Energy Balanced Data Propagation in Wireless Sensor Networks with Diverse Node Mobility

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ABSTRACT

The energy balance property (i.e., all nodes having the same energy throughout the network evolution) contributes significantly (along with energy efficiency) to the maximization of the network lifespan and network connectivity. The problem of achieving energy balanced propagation is well studied in static networks, as it has attracted a lot of research attention.

Recent technological advances have enabled sensor devices to be attached to mobile entities of our every day life (e.g. smartphones, cars, PDAs etc), thus introducing the formation of highly mobile sensor networks.

Inspired by the aforementioned applications, this work is (to the best of our knowledge) the first studying the energy balance property in wireless networks where the nodes are highly and dynamically mobile. In particular, in this paper we propose a new diverse mobility model which is easily parameterized and we also present a new protocol which tries to adaptively exploit the inherent node mobility in order to achieve energy balance in the network in an efficient way.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication

General Terms

Algorithms, Design, Performance

Keywords

Wireless Sensor Networks, Mobility, Energy Balance, Data Propagation

1. INTRODUCTION

In wireless sensor networks (WSN) one of the many challenges a designer has to face is the energy efficient and balanced data propagation in the WSN. The energy balance property guarantees that the average energy spent per sensor is the same for all sensors in the network at any time during the network operation.

It is well known that for any radio transmission the energy cost is proportionate to the square of the transmission range. In multi-hop greedy propagation algorithms in WSN cause high traffic to nodes close to the $Sink$, creating a bottleneck around the $Sink$ and leading to early depletion of these nodes, thus resulting to a disconnected network where a large partition of the nodes have healthy batteries.

1.1 The Network Model

Advances in microelectronics have made it possible for sensor nodes to be attached to moving objects enabling the sensor to be ubiquitously present in our ambient environment. This motivates us to study the mobile sensor networks, where the behavior of the existing energy balancing protocols is unknown.

For that reason, we design a mobility model that simulates the diversity and complexity of real world movement scenarios. Having such a model will help us to test our proposed protocol in a hostile setting with realistic node movement.

1.2 Related Work

The energy balance property is important since it maximizes the network lifespan by avoiding the creation of network holes. To avoid unbalanced consumption, the authors in [3] proposed a randomized protocol where in each step the node that holds data decides probabilistically and locally using distance information whether to propagate data one-hop towards the $Sink$, or to send it directly to the $Sink$.

In [5] the authors proposed an on-line distributed algorithm for lifespan maximization. Their algorithm in each step decides locally using information about the energy spent in order to propagate data either one-hop towards the $Sink$, or to send it directly to the $Sink$.

Under highly mobile conditions, the protocols and research recommendations for energy balancing algorithms for static wireless sensors networks can not be directly applied or are not that efficient.

In [6] the authors try to quantify the node mobility by proposing a locally computable network parameter the "mobility level", which captures the dislocation of a node from the origin. The authors in [1] propose a different mobility level notion which captures the ability of a node to arrive close to the sink quite fast. Also, they propose adaptive dissemination schemes which goal is to exploit nodes' mobility as a replacement for connectivity, coverage and data redundancy. However, they do not focus to the energy bal-

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ance performance of their protocols. As far as we know, we are the first to address the problem of achieving energy balanced consumption in the context of highly mobile sensor networks.

1.3 Our Contribution

In this paper we propose a new diverse mobility model which is easily parameterized and we also present a new protocol which tries to exploit the inherent node mobility in order to achieve energy balance in the network.

2. MODEL

We define the area of the network as a circle of radius D. The network consists of n mobile sensor nodes that are initially distributed uniformly at random; and one stationary destination node the *Sink* which is placed at the center of the network.

Each sensor has a maximum transmission range R. We also define d_{hop} the maximum *one-hop transmission* distance for which the cost of the transmission is constant (i.e. the maximum distance for which one transmission is considered as a *one-hop transmission*).

Also, each sensor i knows its current position, the position of the *Sink*, its current *distance to the Sink* $d_i(t)$, its speed $u_i(t)$ and its *remaining energy* $E_i(t)$. Finally we consider that events are generated uniformly within the network with a stable rate of $\lambda = messages/sec$.

2.1 Mobility Model

For the experimental evaluation of our proposed protocol we use two completely different mobility models.

The first considered model is a probabilistic mobility model. This model consists of a variety of completely different mobility models and of a state transition diagram which dictates each node's individual mobility model. In this manner our model achieves a diverse mobility pattern for the nodes and thus simulates realistic movement scenarios in a more faithful manner.

The second mobility model with which we test our protocol is a simple random mobility model. In such an environment we expect our protocol to behave poorly and its weaknesses to become more obvious. Such a choice will also unveil critical information for the nature of the problem.

2.1.1 A Composite Mobility Model

Our composite mobility model is inspired by [2] and it is a synthesis of four different and independed mobility models, which are the following:

- **Working**
  In this case we use *Random Walk* model with small V_{min} and V_{max} values and small covered distances d_{change} value in which the velocity's magnitude and direction change.

- **Walking**
  Here, we use of *Gauss-Markov* model. The probabilistic nature and the consideration of older velocity values of this model tend to produce more natural movements like the ones a person does while walking.

- **Bicycle**
  Just like "Walking" model with the exception that the parameters are set in such a way that we have larger velocity values and more often velocity's magnitude and direction change.

- **Car**
  In [2] *City Selection Mobility Model* is introduced, a mobility model that simulates a city environment, which completely suits our needs.

The synthesis of the aforementioned models is achieved via a state transition diagram (see Fig.1). Each state of this diagram represents a mobility model. The edges represent the transitions between states and the weights of the edges represent the probability of such a transition.

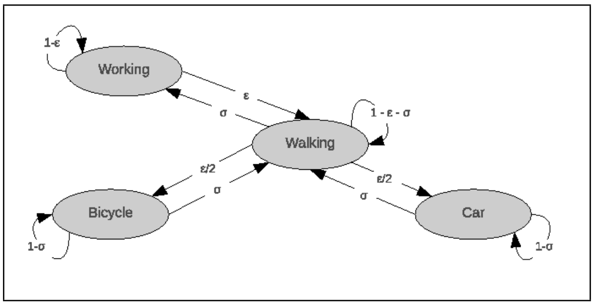

Figure 1: Transition Diagram between Mobility Models

Initially all the nodes are assigned randomly and uniformly to one of the four mobility models. Then and for each t_{mob} time units a random experiment is ran on each node whose result dictates the node's next mobility model according to the state transition diagram. Thus t_{mob} is a parameter that dictates how often we have mobility model changes in our network.

Then we define two new parameters, the *acceleration parameter* ϵ and the *decceleration parameter* σ with which we can control the number of nodes in each mobility model (i.e. large value of ϵ means more nodes accumulate to the faster models *Car* and *Bicycle*, whereas the opposite holds for σ). This means that these parameters give us control of the nodes' tendency for choosing faster or slower mobility models. For ease in our following analysis we define the *network mobility parameter* as follows:

$$\kappa = \sqrt{\epsilon \cdot (1-\sigma)} \quad \text{where} \quad 0 \le \sigma, \epsilon \le 1$$

2.1.2 Random Mobility Model

The second mobility model, as we already noted, is the *Random Walk* which is defined in [2]. Moreover we set the maximum and minimum speed a node can achieve $[V_{min}, V_{max}]$ and the time intervals t_{mob} in which the changes on velocity's direction and magnitude occur. Finally on this model the *network mobility parameter* is defined as follows:

$$\kappa = (1 - \frac{1}{V_{min}}) \cdot (1 - \frac{1}{V_{max}})$$

3. THE PROTOCOL

In this section we firstly define two new metrics, then present the general idea of our protocol and finally we thoroughly present the complete protocol.

3.1 Definitions

3.1.1 Distance Level

Distance level is a characteristic of the nodes and refers to previous values of distance from the sink of that node. We define the *distance level* as follows:

$$Dl_i(t) = \sum_{\tau=1}^{\tau=T} d_i(\tau) \cdot w(\tau)$$

Where:

$d_i(\tau)$: The euclidean distance of node i from the sink, at τ time units ago.

$w(\tau)$: *Exponentially decreasing weight function*:

$$w(\tau) = \frac{\alpha^\tau}{\sum_{i=1}^{i=T} \alpha^i}$$

where $0 < \alpha < 1$ and T is the number of distance samples. We can easily observe that the weight function produces normalized values, and maps discreet time values to a real value between 0 and 1. Thus it satisfies the following conditions:

$$w : T \rightarrow [0,1] \qquad \text{and} \qquad \sum_{\tau=1}^{\tau=\infty} w(\tau) = 1$$

At this point we introduce a new concept, the *memory parameter* α, with which we control the percentage of contribution of older *distance to the sink* values to the *distance level*. More specifically, with a large α parameter we have a bigger contribution of older distance to the sink values, whereas with a small α parameter we have a smaller contribution of these values.

We define α as follows:

$$\alpha = \frac{t_{mob}}{t_{max}} \cdot (1 - \kappa)$$

Where t_{max} is the maximum allowed value of the parameter t_{mob}. κ and t_{mob} values are defined in section 2.2.

The intuitive ideas behind our approach are the following:
a) Small t_{mob} leads to often velocity changes which in turn leads to often distance changes which means that older values might be misleading. Consequently, we need small α, and vice versa.
b) Large *network mobility* (κ) means large velocity values which lead to high dislocation so as previously, former values might be ambiguous. Thus, we need small α, and vice versa.

3.1.2 Mobility Level

The idea for this particular metric was first proposed in [1]. In its essence the *mobility level* is the projection of the node's velocity over the line defined by the current node and the *Sink*. So we define the *mobility level* Ml as follows:

$$Ml_i(t) = u_i(t) \cdot \max\{\cos\phi_i(t),\ 0\}$$

Where:

$u_i(t)$: The magnitude of node's i velocity at time t.

$\phi_i(t)$: The angle between the velocity vector of node i and the line defined by the position of sensor i and the *Sink* at time t.

This definition dictates that nodes that travel away from the sink as well as nodes that retain their distance to sink (i.e. $\frac{2\pi}{2} < \phi_i < \frac{3\pi}{2}$) have a *mobility level* of 0 and not negative. Finally, small *mobility level* values show a tendency for the node to increase their distance from the *Sink*, whilst the opposite holds for higher values.

3.2 General Idea

Our protocol tries to exploit the unforseeable mobility patterns of the nodes to promote energy balance and energy efficiency in the network. Thus, our approach is that the "distant" and/or "more mobile" nodes stop forwarding their messages, instead they store them in local memory and wait until their distance to sink is small enough to begin transmitting messages.

Based upon this idea we define two modes of operation for the nodes:

- **Ferrying Mode**
  When a node operates in this mode, it stops forwarding its messages and simply stores them in its local memory. It is easily understood that nodes with high *mobility level* and/or high *distance to sink* values are favored to operate in this mode. Finally, from now on nodes operating in this mode will be referred as *Ferries.*

- **Normal Mode**
  When a node operating in this mode has to handle a message, it first checks for *Ferries* within a close distance from it (i.e. within a radius of d_{hop}). If a *Ferry* is found then the node transmits the message to that *Ferry*, if not then it handles the message with one of the two following ways:

  1. **Direct Message Propagation**: The node transmits directly its message to the *Sink*. Nodes having small *distance to the sink* values and/or large *remaining energy* values, are favored to choose this way of transmission.
  2. **Message Propagation**: The message is propagated to another node closer to the sink than the original node and for which the distance from the original node is at most d_{hop}. If no such node is found then the message is stored in local memory and handled again in a future time.

  The decision for which of the previous ways a node handles its messages is taken probabilistically with regard to the node's *distance level* $Dl_i(t)$ and its *remaining energy* $E_i(t)$

The flowchart in Fig. 2 summarizes our protocol.

3.3 The Propagation Scheme

In this section we firstly present the manner in which nodes decide about their operation mode. Then for nodes operating in normal mode, we present how the decision between the two possible propagation ways is taken. Finally, for local transmissions we show how the next-hop neighbor is chosen.

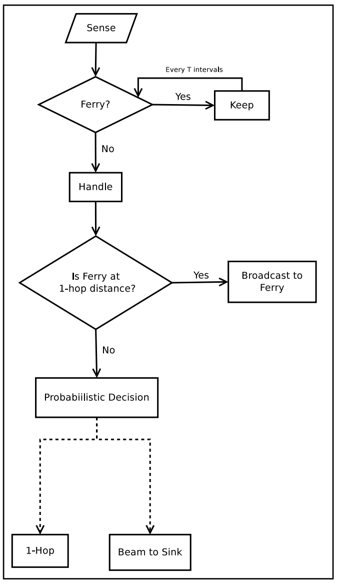

Figure 2: Flowchart Diagram of Protocol

3.3.1 Operation Mode Choice

As we have already stated the possible modes are two: the *Ferrying Mode* and the *Normal Mode*. Following, we describe how the nodes switch between these modes.

Firstly, we define the following:

- Probability of switching to *Ferrying Mode*:

$$f_i = \frac{Ml_i}{Ml_{max}} \cdot \frac{D_i}{D}$$

- Time intervals between mode switchings:

$$t_{ferry} = \frac{1}{\kappa \cdot v_{max}} \cdot d_{hop}$$

Then, in Fig. 3 we define the following state transition diagram, which dictates the manner nodes switch between modes:

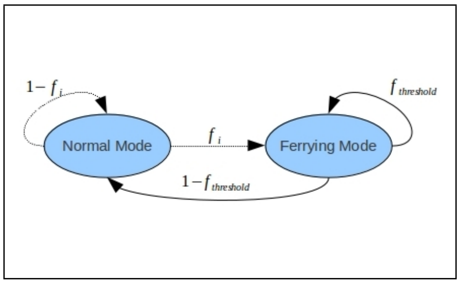

Figure 3: Transition Diagram Between Modes

As we can see in Fig. 3 the decision model is a hybrid one. Nodes currently in normal mode select their next state probabilistically, whilst nodes in ferrying mode select their next state with a hard threshold. In future experimental work we plan to calculate the hard threshold value.

3.3.2 Way of Transmission

When a node operates in *Normal Mode* it starts transmitting its messages. As we have already stated, the transmission can be done in two ways:

- **Direct Transmission**: The node transmits directly to the *Sink* with energy cost of $C \cdot D_i^2$. Where C is the constant one hop propagation cost.
- **One-hop Jump**: Node i propagates the message to node j where $D_j < D_i$ and $D_i - D_j \leq d_{hop}$ with energy cost of C.

Now we define the probability p_i with which a node decides to transmit via *one-hop Jump*:

$$p_i = \frac{Pl_i}{Pl_{max}} \cdot (1 - \frac{E_i}{E_{max}})$$

We also define the probability q_i with which a node decides to transmit directly to the *Sink*:

$$q_i = 1 - p_i$$

Each time a node has data to transmit, it simulates a random experiment whose result provide the transmission way.

3.3.3 Neighbor Choice

When the *one-hop Jump* method of transmission is chosen the transmitting node chooses a destination node from its neighboring nodes. From previous results [5] the node chooses its neighbor with the greatest *remaining energy*. Thus node i will propagate to node j that:

$$E_j > E_k \quad \forall j,k \quad for\,which: \begin{cases} D_i - D_j \leq d_{hop} \\ D_i - D_k \leq d_{hop} \end{cases}$$

4. FUTURE WORK

In the future, we plan on implementing, evaluating and validating our protocol on ns-2 platform. Moreover, we intent to compare the performance of our protocol by an extensive simulation study with other state of the art protocols like [5] and [3] as well as with non-energy balancing protocols like *Flooding* and *Gossiping*.

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