Energy Map Construction for Wireless Sensor Network under a Finite Energy Budget

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ABSTRACT

A fundamental issue in the design of a wireless sensor network is to devise mechanisms to make efficient use of its energy, and thus, extend its lifetime. Due to the paramount importance of energy conservation, it is highly desirable to define the amount of energy each protocol can spend to perform its goal. Using this idea, we can associate a finite energy budget for each network activity, and ask this activity to achieve its best performance using only its budget. This should be considered a new paradigm to design algorithms for networks that are battery powered, specially for wireless sensor networks. In this paper, we present this new paradigm, and show how it can be used to construct the energy map of a wireless sensor network. Our goal is to construct the best energy map using only a defined amount of energy. Simulation results show that we can approach these performance limits using the proposed finite energy budget model.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless communication*; C.4 [**Performance of Systems**]: [Reliability, availability, and serviceability]

General Terms

Design, Performance

Keywords

Wireless Sensor Networks, Energy Map, Budget

1. INTRODUCTION

The large use of wireless sensor networks depends on the design of a scalable and low-cost sensor network architecture. Furthermore, the design must consider the energy conservation a fundamental issue and devise mechanisms for extending the network lifetime. This scenario leads us naturally to the following problem: what is the best performance a protocol can achieve given that it can spend only a finite amount of energy? Using this idea, we can associate a finite energy budget with each network activity, and ask this activity to achieve its best performance using only its budget. This is a new way of dealing with network related problems, and should be considered a new paradigm to design algorithms for networks that are battery powered, specially for wireless sensor networks.

The energy map give us the information about the remaining available energy in each part of the network, and it can aid in prolonging the lifetime of the network. The finite energy budget paradigm is exceedingly appropriate for the energy map construction because it is worthless if we construct the best energy map spending all available energy. It is highly desirable to define the amount of energy we can spend in the energy map construction, thus leaving the remaining energy to be used by other network activities. This scenario leads us naturally to the following question: what is the best energy map we can construct, given a finite amount of energy for its construction? In this work, we extend the prediction-based approaches presented in [2] in order to define a way of constructing the energy map in situations where a finite energy budget is defined. Our goal is to achieve the performance limits in the construction of the energy map under the constraint that each node can spend only a certain amount of energy in this construction.

The rest of this paper is organized as follows. In Section 2, we briefly survey the related work. In Section 3, we show how the finite energy budget model is applied in the energy map construction. In Section 4, we present the simulation results for this model. In Section 5, we expand the basic finite budget model, presenting an adaptive process to build the energy map. Section 6 shows the simulation results for the adaptive energy map construction. Finally, in Section 7, we present the concluding remarks and future directions of this work.

2. RELATED WORK

Sensor networks are a new kind of ad hoc network with some new characteristics and challenges. These networks perform distributed sensing, wireless communication and distributed processing using very limited resources. The design of wireless sensor networks is a very fertile area of research and more work needs to be done in order to set up this new kind of network [1].

The information about the remaining energy available in each part of the network is called the *energy map* and could aid in prolonging the lifetime of the network. Using the energy map, a user may be able to determine if any part of the network is about to suffer system failures in near future due to depleted energy [5]. The knowledge of low-energy areas can aid in incremental deployment of sensors because additional sensors can be placed selectively on those regions short of resources. Routing protocols can also take advantage of the available energy information in each part of the network. A routing algorithm can make a better use of the energy reserves if it selectively chooses routes that use nodes with more remaining energy, so that parts of the network with small reserves can be preserved. This protocol can also form a virtual backbone connecting high energy islands. Other possible applications of the energy map are reconfiguration algorithms, query processing, and data fusion. In fact, it is difficult to think of an application and/or an algorithm that does not need to use an energy map. Therefore, the energy map is an important information for sensor networks.

The work proposed in [5] tries to obtain the energy map of sensor networks by using an aggregation based approach. The technique described in that paper tries to obtain the energy map of sensor networks by using an aggregation based approach. A sensor node only needs to report its local energy information when there is a significant energy level drop compared to the last time the node reported it. Energy information of neighbor nodes with similar available energy are aggregated in order to decrease the number of packets in the network. The main difference between the approach proposed in that article and ours [2] is that in the former solution each node sends to the monitoring node only its available energy, whereas in our work each node sends also the parameters of a model that tries to predict the energy consumption in the near future.

3. NON-ADAPTIVE ENERGY MAP CONSTRUCTION UNDER A FINITE ENERGY BUDGET

Due to the paramount importance of energy conservation in wireless sensor networks, it is highly desirable to define the amount of energy we can spend in the energy map construction, thus leaving the remaining energy to be used by other network activities. In this section, we show how the finite energy budget paradigm can be applied in the construction of the energy map of a wireless sensor network.

In the energy map construction, the term finite energy budget means that each node can spend a certain amount of energy in the process of constructing the energy map of the entire network. This amount of energy can be represented by the number of bytes each node can send with energy information to the monitoring node. Knowing the size of this information, we can transform the number of bytes into the number of packets each node can send with energy information. In this work, the number of packets is used as the metric for energy budget, and we deal with it as the maximum number of times each node can send its energy information to the monitoring node. Our goal is to construct the best energy map under the constraint that each node can send no more than a certain number of packets with energy information.

Ideally, a solution that approaches the performance limits in the construction of the energy map should keep its error almost constant during all time, and the budget should finish exactly at the end of the network lifetime. To achieve this goal, we have to decide when is the best time for each node to send its energy information packet under a finite energy budget. In this section, we propose a way of making this decision.

The moment to send the energy information packet is decided locally by each node without exchanging information with its neighbors. Thus, in each second of simulation, each node should decide if it will send another energy information packet or not. We propose that this decision should be taken according to a certain probability p. In that case, the value of p determines the frequency in which nodes will send their energy information and, thus, the amount of energy spent in the process of constructing the energy map. The value of p depends on the following parameters: the number of packets a node still can spend, the error between the predicted and the correct energy value, and its estimated lifetime. This last supposition is reasonable because given the restriction of the available energy in the sensor network, we can expect to design a wireless sensor network to work for a period of time that can be defined during its design phase.

In order to find the best way to determine the value of the probability p for each node, we start defining the sending of an energy information as a binomial distribution in which the event is the sending of an energy packet and each second of simulation is an experiment. We call T_{total} the estimated lifetime, and T_{now} the current time. In addition, P_{total} is the number of energy information packets each node can send, and P_{used} the number of packets the node has already used. Thus, a node still can send $(P_{total} - P_{used})$ packets in the remaining $(T_{total} - T_{now})$ seconds. The value of p that maximizes the probability of a node sends $(P_{total} - P_{used})$ packets in $(T_{total} - T_{now})$ seconds is:

$$p = \frac{P_{total} - P_{used}}{T_{total} - T_{now}} \tag{1}$$

Using Equation (1), each node can determine the probability in which it will send an energy packet in each second of simulation. This equation defines the value of p only in terms of the energy budget and the estimated lifetime. Nevertheless, each node also knows the error between the energy value predicted by the monitoring node and the correct one. It can locally determine this value by just keeping the parameters of the last prediction sent to the monitoring node. Thus, each node keeps track of the error of its energy value. We use the percentage error because the impact of the difference between the correct and the predicted value depends on the energy available at the node.

We intend to use the information of the error to change the value of the probability p in such a way that, when the error is small, we should decrease the value of p in order to postpone the sending of an energy packet. With this behavior we can save energy to be spent when the error is larger. On the other hand, when the error is large, we should increase the value of the probability in order to force the node to send a new energy information.

The desired adaptation is obtained by Equation (2). In that equation, we redefine the value of p and call it p'. Then, in each second of simulation, each node will send another energy information packet with probability p'. In the first part of Equation (2), the value of p is multiplied by the function $(1 - \frac{1}{c^{error}})$, and p is decreased when the error is small, and it is almost unchanged when the error increases. However, when the error gets larger, the value of the probability of sending a packet should increase and becomes larger than p. This behavior is obtained using the second part of Equation (2), in which the value of $(1-p)$ is multiplied by the same function but with different parameters. The expression $max(0, error - k)$ is different from zero only when the error is larger than k. Using the value of c and k, we can control the shape of the curve that represents the probability of sending a packet.

$$p' = p \times \left(1 - \frac{1}{c^{error}}\right) + (1-p) \times \left(1 - \frac{1}{c^{max(0, error-k)}}\right) \quad (2)$$

Before using Equation (2), we have to decide on the value of k. This value determines when the second curve will start. For example, if we want that the second curve starts when the curve $(1 - \frac{1}{c^{error}})$ is 0.99 (this means that the value of p' is 99% of p), we make $(1 - \frac{1}{c^k}) = 0.99$ and thus we find $k = \log_c 100$. If we want that the second curve starts when the first is 0.999, we make $k = \log_c 1000$. Thus, if we increase the value of k, we are postponing the appearance of the second slope and delaying the increase of the value of p'.

In Figure 1, we plot the curve p' when the value of p is 0.5 and $k = \log_c 1000$ for different values of c. We can see that the larger the value of c, the faster the value of p' will be one. Thus, if a node has only a small number of packets to spend in the construction of the energy map, it should use a small value of c. On the other hand, if a node can spend a lot of packets with energy information, it should use a larger c.

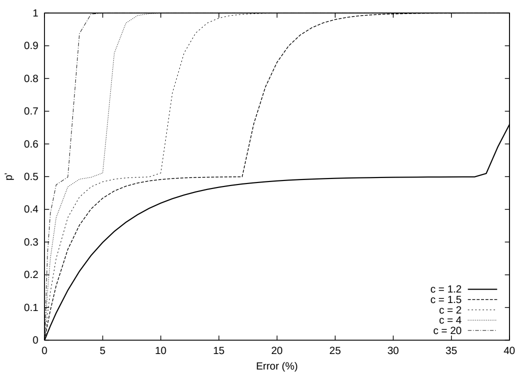


Figure 1: Function p' for $p = 0.5$, $k = \log_c 1000$ and different values of c.

4. SIMULATION RESULTS FOR THE NON-ADAPTIVE ENERGY MAP CONSTRUCTION

In order to analyze the performance of the finite energy budget scheme, we implemented the construction of the energy map in the ns-2 simulator [4]. The kind of sensor network we will work is one in which the nodes are static and homogeneous, and also that there is only one static monitoring node with plenty of energy. We suppose that nodes are deployed randomly forming a high-density network in a flat topology. Also, the events are static and their duration and radius of influence are randomly chosen. In relation to the data delivery model, we simulate an event-driven network in such a way that sensors report information only if an event of interest occurs. In this case, the monitoring node is interested only in the occurrence of a specific event or set of events. The communication model used is a cooperative sensor model in which the communication between nodes is beyond the relay function needed for routing, and sensors communicate with each other to disseminate information related to the event.

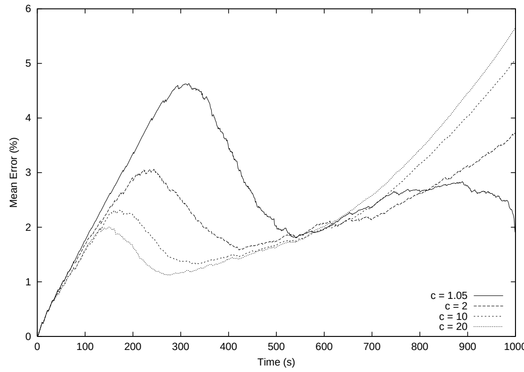
In our simulations, we use the State-based Energy Dissipation Model (SEDM) to describe the behavior of sensor nodes and to simulate their energy dissipation [3]. SEDM is based on a framework in which nodes have various operation modes with different levels of activation and, consequently, different levels of energy consumption. In this model, each node has four operation modes: *mode* 1: sensing off and radio off; *mode* 2: sensing on and radio off; *mode* 3: sensing on and radio receiving; *mode* 4: sensing on and radio transmitting.

In our simulations, we used 100 nodes in a sensor field of 50×50 m^2. All nodes have a initial energy of 100 J and their communication ratio is 15 m. Moreover, we use k = $\log_c 1000$ and the monitoring node is positioned at the center of the field at position $(25, 25)$. The results showed in all simulations correspond to an average of these values for 30 different runs.

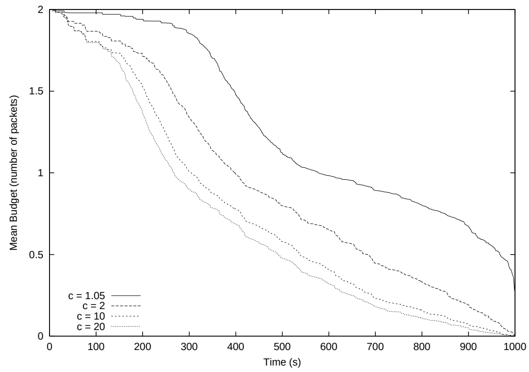
In the finite energy budget, presented in the last section, the choice of the best value for the constant c is of fundamental importance to determine the behavior of probability p' and, consequently, the way each node will spend its budget. In order to analyze the influence of this constant for different values of budget, we ran the prediction-based energy map for 100 nodes in the same scenario described above. Figure 2-a shows the average percentage error when each node can send only 2 energy information packets to the monitoring node, and, in Figure 2-b, we have the mean budget for each value of c. We can see that the larger the value of c, the faster the nodes use their budget. For example, for $c = 20$, the budget is used fast and, at the end of simulation, almost all nodes have already spent their budget, increasing the mean error. On the other hand, for $c = 1.05$, all nodes spend their budget slowly.

Using the constant $c = 1.05$ and a budget size of 2 packets/node, the error starts larger and goes down after the start up period, keeping almost constant until the end of simulation. This behavior can be explained by Equation (1). As the denominator represents the simulation time in seconds, and the numerator the budget size per node, the denominator range value is larger than the numerator one. Therefore, at the beginning of simulation, the value of p tends to be decreased due to the large value in the denominator. This collateral damage is good, because it is better to make an error at the beginning of simulation when nodes have more energy than at the end, when the energy becomes even scarcer. Then, the shape of the error is good for sensor network applications.

We can see in Figure 2-b that, for $c = 1.05$, the nodes do not spend all their budget. In a situation like this, we

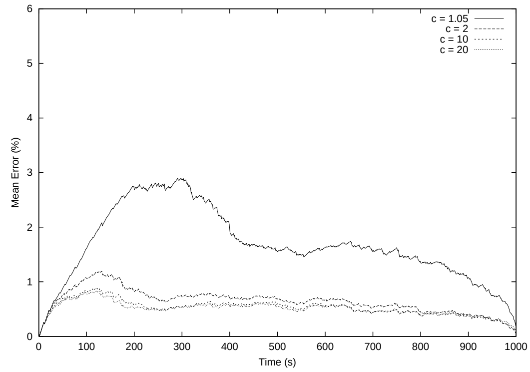


(a) Mean Error (%).

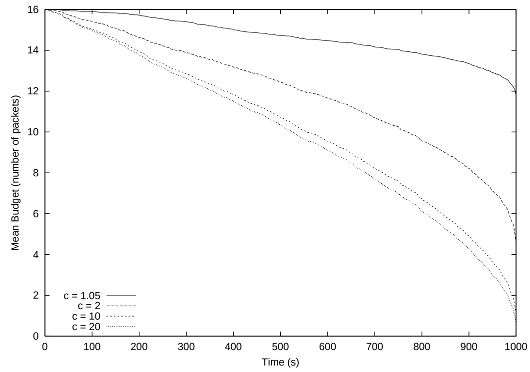


(b) Mean Budget (number of packets).

Figure 2: Changing the value of c when each node can spend 2 packets with energy information and $k = \log_c 1000$.



(a) Mean Error (%).



(b) Mean Budget (number of packets).

Figure 3: hanging the value of c when each node can spend 16 packets with energy information and $k = \log_c 1000$.

can increase the value of c in order to use all the available budget to obtain a smaller error.

When the budget size is increased, we should use a larger constant. Using a budget size of 16 packets/node, the best constant value is $c = 20$, as illustrated in Figure 3. We can see that using $c = 1.05$ is not a good option when we have a large budget to spend. Also, the decrease in the percentage error is not linear compared to the increase in the budget size. When we double the budget size, only a small decrease in the mean error is obtained.

Observing the slope of the budget curve, we can see that Equation (2) provides a small adaptation during the simulation. For all values of c, when time passes, the slope of the budget curve is changed in order to adjust to the remainder budget and simulation time. Nevertheless, this adaptation is not enough to achieve our goal in the energy map construction: use all the available budget keeping the percentage error almost constant. The performance of using Equation (2) to decide when sending the energy packet is highly dependable on the right choice of the constant c. If it is used a wrong value of c, the budget cannot be completely used or it can be used too fast increasing the percentage error. Therefore, in order to achieve the desired behavior, it is necessary to find a way of choosing the value of constant c automatically. This is the topic of the next section.

5. ADAPTIVE ENERGY MAP CONSTRUCTION UNDER A FINITE ENERGY BUDGET

In the previous section, we saw that the performance of the finite energy budget approach is highly dependable on the value of constant c. Now, we present a way of changing the value of this constant automatically such that when we have a large budget, a big value of c is used and, when a small budget is available, its value should be small.

The key information to choose the right value of c is the budget curve. We start the adaptive process analyzing the budget curve periodically. As an example, for each 3% of the simulation time, we apply a linear regression in the budget curve in order to predict when it would be the end of budget. Using this information, we can make the following observations:

1. If the predicted end of budget is beyond the end of simulation, the value of c must be increased, otherwise,

it must be decreased;

2. In order to have a conservative behavior, at the beginning of simulation, we should increase less and decrease more the value of c, depending on the case. On the other hand, at the end of simulation, we should increase more and decrease less its value. This behavior is justified because it is more difficult to keep the percentage error constant at the end of simulation than at the beginning since, at the end, the energy available is small.

3. When the value of c is small, we should increase less its value. This is true because for a small c, small changes in its value produce more distant curves.

The three remarks described above can be seen as the requirements that an adaptive process must follow. Next, we describe how we deal with each one of these requirements.

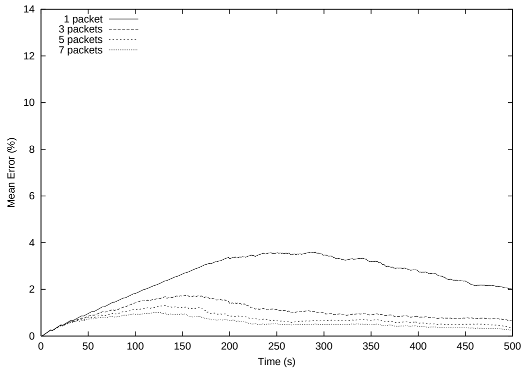
In order to achieve the first requirement, we calculate the value of dif as being the amount in percentage that we should increase or decrease in the predicted end of budget in order to make this value equals to the end of simulation time. If $dif > 0$, we increase the value of c, otherwise we decrease the value of c. The amount of increasing and decreasing is defined taking into account the second requirement. At the beginning of simulation, we increase less the value of c and decrease more. On the other hand, at the end of simulation, we increase more and decrease less its value. This approach provides a conservative behavior since it will try to save budget at the beginning of simulation to be used at the end. This is a good approach because, at the end of simulation, the available energy is smaller, and thus it is more difficult to keep the percentage error constant.

In other to understand the third requirement, we have to notice that the smaller the value of c, the more distant will be the curves when we make a change in its value. The distance between the curves $c = 1.05$ and $c = 1.05 + 10\% = 1.155$ is bigger than the distance between the curves $c = 2$ and $c = 2 + 10\% = 2.2$. This means that when we are working with a small c, the error is bigger, and a small increase in its value will change p' to a curve where the probability of sending a packet for the current error is almost 1. In order to solve the problem of increasing and decreasing the value of c when it is small, we made another modification in the value of inc for small values of c. If the value of c is smaller than 1.001, we make $inc = \frac{inc}{100}$. If the value of c is between 1.001 and 1.01, we make $inc = \frac{inc}{10}$.

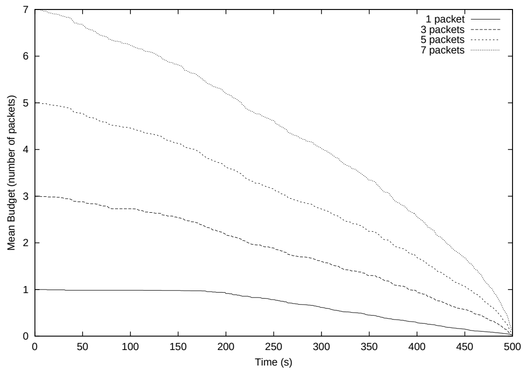
6. SIMULATION RESULTS FOR THE ADAPTIVE ENERGY MAP CONSTRUCTION

The goal of this section is to analyze the adaptive process using the adaptive energy map construction described in the last section. To this end, we change the simulation time and the size of the budget, and plot the error and the available budget in each second of simulation.

Figure 4 shows the results for a simulation of 500 seconds using 1, 3, 5 and 7 packets. For all sizes of budget, the error is almost constant during all the simulation time, and the budget finishes at the end of simulation, meaning that the adaptive process achieved a good performance in these scenarios.



(a) Mean Error (%).

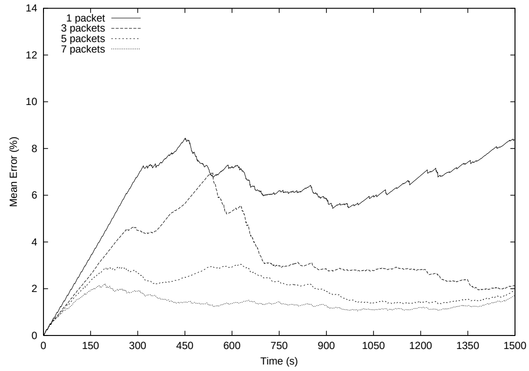


(b) Mean Budget (number of packets).

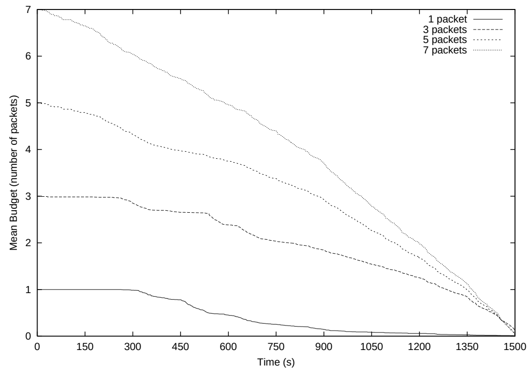
Figure 4: Changing the budget size in a 500 second simulation and $k = \log_c 1000$.

Figure 5 illustrates the results for a simulation period of 1500 seconds. We can see that even when each node can use only 1 packet during all simulation, the use of the budget is distributed during all the simulation time. The same can be seen, in Figure 6, in which a simulation period of 2000 seconds is analyzed. In all cases, the budget is used uniformly during the simulation time in order to keep the error almost constant.

It is important to point out that the adaptive process proposed in this section works fine for the sensor network analyzed in this work. Other kinds of sensor networks must be carefully studied. As an example, the adaptive process is highly dependable on the amount of initial energy. The bigger this value, the more difficult to keep the percentage error constant. In other words, more budget will be necessary at the end of simulation to keep the percentage error constant, meaning that the budget curve should be more above the straight line $y = -\frac{budget}{simulationTime}\, x + budget$ than it was in simulations presented in this work. However, we support the idea that the three requirements described in Section 5 must be achieved by the adaptive processes for all kinds of wireless sensor networks. Consequently, the adaptive process should be guided by the three requirements, but it should also take into account the characteristics of the sensor network.

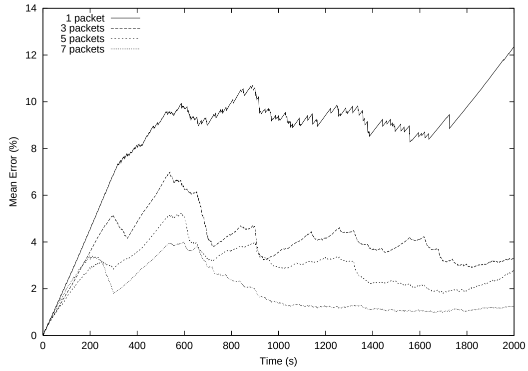


(a) Mean Error (%).

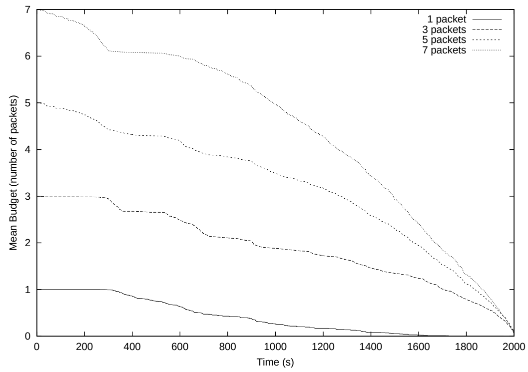


(b) Mean Budget (number of packets).

Figure 5: Changing the budget size in a 1500 second simulation and $k = \log_c 1000$.



(a) Mean Error (%).



(b) Mean Budget (number of packets).

Figure 6: Changing the budget size in a 2000 second simulation and $k = \log_c 1000$.

7. CONCLUSIONS

In this work, we presented a new model for constructing the energy map of wireless sensor networks under a finite energy budget. The energy budget was used in the context of defining the maximum number of packets each node can send with energy information to the monitoring node. We proposed a model to represent the probability in which a node sends an energy information packet, and an approach to adjust this probability in order to construct the best energy map under a given energy constraint. Simulation results indicate that we can approach the performance limits using the proposed finite energy budget model.

It is important to notice that when we design a wireless sensor network that is battery powered, it is important to determine the energy budget associated with each network activity. This is a new paradigm in the design of wireless sensor networks. We plan to investigate the use of this new paradigm in other network activities. As an example, we can design mechanisms that disseminate information to the maximum number of nodes under the constraint that they can use only a determined amount of energy. Another possibility is the design of network management functions to achieve their best performance using only a finite amount of energy.

Acknowledgment

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