the V1 training phase again from the V0 trained phase. Thus we see that the reliability factor controls not only the density of awake nodes but also the rate of reporting and thereby the energy consumption of nodes. A higher reliability requirement for the sensing operation implies a smaller threshold, which can be rapidly exceeded due to faster variation of the sensing environment in the deployment region.

H1 and H0: These states constitute the hidden mode of the learning process. The amount of time spent in the hidden mode is inversely proportional to the time spent by the network in the visible/training mode. This is because, a larger duration of the training phase implies a complex pattern of environment variation which requires longer time for the BS to learn and develop prediction functions for them. Hence, we program the nodes for shorter hidden mode intervals so that the WSN can continue to reliably sense the environment.

The nodes instructed to enter the hidden mode first the H0 (hidden-off mode) for γ % of the hidden mode duration and then switch into the H1 mode for the remaining duration of the hidden mode. This is done so that when the nodes enter the visible-receive (V0) mode again after leaving the hidden mode, the data values sensed by the sensors in the H1 mode can be used as the latest reference with which to compare the BS prediction

Assumptions:

Since the accuracy of the Boltzmann learning rule-based density control algorithm relies on the accuracy of the prediction algorithms and approximating functions at the BS, we assume that the BS has superior processing capacity and is not power-limited like the nodes in the WSN. Nodes have buffer space to store data values obtained in the previous cycle and possess data processors with comparator algorithms. The clocks at individual nodes are synchronized with one another and the BS to achieve correct hidden mode/visible mode transitions. The communications links are assumed to be error-free. The only source of error is the error in the sensed data at nodes, which reflects as an increase in the energy consumption when the nodes perform comparisons with the BS's predicted values and find that the difference fails the reliability requirement.

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III. Analytical Framework Of The Model

A. Training phase/Clamped phase

We model the environment by the Van der Pol system of equations. Van der Pol equations are widely used to model oscillatory equations in systems such as electric circuits and population dynamics. The choice of the equations used to model the environment variation depends on the sensed environment. As we shall show in this section, the choice of the equations used to model the environment bears no influence on the energy model, thereby reducing the model to a set of equations with bifurcation parameters and noise in the sensed data. However, the bifurcation parameters of the system model describing the environment affect the stability of the system and can be used to design the length of the energy saving states within a cycle.

The model for the rate of change of environment is given by the noisy Van der Pol equation [11] in x as a function of time. The node energy level is given by y, whose rate of change is proportional to the rate of change of the environment by a factor p, which we call as the dependence function and also to the residual node energy at that time.

$$x'' + (\beta + \sigma_1 \xi_1)x + \alpha(x^2 - 1)x' + \sigma_2 \xi_2 = 0 \qquad (1)$$

$$y' = y - px - \varepsilon \qquad (2)$$

where, α and β are the bifurcation parameters, $\sigma_1 \xi_1$ and $\sigma_2 \xi_2$ denote the external and parametric noise, ε is the energy per bit per node [10].

Constraint: We evaluate this environment variation vs node-energy variation model subject to a reliability constraint γ. The intuition behind the constraint function is this: for prolonged network operation, we require that the reliability requirement should not require the nodes to remain in the V1 (all-awake) mode at all times, since this causes rapid energy depletion and decrease in network lifetime. Also, the rate of change of the sensing environment should be less than the rate of change of battery level at the nodes to reduce the number of transmissions at nodes. Taking the product of these constraints, we introduce the reliability constraint for the WSN as follows: the product of the reliability requirement and the rate of change of the sensing environment should be proportional and less than or equal to the square of the rate of change of node energy. This constraint ensures that the system remains stable by providing a means by which the WSN trains the BS reliably according to the rate of change in the environment model.

$$\gamma x' \le k y'^2 \qquad (3)$$

Using the Lagrangian to find the extrema of (1) subject to the constraint posed by (3), the optimization function can be written as

$$\Delta(x, y, \lambda) = f(x, y) + \lambda g(x, y) \qquad (4)$$

Where the objective function *f(x,y)* and the constraint function *g(x,y)* are as follows

$$f(x, y) \quad = \quad x'' + \alpha\left[\left((y' - y + \varepsilon)/p\right)^2 - 1\right]x' + \beta(y' - y + \varepsilon)/p \qquad (5)$$

$$g(x, y) = \gamma x' - k y'^2 \qquad (6)$$

To find the extrema of the function, we obtain the partial derivatives of (4) and equating them to zero we get,

$$x' = k y'^2 / \gamma \qquad (7)$$

Assuming that the higher partial derivatives tend to zero, we obtain

$$\frac{\alpha}{\gamma}(y')^2(\varepsilon + y - y' + 1) = 0 \qquad (8)$$

To find the solutions of (8), since $\alpha / \gamma \ne 0$,

$$\text{Case 1) } (y')^2 = 0, \quad \therefore \frac{dy}{dt} = 0 \Rightarrow y = -px - \varepsilon \qquad (9)$$

Battery level is a function of environment variation and node energy consumption.

Case 2) $\left(\varepsilon + y - y' + 1\right) = 0$, $\quad \therefore y' = \varepsilon + y + 1$

(10)

But $y' = y - px - \varepsilon$ (from 1),

$$\therefore x = -\left(2\varepsilon + 1\right) / p \tag{11}$$

Solving the differential equation in (9) to obtain *y*,

$$y = c_0 e^t - \left(\varepsilon + 1\right) \tag{12}$$

where, c_0 is a constant of integration.

From (11), $px = -\left(2\varepsilon + 1\right)$

Let $p(x) = px$, thus the extremum for the objective function are

$$\left(x, y\right) = \left(-\left(2\varepsilon + 1\right) / p, c_0 e^t - \left(\varepsilon + 1\right)\right) \tag{13}$$

Thus, the choice of the system of equations used to describe the environment does not influence the energy model. The dependence function *p* which describes the dependence of node energy on environment variation is used in the calculation of weights to decide the node states.

The objective function *f(x,y)* evaluated at this extremum is

$$f\left(x, y\right) = \beta\left(2\varepsilon + 1\right) / p \tag{14}$$

which is a function of the dependence *p* of node energy on the environmental variation.

B. Trained phase/ Free-running phase

In the free-running phase, the BS uses the data acquired during the training phase to reduce the number of transmissions from the nodes to the BS. The BS broadcasts the predicted values to the visible nodes, which in turn match it with their sensed values. If the difference between the received prediction and sensed data exceeds a threshold, i.e. fails the reliability requirement, the visible nodes enter the visible transmit mode where they broadcast the sensed data to the BS. At the end of the free-running phase, the BS increases the density of visible-receive nodes for the next free-running cycle. This process goes on until the BS error converges to less than the threshold set at the nodes. If the procedure fails to converge until the point where the density of visible node equals the total density of nodes in the network, the BS initiates the training phase over again. The system can thus be modeled as follows [12]:

$$x' = z$$

$$z' = -\left(\beta + \sigma_1 \xi_1\right) x - \alpha\left(x^2 - 1\right) z - \sigma_2 \xi_2 \tag{15}$$

$$y' = c\left(y - px - \varepsilon\right)\left(x - \gamma\right)$$

Proceeding similar to the training phase, the value of the objective function at the extremum is

$$f\left(x, y\right) = p\gamma^2 c\,. \tag{16}$$

This shows that the battery level is a function of i. reliability, ii. dependence of node energy variation on environment variation and iii. energy required per bit per node.

IV. Calculation Of Node Weights For Density Control

In this section, we illustrate the computation performed at the BS to determine the set of visible nodes for the next trained phase. The goal of the weight computation process is to balance the rate of energy consumption across the network. At the end of a trained phase, it assigns the nodes with lowest weights (lowest rate of change of battery energy) to enter the visible mode. The BS calculates the weight of nodes based on the number of transmissions from the node and the history of modes it has been in for the previous cycles.

A. Training phase

We show that the weight of a node is the training phase is only a function of time. The proof leading to the calculation of node weights is shown in the Appendix. Since the weight of a node is proportional to the rate of change of battery level at that node, from (12), we get,

$$w_i = k_c\left[c_0 e^t - \left(\varepsilon + 1\right)\right] \tag{17}$$

where the subscript *i* denotes the *i*th node.

Adapting the Boltzmann rule for weight calculation [9] and equating the node weights from (17), we get $w_i = k_c\left[c_0 e^t - \left(\varepsilon + 1\right)\right] = \eta\left(2^{N_T}\right) / 4$ (18)

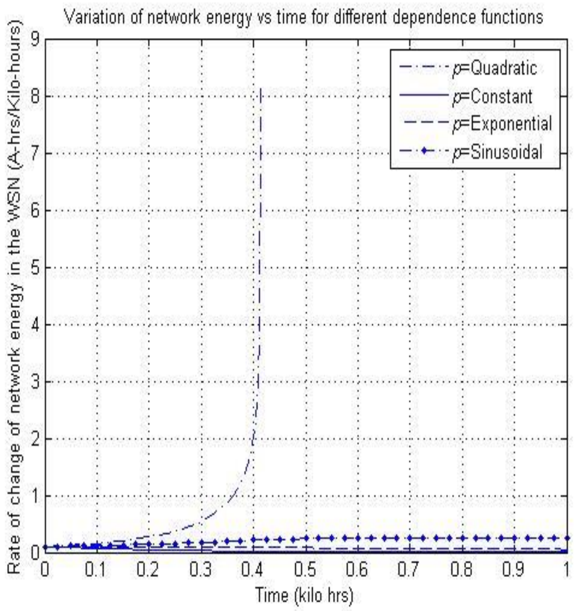
This shows that the weights are only a function of time in the training phase. The intuition behind this is that in the longer the training phase, it implies a complex pattern of environment variation in the deployment region. This requires more number of transmissions from the nodes to the BS for the BS to learn about the environment and hence the weights of a node are only a function of time.

B. Trained phase

Using the method as above, we show the weight of a node in the trained phase is

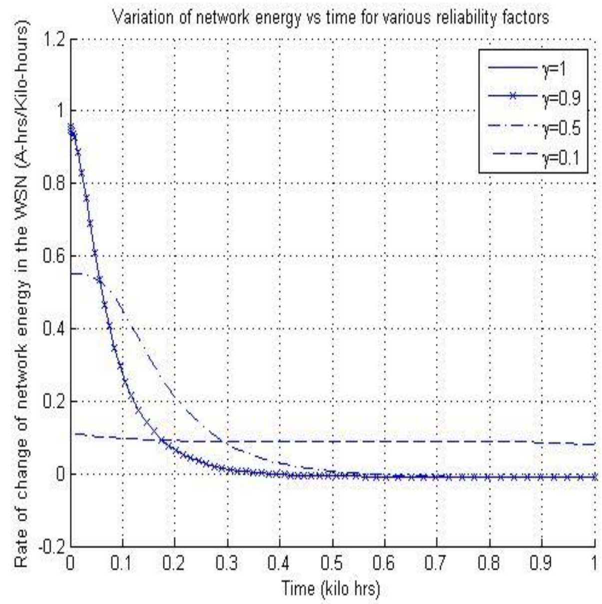
$$w_i = 0 - \rho_i^- = \sum_{\alpha=1}^{2^{N_b}} \sum_{\beta=1}^{2^{\left(N_T - N_b\right)}} \frac{1}{2} s_{j|\alpha\beta} s_{i|\alpha\beta} = k_c\left(\varepsilon - p\gamma\right) \tag{19}$$

This shows that the weights are only a function of the reliability parameter γ. This is because, in the trained phase, the energy expenditure at a node due to communication with the BS is influenced by whether the difference between the BS predicted value and the sensed value stored in the node exceeds γ.



Training phase

Fig.1 Rate of change of network energy as a function of dependence of node energy on environmental model in the training phase. The constant dependence results in lowest rate of change of network energy.



Trained phase

Figure 2. Rate of change of network energy as a function of time for different reliability requirements. The reliability requirements dictate the density of visible nodes, which in turn affects the rate of change of network energy in the WSN.

V. RESULTS

In this section, we obtain the simulation results of the Boltzmann learning-rule based WSN. We simulate a network of 100 nodes randomly scattered across a square deployment region of side 20 meters. Defining network energy as the sum of the battery energy of all nodes in the deployment region, we plot the rate of change of variation of the network energy in Ampere-hours/kilo-hours) as a function of time in kilo-hours for different a. dependence models of battery energy on environmental variation in the training phase (Fig.1) and b. reliability parameters in the trained phase (Fig.2).

Training phase: Fig. 1 shows the variation of the network energy as a function of the dependence model between the node energy and the environment variation model in the training phase. For this study, we use a reliability requirement of 0.5 for a network of 100 nodes. We see that when this dependence assumes the form of a quadratic polynomial, the rate of change of network energy is the highest compared to when the dependence is a constant. This sensitivity analysis to *p* illustrates the energy- conserving nature of the free-running trained phase where the BS optimizes the density of visible nodes to suit the reliability requirements. The rate of change of network energy approaches zero when the BS's prediction error matches the reliability requirement and the network enters the trained phase. A comparison of the rate of change of network energy in training (fig. 1) and trained phase (fig. 2) shows that this transition to the trained phase causes the gradient of the network energy variation to be less than that in the training phase.

Trained phase: In fig. 2, we model the dependence function *p*, as an exponential function of the environment change parameter. The sensitivity analysis to reliability requirements shows that the rate of network energy varies with the desired reliability parameter γ. For high values of reliability of the sensing operation, the rate of change of network energy is higher. This is because, for higher γ, the BS increases the density of nodes in the visible mode, the density of nodes in the hidden-sense mode and also the rate of reporting, thus causing faster network energy depletion. We also model the case, where all the nodes are sensing, processing and transmitting for the entire duration of the deployment, i.e. all nodes are in the visible-transmit mode for γ=1. As seen from Fig.1, this reliability requirement causes higher variation of network lifetime than for lesser values of γ. For γ =0.1, which represents the case where the node energy has minimal dependence on the environment variation due to majority of the nodes always being in the hidden mode, the rate of change of network lifetime is much lower. For instance, for γ=1, the rate of change of network energy for the interval between the first 50 – 80 hours in the trained phase is higher by an order of magnitude than for γ =0.1.

VI. Conclusions And Future Work

In this paper, we presented an energy model for wireless sensor networks by taking into account reliability requirements of the sensing operation and the impact of sensing environment variation on the rate of change of network energy. We presented an analytical framework for a NN- based (Boltzmann-learning rule) model to calculate the density of *'awake'* nodes in the deployment region to satisfy the reliability requirements and accurately model the impact of environment variation on node energy. We observed that a higher reliability requirement and rapidly fluctuating sensing environments increased the rate of change of network energy. These results show the significance of sensitivity analysis of environment modeling on the lifetime of the WSN by creating sensing-environment and reliability-centered WSN topology. Our future work would involve the development of accurate prediction algorithms at the BS by modeling the system with a game-theoretic approach. The aim of the BS would be minimize the prediction error so that it would have to perform fewer computations to determine the set of awake nodes for the next cycle. Future work would also include improvement of this energy model by including lossy communication links in the deployment region.

Appendix

Training phase: Let the total number of nodes in the network be N_T, where $N_T = N_h + N_b$, N_h =number of hidden nodes and N_b is the number of visible nodes. In the training phase, all nodes are visible. Thus, the number of hidden nodes, L = 0. Modifying the equation for the weight of a node according to the Boltzmann rule from [9] to adapt it to the WSN, we get

$$\Delta w_i = \eta\left(\rho_i^+ - \rho_i^-\right), \qquad \text{(A.1)}$$

where

$$\rho_i^+ = \sum_\alpha \sum_\beta P_{\alpha\beta}^+ s_{j|\alpha\beta} s_{i|\alpha\beta}\ ,\ \rho_i^- = \sum_\alpha \sum_\beta P_{\alpha\beta}^- s_{j|\alpha\beta} s_{i|\alpha\beta} \qquad \text{(A.2)}$$

The states of the hidden nodes are denoted by β, $\beta = 1\ldots\ 2^L = 1$, The states of the visible nodes are denoted by α, $\alpha = 1\ldots\ 2^K$.

$P_{\alpha\beta}^-$: joint probability that the visible nodes are in state α and the hidden nodes are in state β, given that the network is in its free-running condition,

$P_{\alpha\beta}^+$: joint probability as above on the states of nodes , but for the network in its clamped condition. $s_{i|\alpha\beta}$: state of node i given that the visible nodes are in state α and the hidden nodes are in state β. η is the learning-rate parameter given by $\eta = \varepsilon / T$. The weight of a node is proportional to the rate of change of battery level at that node. From (12),

$$w_i = k_c\left[c_0 e^t - \left(\varepsilon + 1\right)\right] \qquad \text{(A.3)}$$

Since $s_{j|\alpha 1} = s_{i|\alpha 1} = 1$ in the training phase i.e., V1,

$$\therefore \rho_i^+ = \left(2^{N_T}\right)/4\ ,\ \rho_i^- = 0 \qquad \text{(A.4)}$$

$$w_i = k_c\left[c_0 e^t - \left(\varepsilon + 1\right)\right] = \eta\left(2^{N_T}\right)/4 \qquad \text{(A.5)}$$

which is only a function of time.

A similar procedure is adopted for the trained phase.

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