On the Fault Tolerance of Mobile Ad Hoc Networks

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Abstract. In mobile ad hoc networks, it is crucial to reduce energy consumption satisfying key network properties. In this paper, we investigate the \(k\)-connected transmission power assignment problem with the objective of minimizing power consumption. We address this issue from a decision-theoretic point of view. Specifically, the future network behavior is predicted in order to derive an optimal transmission power assignment which tracks the wanted connectivity level minimizing energy.

Keywords. Mobile ad hoc network, topology optimization, \(k\)-connectivity

1. Introduction

Various civil and military applications possess an inherent need for the rapid deployment of mobile users and concomitant network support. Examples include establishing survivable, efficient, dynamic communication for emergency and rescue operations and disaster relief efforts. Centralized and organized network connectivity is inappropriate for such applications; rather, they require mobile ad hoc networks [10]. For this reason, in the last years, the interest of the scientific community towards these networks is increased.

A mobile ad hoc network is an autonomous collection of mobile devices or nodes that communicate over wireless links. Mobile devices are typically powered by batteries, and it is expensive and sometimes infeasible to recharge them. An important aspect of an ad hoc network is that this is decentralized, meaning that all network activities, including discovering the topology and delivering messages, must be executed by the nodes themselves. The absence of a centralized infrastructure makes these networks an attractive solution for implementing and managing wireless sensor networks and networks of autonomous mobile data collection devices.

In mobile ad hoc networks, hosts are also routers and this poses a major robustness problem. Nodes running out of battery power not only lose their own individual capabilities, but also impact the entire network by influencing network connectivity which in turn influences routing functionality. In addition, connectivity is influenced by topology frequently changes due to node mobility.

The goal of our research is to propose a novel approach for increasing the robustness of mobile ad hoc networks that is characterized by its level of \(k\)-connectivity over time. A \(k\)-connected network has \(k\) disjoint connecting paths between any pair of nodes. The interest in studying the transmission power assignment for a wished \(k\)-connectivity level is motivated by the fact that, when a network is \(k\)-connected, at most \(k - 1\) node faults can be tolerated without disconnecting the network. In particular, we are interested to investigate \(k\)-connected transmission power assignment with the objective of minimizing power consumption.

In order to achieve this objective, we approach the optimization problem from a decision-theoretical point of view. A stochastic model of the network is used by a state estimator to predict network’s future connectivity degree and remaining energy. The predicted states are used by an optimizer to derive an optimal transmission power assignment sequence which, in turn, steers the network behavior for tracking the wanted con-
nectivity level $k$ minimizing energy consumption.

**2. Topology Optimization Algorithm for $k$-connectivity**

The goal of this work is to optimize the lifetime of a mobile ad hoc network at a given degree of connectivity $k$. We address this optimization issue using a model based transmission power adaptation. Recently, model-based predictive approach [3] has been identified as a promising theoretical foundation for performance analysis in complex systems. Applying this approach, we refer to a family of optimization algorithms in which a dynamic model of the network is used to predict and guide the future network behavior in terms of energy and $k$-connectivity. At each sample interval, an optimal sequence of transmission power assignments is calculated in such a way to optimize a cost objective function over a future horizon. In this way, we characterize the dynamic network model using an input-output black-box modeling technique, in which the input $u(t)$ corresponds to transmission power assignments and the outputs $y(t)$ are the $k$-connectivity and the remaining energy level.

The proposed Topology optimization algorithm is characterized by the following steps:

1. Exchange Topology Information with $p$-hop neighbors
2. Measure the local variables $y(t)$ and update state estimation $\hat{x}(t)$;
3. Adjusted sampling interval if the estimation error $e(t)$ is out of a predefined admissible range;
4. Solve the local linear quadratic problem to obtain future transmission power assignments;
5. Apply the first transmission power assignments $u(t)$;
6. Go to step 1 in the next sample interval.

Global topology information require huge communication overhead for its maintenance when nodes are mobile and in large scale ad hoc networks the network delay makes this approach impracticable. Localized solutions are therefore preferred. Using a localized solution, the node makes decisions solely based on local information available from itself and its $p$-hop neighboring nodes. The aggregation of these local information constitute a partial communication graph being used by nodes to estimate the global network state.

In our approach, we learn the dynamic network model based on measured observable data being gathered by several testings. The identified network model is then used by an estimator in order to predict the network behavior over a prediction horizon $P$. Assuming that the estimates are available, an optimizer computes the optimal sequence of transmission power assignments by solving a quadratic problem in order to trace the wished $k$-connectivity and energy level $r(t)$. The sequence is computed over a control horizon $C$. The prediction horizon is the number of sampling intervals where the future outputs are predicted. The control horizon is the number of input actions computed to guide future outputs along the prediction horizon. Figure 1 shows the overall methodology.

![Figure 1: Schema of the application](image)

**2.1. Model Learning**

The dynamic network behavior is unknown and so we apply a black box approach to learn the behavior model [7]. This is a very flexible mathematical approach that allows to build models analyzing the measured data that are obtained by testings. In this way we can derive the model without know the rules that govern the system. The aim is to model the network describing the dynamics in term of transmission power, $k$-connectivity and
energy consumption. A black-box approach consists of analyzing the input-output data relationship to derive the state space model structure and parameters. The most important phases to build the model are: (i) testing design and deployment; (ii) testing data gathering; (iii) data prepossessing in order to remove possible testing error that can affect the final model; (iv) the model identification of a multi-variable linear system that better fits testing data; (v) and model validation.

The testing conditions have been designed for including a wide range of frequencies in order to accurately estimate the model parameters. In this way, given testing input-output data, \(<u(t), y(t)\>: t = 1, \ldots, T\), and a parametrized state space model structure, we estimate the model by the straightforward fit. Moreover, the statistical model validation is performed by the residual analysis using a fresh data set (validation data) for the cross validation [8]. At the end we obtain a state space model in which \(x(t)\) is the internal network state, the input action \(u(t)\) represents the transmission power (input action) and the output \(y_0(t)\) is the \(k\)-connectivity level and the remaining battery level is given by the output \(y_1(t)\).

### 2.2. State Estimator

In a black box approach, the network state \(x(t)\) is not directly measurable. In this case, the issue is to estimate the internal states of the system, given access only to the measured outputs as shown in figure 2. The Kalman filter is an efficient recursive estimator that evaluates the state of a dynamic system from a series of incomplete and noisy measurements. The filter provides an efficient computational (recursive) means to estimate the state of a process, in a way that minimizes the mean of the squared error (i.e. the mean square disagreement between observed value and estimate value). This is called recursive because it does not need to store all previous measurements and reprocess all data each sampling interval. The filter combine the available measurements, plus prior knowledge about the system and the estimation error to estimate the current state in such a way that the error is minimized statistically. The estimator is based on previous learned model:

\[
\begin{align*}
x(t+1) &= Ax(t) + Bu(t) + w(t) \\
y(t) &= Cx(t) + v(t)
\end{align*}
\]

in which the terms \(w(t)\) and \(v(t)\) are random variables. The former is the disturbance caused by node mobility in the state equation and the latter represents error sources in observation equation due to the use of a localized algorithm for the \(k\)-connectivity feedback mechanism. The localized algorithm makes our problem partially observable because we estimate a global network property from local information and for this reason we deal with a partially observable stochastic model.

The random variables are assumed to be independent, white, and with normal probability distributions. The Kalman filter can be described by two phases. In the former, prediction phase, the filter is responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time steps. The latter, correction phase, is responsible for incorporating measurement information at the current sampling interval into the a priori estimate to refine the prediction and to obtain a more accurate posteriori estimate. A more detailed description can be found in [4].

An important aspect of our algorithm is the rate at which it samples the \(k\)-
connectivity and the remaining battery level. The higher the sampling rate, the more accurate the view of the network state. However, the adoption of an high rate implies a computation and communication overhead that scarifies energy resources. For this reason, the idea is to use the Kalman filter estimation error to adaptively adjust the sampling rate. In this way, the new observations will be compared to previous predictions and an error value will be calculated on the basis of these comparisons. If the error value exceeds the predefined admissible error range the sampling rate will be increased, and if it is lower, the sampling rate will be decreased.

2.3. Optimizer

The task of the optimizer is to compute a sequence of $C$ input actions $u$ such that the predicted output $\hat{y}$ follows a specified reference point $r$ in a desirable manner as shown in figure 3.

\[
\begin{align*}
\min_{\Delta u(t), \ldots, \Delta u(t+m-1)} & \sum_{t=1}^{N} \| \hat{y}(t+l|t) - r(t+l) \|_{\Gamma_l}^2 \\
+ & \| \Delta u(t+l-1) \|_{B_l}^2
\end{align*}
\]

in which $\Delta u(t) = u(t) - u(t-1)$ and $\hat{y}(t+l|t)$ is the predicted value of $y$ at time $t+l$ based on the information available at time $t$. The vector $r(t)$ represents the reference points for the network behavior and consists of $r_0(t)$, the desired $k$-connectivity (e.g. 10-connectivity) and $r_1(t)$, the desired remaining battery. $r_1(t)$ is set to the maximum battery charge since the aim is to save energy. $B_l$ and $\Gamma_l$ are weighting matrices. The less the weight, the less important is the behavior of the corresponding variable to track the overall desired behavior.

In the objective function (3), the first term represents the predicted deviation at future instants between the system outputs and the reference points $r(t)$ and is used to track the desired behavior. The second term guides the adjustment in the transmission power assignment. Increasing $B_l$ forces the optimizer to choose smaller, more cautious adjustments $\Delta u$ in the optimal sequence. Though $C$ transmission power adjustments are calculated, only the first one is injected into the network device. In each sampling period, the quadratic problem is solved resulting in new optimal transmission power assignments. A more details description can be find in [5].

<table>
<thead>
<tr>
<th>Table 1: Simulation setting</th>
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<tbody>
<tr>
<td>Simulation Area</td>
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<tr>
<td>Nodes</td>
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<tr>
<td>Start Battery</td>
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<tr>
<td>Simulation Time</td>
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<th>Table 2: Linear quadratic problem setting</th>
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<tr>
<td>$r(t)$</td>
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<tr>
<td>$k$-connectivity</td>
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<tr>
<td>$\Gamma_l$</td>
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<td>$k$-connectivity</td>
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<td>$B_l$</td>
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3. Experimental Result

In order to provide an evaluation of the proposed approach, we simulated a scenario in which nodes move randomly with obstacle-free trajectories. The scenario is
based on Chipcon CC1100 transceivers used in Mica2 motes and has been implemented on Castalia [2], an open source simulator for mobile ad hoc sensor networks built on top of OMNeT++ [11]. The choice of Castalia is motivated by the fact that it provides an accurate channel/radio model based on empirically measured data and takes into account usually neglected issues such as clock drift, sensor bias, sensor energy consumption, CPU energy consumption, and monitors resources such as memory usage and CPU time.

In this experimentation, we deal with mobile symmetric ad hoc networks with omnidirectional transmissions. In other words, we assume that: (i) the network is dynamic, nodes are mobile and the topology of the network can change over the time; (ii) all established links are symmetric or bidirectional, if a node $u$ is assigned to receive transmissions from a node $v$, then it must also be able to transmit to node $v$; (iii) omni-directional transmissions are given by antennas that provide a 360-degree transmission pattern covering an area around the node at a given transmission power. Changing the transmission power, we change the dimension of coverage area.

The wireless channel model is log-normal shadowing model [12] and is given by:

$$PL(d) = PL(d_0) + 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma$$

where $PL(d)$ is the path loss at transmitter-receiver distance $d$, $d_0$ is a reference distance, $n$ is the rate at which signal decays, $X_\sigma$ is a zero-means Gaussian random variable with standard deviation $\sigma$ and models the shadowing effect. In this way, an irregular radio coverage area can be obtained by setting $\sigma \neq 0$.

Tables 1 and 2 show the configuration parameters for the simulation and the linear quadratic problem respectively. For the evaluation, we compare the globalized approach with the localized one that requires only knowledge of five-hop neighborhood. In the globalized case, we assume that an external watcher with a global view of the network is able to decide the transmission power assignment by solving a fully observable problem using the information of all nodes.

![Figure 4: Comparison between the global approach with the local one in node 25](image)

Figure 4(a) compares the transmission power assignments chosen by the global approach (red line) with the assignments selected by the local one (blue line) for node 25.

Instead, figure 4(b) show the corresponding $k$-connectivity and battery levels measured by using global observations (red line) and local observations (blue line).

The comparison reveals that the localized topology optimization and the globalized one provide almost identical optimization policy. Of course, the difference is in scalability of the former that requires less bandwidth and energy for the communication.
4. Conclusion

Guaranteeing a connectivity level, minimizing energy consumption and prolonging the network lifetime is a main design goal for ad hoc and sensor networks.

In literature, there are several efforts [9][6][1]. However these approaches usually do not deal with node mobility and require dedicated hardware. A scalable topology optimization needs to use only local information and to be executed frequently in order to account for the new positions of the nodes due to mobility. Therefore, the reduction of control traffic overhead is fundamental, because data transmission is the main critical factor that sacrifices device limited resources like energy.

In this paper, we addressed this issue by applying a novel decision-theoretic approach to optimize the network lifetime at a given degree of connectivity $k$. The proposed solution is designed for a distributed implementation, where only knowledge of the $n$-hop neighborhood is required and where less communication overhead is incurred by using a model-based prediction. It is clear that the impact of node movements on the effectiveness of topology optimization techniques heavily depends on the mobility pattern. For this reason, we have planned to evaluate the proposed solution using several mobility models.

References


