# Power Optimization in Fault-Tolerant MANETs

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***Abstract*—In this paper, we investigate the problem of optimizing the lifetime of a mobile ad hoc network at a given degree $k$ of connectivity by minimizing power consumption. Our proposed solution is fully distributed and uses a model-based transmission power adaptation strategy based on model-predictive control.**

## I. Introduction

Various civil and military applications possess an inherent need for the rapid deployment of mobile users and concomitant network support. Centralized and organized network connectivity is inappropriate for such applications; rather, they require mobile ad hoc networks (MANETs) [1]. A MANET is an autonomous collection of mobile devices that communicate over wireless links. Mobile devices are typically powered by batteries, and it is expensive and sometimes infeasible to recharge them.

MANETs are intrinsically decentralized, meaning that all network activities, including discovering the topology and delivering messages, must be executed by the nodes themselves. Nodes running out of battery power not only lose their own individual capabilities, but also impact the entire network by changing, for example, routing functionality. In addition, connectivity is strongly influenced by frequently changes in topology due to node mobility.

In this paper, we present a novel, power-aware approach for increasing the robustness of MANETs. The robustness of a wireless ad hoc network is characterized by its level of $k$-connectivity over time. The particular problem we are interested in solving is the *transmission-power assignment (TPA) problem for $k$-connectivity*: optimizing the lifetime of a MANET at a given degree $k$ of connectivity by minimizing power consumption. Algorithms that address this problem are sometimes referred to as *topology control* algorithms [2]. The interest in studying the TPA for $k$-connected MANET is motivated by the fact that, when a network is $k$-connected, up to $k-1$ node failures can be tolerated without disconnecting the network.

We approach this optimization problem from a decision-theoretical point of view. Network's future connectivity degree and remaining energy are predicted in order to derive an optimal TPA sequence that steers the network behavior to the desired connectivity level $k$ while minimizing energy consumption. Our localized topology control algorithm is fully distributed and experimental results reveal that our algorithm provides an almost identical control policy to that of a globalized scheme.

## II. Description of our Approach

Our topology control algorithm uses a TPA scheme based on model-based predictive control [3]. Referring to this methodology, our control algorithm utilizes a dynamic model of the network to predict and guide the future network behavior in terms of energy consumption and connectivity degree. At each sampling interval, an optimal sequence of TPAs 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 inputs $u(t)$ correspond to TPAs and the outputs $y(t)$ are the connectivity and remaining energy levels:

$$x(t+1) = Ax(t) + Bu(t) + w(t) \qquad (1)$$

$$y(t) = Cx(t) + v(t) \qquad (2)$$

where $x(t)$ is the desired, but not know, network state. In (1) and (2), $w(t)$ and $v(t)$ are random variables respectively representing the node mobility disturbance in the state equation and the error sources in the observation equation due to the use of a localized algorithm for the vertex connectivity feedback mechanism. Localized algorithms incur significantly less computation and communication overhead. In our localized algorithm, each node utilizes the connectivity information embedded in the $p$-hop subgraph centered at itself (derived from $p$-hop neighborhood) in order to estimate global $k$-connectivity. The localized algorithm makes our system partially observable because we estimate a global network property from local link-state information. As such, the model we deal with is a *partially observable stochastic model* [4].

The dynamic network behavior is unknown and we thus apply a black-box approach to learn network model [5]. This is a very flexible mathematical approach that allows one to build models by analyzing the measured data obtained by experimentations. As such, we can derive the model without knowing the rules that govern the network.

In the black-box approach, the network state $x(t)$ is not directly measurable. The issue then is to estimate $x(t)$ given access only to the measured outputs $y(t)$ as shown in Figure 1.

The Kalman estimator is an efficient recursive filter that estimates the state of a dynamic dynamic system from a series of incomplete and noisy measurements [4]. An important aspect of our topology control algorithm is the rate at which it samples the output variables $y_0(t)$ (the $k$-connectivity level) and $y_1(t)$ (the remaining battery) of the MANET under

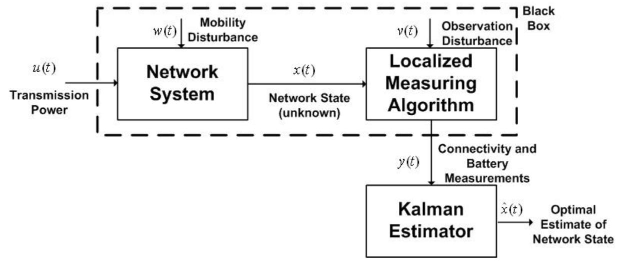


Fig. 1. Kalman Estimator schema used by the topology control algorithm.

observation: the higher the sampling rate, the more accurate the view of the network state. The higher the sampling rate, however, the higher the computation and communication overhead incurred by the control policy, and therefore the greater the drain on the battery energy reserves. We therefore use Kalman estimation error to adaptively adjust the sampling rate. Each node can make predictions of future measurement based on the Kalman estimator prediction/correction paradigm. As such, 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; otherwise, it will be decreased.

Assuming that the estimates of $x(t)$ are available at time $t$, the optimal TPA sequence is obtained by solving the following quadratic problem (notation: $||x||_Q^2$=$x^T Qx$):

$$\min_{\Delta u(t),\ldots,\Delta u(t+C-1)} \sum_{l=1}^{P} \|\hat{y}(t+l|t) - r(t+l)\|_{\Gamma_l}^2 + \|\Delta u(t+l-1)\|_{B_l}^2 \quad (3)$$

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. $B$ and $\Gamma$ are weighting matrices. The less the weight, the less important is the behavior of the corresponding variable to track the overall desired behavior. The sequence of transmission power adjustments $\Delta u$ is computed over a control horizon $C$. The prediction horizon $P$ 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. The proposed 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 TPAs;*
5) *Apply the first transmission power assignments $u(t)$;*
6) *Go to step 1 in the next sample interval.*

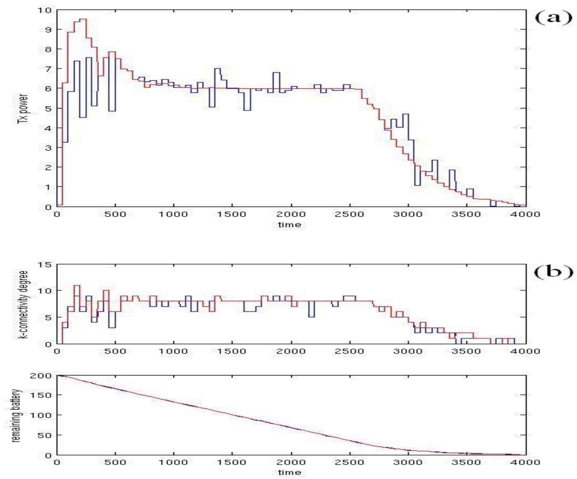


Fig. 2. Comparison of global and local control on node 25.

| Area | Nodes | Batt | Time | $r_0$ | $r_1$ | $\Gamma_0$ | $\Gamma_1$ | $B$ |
|---|---|---|---|---|---|---|---|---|
| 50x50m | 100 | 200J | 4000s | 200 | 8 | 1 | 100 | 0.8 |

TABLE I
SIMULATION SETTING

## III. CONCLUSION

For the experimental evaluation, we conducted a number of simulations, comparing the globalized topology control with a localized one requiring only knowledge of a 5-hop neighborhood. In the globalized case, we assume that an external watcher can access to neighbors tables of all nodes without requesting communication. In this way the external watcher has the exact picture of the network and can find the optimal policy. Our topology control algorithm is implemented on the Castalia open-source simulation environment[6]. Simulation model captures a mobile ad hoc sensor network of Mica2 motes using Chipcon CC1100 transceivers. The movement model is one in which nodes move randomly with obstacle-free trajectories. Table I provides the configuration parameters for the simulation. Figure 2(a) compares the TPAs of the global (red line) and local (blue line) algorithms for node 25. Likewise, Figure 2(b) compares the $k$-connectivity and battery-level measurements of the global (red line) and local (red line) approaches. The comparison reveals that our localized topology control algorithm provides an almost identical control policy to that of the globalized scheme. The difference, of course, is in the scalability of our localized solution, which requires much less communication bandwidth and energy.

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