# Wireless Mesh Network Routing Under Uncertain Demands

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**Abstract** Traffic routing plays a critical role in determining the performance of a wireless mesh network. Recent research results usually fall into two ends of the spectrum. On one end are the heuristic routing algorithms, which are highly adaptive to the dynamic environments of wireless networks yet lack the analytical properties of how well the network performs globally. On the other end are the optimal routing algorithms that are derived from the optimization problem formulation of mesh network routing. They can usually claim analytical properties such as resource utilization optimality and throughput fairness. However, traffic demand is usually implicitly assumed as static and known a priori in these problem formulations. In contrast, recent studies of wireless network traces show that the traffic demand, even being aggregated at access points, is highly dynamic and hard to estimate. Thus, in order to apply the optimization-based routing solution in practice, one must take into account the dynamic and uncertain nature of wireless traffic demand. There are two basic approaches to address the traffic uncertainty in optimal mesh network routing: (1) predictive routing which infers the traffic demand with maximum possibility based in its history and optimizes the routing strategy based on the predicted traffic demand and (2) oblivious routing which considers all the possible traffic demands and selects the routing strategy where the worst-case network performance could be optimized. This chapter provides an overview of the optimal routing strategies for wireless mesh networks with a focus on the above two strategies that explicitly consider the traffic uncertainty. It also identifies the key factors that affect the performance of each routing strategy and provides guidelines towards the strategy selection in mesh network routing under uncertain traffic demands.

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# 1 Introduction

Wireless mesh networks (*e.g.*, [5, 4]) which now offer a rapid and inexpensive solution to last-mile broadband Internet access, are attracting ever greater attention and widespread deployment. A wireless mesh network is composed of local access points and wireless mesh routers which form an organic backbone structure which forwards traffic between mobile clients and the Internet.

Traffic routing plays a critical role in determining the performance of a wireless mesh network. Thus it has attracted extensive recent research. The key challenges come from the scarce wireless channel resource, high dynamic link quality, and the uncertain traffic demands. The proposed approaches address these challenges in different ways. On one end of the spectrum are the heuristic algorithms (*e.g.*, [11, 8, 17, 13]). Although many of them are adaptive to the dynamic environments of wireless networks, these algorithms lack the analytical properties of how well the network performs globally (*e.g.*, whether the scarce channel resource is shared in an optimal and fair fashion). On the other end of the spectrum, there are theoretical studies that formulate mesh network routing as optimization problems (*e.g.*, [6, 18]). The routing algorithms derived from these optimization formulations can usually claim analytical properties such as resource utilization optimality and throughput fairness. In these optimization frameworks, traffic demand is usually implicitly assumed as static and known *a priori*. Recent studies of wireless network traces [16], however, show that the traffic demand, even being aggregated at access points, is highly dynamic and hard to estimate. Such observations have significantly challenged the practicability of the existing optimization-based routing solutions in wireless mesh networks.

There are two basic approaches to address the traffic uncertainty in optimal mesh network routing:

- *Predictive routing [10, 9]*, which infers the traffic demand with maximum probability based in its history and optimizes the routing strategy based on the predicted traffic demand. Underlying predictive routing is the assumption that past behavior is a good indicator of the future.
- *Oblivious routing [20]*, which makes no assumption on traffic demand and considers all the possible traffic demands and selects the routing strategy where the worst-case network performance is optimized.

This chapter provides an overview of optimal routing algorithms for wireless mesh networks: optimal routing under fixed demand, predictive routing, and oblivious routing. It focuses on the latter two routing strategies and show how they explicitly consider the traffic uncertainty in their problem formulation and algorithm design. In this chapter, we also identify the key factors that affect the performance of each routing strategy and provide guidelines towards the strategy selection in mesh network routing under uncertain traffic demands.

The remainder of this chapter is organized as follows. Sec. 3 presents the network and system model. Sec. 4 reviews the background knowledge, *i.e.*, the optimal routing algorithm under fixed demand. Sec. 5 presents the predictive mesh network routing strategy. Sec. 6 presents the oblivious mesh network routing formulation and algorithm. Sec. 7 evaluates and compares the performance of different routing strategies. Sec. 8 and Sec. 9 provide thoughts for practitioners and the directions for future research. Finally, Sec. 10 concludes the chapter.

## 2 Terminology and Definitions

Some of the most important terms in this chapter are defined below.

**Transmission Range** *The upper limit of the distance between two routers such that messages are intelligible between them.*

**Interference Range** *The upper limit of the distance between two routers such that their messages collide when sent on the same channel at the same time. The interference range is always at least as large as the transmission range.*

**Wireless Mesh Network** *A set of interconnected nodes which aggregate and route traffic to and from end users and the Internet. A WMN is often two-tiered, consisting of a backbone with hard links to the Internet and a mesh of routers that extend the reach of the network. WMNs can be used to extend the last-mile of Internet access in rural areas or provide a cost-effective solution in urban areas.*

**Interference Set** *The Interference Set of an edge $e$ is the set of other edges which it interferes with. One or both of the endpoints for an edge in the interference set of $e$ is within the interference range of one of $e$'s endpoints.*

**Channel** *A section of the radio spectrum that a router can be configured to broadcast on.*

**Radio** *A component of a wireless router which can broadcast on one channel. Routers often have several radios.*

**Routing** *A full set of pathways in a graph which specify the exact routes by which all traffic flows between any two nodes.*

**Wireless Routing** *A routing in a wireless network, which includes additional information to accommodate channels. Such information may include channel assignments and scheduling*

**Oblivious Routing** *A routing system that takes no account of the actual demands on a network. Note that such a routing is static even as demand changes over time.*

**Predictive Routing** *A routing system that attempts to extrapolate future routing demands and plan the network flows accordingly. This can perform well, if the traffic is regular in which case it approaches the optimal routing, or it can perform poorly if subsequent demands are near the worst-case for the routing chosen by the algorithm.*

## 3 Model

### *3.1 Network and Interference Model*

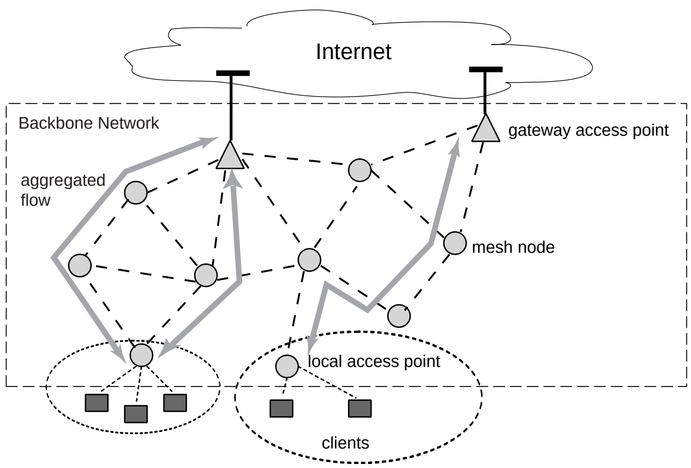



**Fig. 1** Illustration of Wireless Mesh Network

In a multi-hop wireless mesh network, local access points aggregate and forward traffic for the mobile clients which are associated with them. They communicate with each other and with the stationary wireless routers to form a multi-hop *backbone* network, which forwards the user traffic to the Internet gateways. Fig. 1 shows an example of wireless mesh network. We use $w \in W$ to denote the set of gateways in the network and $s \in S$ to denote the set of local access points that generate traffic in the network. Local access points, gateways and mesh routers are collectively called mesh nodes and denoted by the set $V$.

In a wireless network, packet transmissions are subject to location-dependent interference. Here we consider the *protocol model* presented in [12]. We assume that all mesh nodes have the uniform transmission range denoted by $R_T$. Usually the interference range is larger than its transmission range, which is denoted as $R_I = (1+\Delta)R_T$, where $\Delta \geq 0$ is a constant. For simplicity, in this chapter we

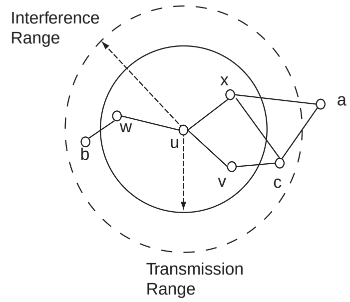



**Fig. 2** Transmission and Interference Range

assume that each node is equipped with one radio interface which operates on the same wireless channel as others. Let $r(u, v)$ be the distance between two nodes $u$ and $v$ ($u, v \in V$). In the protocol model, packet transmission from node $u$ to $v$ is successful, if and only if (1) the distance between these two nodes $r(u, v)$ satisfies $r(u, v) \leq R_T$; (2) any other node $x \in V$ within the interference range of the receiving node $v$, *i.e.*, $r(x, v) \leq R_I$, is not transmitting. If node $u$ can transmit to $v$ directly, they form an edge $e = (u, v)$. As an example shown in Fig.2, nodes $w, x, v$ are within the transmission range of node $u$, thus they can transmit the node $u$ directly. At the same time, nodes $w, v, x, b, c$ are all within the interference range of node $u$, which means the signal from node $u$ could be heard by any node of $w, v, x, b, c$, and vice versa. Thus they must be silenced, if they are not the intended sender, when $u$ is receiving a packet.

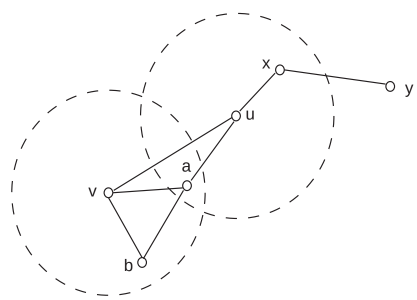



**Fig. 3** Interference Set

We assume that the maximum data rate that can be transmitted along an edge is the same for all edges, and denote it as $c$ (also called the channel capacity). Let $E$ be the set of all edges. We say two edges $e, e'$ interfere with each other, if they can not transmit simultaneously based on the protocol model. Further we define *interference set* $I(e)$ which contains the edges that interfere with edge $e$ and $e$ itself. Fig. 3 is an illustration of the interference set of edge $(u, v)$. The circles are the interference ranges of node $u$ and $v$, and the union of these two circles is the interference range of edge $(u, v)$. So the interference set $I(u, v)$ of edge $(u, v)$ includes $(u, v)$, $(a, b)$, $(v, b)$, $(v, a)$, $(a, u)$, $(x, u)$ and $(x, y)$.

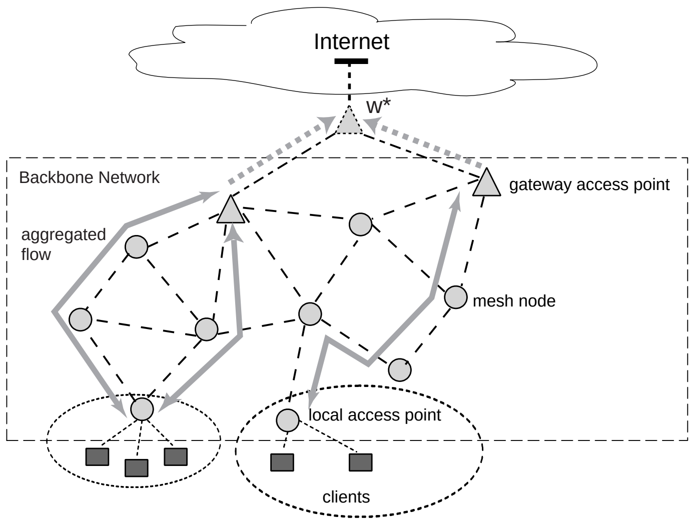



**Fig. 4** Illustration of Virtual Node

Finally, we introduce a virtual node $w^*$ to represent the Internet, as shown in Fig. 4. $w^*$ is connected to each gateway with a virtual edge $e^* = (w^*, w), w \in W$. Further, let $E' = E \cup \{e^*\}$ and $V' = V \cup \{w^*\}$. For simplicity, we assume that the link capacity in the Internet is much larger than the wireless channel capacity, and thus the bottleneck always appears in the wireless mesh network. Under this assumption, the virtual edges could be regarded as having unlimited capacity, and they do not interfere with any of the wireless transmissions.

## 3.2 Traffic Model and Schedulability

This chapter studies the routing strategies for wireless mesh *backbone* networks. Thus it only considers the aggregated traffic between the local access points and the Internet gateways. Here we call the aggregated traffic in (or out) a local access point a *flow* and denote it as $f \in F$, where $F$ is the set of all aggregated flows. All flows will take $w^*$ as their source (or destination). We denote the traffic demand of flow $f$ as $d_f$ and use vector $\boldsymbol{d} = (d_f, f \in F)$ to denote the demand vector consisting of all flow demands.

Now we proceed to study the constraint of the flow rates. Let $\boldsymbol{y} = (y(e), e \in E)$ denote the edge rate vector, where $y(e)$ is the aggregated flow rate along $e$. Edge rate vector $\boldsymbol{y}$ is said to be schedulable, if there exists a stable schedule that ensures every packet transmission with a bounded delay. Essentially, the constraint of the flow rates is defined by the schedulable region of the edge rate vector $\boldsymbol{y}$.

The edge rate schedulability problem has been studied in several existing works, which lead to different models [14, 15, 21]. In this chapter, we adopt the model in [15], which is also extended in [6] for multi-radio, multi-channel mesh network. In particular, [15] presents a sufficient condition under which an edge scheduling algorithm is given to achieve stability with bounded and fast approximation of an ideal schedule. [6] presents a scheme that can adjusts the flow routes and scale the flow rates to yield a feasible routing and channel assignment. Based on these results, we have the following claim as a sufficient condition for schedulability.

**Claim 1.** (*Sufficient Condition of Schedulability*) The edge rate vector $\boldsymbol{y}$ is schedulable *if* the following condition is satisfied:

$$\forall e \in E, \sum_{e' \in I(e)} y(e') \leq c \tag{1}$$

## 4 Background

This section provides the background of optimal mesh network routing, introduces its problem formulations, and reviews its algorithm under fixed traffic demand.

The existing works on optimal multihop wireless network routing [6, 18, 14] usually formulate it as a throughput optimization problem which maximizes the flow throughput, while satisfying the fairness constraints. In this formulation, traffic demand is fixed and reflected as the flow weight in the fairness constraints. Recall that $f \in F$ is the aggregated traffic flow between the local access points and the virtual gateway (*i.e.*, Internet) and $\boldsymbol{d} = (d_f, f \in F)$ is the demand vector consisting of all flow demands. Consider the fairness constraint that, for each flow $f$, its throughput being routed is in proportion to its demand $d_f$. The goal of throughput maximization routing is to maximize $\lambda$ (so called *scaling factor*) where at least $\lambda \cdot d_f$ amount of throughput can be routed for flow $f$.

To balance the traffic load, flow $f$ could be routed over multiple paths, let $\mathcal{P}_f$ be the set of unicast paths that could route flow $f$, and $x_f(P)$ be the rate of flow $f$ over path $P \in \mathcal{P}_f$. Obviously the aggregated flow rate $y_e$ along edge $e \in E$ is given by $y_e = \sum_{f:P \in \mathcal{P}_f \& e \in P} x_f(P)$, which is the sum of the flow rates that are routed through paths $P$ passing edge $e$. Based on the sufficient condition of schedulability in Claim 1 (Eq.(1)), we have that

$$\sum_{e' \in I_e} \sum_{f:P \in \mathcal{P}_f \& e' \in P} x_f(P) \leq c \tag{2}$$

To simplify the above equation, we define $A_{eP} = |I_e \cap P|$ as the number of wireless links path $P$ passes in the interference set $I_e$. The throughput optimization routing with fairness constraint is then formulated as the following linear programming (LP) problem:

$$\mathbf{P_T} : \text{maximize } \lambda \tag{3}$$

$$\text{subject to} \sum_{P \in \mathcal{P}_f} x_f(P) \geq \lambda \cdot d_f, \forall f \in F \tag{4}$$

$$\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x_f(P) A_{eP} \leq c, \forall e \in E \tag{5}$$

$$\lambda \geq 0, x_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \tag{6}$$

In this problem, the optimization objective is to maximize $\lambda$, such that at least $\lambda \cdot d_f$ units of data can be routed for each aggregated flow $f$ with demand $d_f$. Inequality (4) enforces fairness by requiring that the comparative ratio of traffic routed for different flows satisfies the comparative ratio of their demands. Inequality (5) enforces the capacity constraint by requiring the traffic aggregation of all flows passing wireless link $e \in E$ satisfy the sufficient condition of schedulability. This problem formulation follows the classical maximum concurrent flow problem.

While the above throughput maximization routing problem formulation is widely used in designing optimal mesh network routing strategies under known demands, it is not suitable to study the routing performance under dynamic and uncertain traffic demand. Here we consider a formulation based on another routing performance metric – network *congestion* (or *utilization*). In the Internet, *link utilization* is commonly used for traffic engineering [19], whose objective is to minimize the utilization at the most congested link under given traffic demand. However, link utilization can not be straightforwardly applied to multihop wireless networks, such as mesh backbone network, as a metric of routing performance due to the location-dependent interference. In what follows, we define the *network congestion based on the utilization of the interference set* as the routing performance metric and outline the relation between the formulation of the throughput optimization problem and the congestion minimization problem.

Let $x'_f(P)$ be the rate of flow $f$ on path $P$ under traffic demand $d_f$. It is obvious that $\sum_{P \in P_f} x'_f(P) = d_f$. The traffic being routed within the interference set $I_e$ is then given by $\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP}$. Formally, the *congestion* of an interference set $I_e$ is defined as its *utilization* (*i.e.,* the ratio between its load and the channel capacity) and denote it as $\theta_e$:

$$\theta_e = \frac{\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP}}{c} \tag{7}$$

Further, the *network congestion* is defined as the maximum congestion among all the interference sets, *i.e.,*

$$\theta = \max_{e \in E} \theta_e \tag{8}$$

The network congestion minimization routing problem is then formulated as follows:

$$\mathbf{P_C} : \text{minimize } \theta \tag{9}$$
$$\text{subject to} \sum_{P \in \mathcal{P}_f} x'_f(P) \geq d_f, \forall f \in F \tag{10}$$
$$\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP} \leq c \cdot \theta, \forall e \in E \tag{11}$$
$$\theta \geq 0, x'_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \tag{12}$$

To reveal the relation between $\mathbf{P_T}$ and $\mathbf{P_C}$, we let $\theta = \frac{1}{\lambda}$ and $x'_f(p) = \frac{x_f(p)}{\lambda}$. Problem $\mathbf{P_C}$ is then transformed to:

$$\mathbf{P'_C} : \text{minimize } \frac{1}{\lambda} \tag{13}$$
$$\text{subject to } \frac{1}{\lambda} \sum_{P \in \mathcal{P}_f} x_f(P) \geq d_f, \forall f \in F \tag{14}$$
$$\frac{1}{\lambda} \sum_{f \in F} \sum_{P \in \mathcal{P}_f} x'_f(P) A_{eP} \leq c \cdot \theta, \forall e \in E \tag{15}$$
$$\lambda \geq 0, x'_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \tag{16}$$

which is obviously equivalent to the throughput optimization problem $\mathbf{P_T}$.

If the demand vector $\boldsymbol{d}$ is known, both problem $\mathbf{P_T}$ and $\mathbf{P_C}$ could be solved by a LP-solver such as [2, 3]. To reduce the complexity for practical use, the work of [10] also presents a fully polynomial time approximation algorithm for problem $\mathbf{P}_T$, which finds an $\epsilon$-approximate solution. The key to a fast approximation algorithm lies on the dual of this problem, which is formulated as follows. First we assign a price $\mu_e$ to each set $S_e$ for $e \in E$. The objective is to minimize the aggregated price for all interference sets. As the constraint, Inequality (18) requires that the price $\sum_{e \in E} A_{eP} \mu_e$ of any path $P \in \mathcal{P}_f$ for flow $f$ must be at least $\mu_f$, the price of flow $f$. Further, Inequality (19) requires that the weighted flow price $\mu_f$ over its demand $d_f$ must be at least 1.

$$\mathbf{D_T} : \text{minimize} \sum_{e \in E} c \cdot \mu_e \tag{17}$$
$$\text{subject to} \sum_{e \in E} A_{eP} \mu_e \geq \mu_f, \forall f \in F, \forall P \in \mathcal{P}_f \tag{18}$$
$$\sum_{f \in F} \mu_f d_f \geq 1 \tag{19}$$

Based on the above dual problem $\mathbf{D_T}$, the fast approximation algorithm is presented in Table 1. The properties of this algorithm are shown as follows.

**Mesh Network Routing Under Fixed Demand**

$\forall e \in E, \mu_e \leftarrow \beta/c$
$x_f(P) \leftarrow 0, \forall P \in \mathcal{P}_f, \forall f \in F$
**while** $\sum_{e \in E} c \cdot \mu_e < 1$
  **for** $\forall f \in F$ **do**
    $d'_f \leftarrow d_f$
    **while** $\sum_{e \in E} c \cdot \mu_e < 1$ **and** $d'_f > 0$ **do**
      $P \leftarrow$ lowest priced path in $\mathcal{P}_f$ using $\mu_e$
      $\delta \leftarrow \min\{d'_f, \min_{e \in P} A_{eP}\}$
      $d'_f \leftarrow d'_f - \delta$
      $x_f(P) \leftarrow x_f(P) + \delta$
      $\forall e$ s.t. $A_{eP} \neq 0$, $\mu_e \leftarrow \mu_e(1 + \epsilon\delta A_{eP})$
    **end while**
  **end for**
**end for**

**Table 1** Routing Algorithm Under Fixed Demand

**Property**: If $\beta = (|E|/(1-\epsilon))^{-1/\epsilon}$, then the final flow generated by **FMR** is at least $(1-3\epsilon)$ times the optimal value of $\mathbf{P}$. The running time is $O(\frac{1}{\epsilon^2}[\log |E|(2|F| \log |F| + |E|) + \log U)]) \cdot T_{mp}$, where $U$ is the length of the longest path in $G$, and $T_{mp}$ is the running time to find the shortest path.

## 5 Predictive Mesh Network Routing

The predictive mesh network routing is based on a two-tier framework as shown in Fig. 5, which integrates traffic modelling and routing optimization.

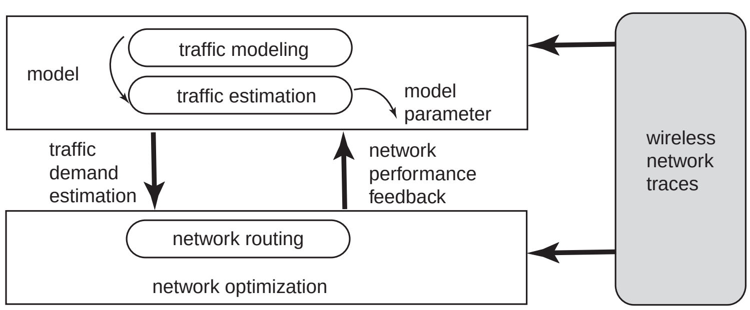



**Fig. 5** Integrated Framework of Traffic Modelling and Network Optimization.

- *Traffic modelling* derives the traffic model of a wireless mesh network. The model should be dependable at characterizing the long term traffic demand, yet agile at containing the uncertain traffic dynamics in the short term. The traffic modelling component needs to produce traffic demand estimations as inputs to the network optimization component.

- *Routing optimization* determines the routing strategy which distributes the traffic along different routes so that minimum congestion will be incurred even under dynamic traffic. To achieve this goal, the routing optimization decision should effectively take into account the traffic demand estimation results from the traffic modelling component.

## *5.1 Traffic Prediction*

First we study the dynamic behavior of aggregated traffic at access points. Our goal is to (1) develop a reliable prediction method that is able to estimate the aggregated traffic demand of an access point based on its historical data, and (2) develop a statistical model to characterize the prediction errors. The predicted traffic demand will serve as the input of predictive mesh network routing algorithms which will be presented in the next section.

In order to develop such a traffic demand model, we study the traces collected at the campus wireless LAN network of Dartmouth College in Spring 2002 [1]. By analyzing the *snmp* log from each access point, we derive the dynamic behavior of aggregated traffic demand. To illustrate our analysis procedure, we choose one of the access points (ResBldg97AP3) as an example. The time series of its incoming traffic is plotted in Fig. 6. From the figure, we can easily observe that (1) the traffic demand is non-stationary over large time scales due to the diurnal and weekly working cycles; (2) compared with the traffic behavior in the backbone Internet [19], the traffic at an access point is significantly bursty due to the insufficient level of multiplexing. The above observations are consistent with the findings in [16].

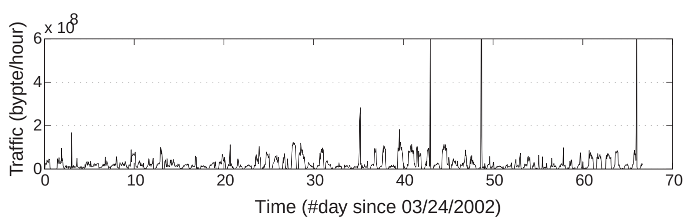
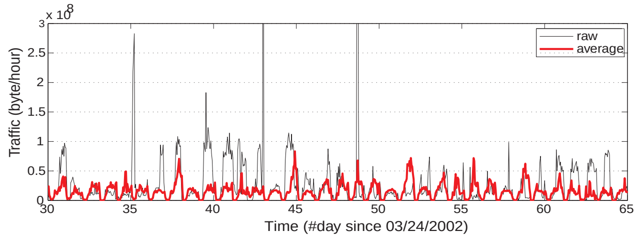
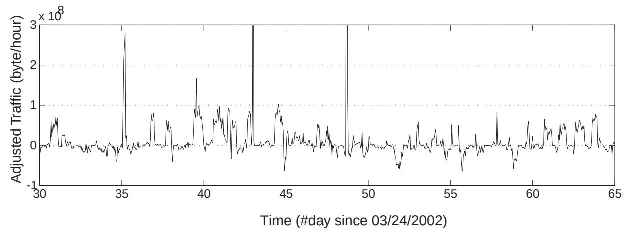



**Fig. 6** Incoming Traffic Time Series of ResBldg97AP3 (March 24, 11pm, 2002 - June 9, 10pm, 2002).

The first step of our analysis is to identify and remove the daily and weekly cyclic patterns in the time series. This requires us to calculate the weekly/daily cyclic average. Formally, let us denote $x(t)$ as the *raw traffic series*. We estimate the moving average of this series based on the same time of the same day of the week, *i.e.*,




(a) Raw Traffic vs. Moving Average Series




(b) Adjusted Traffic Series

**Fig. 7** Traffic Series in 5 weeks

$$\bar{x}(t) = \sum_{i=1}^{W} x(t - 24 \times 7 \times i)/W \tag{20}$$

where $W$ is the size of moving window. To eliminate the effect of bursty traffic, we also filter out the spike traffic during the above averaging procedure. Fig. 7(a) plots the raw traffic as well as its moving average with $W = 5$. By removing the cyclic effect from the raw data, we derive the *adjusted traffic series* $y(t)$ as follows.

$$y(t) = x(t) - \bar{x}(t) \tag{21}$$

The adjusted series of the one shown in Fig. 7(a) is given in Fig. 7(b). This adjusted traffic exhibits short-term (a few hours) traffic correlations. We model the adjusted traffic series with an autoregressive process as follows[1].

$$y(t) = \beta_1 y(t-1) + \beta_2 y(t-2) + ... + \beta_K y(t-K) + \epsilon \tag{22}$$

where $K$ is the process order. To apply this model for prediction, we estimate the parameters of this process. Given $N$ observations $y_1, y_2, ..., y_N$, the parameters $\beta_1$, ..., $\beta_K$ are estimated via least squares by minimizing:

$$\sum_{t=K+1}^{N} \left[y(t) - \beta_1 y(t-1) ... - \beta_K y(t-K)\right]^2 \tag{23}$$

[1] Ideally, $y(t)$ should have zero mean. In some cases, $y(t)$ has a small mean value which needs to be removed before fitting an autoregressive process.

Based on these parameters, we further derive the adjusted traffic prediction $\hat{y}(t)$ as follows:

$$\hat{y}(t) = \beta_1 y(t-1) + \beta_2 y(t-2) + ... + \beta_K y(t-K) \quad (24)$$

Fig. 8 illustrates the estimation results for the adjusted traffic series in Fig. 7(b), where $K = 2$, $\beta_1 = 0.531$, $\beta_2 = 0.469$. The figure plots the predicted series for the adjusted traffic as well as its raw data. In this figure, the number of observations used for parameter estimation is $N = 60$. The fitted traffic series is also plotted for the interval $[720, 779]$ hour for the purpose of comparison.

We now consider the errors involved in this prediction process. In particular, we define the adjusted traffic prediction error as follows.

$$\epsilon_y(t) = y(t) - \hat{y}(t) \quad (25)$$

Based on this definition, Fig. 9(a) plots the cumulative distribution function of the prediction error of the adjusted traffic series shown in Fig. 8. It is obvious that the error distribution follows normal distribution with a mean close to zero.

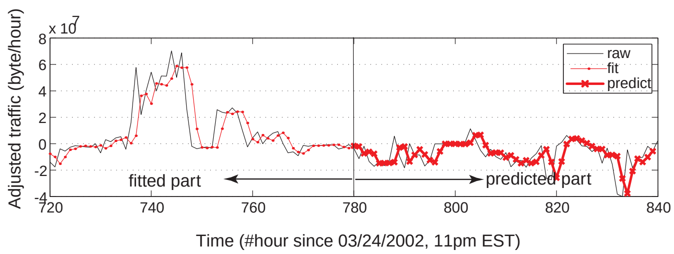



**Fig. 8** Adjusted Traffic and Its Prediction

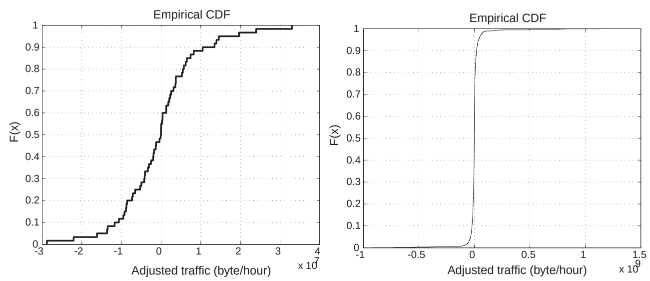
Finally, we define traffic prediction $\hat{x}$ as follows:

$$\hat{x}(t) = [\bar{x}(t) + \hat{y}]^+ \quad (26)$$

Fig. 10 plots the predicted traffic series $\hat{x}(t)$ in comparison with the raw traffic. We can see the predicted traffic closely matches the real(raw) traffic. The cumulative distribution function of the prediction error $\epsilon_x(t)$, which is defined as $\epsilon_x(t) = x(t) - \hat{x}(t)$, is plotted in Fig. 9(b). It clearly shows that this distribution also follows normal distribution with a near-zero mean.

Thus we could consider the traffic demand at time $t$ as a random variable $X(t)$ which follows normal distribution with mean $\hat{x}(t)$ and the same variance as $\epsilon_x$. Fig. 11 shows an example distribution of the predicted traffic demand of $\#976$ hour.

To summarize, the presented prediction method provides two prediction models: mean value and statistical distribution. These two traffic prediction models will serve as the inputs for predictive routing algorithms which are presented in the next section.




(a) Prediction error for adjusted traffic (b) Prediction error for entire series

**Fig. 9** Cumulative Density Function of Prediction Error

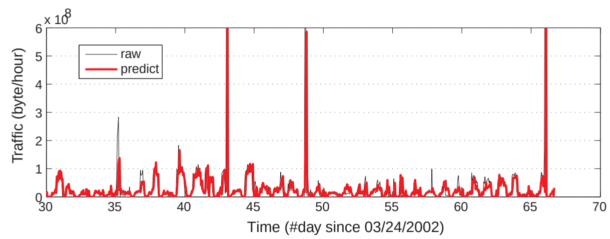



**Fig. 10** Raw Traffic vs. Predicted Traffic

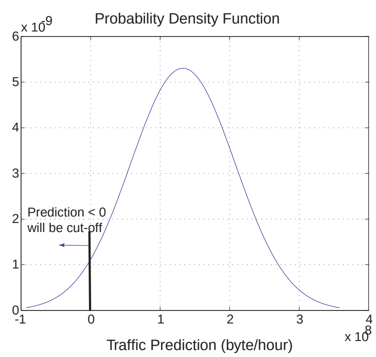



**Fig. 11** Predicted Traffic Distribution

## *5.2 Predictive Routing Optimization*

There are two predictive routing algorithms [9] – one takes the mean value of the predicted traffic demand as input, the other takes the statistical distribution of the predicted traffic demand as input.

The mean-value predictive routing algorithm is a natural integration of the optimal routing algorithm under fixed demand (Sec. 4), where the traffic demand $d_f$ at time $t$ takes the mean value of the predicted traffic demand $\hat{x}(t)$. In what follows, we will focus on the statistical-distribution predictive routing.

First we model the traffic demand of an aggregated flow $f \in F$ using a random variable $D_f$, which follows the following discrete probability distribution

$$Pr(D_f = d_f^i) = q_f^i \tag{27}$$

where $\mathcal{D}_f = \{d_f^1, d_f^2, ..., d_f^m\}$ is the set of of values for $D_f$ with non-zero probabilities. Let $\boldsymbol{d} = (d_f, d_f \in \mathcal{D}_f, f \in F)$ be a sample traffic demand vector, $\boldsymbol{D}$ be the corresponding random variable, and $\mathcal{D}$ be the sample space. We further assume that the demand from different access points are independent from each other. Thus the distribution of $\boldsymbol{D}$ is given by the joint distribution of these random variables as follows.

$$Pr(\boldsymbol{D} = \boldsymbol{d}) = Pr(D_f = d_f^i, f \in F) = \Pi_{f \in F} q_f^i \tag{28}$$

Let us consider a traffic routing solution $(x_f(P), P \in \mathcal{P}_f, f \in F)$ that satisfies the capacity constraint (Inequality (5)). It is obvious that $\lambda$ is a function of $\boldsymbol{d}$:

$$\lambda(\boldsymbol{d}) = \min_{f \in F}\{\frac{x_f}{d_f}\} \tag{29}$$

where $x_f = \sum_{P \in \mathcal{P}_f} x_f(P)$. Further let us consider the optimal routing solution under demand vector $\boldsymbol{d}$. Such a solution could be easily derived based on Algorithm I shown in Table 1. We denote the optimal value of $\lambda$ as $\lambda^*(\boldsymbol{d})$. We further define the *performance ratio* $\omega$ of routing solution $(x_f(P), P \in \mathcal{P}_f, f \in F)$ as follows:

$$\omega(\boldsymbol{d}) = \frac{\lambda(\boldsymbol{d})}{\lambda^*(\boldsymbol{d})}$$

Obviously, the performance ratio is also a random variable under uncertain demand. We denote it as $\Omega$. $\Omega$ is a function of random variable $\boldsymbol{D}$. Now we extend the wireless mesh network routing problem to handle such uncertain demand. Our goal is to maximize the expected value of $\Omega$, which is given as follows.

$$E(\Omega) = Pr(\boldsymbol{D} = \boldsymbol{d}) \times \frac{\lambda(\boldsymbol{d})}{\lambda^*(\boldsymbol{d})} \tag{30}$$

We abbreviate $Pr(\boldsymbol{D} = \boldsymbol{d})$ as $p(\boldsymbol{d})$. It is obvious that $\sum_{d \in \mathcal{D}} p(\boldsymbol{d}) = 1$. Formally, we formulate the throughput optimization routing problem for wireless mesh backbone network under uncertain traffic demand as follows.

$$\mathbf{P_U} : \text{maximize} \sum_{\boldsymbol{d} \in \mathcal{D}} p(\boldsymbol{d}) \frac{\lambda(\boldsymbol{d})}{\lambda^*(\boldsymbol{d})} \tag{31}$$

$$\text{subject to } \forall \boldsymbol{d} \in \mathcal{D}, \text{where } \boldsymbol{d} = (d_f, f \in F)$$

$$\sum_{P \in \mathcal{P}_f} x_f(P) \geq \lambda(\boldsymbol{d}) \cdot d_f, \forall f \in F \tag{32}$$

$$\sum_{f \in F} \sum_{P \in \mathcal{P}_f} x_f(P) A_{eP} \leq c, \forall e \in E \tag{33}$$

$$\lambda \geq 0, x_f(P) \geq 0, \forall f \in F, \forall P \in \mathcal{P}_f \tag{34}$$

Similar to problem $\mathbf{P_T}$, the constraints of $\mathbf{P_U}$ come from the fairness requirement and the wireless mesh network capacity. In particular, Inequality (32) enforces fairness for all demand $\boldsymbol{d} \in \mathcal{D}$, and Inequality (33) enforces capacity constraint as Inequality (5) in problem $\mathbf{P_T}$.

Now we consider the dual problem $\mathbf{D_U}$ of $\mathbf{P_U}$. Similar to $\mathbf{D_T}$, the objective of $\mathbf{D_U}$ is to minimize the aggregated price for all interference sets. However, in Inequality (37), for each sample demand vector $\boldsymbol{d}$, the aggregated price of all flows weighted by their demand needs to be larger than its probability.

$$\mathbf{D_U} : \text{minimize} \sum_{e \in E} c \cdot \mu_e \tag{35}$$

$$\text{subject to} \sum_{e \in E} A_{eP} \mu_e \geq \mu_f, \forall f \in F, \forall P \in \mathcal{P}_f \tag{36}$$

$$\sum_{f \in F} \mu_f d_f \geq \frac{p(\boldsymbol{d})}{\lambda^*(\boldsymbol{d})}, \forall \boldsymbol{d} \in \mathcal{D} \tag{37}$$

$$\text{where } \boldsymbol{d} = (d_f, f \in F)$$

Now we present an approximation algorithm for $\mathbf{P_U}$ in Table 2. Note that since the channel capacity $c$ will not affect the final result of the algorithm, we simply omit it here. In the work of [9], we are able to prove the following properties with this algorithm.

**Property**: If $\beta = (|E|/(1-\epsilon))^{-1/\epsilon}$, then the final flow generated by the above algorithm is at least $(1-3\epsilon)$ times the optimal value of $\mathbf{P_U}$. The running time is $O(\frac{1}{\epsilon^2}[\log |E|(2|\mathcal{D}||T_{fmr}||F| \log |F| + |E|) + \log U)]) \cdot T_{mp}$, where $U$ is the length of the longest path in $G$, $T_{mp}$ is the running time to find the shortest path, and $T_{fmr}$ is the running time of the optimal routing algorithm under a fixed demand.

## 6 Oblivious Mesh Network Routing

In contrast to the predictive routing which establishes traffic models based on time-series analysis and optimizes towards the traffic demands with maximum possibility,

**Mesh Network Routing Under Uncertain Demand**

$\forall e \in E, \mu_e \leftarrow \beta$
$x_f(P) \leftarrow 0, \forall P \in \mathcal{P}_f, \forall f \in F$
**loop**
  **for** $\forall f \in F$ **do**
    $\bar{P} \leftarrow$ lowest priced path in $\mathcal{P}_f$ using $\mu_e$
    $\mu_f \leftarrow \sum_{e \in E} A_{e\bar{P}} \mu_e$
  **end for**
  **for** $\forall \boldsymbol{d} \in \mathcal{D}$ **do**
    $\mu_{\boldsymbol{d}} \leftarrow \sum_{f \in F} \mu_f d_f \frac{\lambda^*(\boldsymbol{d})}{p(\boldsymbol{d})}$
  **end for**
  $\mu^{\min} \leftarrow \min_{\boldsymbol{d} \in \mathcal{D}} \mu_{\boldsymbol{d}}$
  $\boldsymbol{d}^{\min} \leftarrow \arg\min_{\boldsymbol{d} \in \mathcal{D}} \mu^{\min}$
  **if** $\mu^{\min} \geq 1$
    **return**
  **for** $\forall f \in F$ **do**
    $d'_f \leftarrow d_f^{\min}$
    **while** $d'_f > 0$ **do**
      $P \leftarrow$ lowest priced path in $\mathcal{P}_f$ using $\mu_e$
      $\delta \leftarrow \min\{d'_f, \min_{e \in P} \frac{1}{A_{eP}}\}$
      $d'_f \leftarrow d'_f - \delta$
      $x_f(P) \leftarrow x_f(P) + \delta$
      $\forall e$ s.t. $A_{eP} \neq 0$, $\mu_e \leftarrow \mu_e(1 + \epsilon\delta A_{eP} \times \frac{\lambda^*(\boldsymbol{d}^{\min})}{p(\boldsymbol{d}^{\min})})$
    **end while**
  **end for**
**end loop**

**Table 2** Routing Algorithm Under Uncertain Demand

oblivious routing makes no assumptions on the traffic model, rather it considers all traffic demand possibilities and optimizes towards the worst-case scenario. To formally study the oblivious routing strategy, we need a performance metric that could characterize the worst-case congestion under all possible traffic demand.

*(1) Routing*:

First, let's examine the formal description of *routing*, which specifies how traffic of each flow is distributed across the network. In the previous formulation ($\mathbf{P_C}$), a routing is characterized through the traffic load distribution along different paths (*i.e.*, $x'_f(P)$). This description of a routing depends on the traffic demand of each flow. When we have to consider all possible traffic demands, it becomes infeasible. In fact, a routing strategy could be modeled independently of the traffic demand, which is the core of the oblivious routing problem formulation.

Formally, we define a *routing* by the fraction of each flow that is routed along each edge $e \in E'$. We use $\phi_f(e)$ to denote the fraction of demand of flow $f$ that is routed on the edge $e \in E'$. Thus, a routing could be specified by the set $\boldsymbol{\phi} = \{\phi_f(e), f \in F, e \in E'\}$. Recall that the demand of flow $f \in F$ is denoted by $d_f$. Therefore, the amount of traffic demand of $f$ that needs to be routed over $e$ in routing $\boldsymbol{\phi}$, denoted by $y'_f(e)$, is given as follows:

$$y'_f(e) = d_f \cdot \phi_f(e) \tag{38}$$

Thus the *congestion* $\theta_e$ *of an interference set* $I(e)$ is given by

$$\theta_e = \sum_{e' \in I(e)} \sum_{f \in F} \frac{y'_f(e')}{c} = \sum_{e' \in I(e)} \sum_{f \in F} \frac{d_f \cdot \phi_f(e')}{c} \tag{39}$$

We further use $\theta(\boldsymbol{\phi}, \boldsymbol{d}) = \max_{e \in E} \theta_e(\boldsymbol{\phi}, \boldsymbol{d})$ to denote the network congestion under a certain routing $\boldsymbol{\phi}$ and traffic demand vector $\boldsymbol{d}$.

*(2) Oblivious Performance Ratio*:

Now we proceed to study the performance metric that could characterize a "good" routing solution under all possible traffic demands. We start with the *optimal routing* $\boldsymbol{\phi}^{opt}(\boldsymbol{d})$ for a certain demand vector $\boldsymbol{d}$, which would give the minimum congestion under this demand, *i.e.*,

$$\theta^{opt}(\boldsymbol{d}) = \min_{\boldsymbol{\phi}} \theta(\boldsymbol{\phi}, \boldsymbol{d}) \tag{40}$$

Now we define the *performance ratio* $\gamma(\boldsymbol{\phi}, \boldsymbol{d})$ of a given routing $\boldsymbol{\phi}$ on a given demand vector $\boldsymbol{d}$ as the ratio between the network congestion under the routing $\boldsymbol{\phi}$ and the minimum congestion under the optimal routing, *i.e.*,

$$\gamma(\boldsymbol{\phi}, \boldsymbol{d}) = \frac{\theta(\boldsymbol{\phi}, \boldsymbol{d})}{\theta^{opt}(\boldsymbol{d})} \tag{41}$$

Performance ratio $\gamma$ measures how far $\boldsymbol{\phi}$ is from being optimal on the demand $\boldsymbol{d}$. Now we extend the definition of performance ratio to handle uncertain traffic demand. Let $\boldsymbol{D}$ be a set of traffic demand vectors. Then the performance ratio of a routing $\boldsymbol{\phi}$ on $\boldsymbol{D}$ is defined as the worst-case performance ratio for all demands in $\boldsymbol{D}$, *i.e.*,

$$\gamma(\boldsymbol{\phi}, \boldsymbol{D}) = \max_{\boldsymbol{d} \in \boldsymbol{D}} \gamma(\boldsymbol{\phi}, \boldsymbol{d}) \tag{42}$$

A routing $\boldsymbol{\phi}^{opt}$ is optimal for the traffic demand set $\boldsymbol{D}$ if and only if

$$\boldsymbol{\phi}^{opt} = \arg\min_{\boldsymbol{\phi}} \gamma(\boldsymbol{\phi}, \boldsymbol{D}) \tag{43}$$

which means $\boldsymbol{\phi}^{opt}$ minimizes the performance ratio under the worst-case scenario. When the set $\boldsymbol{D}$ includes all possible demand vectors $\boldsymbol{d}$, we refer to the performance ratio as the *oblivious performance ratio*. The oblivious performance ratio is the worst performance ratio a routing obtains with respect to all possible demand vectors. To study the optimal routing strategy under uncertain traffic demand, we are interested in the *optimal oblivious routing* problem which finds the routing that minimizes the *oblivious performance ratio*. We call this minimum value the *optimal oblivious performance ratio*.

It is worth noting that the performance ratio $\gamma$ is invariant to scaling. Thus to simplify the problem, we only consider traffic demand vectors $\boldsymbol{D}$ that satisfy $\theta^{opt}(\boldsymbol{d}) = 1$, instead of considering all possible traffic vectors. In this case,

$$\gamma(\boldsymbol{\phi}, \boldsymbol{D}) = \max_{\boldsymbol{d} \in \boldsymbol{D}} \theta(\boldsymbol{\phi}, \boldsymbol{d}) \tag{44}$$

Thus the goal of oblivious routing is given by

$$\min_{\boldsymbol{\phi}} \max_{\theta^{opt}(\boldsymbol{d})=1} \theta(\boldsymbol{\phi}, \boldsymbol{d}) \tag{45}$$

*(3) Flow Conservation*

Traffic into and out of a mesh node must be conserved. In $\mathbf{P_C}$, a *path representation* of the routing is being used ($x'_f(P)$), which implicitly formulates the flow conservation. Here, since we use an *edge representation* of the routing ($\phi_f(e)$), the flow conservation has to be explicitly formulated. In particular, for the node $v \in V'$ that only relays for flow $f$ (*i.e.*, neither source or destination), we have the following relations:

$$\forall f \in F, \sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = 0 \quad \text{if } v \text{ is a relay of } f \tag{46}$$

If $v$ is the source node of flow $f$, then we have

$$\forall f \in F, \sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = -d_f \quad \text{if } v \text{ is the source node of } f \tag{47}$$

Summarizing the above discussions, the *oblivious mesh network routing* problem is formulated as follows.

$$\mathbf{P_O}: \tag{48}$$

$$\text{minimize } \theta \tag{49}$$

$$\text{subject to } \sum_{e' \in I(e)} \sum_{f \in F} \frac{y'_f(e')}{c} \leq \theta, \forall e \in E \tag{50}$$

$$\sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = 0 \tag{51}$$

$\forall f \in F, \forall v \in V'$, if $v$ is a relay of $f$

$$\sum_{e=(u,v)} y'_f(e) - \sum_{e=(v,u)} y'_f(e) = -d_f \tag{52}$$

$\forall f \in F, \forall v \in V'$, if $v$ is the source node of $f$

$$\forall f \in F, \forall e \in E, y'_f(e) = d_f \cdot \phi_f(e) \geq 0 \tag{53}$$

$$\theta \geq 0, \forall \boldsymbol{d} \text{ with } \theta^{opt}(\boldsymbol{d}) = 1 \tag{54}$$

Different from $\mathbf{P_C}$, the oblivious mesh routing problem $\mathbf{P_O}$ cannot be solved directly, because it is taken over all demand vectors, and $\theta^{opt}(\boldsymbol{d})$ is an embedded maximization in the minimization problem.

Here we use a similar method as in [7], which provides a LP formulation of the oblivious routing problem. The key insight is to look at the dual problem of the slave LPs of the original oblivious routing problem. So let's first examine the following slave problem which computes the slave demands for each possible edge.

$$\max \quad \sum_{f \in F} \frac{d_f \cdot \phi_f(e)}{c} \tag{55}$$

$$\text{subject to } \phi_f(e) \text{ is a routing} \tag{56}$$

In the dual formulation, we first introduce interference set weights $\pi_e(e')$ for every pair of interference sets $e, e'$. $\pi_e(e')$ corresponding to the fraction of the flow on the interference set $I_e$ that is routed over the interference set $I_{e'}$. Each $\pi$ variable can be thought of as a weighted multiplier in an LP dual formulation. There are three essential properties shown in **Theorem 1**. The proofs of these properties follow the similar idea of [7], which is provided in our technical report[20] due to the space constraint.

**Property**: Weights $\pi_e(e'), e, e' \in E$ on a routing $\phi_f(e)$ with oblivious ratio $\leq \theta$ have the following properties,

P1 $\sum_{e'} c \cdot \pi_e(e') \leq \theta, \forall e \in E$

P2 $\forall$ paths $h_1, h_2, ...h_k$ and each flow $f$

$\phi_f(e) \leq c \cdot \sum_{k=1}^{p} \pi_e($ interference-set-of $(h_k))$

P3 $\forall$ interference sets $I_e, I'_e, \pi_e(e') \geq 0$

Because the interference must be minimized, each interference set of the path is weighted according to how many other interference sets in the path it interferes with. The number of such paths between any two nodes grows exponentially with the size of the network. In order to retain polynomial solvability, we may encode the shortest interference path requirement (in P2) in such a way that we only need as many such variables and constraints as there are pairs of interference sets. Thus we introduce $p_e(f)$ as the length of the shortest path flow $f$ according to interference set weights $\pi_e(e')$ (for all $e' \in E$). This definition is equivalent to the following form:

$$\begin{aligned}
&\forall e \in E, \forall f \in F, \\
&\forall e' = (v, u), \text{ where } v \text{ is the destination of } f, \\
&\text{and } u \text{ is the destination of flow } f' \\
&\qquad \pi_e(e') + p_e(f) - p_e(f') \geq 0
\end{aligned}$$

Summarizing the above discussions, the dual problem is given as follows:

$$\mathbf{D_O}: \tag{57}$$

$$\text{minimize } \theta$$

$$\forall e, e' \in E : \sum_{e} c \cdot \pi_e(e') \leq \theta$$

$$\forall e \in E, \forall f \in F : \tag{58}$$

$$\sum_{e' \in I(e)} \phi_f(e')/c \leq p_e(f)$$

$$\forall e \in E, \forall f \in F, \tag{59}$$

$$\forall e' = (v,u), \text{ where } v \text{ is the destination of } f,$$

$$\text{and } u \text{ is the destination of flow } f'$$

$$\pi_e(e') + p_e(f) - p_e(f') \geq 0$$

$$\forall e, e' \in E, \pi_e(e') \geq 0 \tag{60}$$

$$\forall e \in E, \forall f \in F : p_e(f) \geq 0$$

In the dual problem, Eq. (58) can be explained by property P1. Property P2 and the shortest interference set paths account for Eq. (60), and finally property P3 appears at Eq. (60). The dual problem is a single polynomial-size LP instance, which can be solved with any LP solver. Our choice of LP solver was *lp_solve* [3], an open source Mixed Integer Linear Programming (MILP) solver.

## 7 Simulation Study

In this section, we simulate the predictive and oblivious routing strategies over a variety of mesh network setups. Our goal is to evaluate and compare their performance and identify the key factors that impact the performance. Two other routing strategies, namely oracle routing and shortest-path routing, are used as the baseline strategies for comparison. We describe the routing strategies that are evaluated in the simulation study as follows.

- *Oracle Routing (OR)*. In this strategy, the traffic demand is known *a priori*. It runs every hour based on the up-to-date traffic demand and returns the optimal set of routes. As a result, no other routing strategies can outperform *OR*, and we used it to provide a performance upper bound.
- *Shortest-Path Routing (SPR)*. This strategy is agnostic of traffic demand, and returns a fixed routing solution purely based on the shortest distance (number of hops) from each mesh node to the gateway. Many mesh network routing heuristics resemble the shortest-path routing strategy. We evaluate this strategy to quantitatively contrast the advantage of routing strategies which explicitly consider traffic uncertainty.

- *Predictive Routing (PR)*. This strategy attempts to adjust to changing the traffic demand. Future demand is estimated based on the historical data every hour based on the traffic prediction method presented in Sec. 5.
- *Oblivious Routing (OBR)*. This strategy is oblivious to the traffic demands. It considers all possible traffic demands that may be imposed on the network and finds a routing that optimizes the worst-case congestion using the algorithm presented in Sec. 6.

It is worth noting that the *SPR* and *OBR* will compute the traffic routes only once and use them during the entire simulation time, while the *OR* and *PR* need to compute and update the routes every hour.

To realistically simulate the traffic demand at each LAP, we employ the traces collected in the campus wireless LAN network. The network traces used in this work are collected in Spring 2002 at Dartmouth College and provided by CRAWDAD [1]. By analyzing the *snmp* log trace at each access point, we are able to derive its 1108-hour incoming and outgoing traffic volume beginning 12:00AM, March 25, 2002 EST. We select the access points from the Dartmouth campus wireless LAN and assign their traffic traces to the LAPs in our simulation. The traffic assignment is given in Table 3 in one of the random topologies as shown in Fig. 12.

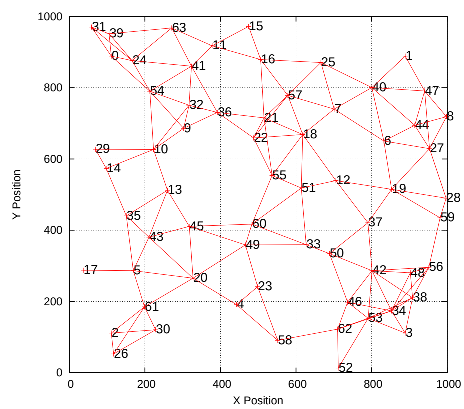



**Fig. 12** Mesh Network Topology

| AP | 31AP3 | 34AP5 | 55AP4 | 57AP2 | 62AP3 | 62AP4 | 82AP4 | 94AP1 | 94AP3 | 94AP8 |
|---|---|---|---|---|---|---|---|---|---|---|
| Node ID | 22 | 18 | 57 | 5 | 55 | 20 | 53 | 3 | 56 | 27 |

**Table 3** Traffic Assignment from Trace File

We experiment with the above routing strategies along the time range $[108, 1108]$, a 1000-hour period excerpted from the trace[2]. Note that all the simulation results presented in this section use $108$ as the zero point.

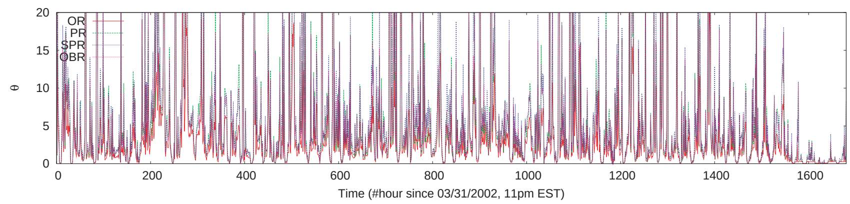



**Fig. 13** Overview of All Strategies

We start by presenting the congestion achieved by all strategies during the entire $1000$-hour simulation period. As seen in Fig. 13, *OR* constantly achieves the minimum worst-case congestion among others, due to its unrealistic capability to know the actual traffic demand. We note that the burstiness of $\theta$ applies to all strategies including *OR*. This observation comes from the burstiness of the traffic load in the *snmp* log trace, which is caused by the insufficient level of traffic multiplexing at wireless local access points.

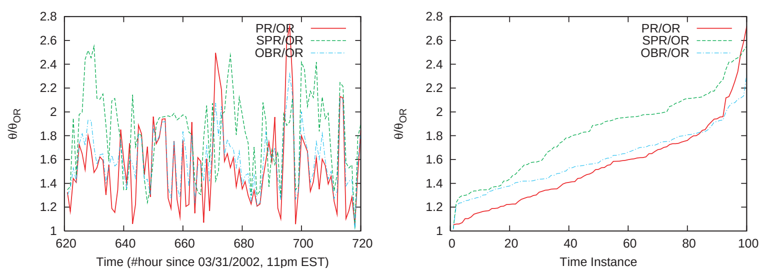



**Fig. 14** (a) Congestion Ratio ($\frac{\theta}{\theta_{OR}}$) (b) Sorted View

To filter out the noise caused by traffic burstiness, in Fig. 14(a), we normalize $\theta$ achieved by other strategies by the same value of *OR*. Since *OR* always achieves the minimum $\theta$ among others, this ratio will end up at least 1. Also we take a close-up look during the hour range $[190, 290]$. Here, *PR*, *SPR*, and *OBR* achieve less than 2 times the optimal congestion in most cases. The above observations get clearer when we sort out the normalized congestion ratio for the three strategies in Fig. 14(b). It is clear that both *PR* and *OBR* which integrate the traffic prediction with the optimal routing outperform the *SPR* strategy which is agnostic about the traffic demand.

[2] Note that the beginning of the trace $[0, 107]$ is used as training data, thus it is not included in the simulation result.

Further, *PR* achieves lower congestion than *OBR* for many time points due to more comprehensive representation of the traffic demand estimation. However, in other cases (less than $10\%$ of the time), the worst-case congestion of *PR* is substantially higher than *OBR*. This problem can be mostly attributed to the fundamental inaccuracy of traffic prediction which is highly sensitive to the traffic's erratic behavior.

We also investigate the performance of *PR* and *OBR* in a representative random topologies with Internet gateways near the perimeter. For a more complete picture, we also investigate cases with 2 gateways and with 4 gateways. Each of these topologies has a total of 64 nodes, including 10 access points receiving traffic from mobile clients, the gateways, and the remaining nodes forwarding traffic on behalf of the Internet and the access points. The points are distributed at random over a simulation square $1000m$ on the side, with an interference range of $155m$. For simplicity, the transmission range is equal to the interference range.

In both the 4-gateway and the 2-gateway scenarios, we run *PR*, *OBR* and *SPR* using the demand data from the Dartmouth trace. Fig. 15 plots the congestion ratios of *PR* over *SPR* and *OBR* over *SPR*. In both pictures, *OBR* and *PR* outperform *SPR* in more than $50\%$ of the cases. During the time when they are inferior to *SPR*, the worst-case ratio is bounded by 2. Also when we increase the number of gateways from 2 to 4, both ratios decrease. Obviously, *SPR* takes advantage of this topology change, due to the fact that more gateways will diversify the shortest paths from access points to nearest gateways, and also shrink the lengths of the paths.

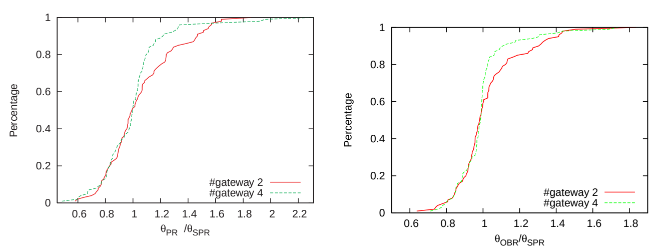



**Fig. 15** (a) CDF of Congestion Ratio ($\frac{\theta_{PR}}{\theta_{SPR}}$) (b) CDF of Congestion Ratio ($\frac{\theta_{OBR}}{\theta_{SPR}}$)

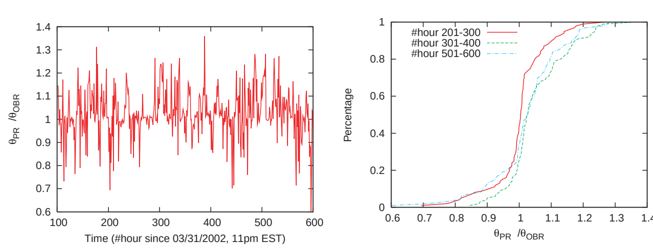



**Fig. 16** (a) Congestion Ratio ($\frac{\theta_{PR}}{\theta_{OBR}}$) (b) CDF of Congestion Ratio

## 8 Thoughts for Practitioners

To summarize this chapter, we provide some thoughts for practitioners:

- Currently, most mesh network routing algorithms and protocols are heuristic-based. Though adaptive to the dynamic environments of wireless networks, they lack the analytical properties of how well the network performs globally. Thus they may lead to sub-optimal resource utilization or unfairness in the network. The optimal mesh routing algorithms that are derived from optimization formulations can usually claim analytical properties such as resource utilization optimality and throughput fairness. However, they usually have strong assumptions on static and known traffic demand, which have been shown to be unrealistic by the studies of wireless network traces [16]. Thus there is a critical need to investigate the optimal mesh network routing strategies that can accommodate traffic uncertainty.
- Predictive routing and oblivious routing are two optimal routing strategies that address the traffic uncertainty in mesh network routing. Their designs, however, are based on different principles. (1) *predictive routing* infers the traffic demand with maximum possibility based in its history and optimizes the routing strategy based on the predicted traffic demand. Underlying predictive routing is the assumption that past behavior is a good indicator of the future. (2) *oblivious routing*, which makes no assumption on traffic demand and considers all the possible traffic demands. In particular, oblivious routing selects the routing strategy where the worst-case network performance is optimized. For a given mesh network, it is important to know which routing strategy would provide a better performance.
- Through the simulation study, we find predictive routing performs better under consistent traffic demand compared to highly variable demand. Furthermore, oblivious routing, being a stateless routing, is unaffected by the traffic behavior. The performance of both algorithms is sensitive to demand and topology, suggesting that the optimal choice for deployment should be based on local parameters.

## 9 Directions for Future Research

This chapter studies optimal routing strategies for wireless mesh networks with attention to traffic demand uncertainty over time and provable robustness. Two approaches are reviewed and discussed in this chapter. Here we outline several possible directions for future research.

- *Traffic Modelling and Estimation*. The predictive routing strategy is sensitive to traffic dynamics and the prediction accuracy. To obtain a higher prediction accuracy, the future research needs to develop appropriate traffic models which can be integrated with network optimization formulations. The key problem involved is how to parameterize the traffic models in order to represent its structure with small number of parameter values that can be estimated from the data. Based on the traffic model, traffic estimation needs to develop reliable estimation methods that determine the values of the parameters that provide robust and high accurate traffic estimate.

- To incorporate traffic uncertainty and dynamics, and integrate different traffic models, future research should explore the full spectrum of research outlined in Fig. 17 from two directions. One side of the spectrum starts with the fixed-demand network optimization, where the traffic demand is known as a fixed single-value scalar; then it extends to handle the scenarios where the traffic demand is represented using a random variable with statistical distribution. The other side of the spectrum starts with the oblivious optimization problem where the traffic demand is completely unknown, where it can be refined to handle the cases where the range of the traffic demand is known.

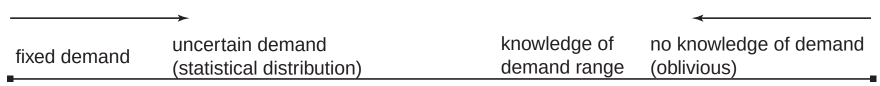



**Fig. 17** Research Space for Route Optimization.

## 10 Conclusions

This chapter studies the optimal routing strategies for wireless mesh networks. Different from existing works which implicitly assume traffic demand as static and known a priori, this chapter considers the traffic demand uncertainty. It presents two approaches to address the traffic uncertainty in optimal mesh network routing: (1) predictive routing which infers the traffic demand with maximum possibility based in its history and optimizes the routing strategy based on the predicted traffic demand and (2) oblivious routing which considers all the possible traffic demands and selects the routing strategy where the worst-case network performance could be optimized. It also identifies the key factors that affect the performance of each routing strategy and provides guidelines towards the strategy selection in mesh network routing under uncertain traffic demands.

## 11 Exercises

*Answers in italics*

1. Explain the factors that must be taken into account when deploying a Wireless Mesh Network.
   *Many answers are possible, but common answers may include*

- *hardware choice, number of supported channels*
- *deployment locations, interference and reflective obstacles*
- *protocol choice and configuration*

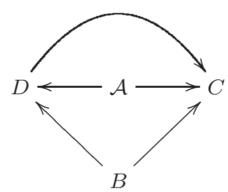
2. What is the intuition behind the differing strengths of oblivious and predictive routing?
*Predictive Routing performs best when traffic history provides an accurate view of future demands. If the traffic is perfectly predictable, it will converge on the optimal routing. However, if it is not predictable, predictive routing makes no allowance for errors and can suffer severe worst case behavior. By contrast, oblivious routing performs with bounded performance regardless of the demands and thus elasticity has no direct impact on its performance.*
3. What affect does traffic aggregation at network endpoints have on the elasticity of the demand?
*Elasticity will be reduced because the sporadic and random bursts will tend to cancel out. In fact, the variance in demand tends to the inverse square root of the number of simultaneous clients.*
4. Name some of the key factors that make traffic more predictable. Name some that make it less predictable.
*More predictable: Corporate access with regular hours Automated Web Queries Less predictable: Streaming video and large downloads that heavily tax network connections alternating with ordinary web browsing or inactivity.*
5. Using Figure 12, how many neighbors would node 55 have if the transmission range was 100m? Suppose it was 200m? In general, with randomly distributed nodes, what is the asymptotic relationship begin degree and transmission range? Your answer should be a simple polynomial, such as "linear".
*The only nodes that appear to be within 100m of node 55 are 51 and 22. Within 200m, there is 22, 21, 57, 18, 51, 42, and 60. In general, we should expect the number of nodes within range to be proportional to the square of the transmission range.*
6. Suppose nodes $A$, $B$, and $C$ in a WMN aggregate traffic as in the following table of load demand.

| Time | A | B | C |
|---|---|---|---|
| 1 | 100 | 200 | 1 |
| 2 | 200 | 200 | 3 |
| 3 | 400 | 100 | 8 |
| 4 | 400 | 400 | 1 |

A) Which of nodes $A$, $B$ and $C$ would you say has the most erratic demand? Which is least erratic? Formalize your intuition.
B) During which of the 3 time intervals shown does demand change the most? Justify your answer.
*This problem has several answers and illustrates the difficulty in quantifying demand variability. Taken in isolation, B has the largest absolute shift from moment to moment (500). However, C has the largest fractional change: 200 % + 167 %*

*+ 88 % = 455 %. By contrast, A has only 100 % + 100 % + 0 % = 200 % and B has 0 % + 50 % + 300 % = 350 %.*

7. Consider the graph topology shown below with the corresponding demand matrix. Assume the rows are the demand sources and the columns are the destinations.




| | A | B | C | D |
|---|---|---|---|---|
| A | – | 0 | 1 | 0 |
| B | 0 | – | 1 | 0 |
| C | 0 | 0 | – | 0 |
| D | 0 | 0 | 0 | – |

**Fig. 18** A) A Simple Topology and B) Demands on this Topology

There are many ways to route this traffic. Calculate the shortest path routing and also the routing that minimizes the maximal congestion.
*Answer:*

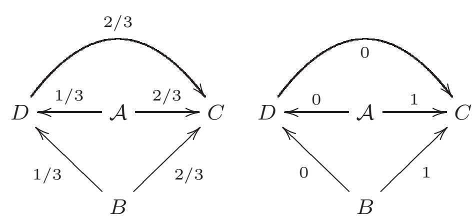



**Fig. 19** Optimal and Shortest Path routings

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