A New Fuzzy-Based Cooperative Movement Model in Support of QoS in Wireless Ad-Hoc Network

Ghassen Brahim, Ala Al-Fuquaha, Dionisyios Kountanis
Dept. of Computer Science, Western Michigan University
Kalamazoo, MI., 49009
gbenbrah@cs.wmich.edu

Bilal Khan
Dept. of Mathematics and Computer Science,
John Jay College of Criminal Justice
899 Tenth Avenue
City University of New York, NY., 10019
bilal@bilalkhan.org

ABSTRACT

In this paper, we develop a Cooperative Mobility Model that captures new salient features of collaborative and mission-oriented MANETs. We propose new techniques to leverage two optimizations for cognitive radio networks that are specific to such contexts: *cooperative mobility* and *opportunistic channel selection*. We present a new formal model for MANETs consisting of cognitive radio capable nodes that are willing to *be moved* (at a cost). We develop an effective decentralized algorithm for mobility planning, and powerful new filtering and fuzzy based techniques for both channel estimation and channel selection. Our experiments are compelling and demonstrate that the communications infrastructure—specifically, connection bit error rates—can be significantly improved by leveraging our proposed techniques. In addition, we find that these cooperative/ opportunistic optimization spaces do not trade-off significantly with one another, and thus can be used simultaneously to build superior hybrid schemes. Our results have significant applications in high-performance mission-oriented MANETs, such as battlefield communications and domestic response & rescue missions.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design; C.4 [**Computer Systems Organization**]: Performance of Systems

General Terms

Algorithm, Design, Performance

Keywords

Cognitive radio, Cooperation, Quality of Service, Ad-hoc network, filter, fuzzy logic. low bit error rate.

1. INTRODUCTION

Mobile wireless ad-hoc networks (MANETs) are an important building block of modern networks, having found fruitful applications in both consumer and mission-oriented settings. Examples of the latter include battlefield and public safety scenarios where MANETs are considered especially well-suited because they support the rapid establishment of communications for mobile platforms over a shared wireless medium, and obviate the need to invest time and expense in developing a fixed infrastructure.

Surprisingly, while MANETs have been applied in mission-oriented rapid-deployment applications such as battlefield communications and domestic response & rescue missions, much of MANET research has not made a concerted effort to leverage the central difference between consumer MANETs and mission-oriented rapid-deployment MANETs: namely that the latter brings with them implicit common group objectives which make inter-node cooperation both logical and feasible. This willingness to cooperate provides designers of rapid-deployment mission-oriented MANETs additional opportunities for new optimizations which have not been thoroughly explored. In this paper, we will consider two such optimizations and describe the tradeoffs inherent between them.

In this work, we develop a realistic model for cooperation in mission-oriented rapid-deployment MANETs that leverages both cooperative mobility and cognitive radio (CR) paradigms. In short, we present solutions to optimizing the performance of MANETs which consist of CR-capable nodes that are sometime able to *be moved*. We evaluate the extent to which the communications infrastructure can be improved by leveraging these two paradigms, and assess the extent to which the two optimization spaces interact with one another.

The remainder of the paper is organized as follows. In Section 2, we present our model of Cooperative Mobility and algorithms for mobility planning. In Section 3, we present our proposed traffic estimation and opportunistic channel selection strategies. Our proposed channel estimation strategy utilizes a combination of Exponentially-Weighted Moving Average (EWMA) and wavelet-based filters. Channel selection employs an extensible fuzzy rule-base to determine the overall cost of a cognitive radio channel, based on its estimated average and auto-correlation metrics. In Section 4, we describe policies for cooperative mobility and opportunistic channel selection. In Sections 5 and 6, we present the experiments and interpret their outcomes. Finally, in

Section 7, we present overall conclusions and the future trajectory of our research efforts.

2. COOPERATIVE MOBILITY

Our focus in this article is on mobile ad-hoc networks, and even within this narrow setting, several models of cooperation have been proposed (albeit at times only implicitly). These models came about in a somewhat ad-hoc manner over the past few years; each arose within concrete research efforts seeking to leverage some new observation or technological development, which was in turn motivated by the over-arching objective of making more efficient use of wireless network resources. In our previous work, we presented a taxonomy of the models of cooperation that have been manifested in MANET research efforts so far. These include the following: (1) Relay Cooperation Models (2) Models of Cooperation using Spatial-Diversity (3) Cooperation Models for Reputation Management (4) Cooperation Models for Power-based Topology Control (5) Cooperation Models for Mobility-based Topology Control, and (6) Cooperation Models for Distributed Control. For more details about these models, the reader is referred to [6].

2.1 The Cooperative Mobility Model

Our proposed model is a natural extension of the initial efforts of Basu et al. [2], extending it by postulating that future MANETs will not be homogeneous in terms of node autonomy. While the authors in [2] consider networks consisting of robots and non-robots, we contend that the general setting requires us to consider heterogenous networks comprised of nodes which exhibit the entire spectrum of personalities: from defiant autonomy to self-sacrificial cooperativeness. We capture this viewpoint by adopting a cost model for mobility. To wit, every node is willing to move for the sake of the common good, but for a price. Each node is assigned a movement cost that is proportional to distance moved; this is the price the node charges to be moved, say, per meter. Defiant autonomy is exhibited when a node declares this cost to be infinite; self-sacrificial cooperativeness is manifest when this cost is declared to be zero.

2.2 The Movement Planning Algorithm

Our approach to node mobility planning begins with the following Gedankenexperiment: Consider a single two-hop connection between a source node s and a destination node t, and assume that this connection goes through a cooperative node c. The following two observations can be easily proven by using the well-known Friis' formula: [4]:

1. If node c is on line (s, t), then it moves towards s if $BER(c, s) \geq BER(c, t)$, and towards t otherwise; moving node c off the line (s, t) yields worse connection performance.

2. If node c is not on the line (s, t), then it should move in towards segment (s, t).

Making the model more quantitative, we assign weights $w(c, s)$ and $w(c, t)$ to links (c, s) and (c, t); the weights are taken to be proportional to $BER(c, s)$ and $BER(c, t)$, respectively. The cooperative node c repositions itself by moving in a direction that maximally improves the total end-to-end connection BER from s to t (see Figure 1); the direction

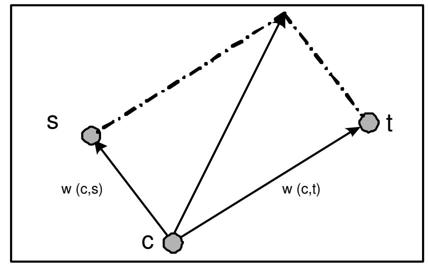

Figure 1: A Gedankenexperiment on Node Mobility

of movement depends on relative positions of the nodes, as well as the relative magnitudes of $w(c, s)$ and $w(c, t)$.

The previously described Gedankenexperiment suggests a natural analogy between finding the cooperative node movement direction and the problem of computing resultant forces. Each node c experiences concurrent forces along all its incident links. The magnitude of the force along link L is proportional to $n_L \cdot BER(L)$, where n_L is the number of connections which transit over link L. Computing the resultant force can be done in many ways, including standard componentwise analysis by projection onto a set of orthogonal axes (see Figure 2). After finding the resultant direction, the available mobility budget can be used to move the cooperative node. There remains the problem of dividing a global mobility budget among the cooperative nodes. In this preliminary investigation, we consider uniform allocations: each of the N nodes receives $1/N$ fraction of the total mobility budget.

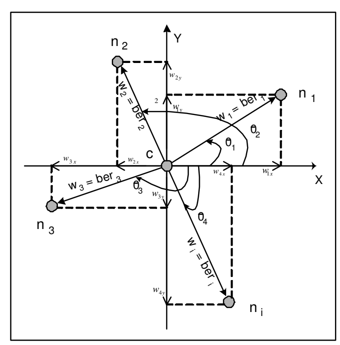

Figure 2: Resultant Algorithm

3. COGNITIVE RADIO

The under-utilization of the pre-assigned frequency bands, has motivated the development of cognitive radio [1]: a new class of radios that can reliably sense the spectral environment over a wide bandwidth, detect the presence/absence of legacy users (primary users) and use the spectrum only if the communication does not interfere with primary users. Cognitive radio systems offer the opportunity to improve spectrum utilization by detecting unoccupied bands and adapting their transmission to those bands while avoiding the interference to primary users. This novel approach to spectrum access introduces unique functions at the physical layer: reliable detection of primary users and adaptive transmission over a wide bandwidth. In order to achieve a better performance, CR-capable nodes adapt their behavior to changing network conditions.

To adapt, CR-capable nodes must first accurately estimate network traffic. Producing quality estimates is challenging because network observations in MANETs are especially noisy and become stale rapidly. Current systems depend on simple, exponentially-weighted moving average (EWMA) filters such as those described in [5]. These parametric filters are either able to detect true changes quickly or to mask observed noise and transients, but can not do both. In [5], the authors designed new filtering techniques to overcome some of the shortcomings of EWMA based filters. Here we extend and improve these filtering techniques for estimating the traffic parameters on the primary channels of cognitive radio enabled nodes. Our first approach uses a *flip-flop* filter based on the technique proposed in [5]. The second approach relies on the wavelet transform to remove the noise from raw traffic measurements. Both approaches serve to provide more accurate estimates (compared to raw measurements) for later use by our fuzzy-based channel selection module.

3.1 The Opportunistic Cognitive Radio Model

In contrast to the Cooperative Mobility Model, in which cooperative nodes are willing to move to a different location with the goal of improving the end-to-end communication channels bit error rates, the Opportunistic Cognitive Radio Model aims to opportunistically benefit from the abundant spectrum that is not fully utilized by primary users, while seeking to enhance the QoS provided on all communication channels, vis-a-vis bit error rate (BER). The model assumes that all nodes operate in a Cognitive Radio network, and each node is able to scan the radio spectrum and determine the set of channels to be used by the primary and secondary users. Techniques for scanning and identifying the set of these channels are beyond the scope of this work.

We present a new wireless channel estimation technique based on the wavelet transform and flip-flop filter techniques. Each node estimates the utilization of each of the primary channels then decides whether exchanging traffic over unused primary channels is feasible and will enhance the quality of the communications[1]. First, we present techniques for estimating the status and utilization of the wireless channels.

3.2 The Wireless Channel Estimation Algorithm

The originality of this work stems from the process through which we are able to apply a combination of EWMA filters, the wavelet transform, fuzzy logic, and time series prediction techniques to perform channel estimation in cognitive radio enabled cooperative networks.

As mentioned earlier, in a cognitive radio enabled network, the traffic flows between two neighboring nodes over either the secondary or any of the unutilized primary channels, based on a decision protocol. Over a period of time, these channels can either be carrying traffic or idle. In the rest of the paper we refer to the period of time during which the channel is idle by T_{off} and to the period of time during which the channel is occupied by T_{on}. Figure 3 depicts this convention; the example shows three primary channels between nodes m and n (traffic can be sent using one of three different frequencies). It is important to note that each of these sub-channels has different sequences of T_{on} and T_{off}.

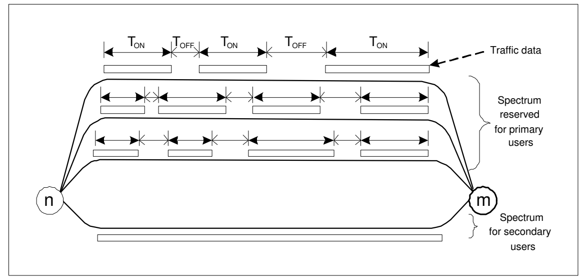

Figure 3: Wireless channel structure in cognitive radio enabled network

The estimation procedure is depicted by the next algorithm.

Begin
(1) Generate simulated traffic signal.
(2) Produce T_{on} and T_{off} time series.
(3) Apply flip-flop filtering technique.
(4) Produce channel status estimate.
End

The first step of this procedure consists of passive monitoring of the channel usage profile. This process produces two distinct time series T_{on} and T_{off}. In the next step, these time series are input to the flip-flop and wavelet filtering modules in order to produce quality estimates of the average and auto-correlation metrics, respectively. These quantities are then given to the Fuzzy logic module which selects the best primary channel to use based on the average and auto-correlation estimates. In the following, we give more details about these three modules.

- *Flip-flop filter module*

  The flip-flop filter consists of two EWMA filters: one agile and the other stable [3]. A controller selects between the two. The underlying principle of the controller is to employ the agile filter when possible, but falls back to the stable filter when observations are unusually noisy. The switching decision is made based on a control chart defined by upper and lower control limits (UCL and LCL respectively). These bounds are based on the 3-sigma rule [3] and are defined as follows:

$$UCL = E_t + 3\frac{|O_t - O_{t-1}|}{d_2}$$
$$LCL = E_t - 3\frac{|O_t - O_{t-1}|}{d_2}$$

  where, d_2 estimates the standard deviation using the moving range, approximately 1.128.

  In this work, we utilize the flip-flop filter to estimate the average of the T_{on} and T_{off} parameters. This enables us to utilize the rich literature of process control (e.g., six sigma) to produce stable estimates of the traffic parameters when the raw observations are within

[1] It is important to mention here that under our scheme, traffic opportunistically sent over the primary channel is preempted when a traffic generated by a primary user arrives—this is done by switching opportunistic traffic back to the secondary channel.

the control limits (i.e., UCL and LCL) but switch quickly to the agile mode when *actual* changes are introduced to the traffic parameters. Thus, the flip-flop filter serves to distinguish between actual and transient parameter changes.

- *Wavelet transform module*

  The wavelet transform is analogous to the Fourier transform which represents a signal as a sum of sinusoids. But while the Fourier transform is localized in the frequency domain, the wavelet transform is localized in the frequency and time domains. The Short Time Fourier Transform (STFT) allows for frequency and time domain localizations but the wavelet transform allows a better resolution through multi-resolution analysis. The wavelet transform is employed in a variety of engineering applications ranging from signal and image processing to digital communication.

  The detail coefficients reflect the change in the time series at various resolutions. In our case, for T_{on} and T_{off} samples of size n each (where n is a power of 2) the following steps are followed in order to find the wavelet transform of the samples.

  Begin
  (1) Find the average of each pair of samples (n/2 low-freq. coefficients).
  (2) Find the difference between each pair of samples (n/2 high-freq. detail coefficients).
  (3) Fill the first half of the array with low-freq. coefficients.
  (4) Fill the second half of the array with high-freq. coefficients.
  (5) Repeat the process for $\log n$ times.
  (6) Calculate the mean and standard deviation of the detail coefficients at stage $\log n$.
  (7) Filter out all detail coefficients with values less than 3*sigma.
  (8) Calculate the auto-correlation metric based on the filtered series.
  End

  We utilize the wavelet transform to get an estimate of the traffic auto-correlation. This is achieved by applying the wavelet transform to the raw T_{on} and T_{off} samples to obtain the series detail coefficients. The standard deviation (sigma) of the detail coefficients is then computed, and detail coefficients that are 3*sigma units lower than the mean of the coefficients are filtered out. Then, the inverse wavelet transform is used to re-create the series in the time domain. We believe that this process reduces the noise in the raw T_{on} and T_{off} measurements, allowing for better estimation of the traffic auto-correlation metric.

- *Fuzzy logic module*

  Since the traffic conditions on the primary cognitive radio channels change frequently, a smart strategy that selects a primary cognitive channel based on the estimated traffic parameters is needed. Our fuzzy-based channel selection policy is based on five simple rules as shown in Figure 4. Rules 2, 3, and 5 cause the overall fuzzy cost of a given channel to be proportional to the utilization estimate that is determined by the flip-flop filtering module as explained previously. Rules 1 and 4 cause the overall fuzzy cost of channels with higher degree of auto-correlation to be lower when compared to channels with the same utilization and a lower degree of auto-correlation.

(1) If (Utilization is LOW) and (autocorrelation is HIGH) then (cost is VeryLow)
(2) if (Utilization is LOW) then (cost is Low)
(3) if (utilization is MEDIUM) then (cost is Medium)
(4) If (Utilization is HIGH) and (autocorrelation is HIGH) then (cost is Medium)
(5) if (utilization is HIGH) then (cost is High)

Figure 4: Fuzzy rules

  The rationale behind these rules is straight-forward. Channels with lower utilization should be preferred over ones with higher utilization, as these yield better QoS and lower blocking probabilities. Channels with higher degree of auto-correlation should be preferred as that indicates that the primary users traffic parameters are repeating. When the auto-correlation is high, this indicates that our estimates are expected to be repeated in the future, and so we assign channels with higher degree of auto-correlation a lower overall fuzzy cost.

  After the selection of a channel with lower cost, a bit error rate estimate is computed as follows:

$$BER_{\text{estimate}} = \frac{BER_s \times C_s + BER_p \times C_p \times U_{\text{estimate}}}{C_s + C_p},$$

  where BER_s represents the bit error rate of the secondary channel, BER_p represents the bit error rate of the primary channel, C_s represents the maximum capacity of the secondary channel, C_p represents the maximum capacity of the primary channels, and $U_{\text{estimate}} = \frac{T_{\text{on}}}{T_{\text{on}}+T_{\text{off}}}$ (T_{on} and T_{off} are the estimated average calculated using the flip-flop filter).

4. HYBRID APPROACHES

The cooperative mobility schemes and opportunistic cognitive radio schemes can be combined and applied simultaneously to achieve superior QoS. We consider using the following two **policies**:

(1) *The cognitive radio scheme with minimum channel selection.* This policy tries to minimize the frequency of switching between the primary channels, while meeting the targeted QoS. This is achieved by first having all nodes that are part of the connection set engage in the cooperative mobility scheme, and then applying the opportunistic channel selection for only those nodes involved in connections whose QoS is still unsatisfied.

(2) *The cognitive radio scheme with minimum mobility budget.* This policy tries to minimize the mobility budget used, while meeting the targeted QoS. This is achieved by first having all nodes that are part of the connection set engage in the opportunistic channel selection scheme, and then using the cooperative mobility scheme for only those nodes involved in connections whose QoS is still unsatisfied.

This model is illustrated through the flowchart of Figure 5.

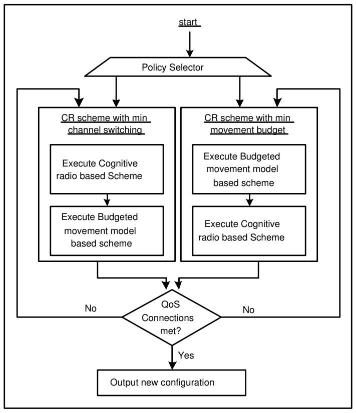

Figure 5: Hybrid Approach

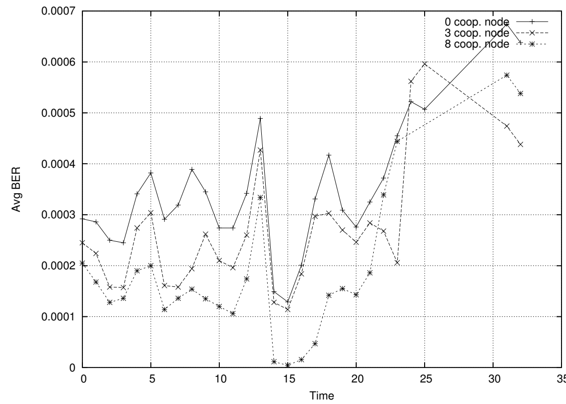

Figure 6: The benefits of increasing the number of cooperative nodes.

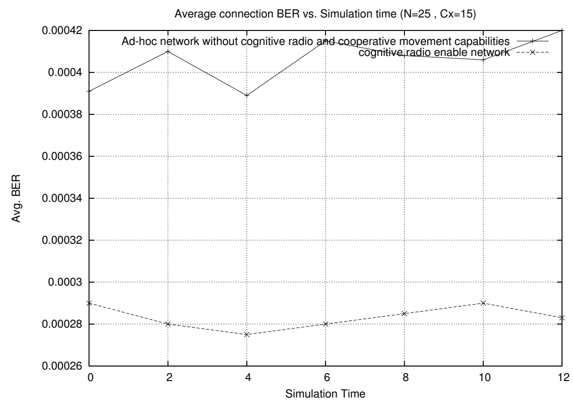

Figure 7: Using opportunistic cognitive radio to reduce average BER.

5. SIMULATION SETUP

Topologies. In our simulations, network topologies were randomly generated by placing nodes uniformly on a $100m$ x $100m$ square and moving them according to the Gauss-Markov mobility model. Two nodes are connected if the received signal power at at the two nodes exceeds a technology dependent power sensitivity parameter P_{min}.

Node capabilities. In experiments involving *CR-capable* nodes, each node supports 8 secondary channels, each with capacity of 150 kbps. In experiments involving *cooperative mobility*, each cooperative node is given a constant initial mobility budget between 50 to 300 units (depending on the experiment). A cooperative node is assumed to charge 1 unit to move a distance of 1 meter. The number of cooperative nodes is taken to be 20% and 60% of the total network size, for networks with small and large degrees of cooperativeness, respectively.

Traffic. We assume the traffic arrival over the primary channels to follow the Poisson process in which the inter-arrival and holding times are exponentially distributed. In our experiments, the T_{off} and T_{on} time series are exponentially distributed based on the parameters of the simulated primary channel.

Connections. We study the routing decision by considering connection requests between random source-destination pairs. Connections are routed using a simple version of the weighted shortest path algorithm based on the link BERs. We consider connection sets ranging from 10 to 20, with the target Quality of Service of each connection is set to be 60% of its initial BER value.

6. RESULTS

The first experiment investigates the effects of increasing the number of cooperative nodes while keeping the total mobility budget fixed. The simulation setup for the graph in Figure 6 consists of 15 autonomous nodes, 0, 3 or 8 cooperative nodes, mobility budget is fixed at 250 units, and a total of 7 random connections with a target Quality of Service to be 60% of their initial BER value for each connection. The top graph shows that having more cooperative nodes permits the routing and optimization layer to lower BER more effectively over time, even when the mobility budget is not increased.

The next experiment illustrates the benefit of using the cooperative model based on the cognitive radio concept. This experiment was conducted for a network of size 25 nodes, connection set size equals to 15, and while using filtering techniques based on wavelet transform and flip-flop filters to estimate the traffic over the primary channels. Figure 7 shows that, over time, we achieve an improvement in the average connection set BER of about 40% when benefitting from the primary channels compared to that of a non cognitive radio capable network.

In the next experiments, we investigate the performance in terms of channels switching and mobility budgets of the proposed policies. This experiment was conducted for a network of size 25 nodes, connection set size equals to 15, and while using filtering techniques based on wavelet transform and flip-flop filters to estimate the traffic over the primary channels. The top graph of Figure 8 shows that the targeted QoS can be achieved while having an average of 20 fewer switches between primary channels of the cognitive radio channel, when using the cognitive radio scheme with minimum channel switching policy. However, if the goal is to reach the target QoS with minimum mobility budget used, the cognitive radio scheme with minimum mobility budget policy would result in an average of 75 fewer units. This could be seen from the bottom graph of Figure 8.

In the last experiment, we investigate the effect of increas-

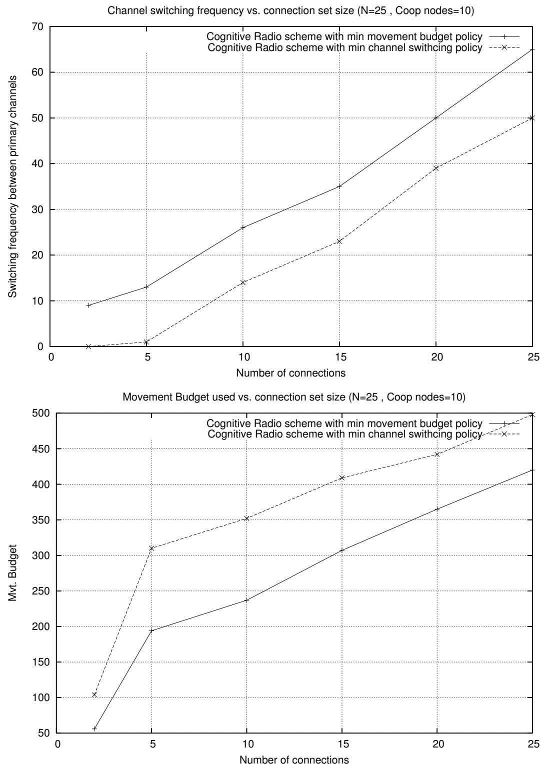

Figure 8: Opportunistic cognitive radio and cooperative mobility

ing the size of the connection set on the performance of the proposed schemes. The simulations setup consists of a network size of 25 nodes, a connection set size of 10, mobility budget per node equals to 300 units, and considering the wavelet transform and flip-flop filtering techniques to estimate the traffic over the primary channels of the cognitive radio channel. The graph of Figure 9 shows that both proposed policies of the cognitive radio based schemes outperforms the cooperative model without cognitive radio capability. Although the percentage improvement in the number of connections that did not meet the required BER decreases as the connections set size increases, the improvement remains in excess of 30% regardless of connection load.

7. CONCLUSION

Our experimental results are compelling and demonstrate that the communications infrastructure—specifically, connection bit error rates—can be significantly improved by leveraging cooperative mobility and opportunistic channel switching using our proposed techniques. The techniques thus have significant impact on practical mission-oriented MANETs, with applications to battlefield communications and response and rescue missions.

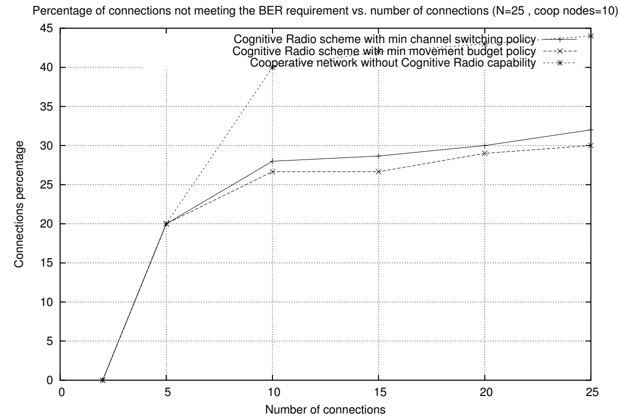

Figure 9: The performance of the proposed schemes when increasing the connection set size

The resultant algorithm improves average connection BER almost linearly as the mobility budget increases (with constant numbers of cooperative nodes). It also improves connection BER almost linearly as the number of cooperative nodes increases (with constant total mobility budgets). The wavelet transform and flip-flop filtering techniques are effective, predict the status of primary channels, enable lower average connection BER especially when coupled with our channel selection scheme. The cooperative mobility and opportunistic channel selection schemes can be hybridized without negative tradeoffs. The schemes scale and continue to provide significant BER reductions (in excess of 30%) even as network load increases.

8. REFERENCES

[1] R.Broderson et Al., Corvus: A Cognitive radio approach for usage of virtual unlicensed spectrum, 2004.

[2] P. Basu and J. Redi. Movement Control Algorithms for Realization for Fault-Tolerant Ad-Hoc Robot Networks. IEEE Network, July 2004.

[3] W. Electric. Statistical Quality Control Handbook. *Western Elctric Corporation, Indianapolis, Inc., 1956.*

[4] H. T. Friis. Noise figures of radio receivers. volume 57, pages 1461–1462. Proc. IEEE, 1969.

[5] M. Kim and B. Noble. Mobile Network Estimation. *In proceedings of the ACM Conference on Mobile Computing and Networking, Rome, Italy, 2001.*

[6] M.Guizani, A.Al-Fuqaha, B.Khan, and G.B.Brahim. A Model for Cooperative Mobility and Budgeted QoS in MANETs with Heterogenous Autonomy Requirements. *Computer Communications Journal: Special Issue on End-to-end Support over Heterogeneous Wired-Wireless Networks. 2007.*