Opportunistic Channel Selection Strategy for Better QoS in Cooperative Networks with Cognitive Radio Capabilities

Ala Al-Fuqaha, Bilal Khan, Ammar Rayes, Mohsen Guizani, Osama Awwad, Ghassen Ben Brahim

***Abstract*—Mission-oriented MANETs are characterized by implicit common group objectives which make inter-node cooperation both logical and feasible. We propose new techniques to leverage two optimizations for cognitive radio networks that are specific to such contexts: *opportunistic channel selection* and *cooperative mobility*. 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.**

***Index Terms*—Cognitive radio, Cooperation, Quality of Service, Ad-hoc network, filter, fuzzy logic.**

I. Introduction

MOBILE wireless ad-hoc networks (MANETs) serve as an important building block for 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.

In the military setting, MANETs have been used to enable communication between mobile infantry units, command and control, field intelligence, aerial surveillance, etc. They can be built using Radio Frequency (RF) communication links both between and within infantry formations, ground armored vehicles (e.g., armored vehicles, tanks), airborne units (e.g., fighters, bombers), and naval/amphibious platforms (e.g., destroyers, troop carriers). The demanding requirements of end users in military and public-safety sectors have led to the development of a variety of unmanned platforms [12]. More specifically, end-user demands have driven the development of Unmanned Ground Vehicles (UGVs) and Unmanned Air Vehicles (UAVs) for use within battlefield and public safety missions, e.g., the UAV-Ground Network [3]. These devices are mobile, mission-capable, and well-suited for use in dull, dirty, difficult, and dangerous settings, including collection of data from sensors [7]. In particular, the ability to maneuver UAVs and UGVs in small increments over a wide variety of terrains makes them well-suited to serve as relays, maintaining mobile communication links by optimizing the reception and transmission of signals among end users.

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.

Cooperative Mobility. Application-level cooperation has been studied in the context of specific tasks (e.g., in [10], Kuwata et al. describe how a group of UAVs can coordinate their activities by solving local optimization problems and then conveying aspects of these solutions to their neighbors). The objective of such investigations is to determine how team members should share and exchange high-level information to best achieve team objectives. In this work, we consider more fundamental questions on the role that cooperation can play in supporting *communication itself*. Prior work on the question of how cooperation can benefit communication [13], [8], [4], [6], [20], [19] has approached this issue from the vantage point of a node's willingness to forward messages along the next hop (toward the intended destination) along a multi-hop path. Almost all prior research adopts the consumer MANET model, where node mobility is considered the sacrosanct domain of the user, autonomously determined and non-negotiable. While this is an appropriate conception of current consumer (e.g., cell phone and laptop) applications, it fails to leverage the

Manuscript received March 1, 2007; revised August 15, 2007.

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Digital Object Identifier 10.1109/JSAC.2008.080114.

0733-8716/08/$25.00 © 2008 IEEE

unique opportunities present in mission-oriented MANETs. Here, we consider mobility to be a fundamental resource of every MANET node; cooperative nodes can potentially contribute their mobility towards the common good vis-a-vis systemic objectives.

Cognitive Radio. The potential applications of MANETs have led to a remarkable surge in research breakthroughs addressing the many technological challenges which stand in the way of their wide scale adoption. These challenges include: the limitations of wireless RF channels in terms of available bandwidth and relatively high bit error rates, inefficient use of available RF channels, energy-efficient communication to extend the network lifetime, and the difficulty of designing QoS aware routing protocols capable of meeting application requirements in a scalable way. We anticipate that as applications requiring new QoS classes arise, the RF environment will become increasingly variable, making it more challenging to optimize radio spectrum allocation and performance. *Cognitive Radio* (CR) technology has been recognized by both the regulatory and technical communities as a possible panacea to this increased variability, because of its capability to support sensing, knowledge formation, and adaptive channel allocation. CR technology [16] [18] offers a new mechanism for flexible usage of radio spectrum. It allows secondary users to operate in an under-utilized licensed frequency otherwise reserved for primary users, without violating their privileges. To achieve this, *CR-capable* mobile nodes must be able to determine (and predict) available unused network capacity that they could potentially leverage.

In this work, we develop a realistic model for cooperation in mission-oriented rapid-deployment MANETs that leverages both cooperative mobility and cognitive radio 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 II, we present our model of Cooperative Mobility and algorithms for mobility planning. In Section III, 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 IV, we describe policies for cooperative mobility and opportunistic channel selection. In Section V, we describe the architectural design of the Coop-Sim platform that we used to evaluate and experiment with parameters of the proposed models and algorithms. In Section VI, we present the experiments and interpret their outcomes. Finally, in Section VII, we present overall conclusions and the future trajectory of our research efforts.

II. Cooperative Mobility

The notion of cooperative communication appeared in the networking literature as early as the 1970's. The phrase "co-operative communication" reflects the fact that each network node has two existential modalities:

(i) a *selfish* existence in which it seeks merely to maximize the transfer of its own data, and
(ii) an *altruistic* existence in which it is willing to cooperate with the ambient system and aid in the transfer of data to and from other nodes.

Indeed, a large fraction of the corpus of literature on networking is, in some sense, concerned with achieving and maintaining a balance between these two modalities in an efficient manner that is mutually agreeable to all participants. In our view, a *model of cooperation* consists of two distinct components:

(i) A lexicon of actions by which to express altruistic tendencies,
(ii) A set of objective criteria to assess benefits of a node's altruistic behavior.

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 [15].

A. 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. That is to say, every cooperative node is willing to move for the sake of a common good, but for a price or a cost. 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.

It is important here to mention that since the quality of the end-to-end communication between end users depends on

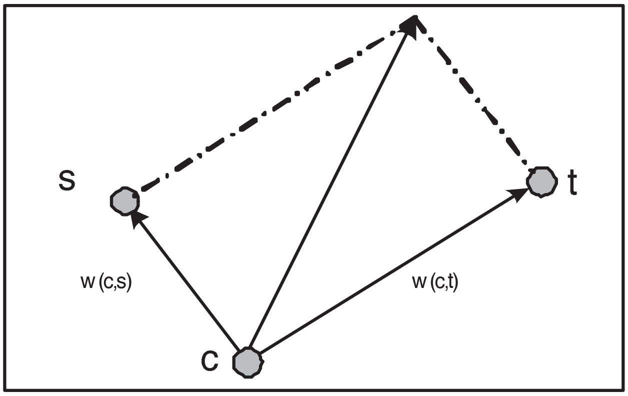

Fig. 1. A Gedanken experiment on Node Mobility.

the quality of the wireless channel, in this work, the network performance metric that we will be considering during our study of the proposed cooperative models is the wireless channel bit error rate (BER), which perfectly captures the quality of the wireless channels.

B. The Movement Planning Algorithm

Our approach to node mobility planning begins with the following Gedanken experiment: 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:

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 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. It is important here to mention that, in our case we assume that cooperative nodes are GPS enabled, and therefore can get information about their current locations.

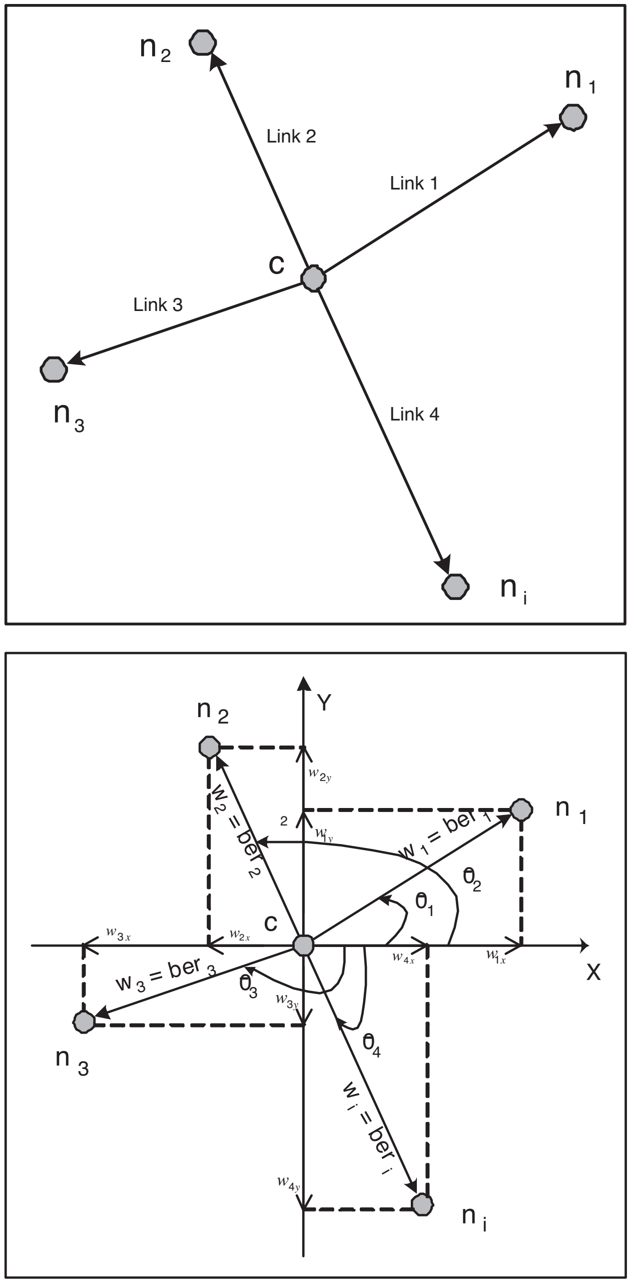

Fig. 2. Resultant Algorithm.

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.

III. Cognitive Radio

It is commonly believed that there is an impending crisis of spectrum availability at frequencies that can be economically used for wireless communications. This misconception is bolstered by the FCC frequency allocation chart [1] which shows multiple allocations over all of the frequency bands. As a result, there is fierce competition for the use of spectra, especially in the bands below 3 GHz. Actual measurements taken in an urban settings, however, reveal an altogether different reality: typical utilization in the 3-4 GHz frequency band is around 0.5% [1]. The utilization drops to 0.3% in the 4-5 GHz band. Thus, we actually have spectrum abundance, and the spectrum shortage is partially an artifact of the regulatory and licensing process.

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 [9]. These parametric filters are either able to detect true changes quickly or to mask observed noise and transients, but can not do both. In [9], 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 [9]. 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.

A. 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 bit error rates, the Opportunistic Cognitive Radio Model aims to opportunistically benefit from the abundant spectrum that is not fully utilized by primary users to enhance the QoS provided on all communication channels. 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.

In this work, we present a new wireless channel estimation technique based on the wavelet transform and flip-flop filtering 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.

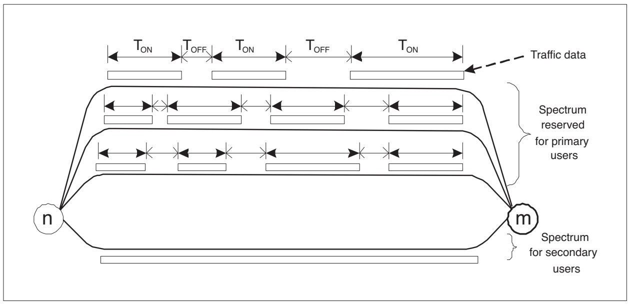

Fig. 3. Wireless channel structure in cognitive radio enabled network.

B. The Wireless Channel Estimation Algorithm

In cognitive radio networks, in order to reduce the overhead caused by switching the traffic back and forth between secondary channels, estimation techniques can help predict the metrics of these channels. Estimation techniques provide a mechanism to filter out the noise from raw measuresments in order to produce quality estimates.

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}.

The estimation procedure is depicted in Figure 4. 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 [8]. A controller selects between the two. The underlying principle of the controller is to employ the agile filter when possible, but falls back to

[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.

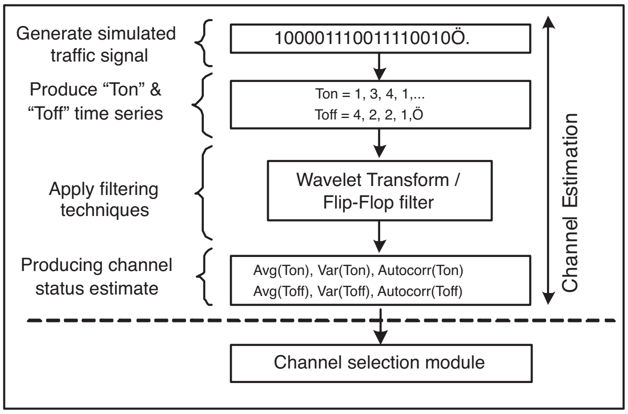

Fig. 4. Wireless channel estimation procedure.

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 [8] and are defined as follows:

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

where, d_2 estimates the standard deviation using the moving range, approximately 1.128, and O_t, O_{t-1} corresponds to the current and prior channel observations, respectively [17].

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 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-frequency coefficients).

2) Find the difference between each pair (n/2 high-frequency detail coefficients).

3) Fill first half of array with low-freq. coefficients.

4) Fill second half of 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 $< 3 * sigma$*.*

8) Calculate the auto-correlation metric based on the filtered series.

End

We utilize the Haar 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 (σ) 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 5. 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.

The rationale behind these rules is straight-forward. Channels with lower utilization should be preferred over

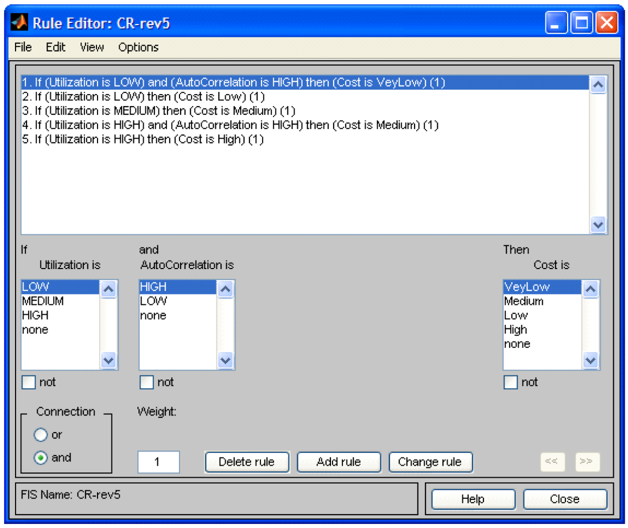

Fig. 5. Fuzzy rules.

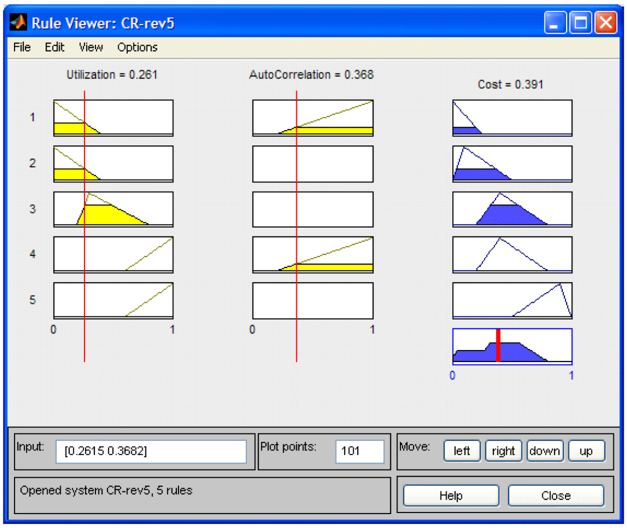

Fig. 6. Fuzzy cost.

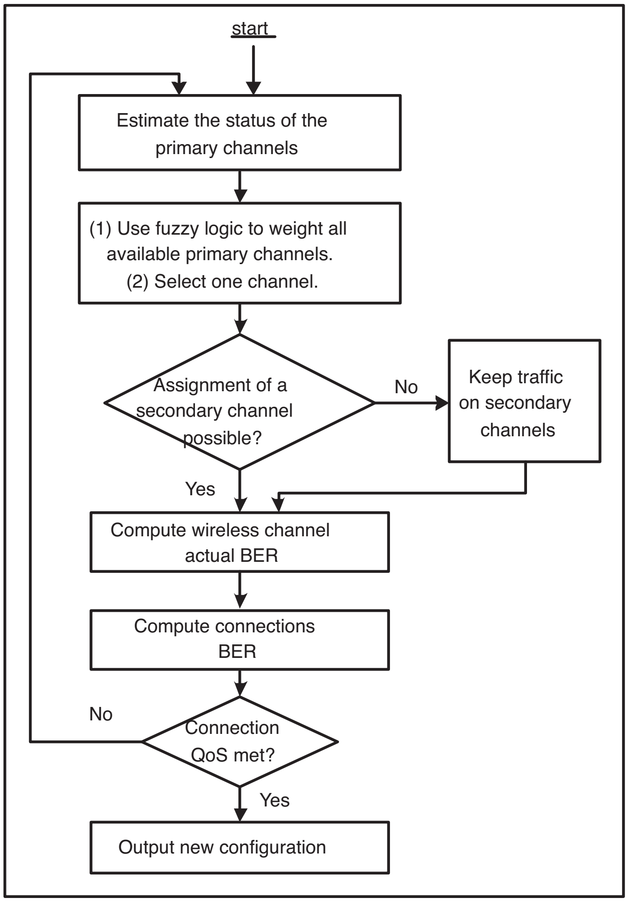

Fig. 7. Primary channel selection algorithm.

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.

Figure 5 provides an example that illustrates the computation of the overall fuzzy cost based on the fuzzy rule base. The recommended rules try to determine the overall fuzzy cost based on the estimated channel utilization and auto-correlation metrics. Higher utilizations result in higher overall fuzzy costs and higher degrees of auto-correlation results in lower overall fuzzy costs. The fuzzy cost increases gradually as the estimated utilization increases. Figure 6 illustrates an example where the estimated utilization level is 0.261 (using the flip-flop filter) and the estimated auto-correlation is 0.368 (using the wavelet transform). After applying the five fuzzy rules, the overall fuzzy cost is 0.391. This overall cost is used to select the primary cognitive radio channel with the lowest overall fuzzy cost. We remark that our channel selection policy utilizes the *min, max, min, max*, and *centroid* methods for the fuzzy *and, or, implication, aggregation* and *defuzzification* operators, respectively.

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).

IV. 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 strives 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 aims at minimizing 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 8.

V. Architecture of the Simulator

We have developed a simulation platform to investigate how parameter, policy and algorithm choices influence the efficacy of systems based on the proposed Cooperative Mobility

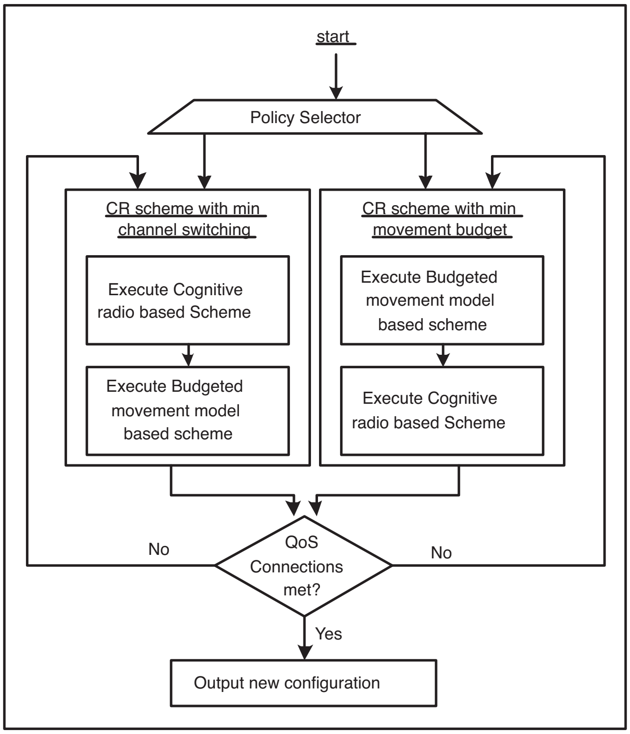

Fig. 8. Hybrid Approach.

Model. The CoopSim platform dynamically updates the communication infrastructure by manipulating its heterogenous constituent network elements; network nodes are assumed to have a wide range of characteristics, including mobility costs and available transmission power. CoopSim continuously seeks to fulfill concrete end-to-end QoS requirements for a set of application level (multi-hop) connections between given endpoint pairs. CoopSim achieves this by leveraging cooperative mobility: it determines new locations for cooperative battlefield MANET nodes, while adhering to its mobility budget constraints. In this exposition QoS requirements are stated in terms of maximum acceptable end-to-end connection bit error rates (BER), but we note that CoopSim can seamlessly integrate arbitrary, richer QoS definitions.

The CoopSim platform is implemented as a modular discrete event simulator that is naturally organized in layers. Figure 9 presents a modular schematic diagram.

The first module of the CoopSim framework is the *Physical Network Manager*, which consists of a collection of wireless components such as UGVs, manned tanks, etc. Important aspects of this layer include:

Network Discovery. These protocols are used to enable all nodes to discover their neighbors and establish wireless communication channels with them. The design of the network discovery protocol is beyond the scope of this article; a good reference can be found in [22]. For simulation purposes CoopSim assumes that wireless channels are unidirectional. A unidirectional channel connecting a transmitter to a receiver arises whenever the distance separating the two nodes is less than the communication range of the transmitter. A wireless channel forms between two battlefield MANET nodes whenever there is unidirectional channel in both directions.

Channel Characteristics. Suppose we have a pair of nodes at distance D communicating using transmission signal power P over a wireless channel L with noise power P_{noise} through a medium with propagation constant α. The relationship between wireless channel bit error rate (BER) and the received power P_{rcv} is a function of the modulation scheme employed. CoopSim considers non-coherent Binary orthogonal Phase Shift Keying (BPSK) modulation scheme, so $P_{rcv} = P/D^{\alpha}$, and the instantaneous channel bit error rate is [11], [14], [21]:

$$BER(L) = \frac{1}{2} e^{-\left(\frac{P}{D^{\alpha}}\right)\frac{1}{P_{noise}}}.$$

The *Routing and Optimization Engine* is the central layer of CoopSim. This layer is responsible for routing the set of connections that need to be maintained and repositioning the cooperative nodes in order to better provide the required QoS. Important aspects of this layer include:

Routing. Connections are routed along shortest paths in the graph using Dijkstra's algorithm, where the weight of link L is taken to be $w_L = -\log(1 - BER(L))$. It is easy to verify that shortest paths in this graph metric yield connections with minimal end-to-end BER.

Mobility. Mobile nodes and tasked unmanned nodes move according to a Gauss-Markov model [5], as follows. In time interval n, node i travels with speed $s_{i,n}$ and direction $d_{i,n}$. The mean speed and direction of movement are taken as constants $\bar{s}_i$ and direction $\bar{d}_i$, respectively. Then a node's new speed and direction during the time interval $n+1$ are given by:

$$\begin{aligned} s_{i,n+1} &= \alpha s_{i,n} + (1-\alpha)\bar{s}_i + \sqrt{(1-\alpha^2)s^*_{i,n}} \\ d_{i,n+1} &= \alpha d_{i,n} + (1-\alpha)\bar{d}_i + \sqrt{(1-\alpha^2)d^*_{i,n}} \end{aligned}$$

where α represents a continuity-determining constant, and $s^*_{i,n}$ and $d^*_{i,n}$ are random variables with a Gaussian distribution. The coordinates of node i at the end of time interval n are then easily computable as follows:

$$\begin{aligned} x_{i,n+1} &= x_{i,n} + s_{i,n}\cos d_{i,n} \\ y_{i,n+1} &= y_{i,n} + s_{i,n}\sin d_{i,n} \end{aligned}$$

QoS Requirements. In this exposition, we consider QoS requirements to be defined in terms of maximum acceptable end-to-end BER, but we note that CoopSim can incorporate any computable definition of QoS. The end-to-end BER of a connection C which traverses links L_1, L_2, ... L_k can then be computed as $BER(C) = 1 - \prod_{i=1}^{k} 1 - BER(L_i)$.

Mobility budget. This is the amount of credit available within each node, for funding the movement of cooperative MANET nodes. The mobility budget is replenished periodically, every T_m time units. In the current simulation, mobility budgets do not accumulate across time intervals.

Channel estimation and selection. The cognitive radio channel estimation module utilizes a combination of flip-flop and wavelet-based filters. On the other hand, the channel selection module employs a fuzzy rule-based scheme to determine the overall cost of the cognitive radio channel based on its utilization and auto-correlation metrics.

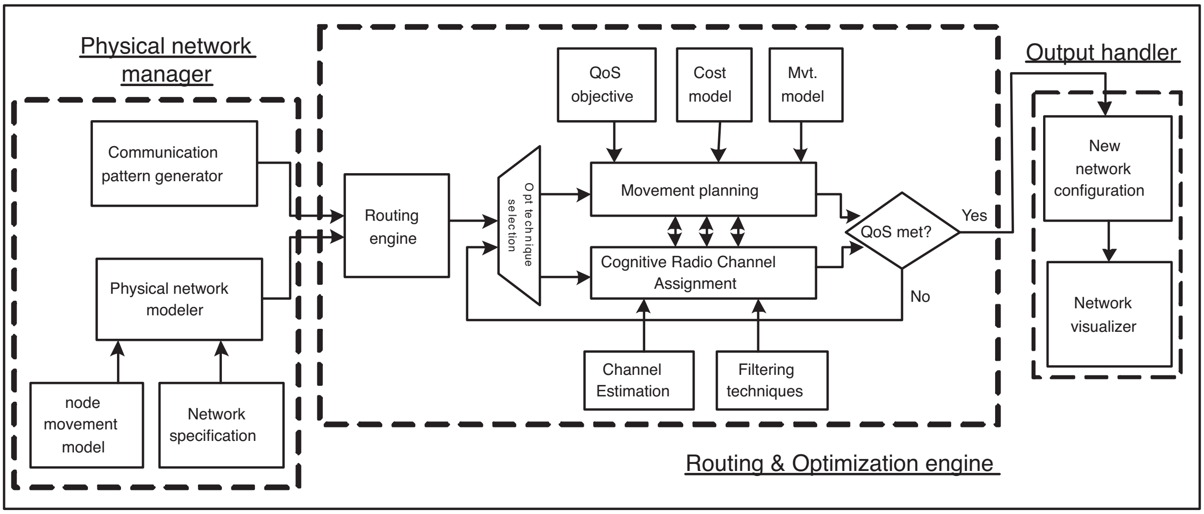

Fig. 9. CoopSim Architecture.

VI. Experiments

A. 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.

We use the current simulation setup to answer the following set of questions:

Q1. What is the impact of using the cooperative mobility scheme in enhancing the end-to-end connections' QoS in terms of BER? How is the impact affected by (a) mobility budgets, and (b) the number of cooperative nodes?

Q2. What is the impact of (a) using flip-flop and wavelet-based filtering techniques on enhancing the end-to-end connections' QoS in terms of BER, and (b) how do these schemes perform when applied as part of an opportunistic cognitive radio scheme?

Q3. How do the two schemes interact? (a) Can the opportunistic cognitive radio scheme benefit from using cooperative mobility, in terms of minimizing the amount of channel switching required to meet the QoS requirements? (b) Can the cooperative mobility scheme benefit from using opportunistic cognitive radio, in terms of minimizing the mobility budget required to meet the QoS requirements? (c) How do hybrid schemes based on the proposed policies (minimize channel switching, mimimize mobility budget) perform, and (d) do they scale to high-load settings?

The graphs in the next section answer these questions by depicting the mean values collected from 1000 trial runs of corresponding appropriately designed experimental scenarios.

B. Experimental Results

Q1-a. The first experiment investigates the effects of increasing the total mobility budget while keeping the number of cooperative nodes fixed. We consider the case of a network size of 23 nodes, 8 cooperative nodes, 7 random connections, and a target connection Quality of Service to be 60% of the initial BER value of the connection. The top graph shows that having higher mobility budgets permits the routing and optimization layer to achieve lower connection BER over time. The bottom chart of Figure 10 depicts this effect in greater detail by considering the same experimental scenario but with varying mobility budget. The graph shows that a mobility budget of 50 units permits the routing and optimization layer to lower average connection BER by almost 8%, and that increasing the mobility budget to 250 units enables BER reduction of almost 40%. The results indicate that connection BER can be improved almost linearly as the mobility budget increases, even under constant numbers of cooperative nodes.

Q1-b. The second experiment investigates the effects of increasing the number of cooperative nodes while keeping the total mobility budget fixed. The simulation setup for the

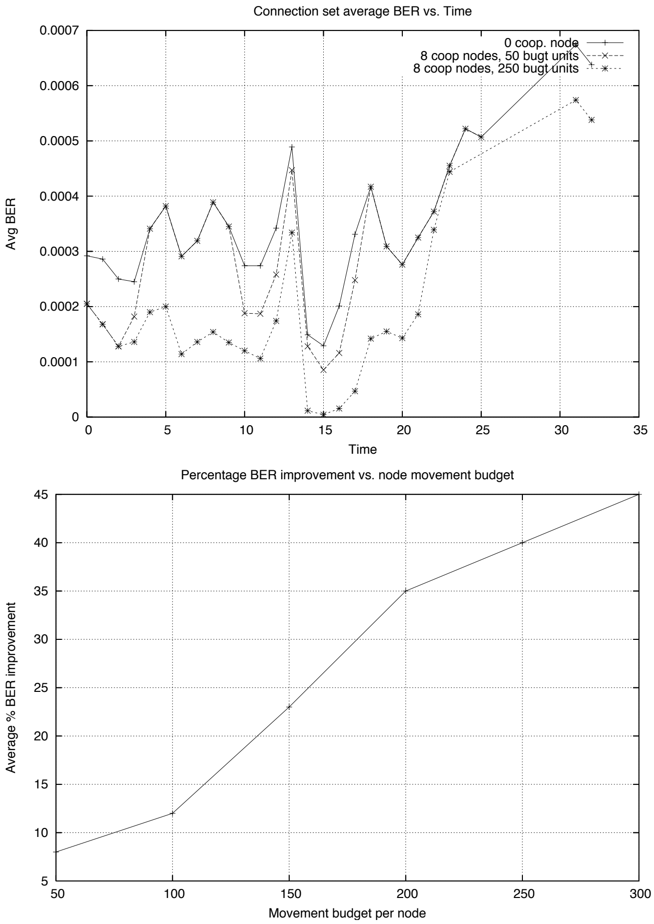

Fig. 10. The benefits of increasing the mobility budget.

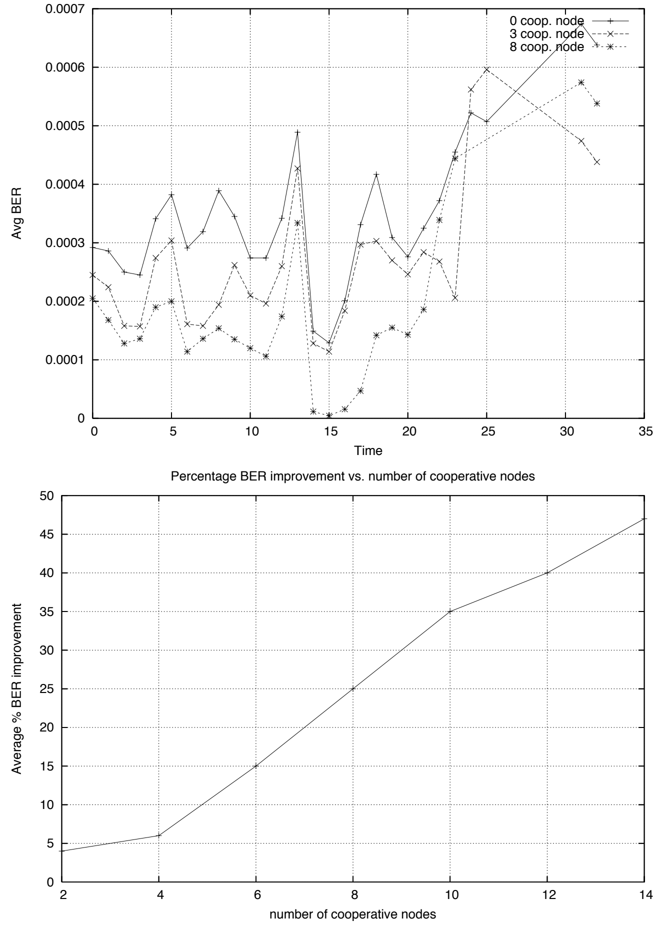

Fig. 11. The benefits of increasing the number of cooperative nodes.

graph in Figure 11 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 bottom chart of Figure 11 depicts this effect in greater detail by considering the same experimental scenario but with varying numbers of cooperative nodes. For example, with 4 cooperative nodes, we can lower average connection BER by almost 8%, while increasing the number of cooperative units to 12 enables BER reduction of almost 40%. The results indicate that connection BER can be improved almost linearly as the number of cooperative nodes increases, even under constant total mobility budgets.

Q2-a. In the next experiment, we investigate the benefit of using filtering techniques in our cognitive radio based cooperative scheme to predict the traffic on the primary channels. We run this experiment of Figure 12 for a network of size 20 nodes and a connection set size equals 15. The charts show that using estimation techniques based on wavelet transform and flip-flop filtering techniques to predict the status of the primary channels, yields a lower average connection set BER compared to the scheme where we consider raw (non-filtered) data.

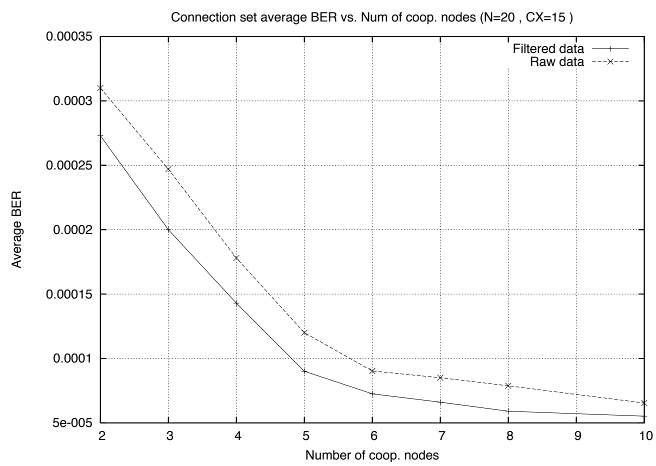

Fig. 12. Using filtered data to reduce wireless channel BER.

Q2-b. The next result 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 13 shows that, over time, we achieve an improvement in the average connection set BER of about 40% when benefitting from the

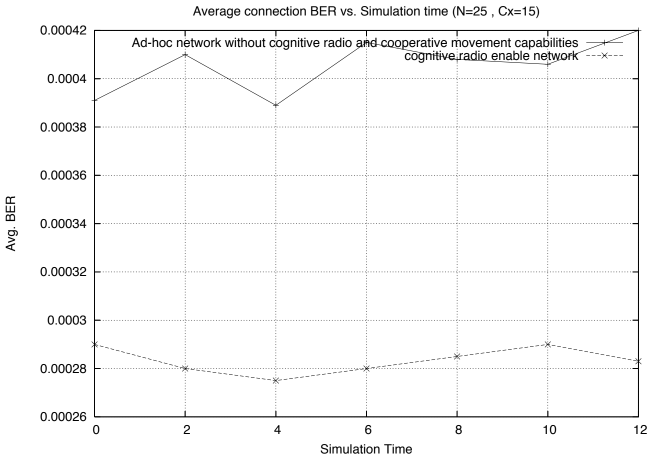

Fig. 13. Using opportunistic cognitive radio to reduce average BER.

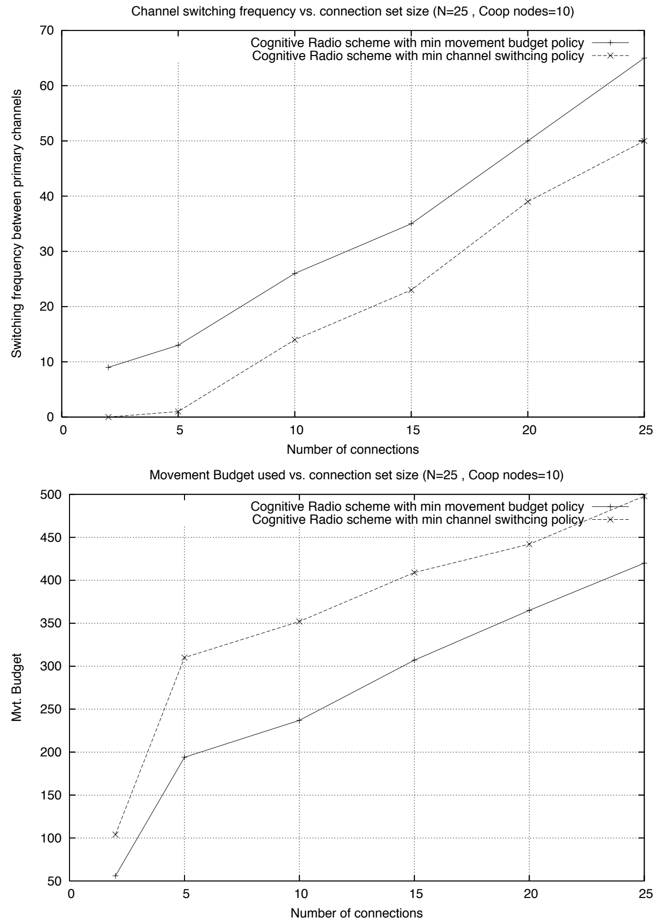

Fig. 14. Opportunistic cognitive radio and cooperative mobility.

primary channels compared to that of a non cognitive radio capable network.

Q3-a & b. 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 14 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 14.

Q3-c. In the next experiment, we investigate the effect of increasing the number of cooperative nodes on the performance of the proposed schemes. The simulation setup consists of a network size of 25 nodes, a connection set size of 15, 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 graphs in Figure 15 show that both proposed policies achieve comparable performance in terms of (i) average connection set BER, (ii) percentage of connections that did not meet the required QoS, and (iii) average improvement percentage. Compared to the cooperative network without cognitive radio, both policies of the cognitive radio based schemes outperform the cooperative mobility model alone. The top graphs of Figure 15 show an improvement of about 50% in the average BER, 25% in the percentage connections that did not meet the required BER, and and average of about 30% in the percentage improvement.

Q3-d. In the last experiment, we investigate the effect of increasing 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 16 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.

VII. Conclusion and Future Work

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.

The resultant algorithm improves the average connection BER almost linearly as the mobility budget increases (with constant numbers of cooperative nodes). It also improves the 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

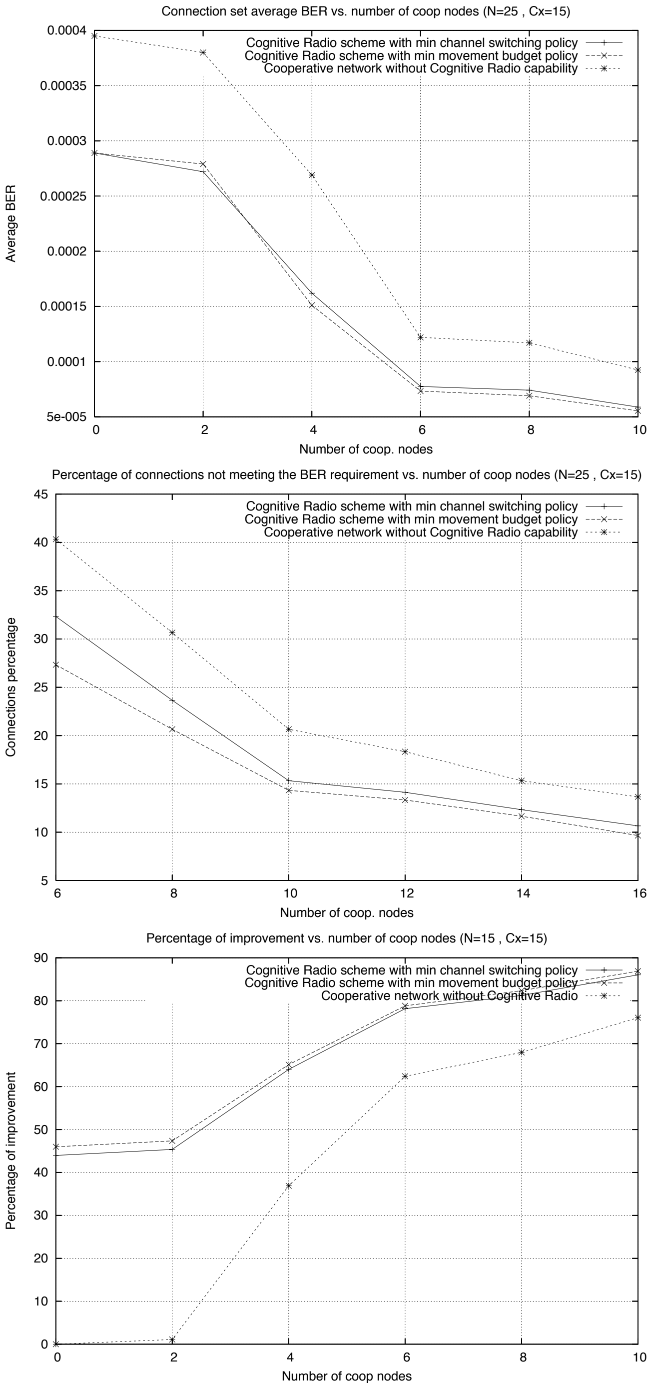

Fig. 15. The effect the number of cooperative nodes on the proposed schemes.

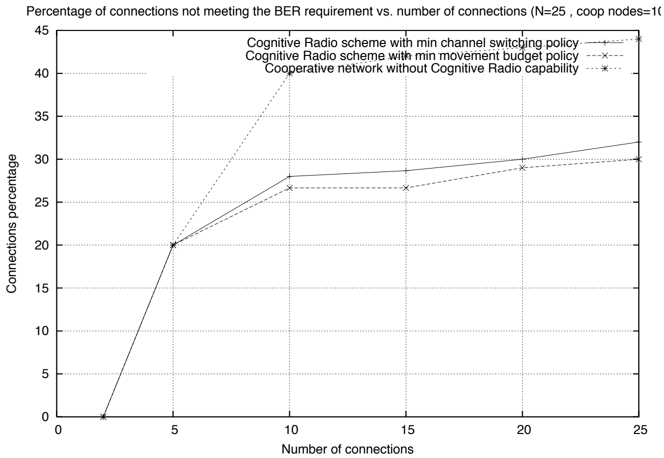

Fig. 16. The performance of the proposed schemes when increasing the connection set size.

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.

In the future, we will extend existing routing protocols to make them aware of cognitive-radio capabilities. We will design provably robust distributed algorithms that further leverage cooperative mobility in MANETs. We will evaluate the scalability, tradeoffs and performance of these ideas through both analysis and simulation experiments conducted using our CoopSim platform.

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