Condition-Based Node Deployment Policies for Reliable Wireless Sensor Networks

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Abstract

Wireless sensor networks (WSNs) consist of a set of sensors distributed over a region of interest that monitor and report on conditions within the network. Network reliability of region coverage is often an important performance metric, as the status of the network degrades over time due to sensor failures. To facilitate network operation over a prolonged period time, failed nodes may be replaced or new sensors deployed to re-establish network capability. We explore a condition-based sensor deployment policy, in which new sensors are periodically deployed based on an observed network state. The destruction spectrum (D-spectrum) has been utilized to estimate network reliability, and offers several advantages over a traditional Monte Carlo approach. While the D-spectrum is a function of the network structure, or the number of sensors and their distribution throughout the network, we discuss how the D-spectrum can be incorporated into a model that estimates reliability in the presence of a condition-based sensor deployment policy. This model is then demonstrated by evaluating various policies with respect to the resulting reliability for region coverage. Finally, the performance of these policies is compared to a simpler time-based sensor deployment strategy.

Keywords
Network Reliability, Destruction Spectrum, Wireless Sensors Networks

1. Introduction
Wireless Sensor Networks (WSNs) are commonly characterized by a large number of low-cost sensor nodes operating in a cooperative manner to monitor a region of interest. Additionally, WSNs require little infrastructure or supporting resources (e.g., physical wire connection) for sensors to route information through the network [1]. These features enable WSNs to be quickly established by randomly deploying sensors over a target location, which may also be necessary when operating in harsh or difficult to access terrain [2].

Over the course of network operation, sensors consume a finite power supply while monitoring the surrounding region and communicating with nearby sensors [3]. Once this power supply is consumed the sensor fails and no longer contributes to network operation. The lifetime of a sensor can be further accelerated by software or hardware complications, which may arise as a result of external (e.g., environmental) factors [1]. While the WSN can likely withstand a few sensor failures with minor impact to network capability, as a larger number of sensors fail the WSN becomes increasingly degraded.

Several different methods have been explored to prolong network lifetime in the presence of sensor failures. Topology control algorithms commonly aim to extend sensor lifetime by managing power consumption. One approach is to modify the communication radius based on the distance of nearby sensors, as a smaller communication range between sensors requires less energy [4]. There may also be redundant sensors in the network that provide little additional coverage or communication capability. In this situation a sleep/wake schedule can be used to turn sensors on and off as necessary, allowing a sensor to conserve energy until needed [5]. Another approach is through the introduction of one or more mobile sensors in the network to reposition sensors over time as necessary [6, 7]. However, there is a significant cost that accompanies this mobile capability, as the cost of such sensors can be significant compared to static sensors [3, 6]. Additionally, the WSN may be in an environment that is not conducive to sensor mobility, such as a forest or steep mountain side.

The use of topology control algorithms and mobile sensor nodes aim to extend network lifetime. That is, determining a policy to maximize the lifetime of a given WSN deployment. To enable the long-term operation of a WSN, we must eventually consider deploying new sensors in the network. The objective of deploying new sensors can be directed towards restoring a level of network coverage, and/or improving sensor communication capability. In [8, 9] the deployment of new sensors is addressed, in addition to seeking a policy that deploys the fewest number of new sensors. This objective adds further complexity to the search for a deployment policy, as problems related to optimal node placement commonly fall in the NP-Hard class of problems [10]. It may also be difficult to locate sensors at a specific location, particularly if we are forced into a random deployment of sensors due to the operating environment.

Whereas the previous focus has primarily been on the deployment of sensors at a single point in time, in this work we consider a problem where the decision to deploy new sensors is made sequentially over a number of time periods. In doing so, we address the frequency with which new nodes are deployed in the network and the associated cost. Further, throughout the previously mentioned topology control algorithms, introduction of mobile sensor nodes, and single-stage sensor deployment, the focus has been on extending network lifetime or maintaining a coverage/connectivity requirement. We focus on evaluating a node deployment policy with respect to network reliability which commonly fall in the #P-Complete class of problems [11], and are therefore routinely estimated by approximate solution methods such as a Monte Carlo simulation.

In the following section, we discuss a condition-based node deployment model where the deployment of new sensors is based on an observed state of the WSN. The objective is to determine a sensor deployment policy that results in a highly reliable network given a fixed budget available. A Monte Carlo simulation can be used to evaluate a given condition-based deployment policy (CBDP), but improving upon and optimizing a policy is a more challenging task. We illustrate how the network destruction spectrum (D-spectrum), or signature, can be used to estimate reliability in the presence of a CBDP, alleviating some of the difficulties encountered in network reliability problems. The model is then illustrated through an example for various policies.

2. Problem Formulation and Methodology

Consider a WSN W that is comprised of a sink node and a collection of sensor nodes. These sensor nodes are deployed throughout some region of interest R, which is partitioned into a number of smaller subregions $\{1,2,\ldots,n_r\}$. The main tasks of a sensor node are communicating with neighboring sensors to route information through the network directed toward the sink node, in addition to monitoring nearby targets. These sensor capabilities are defined by a communication radius $d_1 > 0$, and a monitoring radius $d_2 > 0$.

Due to the failure of sensors the WSN evolves over time, impacting the ability of sensors to communicate with each other and diminishing the collection of targets covered. For a target to be covered at any given time it must be within the coverage radius of a functioning sensor, and there must exist a communication path from this monitoring sensor bask to the sink node. At time $t \geq 0$, the network W consists of sensors that have been deployed in the network and remain functioning at time t. The condition of the network is then defined in relation to network coverage, $C(W)$, and represents the proportion of targets in the network currently covered.

To maintain adequate coverage over a prolonged period of time, new sensors are deployed in the WSN. First, the network is observed and degraded portions of the network can be detected, which informs the deployment of new sensors. It may be impractical or costly to constantly monitor the state of the network [12], but it is assumed that every δ time units the network can be observed. The time intervals between observations now correspond to a series of missions, where mission m refers to the period of time between $m\delta$ and $(m+1)\delta$. If one or more sensors are deployed in the network, a fixed cost c_F is incurred in addition to a variable cost c_V per sensor deployed. It is assumed that all sensors are deployed with an independent and identically distributed (i.i.d.) life distribution, F, and that sensor capabilities are identical.

The observed state of the network is denoted $S_m = (S_{m1}, S_{m2}, \ldots, S_{mn_r})$, where S_{mi} is the number of sensors functioning in subregion $i \in R$ at the beginning of mission m. After the network is observed, a decision $x_m = (x_{m1}, x_{m2}, \ldots, x_{mn_r})$ is made on how new sensors are deployed in the network, where x_{mi} is the number of sensors deployed to subregion $i \in R$ during mission m. Due to the difficulty encountered when attempting to deploy a sensor to a specific coordinate location, the initial deployment of sensors, along with all future deployments, is random within a subregion. A sensor deployment decision is faced repeatedly over a series of missions, and the decision made during mission m may impact the decision of how sensors are deployed in missions $m' > m$. However given the stochastic nature of sensor failures and the potentially enormous state and deployment decision space, we focus on a myopic condition-based deployment policy (M-CBDP) that focuses on the impact on reliability for the current mission.

2.1. Myopic Condition-Based Sensor Deployment

In the myopic formulation of the condition-based sensor deployment problem, a fixed budget β is available each mission and the objective is to maximize the probability of mission success. An individual mission is successful if network coverage over the duration of the mission satisfies a given coverage requirement, α. Equivalently, mission m is successful if coverage at the end of the mission (time $(m+1)\delta$) is at least α. The reliability of the network during mission m is defined as the probability the coverage requirement is satisfied for the duration of the mission, and is denoted $R(S_m, x_m)$ if we observe network state S_m and deploy sensors according to action x_m. The objective in the myopic condition-based sensor deployment problem is therefore

$$\max R(S_m, x_m), \tag{1}$$

subject to a constraint that the cost of deploying sensors, $c_F + c_V * x_m$, not exceed the budget available.

Equation (1) selects an optimal action to maximize network reliability. As previously mentioned, network reliability problems commonly fall in the #P-Complete class of problems. Network reliability can be estimated through the use of a Monte Carlo method by simulating sensor failures over the next δ time units, determining network coverage at the end of the mission, and recording if the mission is successful or not. Repeating this process over a large number of replications allows for an estimation of reliability upon completion. One deterrent of this approach is the unbounded growth of the relative error for highly reliable and highly unreliable networks [13]. Further, improving upon and optimizing a policy through a Monte Carlo method requires significant computational effort.

2.2. Destruction Spectrum

The D-spectrum has been introduced to estimate network reliability [14], and offers several advantages over a traditional Monte Carlo algorithm. First, the D-spectrum yields an efficient representation of the network's reliability but depends only on the system structure. Additionally, while the D-spectrum is also commonly estimated using a Monte Carlo method, it is more efficient than a Monte Carlo algorithm that estimates network reliability [13]. If we consider a network of n sensors subject to failure, the D-spectrum is a probability distribution on the number of failed sensors necessary to cause network failure. Let s_i^n be the probability that in a network of n sensors, the ith sensor failure results in network coverage falling below the requirement α. For the initial WSN that is deployed, every sensor follows an i.i.d. failure distribution F, and network reliability at time t can be estimated by

$$r(t;\alpha,n) = \sum_{i=0}^{n} s_i^n B(i-1; n, F(t)), \tag{2}$$

where $B(i-1, n, F(t))$ is the cumulative binomial probability of no more than $i-1$ successes in n trials with probability of success $F(t)$ [15].

Under a M-CBDP sensors will be deployed in the network over a series of missions based on the budget β available leading not only to a variable network size, but also changing the age composition of sensors in the network. As a result, sensors that were deployed in previous missions and remain functioning now have a residual life distribution, denoted T_x where $x > 0$ represents a sensor's age, and fail according to the cdf

$$F_x(t) = \frac{F(x+t) - F(x)}{\bar{F}(x)}. \tag{3}$$

We can use Equation (3) to determine the residual lifetime of a sensor randomly selected in the network, while considering the randomness of its age, as follows. Since network reliability increases along with the number of sensors in the network, the entire budget will be utilized each mission to deploy new sensors. We can now use the cost constraint, $c_F + c_V * x_m \leq \beta$, to determine the maximum number of sensors that can be deployed each mission by

$$\bar{\beta} = \left\lfloor \frac{\beta - c_F}{c_V} \right\rfloor. \tag{4}$$

Every δ time units $\bar{\beta}$ sensors will be pushed into the network, eventually resulting in a stable mix of sensors where the probability distribution on the age k of a randomly selected sensor does not change from on mission to the next. From [16], this probability distribution is described by

$$\rho_k = \frac{\bar{F}(k\delta)}{\sum_{j=0}^{\infty} \bar{F}(j\delta)}, k \in \mathbb{Z}_{\geq 0} . \tag{5}$$

With Equation (3) and (5), the residual lifetime of a sensor in the network, considering the randomness of its age, is now described by the cdf

$$G(t;\delta) = \sum_{k=0}^{\infty} \frac{F(k\delta + t) - F(k\delta)}{\bar{F}(k\delta)} \rho_k , \tag{6}$$

$$= \frac{\sum_{k=0}^{\infty}[F(k\delta + t) - F(k\delta)]}{\sum_{j=0}^{\infty} \bar{F}(j\delta)} . \tag{7}$$

The D-spectrum is independent on the failure distribution, but it is impacted by the size of the network. Due to a fixed number of sensors $\bar{\beta}$ deployed in the network each mission and variability in the number of sensor failures, the number of sensors in the WSN will also fluctuate over time. However immediately after new sensors have been deployed, the network consists of

$$n_\beta = \bar{\beta} \sum_{j=0}^{\infty} \bar{F}(j\delta) , \tag{8}$$

sensors, on average. The significance of Equation (8) is that we have an expression for the expected size of a WSN in the presence of a M-CBDP with budget β available per mission. Additionally, the remaining life of a sensor randomly selected in the WSN is an i.i.d. random variable with cdf given by Equation (7).

Finally, to apply the D-spectrum to a M-CBDP we must have knowledge about the system structure, or distribution of sensors in the network. For a fixed budget β available we now know this corresponds to a network with approximately n_β sensors. With an expectation on network size we can now search for the allocation of n_β sensors to each of the subregions to maximize network reliability. Let Y be some policy that determines how the n_β sensors are distributed to each subregion. For example, one policy is to distribute sensors so that each subregion contains approximately the same number of sensors. A policy informs the overall configuration of sensors in the network (i.e., the structure of a network that consist of n_β sensors), in addition to how new sensors are deployed in the network based on the observed state. Policy Y now provides a consistent network structure between missions (that is, after the deployment of sensors each mission the network contains n_β distributed throughout the network in a similar manner), and the D-spectrum can be used to estimate network reliability. Let s_i^Y be the probability the ith sensor failure results in $C(W)$ falling below α when following the M-CBDP Y. Network reliability is estimated by

$$r(\delta; \alpha, \beta, Y) = \sum_{i=0}^{n_\beta} s_i^Y B(i-1; n_\beta, G(\delta;\delta)) . \tag{9}$$

Using the network D-spectrum, Equation (9) can be applied to efficiently evaluate network reliability when new sensors are deployed in the network according to a given M-CBDP Y. In the following section we compare the performance of various policies, after which the best policy from those evaluated can be selected.

3. Computational Results

In this section we compare the performance of various M-CBDPs for a varying budget, β, and observation interval, δ. To model the failure of sensors, the lifetime of each sensor is distributed according to a Weibull distribution with a shape parameter 1.5 and scale parameter 10. Sensor capabilities are defined based on a common communication radius of $d_1 = 0.075$ and a monitoring radius of $d_2 = 0.075$. The region of interest R is a $[0,1] \times [0,1]$ square that is partitioned into $n_r = 16$ equal sized regions (i.e., each subregion is of size 0.25×0.25), with a single sink node located centrally in R. The coverage requirement is selected as $\alpha = 0.8$, meaning the WSN must cover 80% of the region to be successful. The fixed cost of deploying sensors is set to $c_F = 100$, with a variable cost $c_V = 1$.

The first M-CBDP we consider is to evenly distribute sensors to each subregion, denoted policy Y_1. That is, after observing the state of the network new sensors are deployed so that each subregion contains approximately $^{n_\beta}/_{n_r}$ sensors. As a result, if we observe a subregion that has suffered more failures compared to another, more sensors will be deployed to this subregion. The second myopic policy, Y_2, is to deploy new sensors to a subregion based on a weight, w_i, assigned to each subregion. Since sensors located closer to the sink node are relied upon more often to route information we may wish to place a larger weight on subregions around the sink in order to deploy a larger number of sensors, providing a level of redundancy and maintaining a communication path in the presence of failures. The weights now influence how new sensors are deployed in the network, where even if we observe a large number of sensors that remain functioning in a subregion it might be advantageous to deploy sensors to this subregion if it is near the sink. For M-CBDP Y_2, the weight of each subregion is inversely proportional to the distance from the sink node to the center of a subregion, and each subregion now contains approximately $(w_i / \sum_{i=1}^{n_r} w_i) * n_\beta$ sensors. Note that policy Y_1 and Y_2 are not necessarily optimal policies resulting from Equation (1). However they are anticipated to be high quality policies and selected to demonstrate the use of the D-spectrum to estimate the reliability of a CBDP. Future work will be directed on efficient methods to determine an optimal policy beyond an enumeration strategy.

These two M-CBDPs are compared against a simpler time-based deployment policy (TBDP), TB. In policy TB, rather than deploy sensors based on a budget available, sensors are deployed to reach a constant network size. Additionally, only the number of sensors functioning in the network is observed and sensors are then randomly deployed throughout the entire region, instead of specifying the subregion a sensor is deployed in. A TBDP is explained in more detail in [17]. Results for the two M-CBDPs along with the TBDP are provided in Table 1, where the values under each policy correspond to the resulting network reliability estimated using Equation (9), given β and δ.

Table 1: Network Reliability for Various Sensor Deployment Policies

β	δ	Y_1	Y_2	TB	β	δ	Y_1	Y_2	TB
278	2.5	0.9998	0.9999	0.9998	388	5.7	0.8004	0.8123	0.7359
364	5.0	0.9499	0.9598	0.9227	383	5.7	0.7503	0.7667	0.6820
353	5.0	0.8999	0.9136	0.8557	594	8.2	0.7003	0.7200	0.6542
353	5.1	0.8507	0.8719	0.7981	438	6.5	0.7002	0.7199	0.6357

In each of the test instances, M-CBDP Y_2 results in the largest reliability, followed by M-CBDP Y_1, and finally the TBDP TB. One of the primary differences between policy Y_1 and Y_2 with TB is that in Y_1 and Y_2 we are able to observe the state of the network and determine how new sensors are deployed in the region (i.e., which subregion sensors are deployed in). This is a significant improvement over policy TB, particularly as the time between network observation increases. For example, in the instance with $(\beta, \delta) = (388, 5.7)$, this results in an improvement in network reliability from 0.7359 for the TBDP to 0.8004 for M-CBDP Y_1. By weighting each subregion and influencing the M-CBDP through this method (policy Y_2), network reliability is improved further.

The test instances also help illustrate the impact of β and δ on each policy. For example, consider the (353, 5.0) instance and the (353, 5.1) instance. The observation interval in the latter instance is slightly larger, but this results in a drop in network reliability from 0.9136 to 0.8719 for policy Y_2, with a similar impact on policy Y_1. In the following set of test instances, (388, 5.7) and (383, 5.7), the observation interval is the same but the mission budget has slightly decreased. With a variable cost $c_V = 1$, this corresponds to 5 fewer sensors available to deploy per mission in the second scenario. However, this again results in a drop in network reliability from 0.8123 to 0.7667 for policy Y_2.

Finally, because we are using an estimate of the D-spectrum for an approximate size of the network to estimate reliability under a CBDP, we are interested in how accurate this estimate is compared to a traditional Monte Carlo simulation. Although a Monte Carlo simulation is more computationally expensive, it provides the ability to model the fluctuation in network size and in the age of sensors over time. For a Monte Carlo simulation of 10000 replications on the (353, 5.0) instance, the resulting reliability estimate is 0.8993 and 0.9151 for policy Y_1 and Y_2, respectively. A

Monte Carlo simulation for the remaining test instances yields a similar performance comparison, demonstrating the suitability of the D-spectrum to estimate reliability of a M-CBDP.

4. Conclusion

To maintain a WSN over a prolonged period of time, new sensors must be deployed in the network to re-establish network coverage and communication capabilities. Towards this goal, we have discussed a myopic condition-based sensor deployment problem in which the network is observed prior to a decision on how new sensors are deployed in the network. We have also demonstrated how the network D-spectrum can be used to estimate network reliability as new sensors are deployed, and compare the performance of different sensor deployment policies. With this insight to a M-CBDP, future work is focused on a model that considers the impact on future mission reliability as well.

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