Interference Aware Routing Using Localized Mobility Prediction for Multihomed Wireless Networks

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Abstract— **In this paper, we present two novel algorithms to deal with mobility prediction and interference aware routing for multihomed wireless networks. First, a localized mobility prediction algorithm, LMP, is developed using the Hidden Markov Model (HMM) in which the multiple fixed relay nodes in the multihomed network architecture act as pseudo-base stations to locally maintain and deliver mobility information collected from surrounding mobile users. We show that the prediction accuracy of our proposed prediction algorithm is better than using common Markov chains to predict user location at a time instant t. We also show that our mobility prediction algorithm adapts better to a user node's change in movement. Second, we present a new interference aware routing algorithm in which the signal to interference noise ratio (SINR) is used as the routing metric to determine least interfering paths. The mobility prediction algorithm is used as input to the routing algorithm in order to accurately calculate the SINR value of a specific link at particular time instances. This information is used to perform route construction based on least interference. We solve the least interference routing problem using a minimal cost flow optimization framework. We show that the integration of the two algorithms outperforms conventional counterparts in the literature in terms of packet delivery ratio and end-to-end-delay. However, we also show that the tradeoff for increased network performance lies in the ability of the algorithm to scale to very large networks.**

*Keywords – **Interference; hidden markov model; SINR routing; prediction accuracy; minimum cost flow optimization***

I. INTRODUCTION

In recent years, services supported by mobile communications have expanded from simple voice traffic to various multimedia applications, resulting in the rise of 4G systems. These 4G cellular systems are required to provide high and homogeneous data rates over the complete cell coverage area while assuring a level of quality of service (QoS). In traditional cellular networks (in which each mobile station (MS) is directly connected to a base station (BS)), mobility management is performed by the base station. In such networks, mobility prediction is concerned with the user's path when it is within the coverage area of that base station. However, the traditional cellular architecture has a structural weakness in providing fair service because each user's QoS depends on its location and mobility within the cell. If a user is near the cell boundary, it experiences severe path loss and poor spectral efficiency compared to users near the base station. Thus, more resources need to be allocated for cell boundary users to obtain the same throughput.

Achieving the defined 4G objectives requires installing either a higher number of base stations, or integrating cellular and ad-hoc networking technologies. The integration of cellular and ad-hoc technologies, also referred to as Multihop Cellular Networks (MCN), has gained significant research attention given its capacity to achieve the 4G objectives [1], [2]. MCNs substitute the direct MS-BS link with multi-hop links using intermediate nodes (relays) to retransmit the information from source to destination. Various architectures are available to MCNs [3], including both fixed and mobile relays. In this paper we focus on MCNs with fixed relay nodes where the base station communicates directly with fixed relay nodes which in turn cooperatively relay information in an ad hoc fashion to other users in connectivity range. In this architecture, each fixed relay behaves as a "pseudo-base station" or "home" for the mobile users by providing services (i.e., routing and mobility management) that would normally be taken care of by the base station in a centralized manner. This is termed a *multihomed* MCN. The concept of multihoming has been extensively discussed in the context of Mobile IP [4] to improve network connectivity and manage mobility. Multihomed architectures have also been predominantly used to develop fault-tolerant routing protocols by ensuring that user nodes have multiple connection opportunities in the event that one home relay fails [5], [6].

A. Motivations and Related Work

Mobility management involving movement prediction relies on the availability of prior information on the user's mobility behavior. Recently, prediction schemes using variations of the Markov model, particularly the Hidden Markov Model (HMM) have been proposed for resource management purposes in ad hoc networks [7], [8]. These schemes use control theoretic frameworks to dynamically allocate resources to users. Similarly, mobility prediction in cellular networks has also been researched in [9], [10], [11].

The cooperation between fixed relays and the base station is the cornerstone for efficient communication at the network layer. A mobile user is served by a nearby relay node that forwards packets (potentially over multiple wireless hops) to the base station. In addition to traffic forwarding and route decision making, the relays also have the responsibility of managing user mobility by collecting information regarding user movements from one home relay to another. This essentially reduces the burden on the base station by localizing mobility management.

A consequence of the increased use of fixed relays is the inherent interference that is induced. Wireless interference is influenced by node mobility and can lead to performance degradation. The time varying mobility patterns of the users (i.e., speed, direction etc.) can cause new interference to be induced at neighboring nodes [12]. Specifically, if a node n moves from an area of low interference, A, to one of high interference, B, then any transmission from n will contribute to the interference of area B.

Interference can be controlled/mitigated in the network layer i.e., with routing. In order to design an effective routing algorithm that mitigates the interference experiences of the wireless links, the mobility of the users must be considered. Mobility assisted routing has been studied in the literature for several years, more recently focusing on ad hoc and delay tolerant networks [13], [14]. However, none of these works discuss the direct impact of interference on the routing protocols. More recently, in [12], mobility aware routing using interference constraints was developed. However, the interference is modeled using the protocol model which induces binary conflicts (either two links interfere or they do not despite neighboring simultaneous transmissions) which is not true in practice. Our focus is on the use of the signal to interference noise ratio (SINR) interference model (also known as the physical interference model), which is based on practical transceiver designs of communication systems that treat interference as noise. Under the SINR model, a transmission is successful if and only if the SINR at the intended receiver exceeds a threshold such that the signal can be decoded with acceptable bit error probability. Although the SINR model has been shown to be more computationally complex than the protocol model, it also provides a more practical and realistic assessment of wireless interference [15]. Routing protocols using SINR to model interference have been studied in both static networks [16], [17], [18] and mobile networks [19]. However, although the work of [19] uses SINR for route selection, the mobility modeling is based on the random waypoint model, and therefore no specific mobility prediction is introduced. In addition, [19] does not correlate wireless interference with mobility.

Our objective in this paper is to study SINR and its relationship to interference based routing using localized mobility management information. We extend our work given in [1] by integrating an interference based routing structure into a refined mobility prediction algorithm.

B. Contributions and Organization

The contributions of this paper are two-fold. First, we propose a localized (distributed) mobility prediction (LMP) algorithm based on the HMM where the mobility information (i.e., location) of each user at a time instant t is collected by the corresponding home relay node for movement prediction purposes. Second, we develop a routing protocol which uses the location information of the mobile user to determine the interference level on links in its surrounding neighborhood. We use SINR as the routing metric to calculate the interference on a specific link. The SINR represents the link cost. We minimize the total cost of routing as a cost function of SINR while guaranteeing that the load on each link does not exceed its capacity, thereby determining least interfering paths from each user to the base station. The routing protocol and the proposed solution are solved using a combinatorial optimization technique, known as the minimum-cost flow problem in the operations research literature.

The rest of the paper is organized as follows: Section II describes the system model. In Section III, we discuss the LMP algorithm used in this paper while in Section IV the SINR based routing algorithm is developed. The performance evaluation of the LMP and SINR routing algorithms is discussed in Section V. We conclude the paper in Section VI.

II. System Model

The network topology used in this paper is based on the MCN model used in emerging 4G broadband wireless access networks [20]. The multihomed MCN that is the focus of this paper is shown in Fig. 1. As shown, the network architecture is based on three tiers of wireless devices: 1) user nodes which are the lowest tier; 2) relay nodes that route packets between the user and base station is the second tier; and 3) the base station is the highest tier. Each home relay interacts with a set of mobile users. It must be noted that a MS can directly interact with a BS rather than a home relay if it is closer to the BS than to the home relay. Let V_N denote the number of relay nodes and let V_M denote the number of users. The BS is connected to the wired infrastructure and behaves as a gateway to the Internet. The LMP algorithm that is used to predict the next location of each user node is handled by the individual home relays. Each home relay collects and maintains information regarding the movement of the mobile users connected to it.

To understand the interaction between the various components of our framework, we provide a block diagram given in Fig. 2. The block diagram shows the LMP algorithm and its relationship to the SINR based routing algorithm. The prediction of the user's movement is driven locally by a HMM that is performed by each home relay. This means that the HMM is used to represent the mobility pattern of the users. The current mobility information and the history of the user's past movements is used to make predictions. This information is maintained in the mobility database of each home relay which keeps track of users that are connected, were connected or will be connected (prediction) to the home relay. Specifically, the database keeps track of which users are connected to the relay and which users have moved away to another relay, base station or cell. The idea of the mobility database was originally developed in [7] and its implementation has been modified to suit the needs of the work presented in this paper.

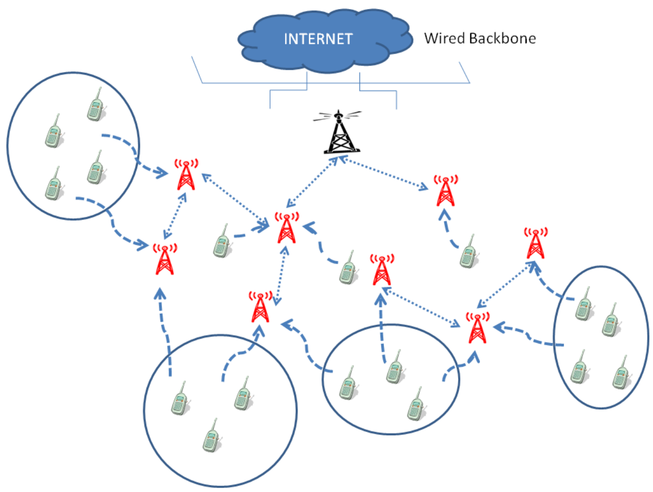


Fig. 1. Multihomed MCN where sets of user nodes are connected to a home relay and home relays communicate with other home relays in its transmission range to transmit information to the base station

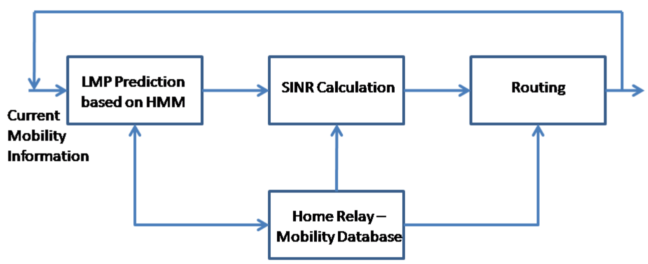


Fig. 2. Block diagram that illustrates the interaction between the LMP algorithm and the interference aware routing algorithm. The home relay runs the prediction algorithm and the SINR calculation for the routing procedure

The next predicted location of the mobile user, as determined by the home relay, is broadcast to other home relays so that they may update their databases accordingly. This updated information is then used to calculate the induced SINR interference at the receiver to proactively construct paths with least interference. The calculation of the SINR value at a time t in a mobile setting must be computed instantaneously. To facilitate the SINR calculation and the execution of the LMP and routing algorithms, it is assumed that the user nodes are quasi-mobile [21]; each user moves with a certain velocity and for a time T stays at one location before moving to a new random location.

III. Localized Mobility Prediction (LMP) Algorithm

The prediction problem discussed in this section aims to solve the following problem: *Consider a mobile user connected to relay node A. The user may move away from A to relay node B after some time. Using the history and transition paths, what is the likelihood that a user makes the transition from A to B?*

This problem has been dealt with using a Markov chain model [8]. However, the drawbacks of using a simple Markov chain model can be illustrated as follows. Referring to Fig. 3, consider a MCN with 4 relay nodes, A,B,C and D. Initially assume that a user connected to A moves from A to connect to any of the other relays, B,C or D. The transition from A to any of the other relay nodes may depend on proximity, signal strength, etc. The Markov model given in Fig. 3 shows the changes in direction as a sequence of probabilities based on past states. The transition probability for the next state is based on the most recent state. However, an external observer may not be able to see all of these transitions. Some transitions may be hidden from the observer by the user or the system. For instance, if a user connects to any of the relay nodes, the observer may only see the movement of the user from one relay to another but may not be able to determine which relay the user is connected to. Thus, the relay nodes are the hidden states and the locations are the observable states. Because there is no one-to-one mapping between these two states, the problem is to identify the relays corresponding to the location of the user.

A. Hidden Markov Model (HMM)

A HMM is a statistical Markov model in which the system being modeled is assumed to be a Markov process with unobserved (hidden) states. In a regular Markov model, the

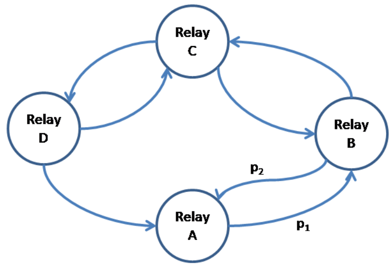


Fig. 3. Example to show a simple Markov chain that depicts the transitions of a mobile user to various relay nodes

state is directly visible to the observer, and therefore the state transition probabilities are the only parameters. In a HMM, the state is not directly visible, but output, dependent on the state, is visible. A HMM has two kinds of stochastic variables: state variables (hidden variable) and the output variables (observable variable). A HMM can be defined as follows:

O : $\{o_1 o_2 ... o_N\}$ are the values of the observed sequences
S : $\{s_1 s_2 ... s_N\}$ are the N hidden states of the system
Π : $\{\pi\}$ is the initial state probabilities. π_i indicates the probability of starting in state i
$A = \{a_{ij}\}$ are the state transition probabilities where a_{ij} denotes the probability of moving from state i to j

$$a_{ij} = P(t_k = s_j | t_{k-1} = s_i)$$

$B = \{b_{ik}\}$ are the observation state probabilities where b_{ik} is the probability of emitting symbol k at state i

$$b_{ik} = P(o_k | t_k = s_j)$$

The 3-tuple (A, B, π) provides a complete specification of the HMM for the system considered in this paper.

To physically translate the HMM variables for the network at hand, O represents the relay node that a user is connected to presently. S represents which relay node a user will be connected to at a future time (where N denotes the number of relays) and Π is the set of state probabilities that indicate the likelihood that a user node is initially connected to a relay node i. A is the set of transition probabilities of a user node moving from a relay node i to a relay node j. Lastly, B represents the state probability of a user being connected to a relay node j given that the user started at relay node k. Essentially, B is the probability of an observed sequence. Given the parameters of the HMM model, the task is to compute the probability of an output sequence (i.e., which relay a user node is connected).

B. Localized Mobility Prediction Using HMM

To track the state of a mobile user we apply two approaches: 1) forward-backward algorithm and 2) re-estimation algorithm for the HMM parameters discussed above. The main steps of the tracking algorithm can be summarized as follows:

1) Apply HMM re-estimation algorithm to obtain initial estimates of (A, B, π) of the HMM.
2) Apply the HMM forward-backward estimation algorithm to predict at time t the next state of a user.
3) Obtain refined estimates of (A, B, π) by again applying the HMM re-estimation algorithm to the given observation sequences.

In mobile systems, up to date information regarding a user's movements is difficult to obtain. Estimation of the mobility model parameters must in general be made based on incomplete data. Due to physical constraints, transmission of location data may not take place frequently enough to allow precise tracking of the user's state at all times. The task of estimation from insufficient data involves two important aspects: (a) estimation and prediction of the user's movement behavior and (b) re-estimation of the model parameters based on incomplete information. These steps are performed at each home relay node during each observation time. We define the observation interval as the time during which observations (mobility information is collected) occur. The observation time is denoted as T, and is indexed by $1, 2, ..., T$. Time T is defined as the time during which the mobile user remains stationary. During this time, observations are collected for the LMP algorithm. Thus, the time during which the node remains stationary is the predicted state of the mobile network in the HMM.

1) Forward-Backward Algorithm: A forward-backward algorithm is an algorithm for computing the probability of a particular observation sequence in the context of hidden Markov models [22]. It is essentially an inference algorithm for HMM and consists of two steps. The first step of the algorithm computes a set of forward probabilities which provide the probability of observing the first k observations in the sequence and ending in each of the possible Markov model states (i.e., probability of ending up in any particular state given the first k observations). The second step of the algorithm computes a set of backward probabilities which provide the probability of observing the remaining observations given an initial state (i.e., probability of observing remaining observations given any starting point). These two sets of probabilities can then be combined to provide the probability of being in each state at a specific time during the observation sequence. The forward-backward algorithm can thus be used to find the most likely state for a hidden Markov model at any time.

For our model, we define the following forward and backward variables:

Forward variables represent the probability of an observation sequence $\{o_1 o_2 ... o_N\}$ and a state s_i at a time T. The forward variables, denoted as α, are determined as follows:

1) Initialization: $\alpha_i = \pi b_i(o_1)$, $1 \leq i \leq N$.
2) Induction: $\alpha_{t+1}(j) = [\sum_{i=1}^{N} \alpha_t(i) a_{ij}] b_j(o_{t+1})$, $1 \leq t \leq T-1$, $1 \leq j \leq N$.

Backward variables represent the probability of an observation sequence $\{o_1 o_2 ... o_N\}$ from $t+1$ to the end, given state s_i at time t. The backward variables, denoted as

β, are determined as follows:

1) Initialization: $\beta_T(i) = 1,\ 1 \leq i \leq N$.
2) Induction: $\beta_t(i) = \sum_{j=1}^{N} a_{ij} b_j(o_{t+1}) \beta_{t+1}(j)\ 1 \leq t \leq T-1,\ 1 \leq j \leq N$.

The forward variables are computed inductively for $t = 1, 2, ..., T$. Similarly, the backward variables are computed inductively for $t = T, T-1, ..., 1$. After computing the forward and backward variables, a state estimate can be found. Let us define,

$$\gamma_t(n) = P[o_t; s_t = n]$$

as the probability that s is observed to be in state n at time t, where s is a user node. Then the estimate of s_t is given by

$$\hat{s}_t = \arg\max_{1 \leq n \leq N} \frac{\gamma_t(n)}{P[o_t]}, t = T, T-1, ..., 1$$

2) Re-estimation Algorithm: A simple iterative procedure for re-estimating the HMM parameters is reported in [22]. By applying the well-known EM (Expectation/Maximization) algorithm [23], it can be shown that this iterative procedure is increasing in likelihood. The overall computational complexity of the re-estimation algorithm is essentially proportional to T. Thus, the parameters of the HMM model can be estimated effectively within our framework.

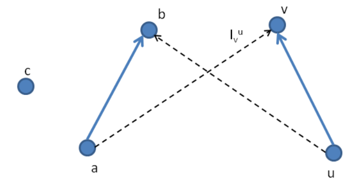
IV. SINR Based Routing Using Localized Mobility Prediction

This section will discuss the formulation of the SINR routing algorithm using the developed LMP algorithm.

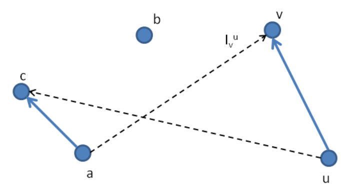
A. Challenge of Routing with Interference and Mobility

Using the LMP algorithm based on the HMM, we are able to track the movement of the users to determine which relay it is connected to. Given this information, routing from the connected relay to the base station can take place through multiple hops. Note that knowing to which relay a user is connected is imperative to the calculation of interference. To route in the presence of mobility and interference using link based metrics is a fundamental challenge. Under generic shortest path routing, the path length (which depends on the link metric) is the only factor that decides the best route between any source and the base station. Various examples of link metrics in the literature, namely Euclidean distance, depend solely on the two nodes forming the link. They are independent of the existence of other paths from other users and the BS or their shortest path routes. This, in turn, has led to the notion of link metrics and link-based routing. However, interference depends on the existence of other sources/intermediate relays and their spatial separation. Thus, the routing decision of a given source-base station pair becomes coupled to the routing decision of other source-BS pairs.

To illustrate this, assume node a is transmitting to next hop b and node u is transmitting to next hop v as shown in Fig. 4(a). According to the non-linear decay of power with distance, governed by $P_r(z) = P_t * z^{-\alpha}$ where P_t is the transmitted power, z is the distance between transmitter and receiver and



(a) Node a is transmitting to node b and node u is transmitting to node v



(b) Node a transmits to node c while node u continues to transmit to node v

Fig. 4. Illustration of the challenge of defining an interference aware routing metric in the presence of simultaneous transmissions and mobility

α is the pathloss exponent, the amount of interference at node v from transmitters other than u is given by $I_u^v = P_{ab} * z_{av}^{-\alpha}$. If node a was transmitting to a different node (i.e., node c), as shown in Fig. 4(b), then the amount of interference seen at node v would be different: $I_v^u = P_{ac} * z_{av}^{-\alpha}$. Note that P_{ab} is different from P_{ac}. Thus, the interference induced on link (u, v) (needed to compute its link metric) depends on the routing decision of transmitter a which, in turn, depends on the routing decision of transmitter u. Couple this scenario with mobility in which node a is moving, then a more refined time based routing metric is required to gauge both interference and the location of the node at that time.

To determine appropriate routing paths from the relay to the BS that are cognizant of interference, we use SINR as a routing metric. The SINR is an effective and practical metric to gauge link quality because it takes interference and noise as well as signal strength into account. Furthermore, with user nodes moving, poor links are unpredictable and thus SINR based routing decisions are useful to discover more robust paths.

B. Problem Formulation

For our analysis, we model the multihomed MCN as a graph, $G(V, E)$, where V is the set of nodes (relays, mobile users and base station inclusive) and E is the set of links. Let V_M be the set of mobile users and let V_N be the set of home relays, where $V_M, V_N \in V$. Note that the network has only one base station. The successful reception of a packet depends on the received signal strength, the interference caused by the simultaneously transmitting nodes, and the ambient noise level η. The SINR of a link (i, j) is given as follows

$$SINR_{ij} = \frac{P_j(i)}{\eta + \sum_{k \in V'} P_j(k)} \geq \beta \qquad (1)$$

where $P_j(i)$ is the received power at node j due to node i, V' is the subset of nodes in the network that are transmitting simultaneously, and β is the SINR threshold. Our proposed routing protocol is implemented to route data using the least interfering path out of all path possibilities. If a link has a high SINR, it is an indication that it is experiencing low interference.

Each link (i, j) has an associated cost which is derived from the SINR value calculation. Each link also has an associated capacity denoted u_{ij}. The capacity is formulated using Shannon's formula, given in Eq.2.

$$u_{ij} = log_2(1 + SINR_{ij}) \qquad (2)$$

In addition, the flow of packets from node i to its neighbor j over wireless link (i, j) is represented by f_{ij}.

C. SINR Based Routing

The position of each user node at time t affects the cumulative SINR on each link. The SINR is also affected by the path loss model and channel gain. The SINR at time t on link (i, j) is given by Eq.3,

$$SINR(t)_{ij} = \frac{G_{ij} P_j(i)(t)}{\eta + \sum_{k \in V'} G_{kj} P_j(k)(t)} \geq \beta \qquad (3)$$

where G_{ij} is the channel gain on link (i, j) (in the simulations, the channel gain of each link is calculated using a Rayleigh fading model and an appropriate path loss factor), $P_j(i)(t)$ is the received power at node j due to node i at time t, and k is a simultaneously transmitting node. The corresponding capacity u_{ij} is then modified to be

$$u_{ij}(t) = log_2(1 + SINR_{ij}(t)) \qquad (4)$$

The SINR is calculated during each observation time, $t \in T$.The cost of each link is associated with the SINR value obtained from Eq. 3.

In order to determine the least cost (least interfering) paths, we use the minimum cost flow optimization technique. In our case, the cost of a link is motivated by the amount of interference on that link due to neighboring transmissions and/or noise. As we are using SINR as the routing metric, the higher the SINR, the better the link quality. Therefore, we want to minimize the *inverse* of the SINR value.

The objective of the SINR routing problem is to deliver all the data packets generated by the user nodes to the base station in the most cost-effective (least interfering) manner without exceeding the link capacities. We can find least interfering paths for each user to the base station using the minimum cost (in this case minimum interference) flow optimization framework. Formally, the problem can be stated as follows.

$$\text{minimize} \quad \sum_{(i,j) \in E} SINR_{ij}(t)^{-1} f_{ij}(t) \qquad (5)$$

subject to

$$\sum_{j:(i,j) \in E} f_{ij}(t) - \sum_{j:(j,i) \in E} f_{ji}(t) = d_i(t), \forall i \in V_M \qquad (6)$$

$$\sum_{k:k \in V_N \cup BS} \Big(\sum_{j:(k,j) \in E} f_{kj}(t) - \sum_{j:(j,k) \in E} f_{jk}(t) \Big) = - \sum_{i:i \in V_M} d_i(t) \qquad (7)$$

$$0 \leq f_{ij}(t) \leq u_{ij}(t) \qquad (8)$$

$$f_{ij}(t) \in Z^{+} \qquad (9)$$

In the above formulation, d_i represents the rate at which the data packets are generated at user node i per unit time. The first constraint (Eq. 6) ensures flow conservation at each node. The second constraint (Eq. 7) ensures that the base station receives all the packets generated by all the nodes. The flow of packets on a link must not exceed its capacity and this is ensured by the third constraint (Eq. 8). The fourth constraint (Eq. 9) ensures that the (packet) flow values are integers.

The complexity of the above minimum cost flow problem is derived from [24] and shown to be $\bigcirc(\epsilon^{-2} E(E + V) logP)$ where E is the number of links in the network, V is number of nodes in the network (users plus relays) and P is an integer parameter that specifies the largest cost on the link (largest SINR value).

1) Solution: The above defined problem is similar to the minimum-cost flow problem, known in the operations research literature [25]. We will convert the above problem into the minimum-cost circulation problem as follows.

1) Add a super source x, and a super base station node y, to the graph $G(V, E)$.
2) Add directed links (x, i), connecting the super source x to node i, for all $i \in V_M \cup V_N$. Set costs of these links to 0 and the capacities to d_i.
3) Add directed links (j, y) connecting the base station and relay nodes to the super base station y. Set costs of these links to 0 and the capacities to infinity.
4) Add a directed link (y, x) connecting the super base station y to the super source x. Set the cost of the link (y, x) to $-|V|\beta$ and the capacity to infinity, where β is the minimum of any link cost (lower bound of SINR).
5) The modified graph is defined as $G'(V \cup \{x, y\}, E \cup E')$, where $E' = \{(x, i) : i \in V_N \cup V_M\} \cup \{(j, y) : j \in V_M \cup BS\} \cup \{(y, x)\}$.

The minimum-cost problem shown above is solved using the well-known minimum-cost flow algorithm given in [26]. An advantage of the minimum-cost flow algorithm is the integrality of flows. If all link capacities and expected data rates of nodes are integers, then the minimum-cost flow algorithm can find paths with integral flow values.

2) Analysis of the Solution: The minimum path cost formulation given in Eqs. 5-9 determines the least interfering paths by minimizing the inverse of the SINR values of the links in the network. In addition, it also routes flows such that the link capacities are not violated.

Pushing more flow from x to y will decrease the overall cost of the flow due to the fact that the link from y back to x has sufficiently large negative cost. It is clear that the maximum flow is bounded from above by $F = d_1 + d_2 + ... + d_{|V_M|}$ because F is the maximum possible flow going out of x, the super source. There are two possibilities that have to be analyzed.

Case 1: $\sum_{i:i \in V_M} f_{xi} = \sum_{i:i \in V_M} d_i$

In this case, all the links of the form (x, i), $i \in V_M$ are saturated. The maximum-flow is restricted by the capacities of these links. Consider a link $(x, 1)$ having the capacity d_1. Since all the (x, i) links are saturated, the input flow at node 1 must be $d_1 + \sum_{j:(j,1) \in E} f_{j1}$ and the output flow must be equal to the input flow (flow conservation). There must be paths from node 1 to base stations which carry the flow $d_1 + \sum_{j:(j,1) \in E} f_{j1}$. The same argument holds for other nodes.

Case 2: $\sum_{i:i \in V_M} f_{xi} < \sum_{i:i \in V_M} d_i$

In this case, the maximum flow is restricted by the capacities on the actual links ($(i, j) \in E$) of the network. The minimum cost flow algorithm will identify the paths from the user node i to the base stations which carry the flow d'_i where $0 \le d'_i \le d_i$, $\forall i \in V_M$. The flow on the links (x, i) would be d'_i, $\forall i \in V_M$.

V. Performance Evaluation

A. Simulation Model and Performance Metrics

The LMP prediction algorithm and SINR based routing scheme have been simulated to verify their performance. The LMP prediction engine is first separately tested for accuracy in predicting the future mobility of users. For comparison, we use a generic Markov chain and a second-order Markov chain to gauge the prediction accuracy of the three methods. A second-order Markov chain can be defined as

$$P = P[Relay_{next} | Relay_{current}, Relay_{previous}]$$

When the users make first contact with a relay, there is no history of data from this user that can be utilized, so the initial parameters of the HMM are randomly generated using a uniform distribution (the number and locations of users and relays, relay-user associations and the initial transition probabilities are randomly generated). Once the users begin to move, its movement history is tracked and stored in the databases of each relay for prediction.

To evaluate the LMP algorithm, we look at its prediction accuracy. The prediction accuracy is one of the most important metrics for the verification of any mobility prediction algorithm. Prediction accuracy is defined as the ratio of the number of times a user moves to different relays to the ability of the system to predict the location. For example if node n moves to relay A and then to relay B, and our prediction algorithm predicts correctly that it moved to A but not B, then the prediction accuracy is 50%.

We use NS-2 to simulate our evaluations and use CPLEX to solve the optimization formulation for the minimum cost SINR based routing algorithm. The simulation environment is based on a 2250m x 2250m region with 14 relay nodes, 120 user nodes and one base station. The network environment is simulated using the NS-2 software platform, with the BS located at the center of the environment. The locations of the user nodes are randomly generated and then fixed in place. The propagation loss is modeled using the Rayleigh fading model. The Rayleigh fading model allows us to capture radio propagation signals that are not in the line of sight (i.e., when there are many objects in the environment that scatter the radio signal before it arrives at the receiver). The received power, $P_j(i)(t)$, is calculated according to the radio propagation model at the receiver. For simplicity, the transmission power of each relay node is set to 35dBm and the transmission power of each user is set to 24dBm. We also assume the radio transmission range to be 250m. The noise, η, is calculated as additive white Gaussian noise (AWGN) that is modeled as a Gaussian random variable. The pathloss exponent (LOS/NLOS) is set to 2.35/3.76. The threshold β for the SINR calculation is set to -18dB. The target SINR, for optimal network performance is -12dB. These values are defined specifically for voice data as is discussed in [27]. The standard deviation of the SINR is 0.5dB. With a data transmission rate of 2 Mbps, each run has been executed for 1000 seconds of simulation time. Constant bit rate (CBR) sources transmit UDP-based traffic at 4 packets per second and the data payload of each packet is 512 bytes long. The speed of the user nodes range from 1.5m/s to 5m/s. The simulated networks have 256 subcarriers with a system bandwidth of 2MHz. We also use different observation times, T. All results shown are an average of 20 different simulations.

To evaluate the SINR based routing scheme, we evaluate the following performance metrics:

- Packet Delivery Ratio: ratio of the number of data packets successfully delivered to the destination over the number of data packets sent by the source.
- End-to-End Delay: the average delay for a packet to reach from the source to the BS.
- Routing Overhead: Routing overhead is defined as the number of packet re-transmissions required because of packet drops/losses due to interference.

As benchmarks we compare with two interference aware routing metrics that use SINR as the routing metric, given in [16] and [19].

B. Simulation Results: Localized Mobility Prediction (LMP)

When the user nodes make first contact with a relay node, the initial, randomly generated parameters of the HMM are used. Each network that is simulated has 14 relay nodes (randomly placed), 120 user nodes (randomly placed) and 1 BS.

We first look at the performance of the LMP algorithm for two random users in the network and compare against the

Markov and 2nd-order Markov chains. Fig. 5 and Fig. 6 show the prediction accuracy in percentages for the two users in the network. From these figures we can conclude that the LMP has an advantage in prediction accuracy compared to the Markov and 2nd-order Markov chains. The results also show that the HMM can better adapt to a user's change in movement. In other words, the LMP learns faster than the generic Markov based approaches.

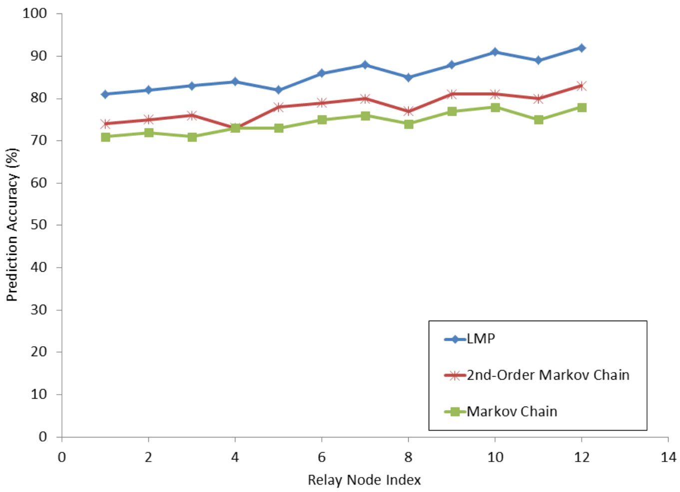


Fig. 5. Comparison of prediction accuracy for the proposed LMP algorithm, generic Markov chain and second-order Markov chain for User Node 1 in networks with 120 users, 14 relay nodes and 1 base station

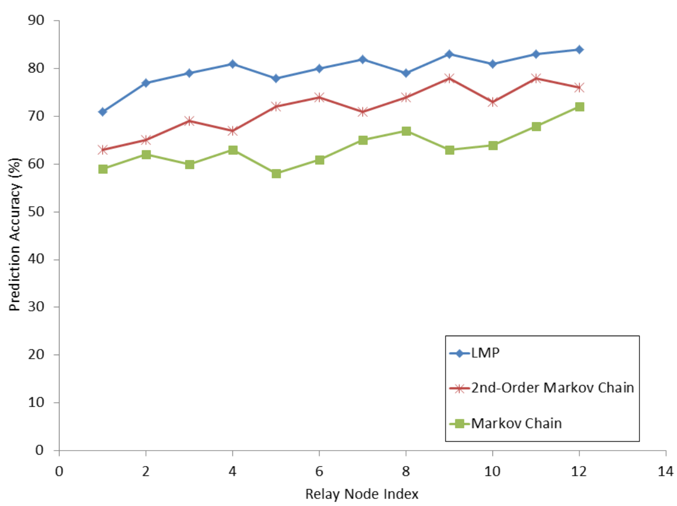


Fig. 6. Comparison of prediction accuracy for the proposed LMP algorithm, generic Markov chain and second-order Markov chain for User Node 2 in networks with 120 users, 14 relay nodes and 1 base station

C. Simulation Results of SINR Based Routing Algorithm

The performance of the SINR routing algorithm is evaluated compared to two SINR based routing algorithms given in [16] and [19]. In [16], an algorithm, 2-HEAR, is developed in which a routing metric is used such that a node calculates the SINR to its neighboring links based on a 2-hop interference range only. In [19], a modified version of the AODV routing algorithm is proposed in which SINR is used to calculate the route quality while using a random waypoint mobility model. We denote the above approaches as 2-HEAR and AODV-INT, respectively, in the simulation graphs. The same networks used in the LMP simulations of Section V-B are used in the simulations of the SINR routing algorithm. To calculate the SINR, we take the following steps.

We first evaluate the packet delivery ratio for our SINR based routing algorithm and its two relevant counterparts in the literature. In Fig. 7 and Fig. 8, the results of the packet delivery ratio for varying node speed and observation times ($T = 10$ms, $T = 1$ms, respectively) are shown. From the results it can be seen that our algorithm provides better packet delivery ratios when compared to the other approaches. We can justify the better performance of our results as follows: In 2-HEAR the SINR calculated by each node only includes those nodes within a 2-hop range which means that even if interference beyond this range occurs, it is not captured in the routing metric. If the interference level is high beyond the 2-hop range, packet drops may occur, requiring re-transmissions.The results of the algorithm from AODV-INT are better than 2-HEAR, however because AODV-INT does not use a specific mobility prediction model, it fails to capture precise interference information as is done in our proposed routing algorithm. It must be noted that the efficiency of the LMP-SINR routing algorithm is decreasing as speed increases (see Figs. 7 and 8). The faster the nodes move, the more likely the channels on which they are transmitting experience greater interference and fading. Thus, if the SINR is low, the efficacy of the LMP-SINR routing algorithm will decrease.

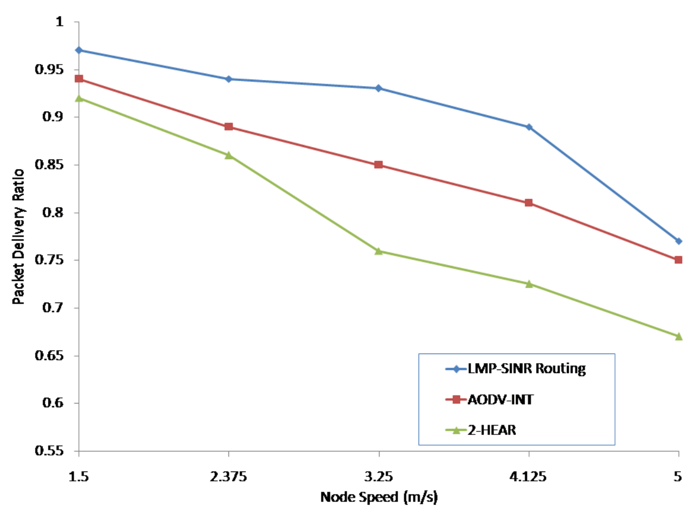


Fig. 7. Packet delivery ratio versus varying node speeds for $T = 10$ms

In addition, we also look at the effect of varying the observation time against the packet delivery ratio and show that with increasing T, the packet delivery ratio increases. The results are shown in Fig. 9, in which node speed is kept

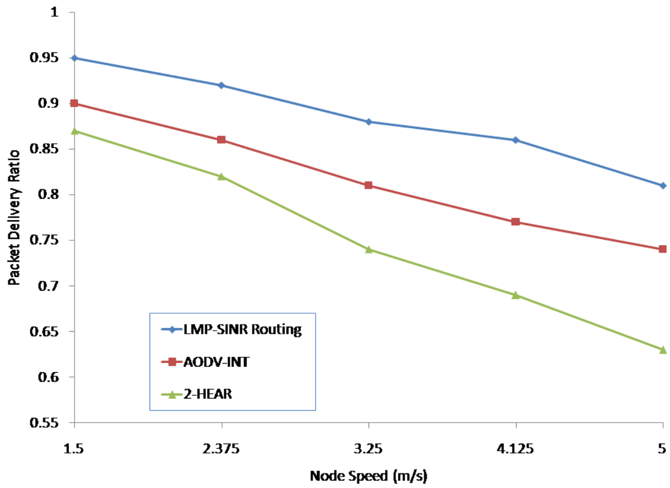


Fig. 8. Packet delivery ratio versus varying node speeds for $T = 1$ms

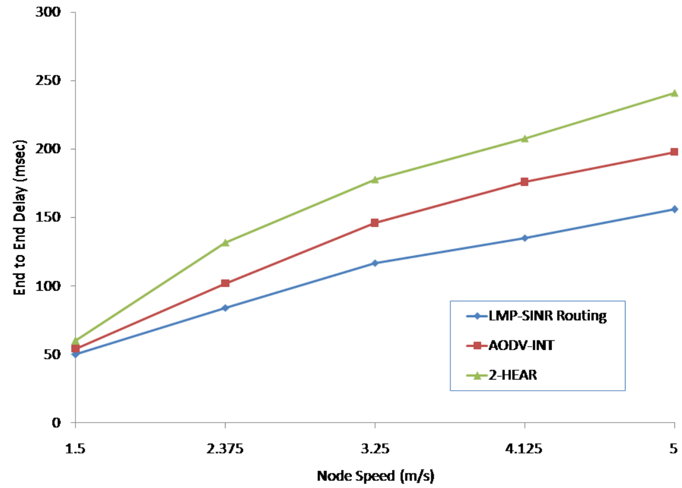


Fig. 10. End-to-end delay for $T = 1$ms and varying node speed

constant at 3m/s. This intuitively makes sense because T is essentially the amount of time used to observe the mobility of a node. The larger the value of T, the longer the LMP has to gather information leading to more accurate SINR calculation. This ultimately leads to better routes (less interference) and increases packet delivery ratios. This can also be seen in Figs. 7 and 8 in which packet delivery ratios are higher with $T = 10ms$.

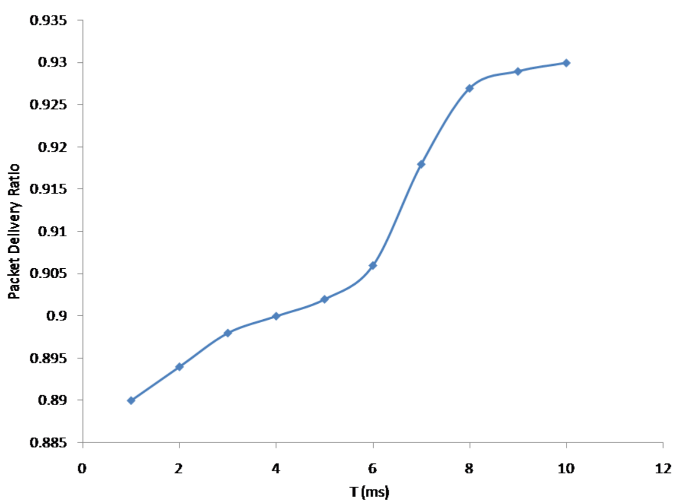


Fig. 9. Effect of varying T values on packet delivery ratio

We next evaluate the end-to-end delay of our algorithm for varying node speeds and $T = 1ms$. The results are shown in Fig. 10. The average end-to-end delay is improved compared to 2-HEAR and AODV-INT mainly due to more robust routes and less route discoveries. Note that the more reliable routes in our scheme significantly reduce the number of route discoveries and re-transmissions. This explanation also holds for the routing overhead produced by our proposed routing algorithm and that of 2-HEAR and AODV-INT. The routing overhead measured in this paper is that of how many packet re-transmissions are required when a routing path fails due to increased interference. The routing overhead is a measure of the number of data re-transmissions required per connection between a transmitter and receiver. Our calculation of interference is significantly more robust and inclusive than that of 2-HEAR and AODV-INT. Thus, the paths determined using our scheme are much more reliable, thereby indicating that the transmissions will be successful more often, requiring fewer re-transmissions of data. The results of the routing overhead, shown in Fig. 11, illustrate that the overhead of our scheme is less than that of the other two benchmarks.

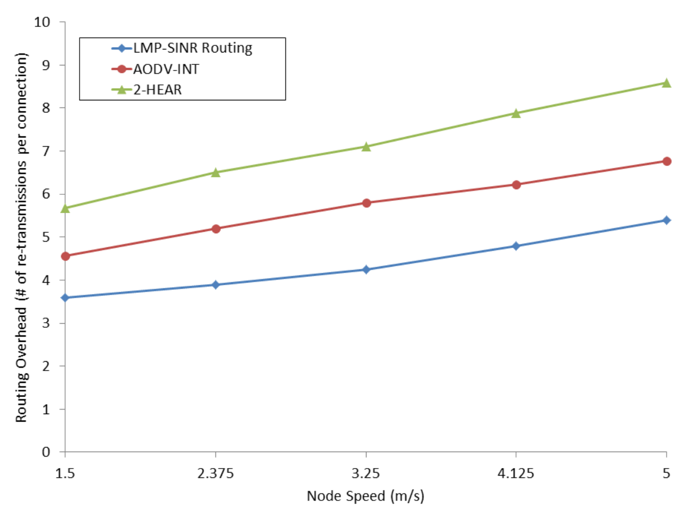


Fig. 11. Routing overhead for $T = 1$ms and varying node speed

Lastly, we look at the ability of our routing algorithm to scale to larger networks. The simulations shown in this paper were performed on networks with 120 user nodes and 14 relay nodes. When the algorithm is simulated on networks with 200 nodes or more, we found that the algorithm takes an inordinate amount of time to converge. The primary reason for this is the time it takes to solve the minimum cost optimization formulation given in Eqs. 5-9. The running time of the optimization formulation, which is a function of the number of links and nodes in the network, does not scale to large networks. Thus, the performance improvement we see in terms of packet delivery ratio and end-to-end delay is a tradeoff for scalability.

VI. Conclusion

Mobility and wireless interference jointly influence the performance of wireless networks. In this paper we first developed a localized mobility prediction (LMP) algorithm using a Hidden Markov Model (HMM) for multihomed wireless networks. The mobility of each user is governed locally by individual home relays that capture and store mobility information. We then developed an interference aware routing algorithm using SINR as the routing metric, in which least interfering paths between each user and base station are found. In order to take into consideration the mobility of the user nodes within the routing algorithm, we use the LMP as input to the routing algorithm to predict the location of a user at time t. This predicted location is then used to proactively determine the SINR on each individual link. We formulated and solved the routing algorithm using a minimum cost (in our case minimum interference) flow optimization technique such that the link capacities are not violated. We showed that our LMP algorithm provides better prediction accuracy when compared to conventional Markov based mobility predictors. We also show that our SINR based routing algorithm guarantees minimum interference paths by increasing the packet delivery ratio and reducing latency compared to established SINR based routing approaches in the literature. In our future work, we plan to integrate the mobility of relay nodes to analyze the impact of SINR induced interference on routing and overall network performance.

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References

[1] P. Thulasiraman, "Mobility aware routing for multihomed wireless networks under interference constraints," in *Proceedings of International Conference on Emerging Network Intelligence (EMERGING)*, 2011, pp. 57–62.

[2] Y.-D. Lin and Y.-C. Hsu, "Multihop cellular: a new architecture for wireless communications," in *Proceedings of IEEE INFOCOM*, 2000, pp. 1273–1282.

[3] X.J. Li, B.-C. Seet, and P.H.J. Chong, "Multihop cellular networks: Technology and economics," *Computer Networks (Elsevier)*, vol. 52, no. 9, pp. 1825–1837, June 2008.

[4] Y. Li, D.-W. Kum, W.-K. Seo, and Y.-Z Cho, "A multihoming support scheme with localized shim protocol in proxy mobile ipv6," in *Proceedings of IEEE ICC*, 2009, pp. 1–5.

[5] P. Thulasiraman, S. Ramasubramanian, and M. Krunz, "Disjoint multipath routing to two distinct drains in a multi-drain sensor network," in *Proceedings of IEEE INFOCOM*, 2007, pp. 643–651.

[6] Y. Amir, C. Danilov, R. Musaloiu-Elefteri, and N. Rivera, "An interdomain routing protocol for multi-homed wireless mesh networks," in *Proceedings of IEEE WoWMoM*, 2007, pp. 1–10.

[7] P.S. Prasad and P. Agrawal, "Movement prediction in wireless networks using mobility traces," in *Proceedings of IEEE CCNC*, 2010, pp. 1–5.

[8] P.S. Prasad and P. Agrawal, "Mobility prediction for wireless network resource management," in *Proceedings of IEEE SSST*, 2009, pp. 98–102.

[9] W. Cui and X. Shen, "User movement tendency prediction and call admission control for cellular networks," in *Proceedings of IEEE ICC*, 2000, pp. 670–674.

[10] W.-S. Soh and H.S. Kim, "Dynamic bandwidth reservation in cellular networks using road topology based mobility prediction," in *Proceedings of IEEE INFOCOM*, 2004, pp. 2766–2777.

[11] H. Si, Y. Wang, J. Yuan, and X. Shan, "Mobility prediction in cellular network using hidden markov model," in *Proceedings of IEEE CCNC*, 2010, pp. 1–5.

[12] R. Langer, N. Bouabdallah, and R. Boutaba, "Mobility-aware clustering algorithms with interference constraints in wireless mesh networks," *Computer Networks*, vol. 53, no. 1, pp. 25–44, January 2009.

[13] L. Badia, N. Bui, M. Miozzo, M. Rossi, and M. Zorzi, "Mobility-aided routing in multi-hop heterogeneous networks with group mobility," in *Proceedings of IEEE GLOBECOM*, 2007, pp. 4915–4919.

[14] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Efficient routing in intermittently connected mobile networks: the multiple-copy case," *IEEE/ACM Transactions on Networking*, vol. 16, no. 1, pp. 77–90, February 2008.

[15] A. Iyer, C. Rosenberg, and A. Karnik, "What is the right model for wireless channel interference?," *IEEE Transactions on Wireless Communications*, vol. 8, no. 5, pp. 2662–2671, May 2009.

[16] R.M. Kortebi, Y. Gourhant, and N. Agoulmine, "On the use of sinr for interference-aware routing in wireless multi-hop networks," in *Proceedings of ACM MSWiM*, 2007, pp. 395–399.

[17] S. Kwon and N.B. Schroff, "Energy-efficient sinr-based routing for multihop wireless networks," *IEEE Transactions on Mobile Computing*, vol. 8, no. 5, May 2009.

[18] P. Thulasiraman, J. Chen, and X. Shen, "Multipath routing and max-min fair qos provisioning under interference constraints in wireless multihop networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 22, no. 5, pp. 716–728, March 2011.

[19] J. Park, S. Moh, and I. Chung, "A multipath aodv routing protocol in mobile ad hoc networks with sinr-based route selection," in *Proceedings of IEEE International Symposium on Wireless Communication Systems (ISWCS)*, 2008, pp. 682–686.

[20] W. H. Park and S. Bahk, "Resource management policies for fixed relays in cellular networks," *Elsevier Computer Communications*, vol. 32, no. 34, pp. 703–711, March 2009.

[21] R.C. Ramos and L.F.G. Perez, "Quasi mobile ip-based architecture for seamless interworking between wlan and gprs networks," in *Proceedings of IEEE Conferences on Electrical and Electronics Engineering (CIE)*, 2005, pp. 455–458.

[22] S.-Z. Yu and H. Kobayashi, "Practical implementation of an efficient forward-backward algorithm for an explicit-duration hidden markov model," *IEEE Transactions on Signal Processing*, vol. 54, no. 5, pp. 1947–1951, May 2006.

[23] W. Turin, *Digital Transmission Systems*, McGraw Hill, 1998.

[24] L.K. Fleischer, "Approximating fractional multicommodity flow independent of the number of commodities," *SIAM Journal of Discrete Mathematics*, vol. 13, no. 4, pp. 505–520, October 2000.

[25] R. Ahuja, T. Magnanti, and J. Orlin, *Network Flows*, Prentice Hall, 1993.

[26] J. Orlin, "A faster strongly polynomial minimum cost flow algorithm," *Operations Research*, vol. 41, no. 2, pp. 338–350, 1993.

[27] M. El-Sayes and M.H. Ahmed, "An upper bound on sinr threshold for call admission control in multiple-class cdma systems with imperfect power-control," in *Proceddings of IEEE VTC-Spring*, 2007, pp. 2817–2821.