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Network Planning for Heterogeneous Wireless Sensor Networks in Environmental Survivability

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***Abstract*—To deal with the problem of hostile environments, we proposed to construct heterogeneous sensor networks composed of both regular nodes and robust nodes, where robust nodes are better equipped for hostile environments and hence are more expensive than regular nodes. We study the problem of network design in heterogeneous wireless sensor networks that involves optimization of network costs associated with different classes of nodes versus maximizing coverage and network lifetime. We consider the design of heterogenous networks with the objectives of minimizing costs and maximizing network lifetime. The association we present in heterogeneous sensor network design between optimizing the number of nodes in each class with cost constraints and network lifetime for corresponding network composition maybe of independent interest in the design of networks in general.**

I. Introduction

Many applications of wireless sensor networks (WSNs) are in outdoor environments, where they are subject to hostile environments. In the past, research in WSNs has mentioned the impact of environment on the efficiency of WSN operation, but no direct effort has been made to address the problem in the face of hostile environmental attributes that can damage/destroy nodes in a WSN, thus hampering normal WSN operation. In this paper, we study the design of WSN modeling with consideration of harsh environmental attributes. We propose to construct a heterogeneous WSN with regular nodes and robust nodes that can withstand harsh environmental conditions to face the unique challenges posed by hostile environments on regular nodes. We use the framework of heterogeneous WSNs to develop a robust WSN that can withstand the harsh environment and still satisfy the objectives of providing coverage and prolonging network operation. Our motivation to the study of heterogeneous WSNs lies in their ability to incorporate fault tolerance by investigating design of networks with robust and regular nodes. Such heterogeneous networks survive better in diverse environmental conditions. Our work directly addresses network design for environmental survivability with the help of heterogeneous WSNs.

Heterogeneous networks provide means to design WSNs that consider various environmental phenomenon that may be detrimental to one type of nodes but can be withstood by another type of nodes. One example would be the design of a heterogeneous network with waterproof nodes and regular nodes. The waterproof nodes and regular nodes are similar in all aspects, except for the waterproof coating that guarantees a higher survival probability than regular nodes in the event of rains in the deployment region. Secondly, heterogeneous WSNs provide the ability for fault-tolerance, for the same reasons of design with consideration of environmental attributes. In hostile environmental condition, waterproof nodes are better than regular nodes in the event of rains. The same can be stated for fire-resistant nodes and regular nodes deployed in the event of a fire.

Network design is the first step in building a heterogeneous WSN with regular nodes and robust nodes that can withstand the harsh environmental conditions. We are interested in problems in which we have to design a heterogeneous network with multiple classes of nodes with different costs. This class of problems is important when we are presented with a network design budget for a heterogeneous network, where nodes of different classes have different efficiency of operation in diverse environments. Since WSNs comprise of nodes with non-replenishable batteries, it is crucial to design such a network with network lifetime in consideration. In the absence of a specified economic constraint on network design, one way to do this would be the deployment of dense heterogeneous networks, where redundancy can aid in prolonging network lifetime by rotation of nodes in the *active* and *sleep* modes of operation. However, most realistic design scenarios impose an economic constraint on network design and it is crucial to develop a framework where economic constraints are balanced with network sensing and lifetime objectives.

For simplification, we consider a heterogeneous network with regular and robust nodes. Both regular and robust nodes are homogeneous with respect to sensing, data processing and communication abilities. However robust nodes possess certain attributes that makes them more robust to a certain environmental attribute than regular nodes. The presence of this additional attribute increases the cost of a robust node, but it also provides a guarantee of high probability of operation in the event of the occurrence of the hostile environmental attribute.

In this paper, we make three contributions: (1) As far as we know, we are the first to consider WSNs for survival

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heterogeneity to deal with hostile environment. (2) We provide a model for characterization of robust nodes that withstand harsh environmental conditions better than regular nodes. (3) We provide guidelines for optimal network design for two-class heterogeneous networks with the help of performance parameters such as cost, coverage and network lifetime.

The two performance evaluation metrics that we consider in this paper are cost optimization for a given budget of network deployment and network lifetime for a given network composition. We also find the minimum number of waterproof sensors for given probability of failure of regular nodes from the hostile environmental attribute. The probability of failure is evaluated with the help of two different models: partial differential equation (PDE) modeling [1] and Poisson models for the hostile environmental attribute.

Our work differs from related work in heterogeneous network design in that we focus on survival heterogeneity. We study the survival heterogeneity of a two-class heterogeneous WSN, where one class of nodes is more robust than the other class due to a protective external feature, such as waterproof sensors to withstand rain in an outdoor sensing application. We study network design in such a scenario, where one class of nodes is more robust and hence more expensive than the other, resulting in a situation where the cost constraints provides for a smaller number of robust nodes and a larger number of regular nodes to be deployed in the deployment region. We study the survival heterogeneity due to the hostile environmental attribute that occurs with probability p. We formulate the cost constraint with a combinatorial optimization problem and obtain the network lifetime in each case for a given network composition of regular and robust nodes.

Related Work: Heterogeneous WSNs of different modalities have been studied for applications such as audio and video fusion in tracking [2], [3], camera sensor networks [4] and medical monitoring [5], to name a few. Heterogeneous network design has been studied in terms of energy efficiency [6], [7], [8], [9], [10] computational heterogeneity, application heterogeneity [5], fault-tolerance heterogeneity [11] and [12] and coverage heterogeneity [13] and [14]. The study of heterogeneous WSNs for topology design is presented in [15] and [16]. Heterogeneity has been studied for fault tolerance in [11] and [12]. Our work differs in that we study survival heterogeneity with the help of heterogeneous WSNs.

Organization: The rest of this paper is organized as follows. Section II presents the cost model and formulation of the network design problem. Section III presents the simulation model and results. Finally, Section IV concludes the paper and presents directions for future research in this direction.

II. Problem formulation and derivation

We study the problem of a two-class heterogeneous WSN consisting of N_1 regular nodes and N_2 robust nodes. The robust nodes may possess external characteristics like waterproof or trample-resistant packaging which makes them better suited than regular nodes to hostile environmental conditions. Thus regular nodes are more expensive than robust nodes. This can be formulated as robust nodes being able to survive a given environmental phenomenon with probability = 1 and regular nodes survive the environmental phenomenon with probability p. For example, regular nodes emerge unharmed from rains with a probability p and waterproof nodes always survive the rains (p=1). The initial WSN of N_1 regular nodes and N_2 robust nodes results in pN_1 regular nodes and N_2 robust nodes after a bout of rains. Hence a certain budget allocation for network deployment can result in economical operation if we have $N_2 < N_1$. The problem we study can then be formulated as follows:

- What is the minimum number of regular and robust nodes for the given budget a, where robust nodes have a higher probability of survival in a natural phenomenon than regular nodes?
- The second part of the problem in network design that we study is related to the network lifetime for given composition of nodes in each class. Since robust nodes are more expensive and more reliable than regular nodes, what will be the network lifetime for a given duty cycle of operation due to given composition?

The problem of network design for heterogeneous networks find applications in a variety of WSN environments, where utility of operation is maximized by having multiple classes of nodes with different costs and modes of operation. Although we have illustrated the problem of network design with the help of a two-class heterogeneous network with regular and waterproof nodes, it can be easily extended to a multi-class network with diverse capabilities assigned to each class of nodes. With the help of our simulation results, we provide guidelines on network design for cost constraints while still satisfying a certain degree of coverage.

A. Cost model

Consider a WSN with N_1 number of regular nodes and N_2 be the number of robust nodes in a two-class heterogeneous network. We assume that we have a budget of $a = a_1 + a_2$ for nodes in classes N_1 and N_2, where a_1 is allocated for N_1 number of regular nodes with cost of C_1 per regular node, and a_2 is allocated for N_2 number of robust nodes with cost of C_2 per robust node. For simplicity, let the cost of the regular nodes and robust nodes be related inversely to the number of nodes in each class, i.e., the cost of a regular node is a_1/N_1 and a_2/N_2. Here N_1 and N_2 are expressed as a change of variable and are represented in this manner only for notation convenience. The costs of nodes in each class are fixed, implying that we can buy a fixed amount of nodes from each class with a given budget. We formulate the design problem as a vector S, where

$$\mathbf{S} = \mathbf{b}^t\mathbf{X}.$$

Here $\mathbf{b}$ is the ratio of the number of nodes in each class to the total number of nodes in the heterogeneous network. $\mathbf{X}$ is the ratio of node lifetime at the beginning of a cycle to the node lifetime at the end of a cycle. Defining a cycle as the time that a node spends in one *active* state and its consecutive *sleep* state, we see that the ratio $\mathbf{X}$ depends on the duty cycle that dictates the amount of time that a node spends in the active state. We assume that the nodes in each class are homogeneous except for external features, such as waterproofed exteriors for rainy weather. We assume that power consumption in the *sleep* state is negligible compared to power consumption in the *active* state, and hence the *sleep* state power consumption is neglected.

B. Derivation of the number of nodes in each class of the heterogeneous WSN

Our goal is to maximize the vector **S**, since maximizing **S** maximizes the lifetime of nodes at the end of a cycle. We perform this maximization subject to the constraint that the cost of both regular and robust nodes does not exceed a value Γ. Hence the optimization problem for a 2-class heterogeneous network takes the form

$$S = \begin{bmatrix} b_1 & b_2 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \tag{1}$$

s.t.

$$\frac{a_1}{N_1} + \frac{a_2}{N_2} < \Gamma. \tag{2}$$

The formulation of the cost constraint in (1) is equivalent to the restriction a on the total network cost for N_1 regular and N_2 robust nodes. In general, for a multi-class network with *i* classes of nodes, where $i = \{1, 2...n\}$, the optimization problem takes the form

$$S = b^t X \tag{3}$$

s.t.

$$\sum_{i=1}^{n} a_i / N_i. \tag{4}$$

We introduce some notations for **b** and **X**. Let

$$b_i = \frac{N_i}{\sum N_i}. \tag{5}$$

Since X_i is a ratio of node lifetime at the end of a cycle to that at the beginning of the cycle, we denote

$$X_i = \frac{L_{e_i}}{L_{b_i}}, \tag{6}$$

where L_{ei} is the lifetime of a node in class *i* at the end of the cycle, and L_{bi} is the lifetime of a node in class *i* at the beginning of the cycle. Let γ be the power spent by a node in the 'active' part of its cycle. Then,

$$L_{ei} = L_{bi} - D_{ci}\gamma, \tag{7}$$

where D_{ci} is the duty cycle of nodes in class *i*. Hence,

$$X_i = \frac{L_{bi} - D_{ci}\gamma}{L_{bi}} \tag{8}$$

We define the number of nodes at the end of a cycle as follows:

$$N_i = N_{bi} - \left[\frac{N_{bi}L_{bi} - N_{ei}L_{ei}}{L_{ini}} \right], \tag{9}$$

where N_{bi} and N_{ei} are the number of nodes respectively at the beginning and end of a cycle, and L_{ini} is the initial lifetime of a node. The lifetime of a regular node at the end of its cycle depends on its duty cycles and the amount of energy it spends in environmental modeling.

Assuming that the duration of the hostile environmental attribute is exponential with parameter l, we obtain the probability of next occurrence of the hostile attribute (Poisson distribution). Let this probability be denoted by $p(l)$. If the probability of failure of a regular node from the hostile environmental attribute is p, then the number of regular nodes at the end of a cycle is $pN_1 p\,(l)$ and the network lifetime for N_1 regular nodes and N_2 robust nodes is given by

$$pN_1 p\,(l) \left(L_{ini} - N_t \left(\delta + E_{Dc_1} \right) \right) + N_2 \left(L_{ini} - N_t E_{Dc_2} \right)$$

where N_t is the number of time slots in a cycle and E_{Dc1} and E_{Dc2} is the power consumption in the active and sleep parts of the respective duty cycles of regular and robust nodes.

For a two-class network, the optimization problem is given by the objective function f that maximizes the network lifetime for the nodes in each class as follows:

$$f\,(N_1, N_2) = \begin{pmatrix} \frac{N_1}{N_1+N_2} & \frac{N_2}{N_1+N_2} \end{pmatrix} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} \tag{10}$$

subject to the constraint equation g on the available budget Γ for network deployment given by

$$g\,(N_1, N_2) = \frac{a_1}{N_1} + \frac{a_2}{N_2} < \Gamma. \tag{11}$$

We solve this optimization problem by formulating (10) and (11) as a Lagrangian dual problem. The Lagrangian is formulated as

$$\frac{\partial f}{\partial N_1} - \lambda \frac{\partial g}{\partial N_1} = 0, \tag{12}$$

$$\frac{\partial f}{\partial N_2} - \lambda \frac{\partial g}{\partial N_2} = 0, \tag{13}$$

and

$$\frac{a_1}{N_1} + \frac{a_2}{N_2} - \Gamma = 0. \tag{14}$$

Here λ is the Lagrangian optimizing variable.

Procedure: In order to obtain the number of nodes in each class of the network, we perform the optimization subject to the initial number of nodes in each class. Thus the first step of the optimization problem becomes

$$\frac{\partial f}{\partial N_{b1}} - \lambda \frac{\partial g}{\partial N_{b1}} = 0, \tag{15}$$

$$\frac{\partial f}{\partial N_{b2}} - \lambda \frac{\partial g}{\partial N_{b2}} = 0 \tag{16}$$

and

$$\frac{a_1}{N_1} + \frac{a_2}{N_2} - \Gamma = 0. \tag{17}$$

Having obtained the values of N_{b1} and N_{b2}, we perform the optimization again to find the number of nodes N_{e1} and N_{e2} at the end of the cycle.

$$\frac{\partial f}{\partial N_{e1}} - \lambda \frac{\partial g}{\partial N_{e1}} = 0, \tag{18}$$

$$\frac{\partial f}{\partial N_{e2}} - \lambda \frac{\partial g}{\partial N_{e2}} = 0 \tag{19}$$

and

$$\frac{a_1}{N_1} + \frac{a_2}{N_2} - \Gamma = 0. \tag{20}$$

Let p_i denote the probability that a node in class *i* has turned 'off' due to the hostile environmental conditions. Since the relationship between number of nodes at the beginning and end of a cycle is a function of the duty cycle, we can obtain the optimal duty cycle for given constraints of cost in a heterogeneous network.

The values of N_{b1} and N_{b2} are given by solving the following equations:

$$\frac{\partial f}{\partial N_{b1}} - \lambda \frac{\partial g}{\partial N_{b1}} = 0 \tag{21}$$

yields

$$\frac{1}{(N_1+N_2)}\left(L_{b_1} - D_{c_1}\gamma\right)\left(\frac{1}{L_{b_1}-L_{ini}}\right) - \left(1 - \frac{L_{b_1}}{L_{ini}}\right)\left[\frac{1}{(N_1+N_2)^2}\left(N_1X_1 + N_2X_2\right) + \frac{a_1\lambda}{N_1^2}\right] = 0 \tag{22}$$

Similarly,

$$\frac{\partial f}{\partial N_{b2}} - \lambda \frac{\partial g}{\partial N_{b2}} = 0 \tag{23}$$

yields

$$\frac{1}{(N_1+N_2)}\left(L_{b_2} - D_{c_2}\gamma\right)\left(\frac{1}{L_{b_2}-L_{ini}}\right) - \left(1 - \frac{L_{b_2}}{L_{ini}}\right)\left[\frac{1}{(N_1+N_2)^2}\left(N_1X_1 + N_2X_2\right) + \frac{a_2\lambda}{N_2^2}\right] = 0 \tag{24}$$

We perform the optimization to obtain the equations for N_{e1} and N_{e2} resulting in

$$\frac{\partial f}{\partial N_{e1}} - \lambda \frac{\partial g}{\partial N_{e1}} = 0 \tag{25}$$

which yields

$$\frac{\left[(N_1+N_2)\left(1-\frac{D_{c_1}\gamma}{L_{b_1}}\right)-(N_1X_1+N_2X_2)\right]}{(N_1+N_2)^2} = -\frac{a_1\lambda}{N_1^2}. \tag{26}$$

Similarly,

$$\frac{\partial f}{\partial N_{e2}} - \lambda \frac{\partial g}{\partial N_{e2}} = 0 \tag{27}$$

yields

$$\frac{\left[(N_1+N_2)\left(1-\frac{D_{c_2}\gamma}{L_{b_2}}\right)-(N_1X_1+N_2X_2)\right]}{(N_1+N_2)^2} = -\frac{a_2\lambda}{N_2^2}. \tag{28}$$

We now present some approximations to obtain closed form solutions for the optimizations in two special cases: low and high duty cycles of operation. The duty cycle setting actually depends on the scheduling algorithms. Here we present closed form solutions to obtain the number of regular and robust nodes for the two special cases simply as a guideline. The qualifying assumptions on network lifetime are stated at the beginning of each approximation below.

Low duty cycle: For low duty cycle, the node lifetime at the end of a cycle is approximately equal to the initial lifetime, i.e.,

$$L_{e1} \approx L_{ini}$$

Using this approximation in (22) and (24), we get

$$N_{b_1} = \frac{N_1 - \frac{N_{e_1}L_{e_1}}{L_{ini}}}{1-\frac{L_{b_1}}{L_{ini}}} \qquad N_{b_2} = \frac{N_2 - \frac{N_{e_2}L_{e_2}}{L_{ini}}}{1-\frac{L_{b_2}}{L_{ini}}} \tag{29}$$

where N_{e1} and N_{e2} are obtained by the probability p_i of node survival in hostile environmental condition.

Similarly, the number of nodes at the end of a low-duty cycle operation is given from (26) and (28)

$$N_{e_1} = \frac{N_{b_1}L_{b_1} - L_{ini}\left(N_{b_1}-N_1\right)}{L_{e_1}} \qquad N_{e_2} = \frac{N_{b_2}L_{b_2} - L_{ini}\left(N_{b_2}-N_2\right)}{L_{e_2}} \tag{30}$$

High duty cycle: For high duty cycle of operation in the heterogeneous network, since nodes in both classes have a high duty cycle, we use the following approximation:

$$D_{c1} \approx D_{c2} \tag{31}$$

Also, due to the duty cycle value, the node lifetimes for both classes at the beginning of a cycle are identical. Hence,

$$L_{b1} \approx L_{b2} \tag{32}$$

Substituting (31) and (32) in (22)- (28), we get

$$\frac{N_1}{N_2} = \sqrt{\frac{a_1}{a_2}}, \tag{33}$$

which implies that the ratio of nodes for a high duty cycle of operation is proportional to the cost coefficients a_i. This shows that for a high duty cycle, the cost of network deployment depends only on the cost of nodes in the classes of the heterogeneous WSN. This is because at high duty cycles, the probability p_i of node survival does not impact the decision of number of nodes to be turned in the active state in each class. The entire network is a mostly active network irrespective of node class.

III. Simulation Model and Results

A. Simulation parameters

In this section, we present the results of network costs, lifetime and coverage obtained for various network compositions. We assume the regular nodes and robust nodes can be in any of two states: active or sleep. We use the specifications of the Imote2 sensor node from Crossbow to determine the currents drawn in active and sleep state. The currents drawn in the active state and sleep state are assumed to be 44 mA and 390 μA respectively. These values are used to determine energy consumption in different duty cycles. Since the Imote 2 sensor uses a PXA 271 processor, we assume the computational energy based on the number of duty cycles and energy consumption per cycle for the PXA 27x processor.

We assume that the hostile attribute occurs with intensity λ=3 in a sixty-day period. The occurrence of the hostile attribute causes the regular node to fail with a probability p that is varied from 0.3 to 0.7. The Poisson model is used to simulate the occurrence of the hostile attribute, while the PDE model can be used to simulate more complex weather systems. In each case, we only use the results of simplified weather models studied in [17] and [18] to obtain optimal network composition and lifetime results.

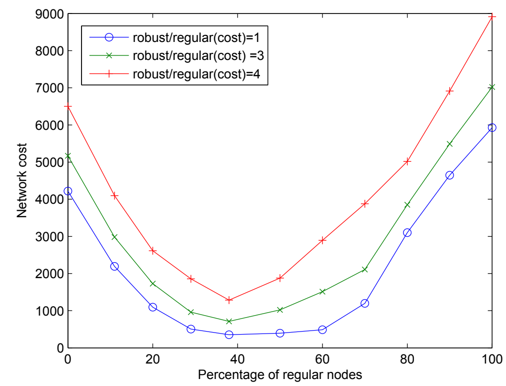
B. Optimal network composition

In this section, we present network costs with varying network composition when the hostile environment attributes are modeled using Poisson and PDE models. In each case, we study the relationship between network costs and composition for p = 0.3 and 0.7. Figure 1 shows the network costs to maintain 90% coverage for 60 days. Our results show the optimal costs to maintain 90% coverage with Poisson modeling of the hostile attribute which occurs with an intensity λ. The modeling and occurrence of the attribute causes regular nodes to die. Hence, in order to maintain a given degree of coverage, (in our case, 90 %), the network costs increase due to increased number of regular nodes that are deployed to accommodate the scenario that regular modes may die due to hostile environment in the future. For lower probability of failure (p =0.3), the cost of network deployment is lower since the regular nodes are more resilient to the hostile environmental attribute and their quantities need not be compensated as much as when they fail with a higher probability. For p =0.3, the network costs are lowest for 38% regular nodes. The higher network costs for different compositions are due to the higher number of regular nodes required to satisfy coverage. For p =0.7, the lowest costs are achieved for around 19% regular nodes. The composition for lowest cost is different from that in Figure 1(a) due to higher probability of failure consuming higher number of regular nodes.

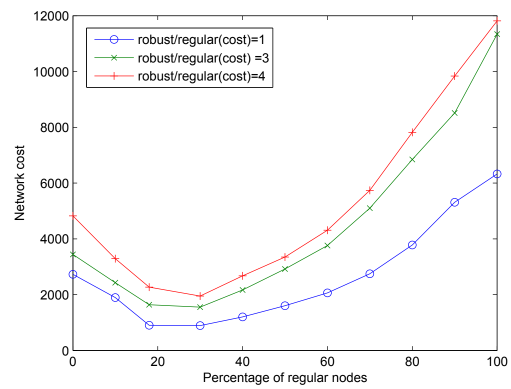
Figure 2 shows the network costs when the hostile environment is modeled using PDE models. In comparison with Figure 1, we see that PDE modeling results in higher costs to maintain a similar degree of coverage. Similar to the results in Figure 1, a higher probability of failure (p=0.7) of regular nodes results in higher network cost.

Figure 3 shows the network composition for varying failure probabilities of regular nodes for a given network budget when the duty cycle of regular nodes is greater than that of robust nodes. As the failure probability of regular nodes increases, we need a greater number of nodes to obtain 90 % degree of coverage. The number of regular nodes is much higher than the number of robust nodes due to the cost constraints. Figure 3(b) shows the plot of percent decrease in number of regular and robust nodes for increasing probability of failure when the duty cycle of robust nodes is made higher than that of regular nodes. This is because the number of robust nodes needed for a given degree of coverage increases with increasing failure probability of a regular node. We see that when the robust nodes are active more than regular nodes, the percentage

Fig. 1. **Cost to obtain 90 % coverage with Poisson models**



(a) ***p*=0.3**



(b) ***p*=0.7**

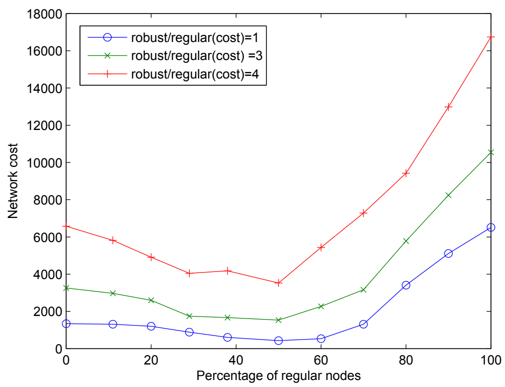
decrease in the number of regular nodes is substantial, leading to higher savings in cost of network deployment.

C. Relationship to network lifetime

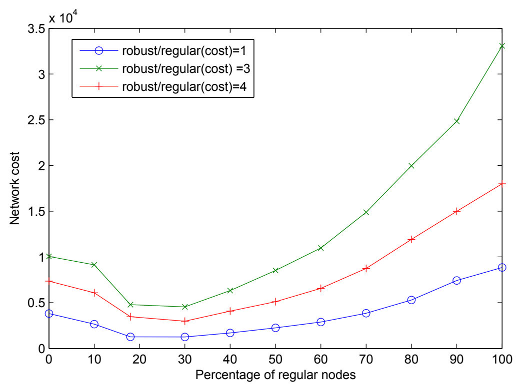
In this section, we present the results of network composition and failure probability of regular nodes to the network lifetime. D_{c1} and D_{c2} are the duty cycles of the regular and robust nodes respectively. Figure 4 shows the network costs for different duration of operation. The results in Figure 4 are for 60% regular nodes, where the robust nodes are twice as expensive as regular nodes. We see that when the network operation is designed for maximum of 10 days, the network costs are lowest, since a greater number of robust nodes used can compensate for more vulnerable regular nodes. However, for larger operation time, larger number of nodes need to be deployed. This is because regular nodes succumb to the hostile attribute and robust nodes run out of battery energy from staying in the *active* state.

Figure 5 shows the plot of networks costs versus the network lifetime that can be obtained from optimal composition of the heterogeneous WSN for fixed budget. We obtain network lifetime results (mA-hrs) from increasing network costs for varying duty cycle ratios. We assume Poisson modeling in

Fig. 2. **Cost to obtain 90 % coverage with PDE models**

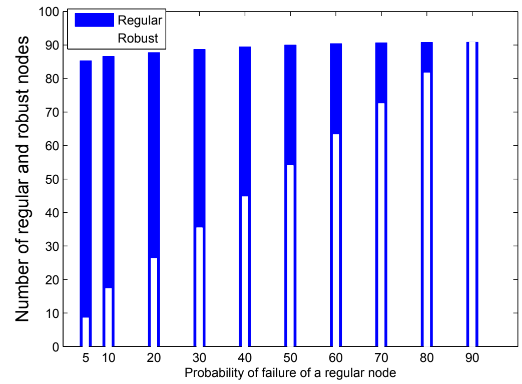


(a) ***p*=0.3**

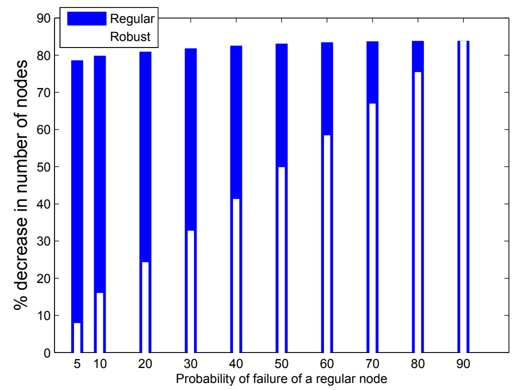


(b) ***p*=0.7**

Fig. 3. **Optimal Network composition for 90 % coverage**



(a) **Network composition for varying probabilities of failure of regular nodes**



(b) **Change in network composition versus probability of failure**

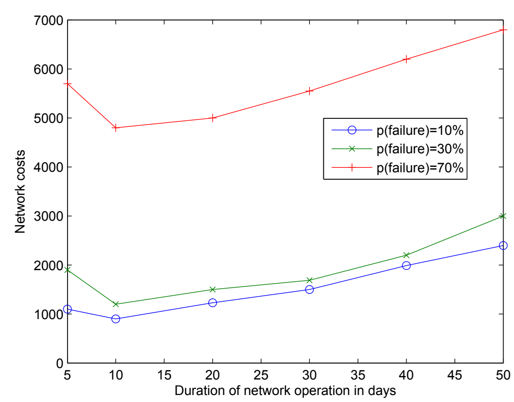
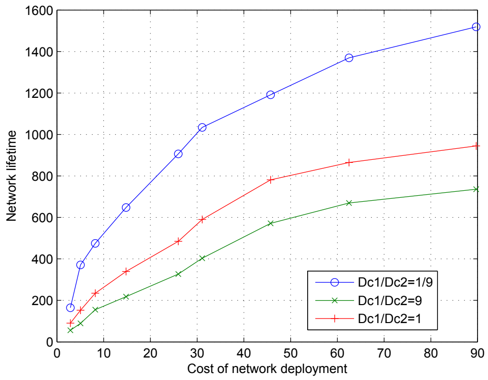


Fig. 4. Network costs with varying operation time

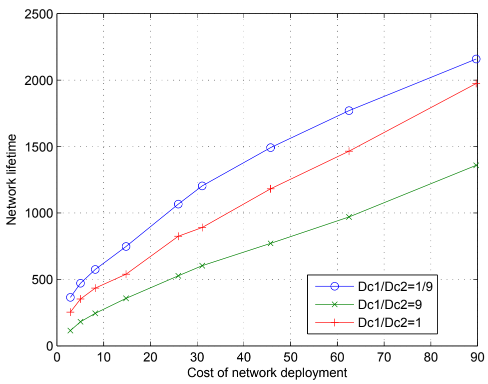
each case. We see that as network costs increase, we can obtain increased network lifetime. This can be explained as follows: Increased network costs result from higher number of regular nodes that are deployed to compensate for the failed regular nodes. With regards to the duty cycle, we see that when the duty cycle of robust nodes is higher than that of regular nodes, the network lifetime is highest. The lowest network lifetime is obtained when the duty cycle of regular nodes and robust nodes are set equal to 0.5, since the regular nodes are prone to failure from the environmental attribute as well as higher energy consumption in modeling which is not prevalent in robust nodes.

Figure 6 shows the network lifetime as a function of the percentage of robust nodes in the heterogeneous WSN for two different duty cycle ratios with a fixed network budget. As the percentage of robust nodes increases, the network lifetime increases, since the robust nodes are immune to failure from the hostile environmental attribute and unlike regular nodes, they do not spend computational energy in modeling the hostile attribute. When the duty cycle of regular nodes is higher than that of robust nodes, the network lifetime obtained is lower than the case when duty cycle of robust nodes is higher than that of regular nodes. This is also attributed to the savings in network energy from computation and immunity of robust nodes from damage caused by the hostile environment. Here we note that as the percentage of robust nodes increases, the network lifetime and the cost to deploy the network increases. For a fixed network budget

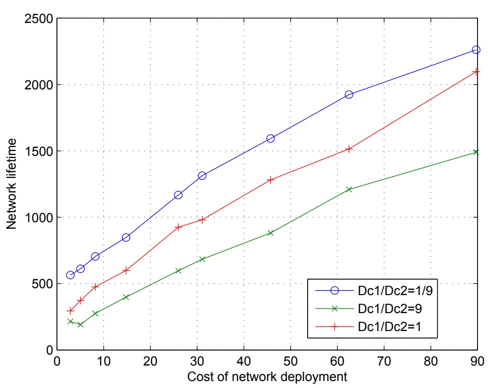
Fig. 5. **Network lifetime versus network costs for varying duty cycle ratios**



(a) ***p*=0.3**



(b) ***p*=0.7**



(c) ***p*=0.9**

where robust nodes are more expensive than regular nodes, employing a homogeneous network of robust nodes will yield the highest lifetime. However, the high cost of a robust node constrains the number of nodes that can be deployed with that budget. A lower number of nodes will result in larger coverage holes, i.e. parts of the deployment region that are not covered by sensor nodes. Our results show that heterogeneous WSNs provide environmental survivability with high network lifetime and adequate coverage in the deployment region.

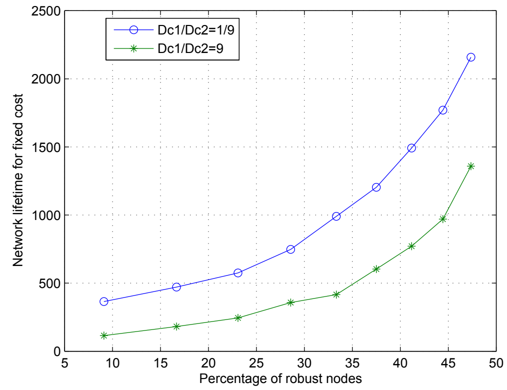


Fig. 6. Percentage of robust nodes versus network lifetime for given network budget

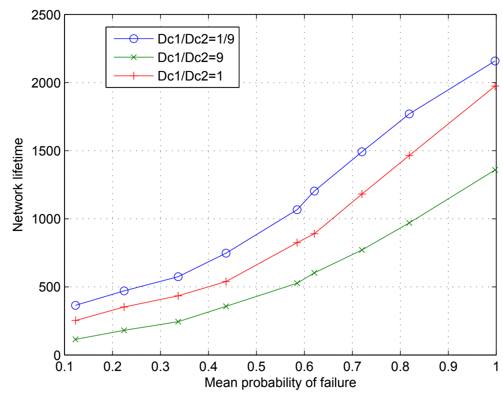


Fig. 7. Network costs vs Gaussian probability of failure

D. Impact of Gaussian probability of failure

In this section, we use the Gaussian probability of failure of a regular node instead of the fixed probability of failure that we used in the previous section. Each point on the X-axis in Figures 7 and 8 denotes the mean probability of failure for a Gaussian distribution. Figure 7 shows the network costs for Gaussian probability of failure of regular nodes for various duty cycle ratios. For higher failure probability, when the duty cycle of robust nodes is greater than that of regular nodes, it is expensive to deploy the network. The converse is true for lower duty cycle of robust nodes than regular nodes. For lower duty cycle of robust nodes than regular nodes, we have lower network costs.

Figure 8 shows a plot of network lifetime versus the Gaussian probability of failure of regular nodes for various duty cycle ratios. When the duty cycles of robust nodes is higher, we obtain higher network lifetime due to immunity from damage from the hostile environmental attribute. Sim-

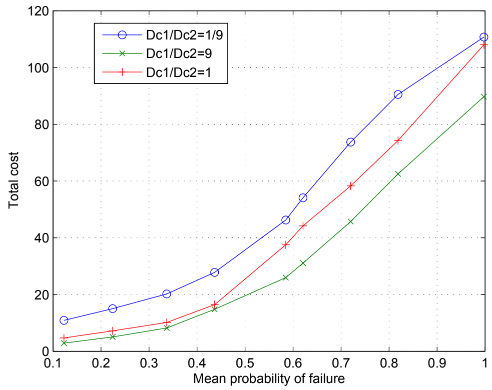


Fig. 8. Network lifetime vs Gaussian probability of failure

ilarly, when the duty cycle of regular nodes is higher, it results in lower network lifetime. The slope of the graph indicated by the relationship of the network lifetime and costs to the probability of failure of regular nodes is due to the harshness of the environmental attribute. A harsher environment indicated by high probability of failure (0.45) drives up the costs, since a higher number of regular nodes fail and have to be compensated by a higher number of nodes in initial deployment to satisfy a 90% degree of coverage. For milder environments, i.e. probability of failure <0.45, the slope of cost and lifetime versus failure does not change as drastically as in the converse case. A comparison of Figures 5 and 8 shows that for a higher probability of failure in the Gaussian distribution, the network lifetime and associated network costs are higher than for a fixed probability of failure. These results draw attention to the need for WSN design with heterogeneous networks comprising of different classes of nodes, each of which possesses varying degree of immunity to hostile environmental attributes that may obstruct efficient WSN operation.

IV. Conclusions

In this paper, we studied the design of a heterogeneous WSN, where the heterogeneity arose due to survival probability of one class of nodes being higher than the other class of nodes. This heterogeneity was analyzed in terms of its impact on network design, since the robustness and associated higher costs of one class of nodes achieved conflicting objectives: higher network costs, higher coverage and higher network lifetime. We studied the optimal heterogeneous network design in terms of the ratios of nodes in each class to satisfy network objectives of coverage and lifetime, with a given constraint on the network budget. We also performed preliminary investigation in the design of a two-class heterogeneous WSN with environmental modeling.

Our ongoing work in this direction is to extend the network design formulation and analysis to multi-class, multi-constrained heterogeneous WSNs. The results of our paper contribute significantly to network design problems. Other directions of our future work are detailed analyses of environmental modeling on the performance parameters of heterogeneous WSNs.

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