On the Performance and Fairness of Dynamic Channel Allocation in Wireless Mesh Networks

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SUMMARY

Channel assignment in multi-channel multi-radio wireless mesh networks is a powerful resource management tool to exploit available multiple channels. Channels can be allocated either statically based on long-term steady state behavior of traffic or dynamically according to actual traffic demands. It is a common belief that dynamic schemes provide better performance; however, these two broad classes of channel allocation schemes have not been compared in detail. In this paper, we quantify the achievable performance gain and fairness improvement through an *optimal* dynamic channel allocation scheme. We develop optimal algorithms for a dynamic and three static schemes using mixed integer linear programming, and compare them in the context of QoS provisioning, where network performance is measured in terms of acceptance rate of QoS sensitive traffic demands.

Our extensive simulations show that static schemes should optimize channel allocation for long-term traffic pattern, and maintain max-min fairness to achieve acceptable performances. Although the dynamic and max-min fair static schemes accomplish the same fairness, the dynamic channel allocation outperforms the static scheme about 10% in most cases. In heavily overloaded regimes, especially when network resources are scarce, both have comparable performances, and the max-min fair scheme is preferred since it incurs less overhead. Copyright © 2010 John Wiley & Sons, Ltd.

KEY WORDS: Multi-Channel Multi-Radio Wireless Mesh Networks; Static Channel Assignment; Dynamic Channel Assignment; Max-Min Fairness; Joint QoS routing and Channel Assignment

1. INTRODUCTION

Resource allocation is an essential issue in all communication networks. It specifies how network resources are configured and shared among traffic demands. There are two broad classes of resource allocation schemes: *static* and *dynamic*. In the former schemes, network resources are allocated for a long time according to long-term steady state behavior of traffic in order to optimize a utility function, e.g., aggregate network throughput. However, in the latter schemes, resource allocation frequently changes over time according to dynamic traffic demands; at any given time, if needed, resource allocation is reoptimized for the current flows in the network to meet their requirements.

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In general, dynamic resource allocation schemes provide better performance at the cost of updating network configuration. This is because of the capability of dynamic schemes to adapt resource allocations on-demand. Static schemes optimize resource allocation based on steady state traffic pattern; therefore, when the actual traffic varies from the nominal case, these schemes cannot provide sufficient resources for it that leads to performance degradation. However, dynamic schemes adapt network resource allocation over time for the actually existing traffic demands to provide the required resources of the demands that improves network performance.

In multi-channel multi-radio Wireless Mesh Networks (WMN), in order for a pair of nodes in transmission range of each other to communicate, they need to configure their radios on a common available channel. A common channel between each pair of neighboring nodes is considered as a communication link. Two links interfere with each other if they are in interference range of each other and use the *same channel*. Interference is the main factor that determines network available resources because the available bandwidth of each link is determined by the interference pattern; that is, since interfering links cannot transmit simultaneously, each link has to share physical channel capacity with other interfering links. Therefore, the issue of resource management in WMN can be defined as the *channel allocation pattern* in the network at any given time per link due to the fact that interference is specified by channel assignment. In WMNs, channel assignment is a powerful resource management tool in order to determine the available bandwidth of each link. Similar to other resource allocation schemes, channel allocation can be either static or dynamic. In static channel allocation schemes [1, 2, 3, 4, 5], channels are assigned to links for a long time, which is usually optimized for steady state traffic pattern. In dynamic schemes [6, 7, 8, 9, 10, 11, 12, 13, 14], channel allocation pattern changes over time; it is (re)optimized for time-varying traffic. Related work is reviewed in Section 2.

Static and dynamic channel assignments have been compared in previous studies [6, 7, 8, 11, 15] that show that dynamic channel allocation schemes give better performance than static ones. However, almost all the results either have been obtained by heuristic dynamic solutions and/or compared to heuristic static mechanisms. Therefore, validity of these comparisons is influenced by the efficiency of the heuristic solutions. To our best knowledge, there is not any comprehensive comparison between *optimal* solutions for dynamic and static channel allocation schemes in multi-channel multi-radio WMNs. Moreover, all the existing comparisons have been performed from the network performance point of view. Fairness in resource allocation, which determines how network resources (available channels) are shared among demands, has not been considered in the previous studies in spite of the fact it is a key issue in all resource allocation schemes.

In this paper, we study the problem of quantifying the performance gain and fairness enhancement achievable through an optimal dynamic channel allocation scheme in comparison to optimal static schemes. The comparison is performed in the context of *QoS provisioning*. The reason why we compare channel allocation schemes in this context and the formal specification of the context will be discussed in more detail in Section 3.5. Briefly, the context is as follows. In this context, traffic is time-varying; i.e., traffic demands arrive to the network randomly and each demand has a (random) limited lifetime. The source and destination of each demand belong to a pre-defined set of source-destination pairs. Each traffic demand requires a fixed amount of bandwidth from its source node to the corresponding destination node as its QoS constraint. A demand is either completely accepted or rejected. If the network can provide the required end-to-end bandwidth, i.e., can meet the QoS constraint, then the demand is admitted. In this case, it transmits data at the fixed requested rate during its lifetime. If the required bandwidth cannot be guaranteed, the demand is rejected. A higher number of accepted demands implies better resource utilization and higher performance; hence, in the QoS provisioning context, the network performance is usually measured in terms of the *acceptance rate* of the traffic

demands [16, 17, 18, 19, 20]. Consequently, to perform the desired comparisons between channel allocation schemes in the context, we need to measure acceptance rates obtained by dynamic and static channel allocation schemes. These measurements are performed as follows.

In static channel allocation schemes, channels are assigned at the beginning before demands arrive. This channel assignment pattern is fixed and is not changed later. For each demand, if the required bandwidth can be routed from its source to the destination, which *QoS routing* algorithm is responsible for, then the demand is accepted; otherwise, it is rejected. The static channel allocation is performed based on the available information about long-term traffic pattern, which is specified by the pre-defined set of source-destination pairs since as mentioned, source and destination of all traffic demands belong to the set. In dynamic schemes, channel assignments in the network are continuously adapted according to the actual traffic load. For a given demand, channel assignment pattern is modified in order to provide sufficient available bandwidth from the source of the demands to its destination. If the network can provide the required bandwidth through an appropriate channel (re)assignment and routing, which is performed by *joint QoS routing and channel assignment* algorithm, then the demand is accepted; otherwise it is rejected. Through comparing the numbers of accepted demands by each scheme, we measure the performance gain of dynamic schemes over static mechanisms. Moreover, we investigate the fairness of the schemes in terms of the number of accepted demands per source-destination pair.

In the remaining of this paper, our goal is to compare the *maximum achievable* acceptance rates by the *optimal* static and dynamic channel allocation schemes. For this purpose, dynamic and static schemes are implemented using mathematical optimization models. For ease of discussion, at the first step, the optimization models are developed for *static demands*, wherein all demands arrive at the same time. Then, in the second step, we consider *dynamic demands*, in which traffic demands arrive to and leave from the network randomly over time, and extend the optimization models to implement the dynamic and static channel allocation schemes for this case. Through comparing the acceptance rates obtained by the optimization models in the case of dynamic demands, we measure the performance and fairness gain of the dynamic scheme. More specifically, our contributions to the problem are the following:

- In the case of static demands, QoS routing and joint QoS routing and channel assignment optimization models are formulated using the well-known constraints in the literature. We show that these models provide an *upper bound* on the acceptance rate in this case.
- For dynamic demands, we develop optimal online QoS routing and joint QoS routing and channel assignment algorithms by extending the optimization models developed for static demands and using the idea of *rerouting existing flows* in the network.
- We develop a max-min fair static channel assignment algorithm based on our proposed mixed integer linear programming (MILP) optimization model.
- Through extensive simulations in different topologies and various traffic parameter settings, we compare the maximum achievable acceptance rate, fairness index [21], and overhead of the dynamic and static channel allocation schemes.

The remainder of this paper is organized as follows. Related work is briefly reviewed in Section 2. In Section 3, models and problem formulation are discussed. We give an overview of solution approach in Section 4. The MILP models of the QoS routing and joint QoS routing and channel assignment problems in the case of static demands are developed in Section 5. The optimal static and dynamic channel allocation schemes in the case of dynamic demands are developed in Section 6. We present the static channel assignment algorithms in Section 7. Simulation results are presented and analyzed in Section 8, and Section 9 concludes this paper.

2. RELATED WORK

Channel allocation problem in multi-channel multi-radio WMNs is an active research area. The existing studies on this problem can be classified as shown in Fig. 1. In static channel allocation category, channel assignment *pattern* is static, which is performed based on topological information and/or long-term prediction of traffic pattern [1, 2, 3, 4, 5]. In these schemes, radios can switch between channels; however, the pattern of the switching should be static and independent of instantaneous actual traffic load. On the other hand, dynamic schemes modify the channel assignment pattern over time [6, 7, 8, 9, 10, 11, 12, 13, 14].

Dynamic channel allocation schemes are either opportunistic or non-opportunistic. In the former schemes, the channel assignment algorithm aims to mitigate interference from external sources, e.g., coexisting networks [6, 7, 8]. For this purpose, each node measures interference periodically, and switches to the least interfered channel if the level of interference exceeds a threshold. In dynamic non-opportunistic schemes, channels are assigned according to interference in the network, which is proportional to the offered load. These schemes adapt channel assignment pattern for the load offered to the network at any given time in an either a centralized or a distributed manner.

In the distributed approaches [12, 13, 14], each node *locally* measures the load on each of its links. In the case of detecting an overloaded link, the link is switched to a lesser interfered channel. The main goal of these approaches is to maximize the total one-hop capacity of the network using the local information. In the global non-opportunistic schemes, the global routing and traffic information is used to optimize channel assignment. These schemes either assume that flow routes are given [9, 10, 11] or *jointly* optimize channel assignment and routing [22, 23, 24, 25, 26] (and scheduling [27, 15] and power level [28]). In [9, 10], channels are assigned according to congestions in the network. The authors in [11] proposed a maximum fair bandwidth approach for channel assignment. For a given traffic matrix, the joint algorithms [15, 22, 23, 24, 25, 26, 27, 28] find an efficient network configuration including routes and channel assignments (and scheduling and power levels) to maximize the aggregate network throughput subject to a fairness constraint. When the traffic matrix changes, these algorithms find a new (near) optimal feasible configuration for the new traffic demands.

3. SYSTEM MODEL AND PROBLEM STATEMENT

In this section, after description of assumptions and system models, we formulate the problem considered in this paper. Notations used throughout the paper are shown in Table I; we use bold symbols for vectors.

3.1. Assumptions

We consider contention based, e.g., IEEE 802.11, multi-channel multi-radio WMNs. In the networks, all nodes are static and have q_u radios. All the radios have the same transmission range T_R and the same interference range I_R ($> T_R$). It is assumed that the RTS/CTS mechanism is enabled. There are κ orthogonal channels with the same physical capacity c Mb/s. To maintain network connectivity and to exchange information among nodes, it is assumed that in addition to the κ channels, a control channel exists. In addition to the q_u radios, there is a dedicated radio for the control channel. This channel and radio are not considered in the optimization models since they are not used for data transmission.

Traffic demands are from specific source nodes to their corresponding destinations. These source-
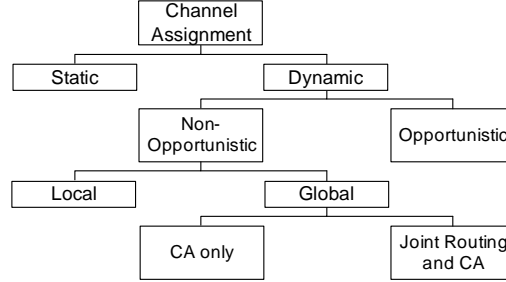
Figure 1. Classification of channel allocation schemes

Table I. Notations

Notation	Description	Notation	Description
u and v	Node	V	Set of nodes, $|V| = n$
(u, v)	Link	E	Set of edges, $|E| = m$
k	Channel	K	Set of channel, $|K| = \kappa$
c	Physical channel capacity	T_R	Transmission range
I_R	Interference range	(s, d)	Source-Destination pair
Δ	Pairs set, $\Delta = \{(s_i, d_i)\}$	b	The required bandwidth
t	Arrival time	e	Exit time
F	Demands, $F = \{(s_i, d_i, b_i, t_i, e_i)\}$	q_u	The number of radios of node u
$l^k_{(u,v)}$	Load on link (u, v) on channel k	$f^i_{(u,v)}$	Flow of demand i on link (u, v)
Q_i	Maximal clique in interference graph	Φ	Maximal cliques set, $\Phi = \{Q_i\}$
p_i	Profit of demand i	$\boldsymbol{p}$	Profit vector, $\boldsymbol{p} = [p_i]_{1 \times |F|}$
β_i	Allocated flow for demand i	Ψ	Channel assignment, $\Psi = [x^k_{(u,v)}]_{\kappa \times m}$
$x^k_{(u,v)}$	Fraction of time link (u, v) transmits on channel k		

destination pairs are predetermined by set $\Delta = \{(s_i, d_i)\}$, where s_i and d_i are the ith source and destination, respectively. Flows are splittable; hence, multi-path routing is used. Similar to previous work, we assume that radios are capable to switch between channels with a negligible delay [15, 29], which is called *fast switching*. Although this assumption may seem unrealistic considering off-the-shelf wireless NICs, we believe that this technological issue will be addressed in the future. For example, in [29] (and the references therein), it is argued that the channel switching time could be decreased to 40-80 μs in commercial IEEE 802.11 interfaces. It is supposed that channels can be reassigned and flows can be rerouted at any given time. The last assumption, the rerouting capability, is necessary to develop optimal QoS routing algorithm, as we explain in Sections 3.5 and 6.

3.2. Network Model

Network is modeled by a digraph $G = (V, E)$, where V is a set of n vertices and E is a set of m edges. Each $v \in V$ corresponds to a node in the network. For a given pair of nodes u and v, there is a link $(u, v) \in E$ if $d(u, v) \leq T_R$, where $d(u, v)$ is the Euclidean distance between u and v.

3.3. Interference Model

Interference is modeled by Interference Graph IG. Each link $(u, v) \in E$ is represented by a vertex in IG. If two links interfere with each other, there is an edge between their corresponding vertices in

IG. Since we assume channels are orthogonal to each other, only links assigned to the same channel interfere with each other. To construct the interference graph, we use the widely used *interference range* model [2, 6, 27, 15, 28, 30, 31, 32], which is a special case of the protocol model [33][†]. This model, in conjunction with the RTS/CTS mechanism, yields that two links (u_1, v_1) and (u_2, v_2) on a common channel interfere with each other if $d(u_1, u_2) \leq I_R$ or $d(u_1, v_2) \leq I_R$ or $d(v_1, u_2) \leq I_R$ or $d(v_1, v_2) \leq I_R$ [2, 27].

3.4. Available Bandwidth Model

The authors in [34] proposed two sufficient conditions for feasibility of bandwidth allocation in multi-hop wireless networks: the *row* constraint and the *scaled clique* constraint. In this paper, we use the scaled clique constraint. It imposes that the aggregate load on the links in each maximal clique of the interference graph must be at most the scaled physical channel capacity. The physical capacity should be scaled since without scaling, this constraint is a sufficient condition only in *perfect* interference graphs [34].

It is known that the value of the scale depends on the *imperfection ratio* of the interference graph [34]. A recent simulation based study on the imperfection ratio of interference graphs [35] showed that scale 1.0 is a good approximation; however, to be more conservative, scale $\frac{1}{1.21} = 0.826$ should be used. We use scale 0.826 in this paper, but it must be noted that our approach and results do not depend on the exact value of the scale.

The number of cliques in another issue. Theoretically, it can be exponential in an arbitrary graph; however, in practice, in interference graph of multi-hop wireless networks, the number is limited, and all maximal cliques can be found very easily. In our experiments, all maximal cliques of interference graph of a 50-node network were found in less than one second on an Intel Pentium IV 3.0GHz machine[‡].

3.5. Problem Statement

Our goal is to measure differences between *optimal* static and dynamic channel allocation schemes in multi-channel multi-radio WMNs in three aspects: performance, fairness, and overhead. Three requirements need to be met to carry out these measurements. First, we need to know the long-term behavior of traffic because static schemes optimize channel assignment based on it. The long-term behavior can be expressed as a set of source-destination pairs, $\Delta = \{(s_i, d_i)\}$, where all the actual traffic in the network will only be from these sources to their corresponding destinations. Second, it is required that traffic load changes over time but changes must be consistent with the long-term behavior. A change can be considered as arrival of a new traffic demand whose source and destination belong to Δ. Third, we need a metric to measure network performance, which does not affect the achievable performance gain. A metric could be the maximum aggregate throughput subject to a fairness constraint. However, in this case, the fairness constraint is an issue; various constraints may yield different performance gains. To deal with this issue, instead of measuring aggregate network throughput, we assume that traffic is QoS sensitive that implies each traffic demand has a specific end-to-end bandwidth requirement. Resource allocation schemes either accept a demand if they can provide the required end-to-end bandwidth or reject it, otherwise. The required bandwidth of each demand

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[†]Although this model is not as accurate as the physical interference model [33], it leads to more tractable optimization problems.
[‡]We used MACE program [36] to enumerate maximal cliques.

depends on the traffic characteristics and multiplexing strategy in the network. If traffic is CBR or the peak rate allocation strategy is desired, the *maximum* required bandwidth should be guaranteed for each demand. However, if statistical multiplexing is used and traffic is stochastic, e.g., on-off or VBR traffic, the required bandwidth is the *effective bandwidth* of the traffic [37][§]. With these assumptions, the problem studied in this paper is very similar to the bandwidth constrained routing in wired networks, where a demand is accepted if and only if the network can provide the required bandwidth. The problem was studied in the context of LSP routing in MPLS networks, wherein the number of accepted demands (or equivalently, demand acceptance rate) is a widely used measure of the network performance [16, 17, 18, 19, 20].

These three requirements and their corresponding assumptions yield that the desired measurements should be made in the context of *QoS provisioning*. In this context, there is a set of dynamic demands, $F = \{(s_i, d_i, b_i, t_i, e_i)\}$ where $(s_i, d_i) \in \Delta$. Demand i arrives at time t_i, needs end-to-end bandwidth b_i from node s_i to node d_i. If the required bandwidth can be routed from s_i to d_i, the demand is accepted, which later, at time e_i, leaves the network. Otherwise, the demand is rejected. For QoS provisioning in multi-channel multi-radio WMNs, channel allocation schemes either statically or dynamically optimize channel assignments to maximize the number of accepted demands. In the following sections, we develop optimal static and dynamic channel assignments, and compare their provided acceptance rates to measure the performance gain.

In addition to channel assignment algorithms, we need to develop a QoS routing algorithm because the requirement bandwidth must be *routed*. Since acceptance rate of demands is affected by the efficiency of the QoS routing algorithm, a heuristic algorithm influences our analyses. To avoid this problem, an optimal QoS routing algorithm needs to be used. This algorithm in conjunction with the optimal channel assignment algorithms yields two optimal schemes: *static scheme* and *dynamic scheme*.

In the static scheme, the QoS routing and channel assignment algorithms are applied separately. The channel assignment is an off-line algorithm. It finds an optimal *fixed* channel assignment pattern before loading the network. Then, upon arrival of each demand, the online QoS routing algorithm attempts to route the required bandwidth of the demand. In the dynamic scheme, these algorithms are combined with each other that creates an online joint QoS routing and channel assignment algorithm. This algorithm is applied at the arrival time of each demand to find a feasible routing and channel assignment. With these optimal algorithms in hand, we are interested to answer the following questions:

- What is the achievable performance gain (improvement in demand acceptance rate) of the dynamic allocation scheme in comparison to the static schemes?
- How fairly do these schemes share resources among source-destination pairs?
- How much is the extra overhead of the dynamic scheme to update channel assignments?

4. SOLUTION OVERVIEW

To answer the questions in the previous section, we need to develop the aforementioned static and dynamic allocation schemes. As explained, the dynamic scheme is, in fact, the optimal online *joint*

[§]Effective bandwidth and statistical multiplexing are well-developed techniques, especially in the ATM networks. For further details refer to [38, 39].
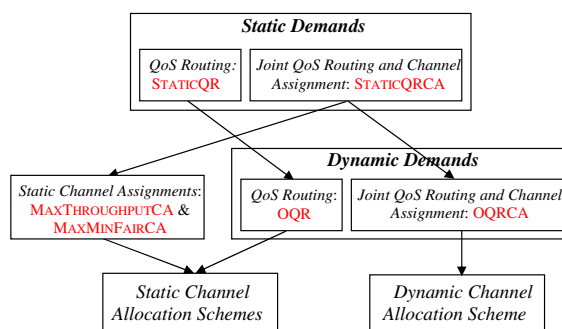
Figure 2. Solution Overview: Starting from the case of static demands, an optimization model is developed for the QoS routing problem and another for joint QoS routing and channel assignment. They are extended to consider the case of dynamic demands that yield the online QoS routing and online joint QoS routing and channel assignment algorithms. Two static channel assignments are implemented by modifying STATICQRCA. The dynamic scheme is the OQRCA algorithm. Each static scheme is a combination of OQR and a channel assignment algorithm.

QoS routing and channel assignment algorithm. The static scheme is implemented by the optimal online *QoS routing* algorithm and the optimal off-line *static channel assignment*. Development of these algorithms, which is shown in Fig. 2, is as follows.

We start from a simple problem, named static demands problem, in Section 5. In this problem, all demands arrive at the same time. We assume that each demand has a profit, and our goal is to find the maximum profit of admissible demands. For this problem, we develop two MILP models; a model for QoS routing named STATICQR, and the other for joint QoS routing and channel assignment, the STATICQRCA model. Then in Section 6, we consider the case of dynamic demands, where demand i arrives at time t_i and leaves the network at time e_i. We use the STATICQR and STATICQRCA models to develop the optimal QoS routing (OQR) and optimal joint QoS routing and channel assignment (OQRCA) algorithms for this case.

Since each static scheme needs a fixed channel assignment pattern, we develop two optimal off-line algorithms for this purpose in Section 7. We use set Δ as the available information about the long-term steady state behavior of traffic, and optimize the channel assignment pattern for it. For a given set of source-destination pairs, we assume a flow for each pair. The first channel assignment algorithm (MAXTHROUGHPUTCA) finds a channel assignment that maximizes the aggregate throughput of the flows. The second one (MAXMINFAIRCA) intends to provide max-min fair (end-to-end) bandwidth allocation among the flows. Both these algorithms are developed by extending the MILP model we build for the joint QoS routing and channel assignment problem in Section 5.

In the following sections, in addition to the notations in Table I, we will use the following variables in the optimization models. Binary variable α_i denotes admission of demand i,

$$\alpha_i = \begin{cases} 1, & \text{if demand } i \text{ is accepted} \\ 0, & \text{otherwise.} \end{cases}$$

Variable β_i is the total flow rate allocated for demand i. In the QoS routing problem where the required bandwidth b_i must be guaranteed, we have $\beta_i = b_i$, however in general, β_i can be more or less than b_i.

5. STATIC DEMANDS PROBLEM

In this section, we develop MILP models for the QoS routing and joint QoS routing and channel assignment problems in the case of *static demands*. By static demands, we mean all demands arrive at the same time, $t_i = 0 \ \forall i \in F$, and have a fixed bandwidth requirement b_i. We assume that each demand has its own profit. It is not specified by the demand set F; we will use it in the following sections to control acceptance probability of each demand. The objective in the following MILP models is to maximize the aggregate profit of the accepted demands through finding feasible routes (and channel assignments).

5.1. QoS Routing Optimal Model

In the optimization model of QoS routing, it is assumed that a static channel assignment of the network is given. As mentioned, we assume that radios are capable to switch between channels. Hence, a given channel assignment $\Psi = [x^k_{(u,v)}]_{\kappa \times m}$ specifies for each link-channel pair (u, v) and k, the fraction of time that the link transmits on that channel, which is denoted by $x^k_{(u,v)}$.

In this model, we want to maximize the aggregate profit of the accepted demands through finding feasible routes for each demand $i \in F$, which are specified by $f^i_{(u,v)} \ \forall (u, v) \in E$. The objective function of the model is

$$\text{maximize} \sum_{i \in F} \alpha_i p_i, \tag{1}$$

where $\boldsymbol{p} = [p_i]_{1 \times |F|}$ is the profit vector, and p_i is the profit of demand i. The following constraints must be satisfied to maintain feasibility of bandwidth allocation and routing.

Load transmitted by link (u, v) on channel k, which is denoted by $l^k_{(u,v)}$, is bounded by the physical channel capacity c, and the fraction of time the link actives on the channel, $x^k_{(u,v)}$; in other words,

$$l^k_{(u,v)} \leq x^k_{(u,v)} c \qquad \forall k \in K, \forall (u,v) \in E. \tag{2}$$

Total load transmitted by a link on different channels, which is $\sum_{k \in K} l^k_{(u,v)}$, must be equal to the aggregate flow offered by the demands in the network on the link; so, we have

$$\sum_{i \in F} f^i_{(u,v)} = \sum_{k \in K} l^k_{(u,v)} \qquad \forall (u,v) \in E. \tag{3}$$

As we mentioned in Section 3.1, available bandwidth is modeled by the scaled clique constraint that imposes

$$\sum_{(u,v) \in Q_i} l^k_{(u,v)} \leq 0.826c \quad \forall k \in K, \forall Q_i \in \Phi. \tag{4}$$

It means that for each maximal clique Q_i in the interference graph, the aggregate load on the links in the clique that transmit on channel k must not exceed the scaled physical capacity. Finally, the routing and flow conservation constraints must be satisfied *if demand is accepted*, which are modeled as follows.

$$\sum_{(u,v) \in E} f^i_{(u,v)} - \sum_{(v,u) \in E} f^i_{(v,u)} = \begin{cases} \beta_i, & \text{if } u = s_i \\ -\beta_i, & \text{if } u = d_i \\ 0, & \text{otherwise} \end{cases} \qquad \forall u \in V, \ \forall i \in F, \tag{5}$$

and

$$\beta_i = \alpha_i b_i \quad \forall i \in F. \tag{6}$$

The model of optimal QoS routing for a set F of static demands with profits $\boldsymbol{p}$ under a given channel assignment Ψ is obtained by putting (1)–(6) altogether as follows.

Model: $\textsc{StaticQR}(F, \boldsymbol{p}, \Psi)$
Objective: (1)
Subject to: (2)–(6).

5.2. *Joint QoS Routing and Channel Assignment Optimal Model*

We develop a MILP model for joint QoS routing and channel assignment in the case of static demands by extending the $\textsc{StaticQR}$ model. In this model, in addition to flow routes, $f^i_{(u,v)}$, channel assignments, $x^k_{(u,v)}$, are also decision variables, which are obtained by solving the model. The objective function is again to maximize the aggregate profit of the accepted demands, (1). Additional constraints must be considered to maintain feasibility of channel assignment. The first constraint is the upper bound of $x^k_{(u,v)}$; obviously, this variable cannot be greater than one, so

$$x^k_{(u,v)} \leq 1 \quad \forall k \in K, \forall (u,v) \in E. \tag{7}$$

The second constraint is the radio constraint. There are q_u radios in each node u. When a link of node u, either (u,v) or (v,u), uses channel k, $x^k_{(u,v)} > 0$, in fact, a radio in the node is tuned to the channel, and utilized for that transmission for $x^k_{(u,v)}$ fraction of time. Clearly, the total utilization of radios of a node cannot exceed the number of radios of the node; in other words,

$$\sum_{k \in K} \left(\sum_{(u,v) \in E} x^k_{(u,v)} + \sum_{(v,u) \in E} x^k_{(v,u)} \right) \leq q_u \quad \forall u \in V. \tag{8}$$

These additional constraints in conjunction with the $\textsc{StaticQR}$ model provide an optimal model for joint QoS routing and channel assignment as follows.

Model: $\textsc{StaticQRCA}(F, \boldsymbol{p})$
Objective: (1)
Subject to: (2)–(8).

There is an important issue about this model; this model provides an *upper bound* because the solution of this model may not be schedulable. An example of unschedulable solution is depicted in Fig. 3. In this example, in the first time-slot, nodes a and b activate channel 1 on their radios to transmit the load on link (a,b). The length of this time-slot is half of the scheduling frame, $x^1_{(a,b)} = 0.5$, because the load on the link is 5 and the physical channel capacity is 10. In the second time-slot, channel 2 is activated on the radios of nodes b and c to transmit the load on link (b,c). The length of this time-slot is also half of the scheduling frame, $x^2_{(b,c)} = 0.5$. It is easy to verify that all the constraints of the $\textsc{StaticQRCA}$ model are satisfied; however, there is not any time-slot to transmit the load on link (c,a) on channel 3.

As this example shows the solution obtained from this model may not be feasible. In general, infeasibility may lead to a loose approximation of the optimal feasible solution. However, our simulations in [40] showed that this is not the case for the joint QoS routing and channel assignment problem. We compared the solutions of $\textsc{StaticQRCA}$ to the optimal feasible solutions obtained by another model, which does *not* assume fast switching capability and uses the *row* constraint. The results showed that $\textsc{StaticQRCA}$ gives a tight bound on the number of admissible demands; the gap between
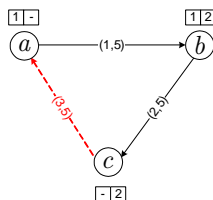
Figure 3. An example of unschedulable solution. Label of each link is (channel, load) pair, label of each node is the schedule of channel activation on the radio of the node, $c = 10$, and $q_u = 1$. Whereas all the constraints of STATICQRCA are satisfied, there is not any feasible scheduling.

two solutions is less than 5% on average. Moreover, this model tremendously improves the solution time, e.g., STATICQRCA is solved in less than one second while the optimal feasible model may not be solved in 10 hours.

6. DYNAMIC DEMANDS PROBLEM

In this section, we develop the desired channel allocation schemes. The channel assignment part of the static schemes will be discussed in the next section. In this section, we focus on the optimal QoS routing (OQR) and optimal joint QoS routing and channel assignment (OQRCA) algorithms in the case of *dynamic demands*.

As explained in Section 3.5, these algorithms run upon arrival a new demand, and attempt to find a feasible network configuration (including routing and channel assignment) to accept the demand. Both algorithms have the same skeleton, and can be implemented in the context of the Optimal Call Admission Control (OCAC) algorithm. The OCAC algorithm does not know any information about a demand before its arrival; in other words, it is an online algorithm. At the arrival time of a demand, it decides whether to accept the demand or reject it. A demand is accepted if OCAC can find a feasible network configuration; otherwise, the demand is rejected. OCAC guarantees the required bandwidth of the accepted demands during their lifetime, $e_i - t_i$. The OCAC algorithm checks the existence of a feasible configuration through solving an optimization model named ADMISSION.

The key observation in the development of OCAC is that ADMISSION is indeed a static demands problem. When demand i arrives at time t_i, the problem is to accept the demand, besides a set of already admitted demands that exist in the network at the time, which are $\{j \in F \text{ s.t. } \alpha_j = 1 \text{ and } t_j < t_i \text{ and } e_j > t_i\}$. Since we assume that flow routes and channel assignments can be modified at any given time, this problem can be seen as a static demands problem in which demands $\{(s_i, d_i, b_i, t_i, e_i)\} \cup \{j \in F \text{ s.t. } \alpha_j = 1 \text{ and } t_j < t_i \text{ and } e_j > t_i\}$ have just arrived at time t_i, and we want to accept all of them.

There is an important issue in OCAC that should be treated carefully. Flows are not *preemptable*. This implies that we are not allowed to reject an already accepted demand j in order to accept a new demand i. If demand j is accepted by solving an instance of ADMISSION corresponding to the arrival of ith demands, it must be accepted in the instance corresponding to the arrival of kth demand where $t_k > t_i$ and $e_j > t_k$. To model the non-preemption of flows, we use the profit assignment vector

---

Algorithm 1 : OCAC(F, ADMISSION)

Require: F is sorted in ascending order of t_i
 1: Create two empty sets W and A
 2: **for** $i = 1$ **to** $|F|$ **do**
 3:     $\delta \leftarrow F[i]$
 4:     Add δ to W
 5:     $\boldsymbol{p} \leftarrow$ Assign profits according to (9)
 6:     $\boldsymbol{\alpha} \leftarrow$ ADMISSION($\boldsymbol{p}, W$)
 7:     **if** $\alpha_i = 1$ **then**
 8:         Add δ to A
 9:     **else**
10:         Remove δ from W
11:     **for** $\forall j \in W$ **do**
12:         **if** $e_j < t_{i+1}$ **then**
13:             Remove demand j from W
14: **return** A

$\boldsymbol{p} = [p_i]$. At the arrival of ith demand, profits are assigned as follows:

$$p_j = \begin{cases} 2, & \text{if } j \text{ is an already accepted demand } (\alpha_i = 1 \text{ and } t_j < t_i \text{ and } e_j > t_i) \\ 1, & \text{if } j = i. \end{cases} \tag{9}$$

This profit assignment implies that first, if not all demands can be accepted, the new one, demand i, should be rejected. Rejecting demand i is sufficient because the set of demands without demand i were considered in $(i-1)$th instance and accepted. Second, if demand i is accepted at its arrival time where $p_i = 1$, it will not be rejected later where $p_i = 2$; this is the behavior of the *online* call admission control algorithms.

Algorithm 1 shows the pseudo-code of the OCAC algorithm. In this algorithm, W is the set of working demands, which were accepted and have not left the network yet, and A is the set of accepted demands. This algorithm assumes that demands are sorted in ascending order of their arrival times. OCAC picks demands one-by-one; for each demand, adds it to W, searches a feasible configuration for W, and accepts the demand if a feasible configuration exists. Note that demand i is removed from set W either if it is rejected in the ith subproblem, line 10, or it does not overlap with the next demand, line 13, that means it leaves the network before the next demand arrives.

The OQR and OQRCA algorithms are implemented by appropriate substitutions of ADMISSION in OCAC. For the OQR algorithm, ADMISSION is the STATICQR model. In the OQRCA algorithm, it is substituted by STATICQRCA. By these substitutions, we obtain the resource allocation schemes explained in Section 3.5. Whereas OQRCA is a complete algorithm to find the maximum number of admissible demands of a given set of dynamic demands, OQR needs a static channel assignment as STATICQR supposes that a channel assignment Ψ is given. In the next section, we develop two algorithms to find it.

7. STATIC CHANNEL ASSIGNMENTS

In this section, two algorithms are developed to find the static channel assignment Ψ, which is needed by STATICQR. Since we assume that the source and destination of each demand belong to a given set

of pairs, Δ, one of the most appropriate static channel assignments is to consider a flow for each pair and maximize the rate of the flows that implies reserving as much as possible resources (bandwidth) for demands of each pair. Note that this is the traditional *multi-commodity maximum flow* problem. In multi-channel multi-radio WMNs, the multi-commodity maximum flow is achieved through jointly optimizing routing and channel assignment. The solution of the joint problem specifies both optimal routing and channel assignment, that the channel assignment part is the static channel assignment that we need. Various objective functions can be optimized in the multi-commodity maximum flow problem [41]; we consider two different objectives. The first one is to maximize the aggregate network throughput without any fairness constraint, and the second objective is to provide max-min fairness among the source-destination pairs.

The desired static channel assignment algorithms are obtained by appropriate modifications in the STATICQRCA model, which are discussed in detail in the following sections, and using a special set of static demands. In this set, as mentioned before, there is a demand (flow) for every source-destination pair; more specifically, $\exists (s_i, d_i, b_i = 1, t_i = 0, e_i = 1) \in F \ \forall (s_i, d_i) \in \Delta$. Hence, in the remaining of this section, terms 'demand' and 'pair' are used interchangeably.

7.1. Maximum Throughput Channel Assignment

In the maximum throughput channel assignment problem, the objective is to maximize the aggregate network throughput regardless of any fairness. The optimal solution of this problem is found by the following modifications in the STATICQRCA model. In this problem, since we do not want to guarantee an amount of bandwidth for each demand, constraint (6) is removed. Moreover, the objective function (1) is changed to

$$\text{maximize} \sum_{i \in F} \beta_i, \tag{10}$$

where β_i is the total flow rate from s_i to d_i. By these modifications, we get the following model for maximum throughput channel assignment problem:

> **Model**: MAXTHROUGHPUTCA(F)
> **Objective**: (10)
> **Subject to**: (2)–(5), (7), and (8).

7.2. Max-Min Fair Channel Assignment

In this channel assignment problem, we need to satisfy the max-min fairness constraint. It is known that the max-min fairness is achieved through maximizing the utility function $\sum_{i \in F} U(\beta_i, \zeta)$ where $U(\beta_i, \zeta) = (1-\zeta)^{-1} \beta_i^{1-\zeta}$ and $\zeta \to \infty$ [42]. However, it is not practical since the optimization model is non-linear in this case, which is not easily solvable using the available solvers [43, 44]. The *progressive filling* algorithm is an alternative method to achieve the max-min fairness [45]. This algorithm starts with all rates β_i equal 0 and grows all the rates equally until rates of a set of source-destination pairs cannot be increased anymore. These are called *saturated* pairs. The rates of the saturated pairs are fixed at this value, and the algorithm continues to increase rates of unsaturated pairs until a new set of saturated pairs is found, and so on. The algorithm terminates when all pairs are saturated.

Growing rates of all source-destination pairs equally is achieved by a few modifications in STATICQRCA, which will be explained later. However, the problem to implement the progressive filling algorithm is that the STATICQRCA model does not determine which source-destination pairs are saturated and which are not. Therefore, we develop an auxiliary model to find the unsaturated pairs.

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First, we introduce the variables and parameters used in the model. Saturation of demand i is denoted by binary variable δ_i,

$$\delta_i = \begin{cases} 1, & \text{if demand } i \text{ is } \textbf{not} \text{ saturated} \\ 0, & \text{otherwise.} \end{cases}$$

Parameter r_i is the current allocated flow rate for demand i in an iteration of the progressive filling algorithm, and parameter ϵ is a very small real number.

We use the following observation to develop the auxiliary model. If demand i is not saturated, its maximum achievable flow rate, β_i, can be more than the current allocated rate r_i. Hence, setting $\delta_i = 1$ satisfies this inequality

$$\beta_i \geq r_i \delta_i (1 + \epsilon) \quad \forall i \in F. \tag{11}$$

To find unsaturated demands, we need to force δ_i to be non-zero for all of them. This is achieved by the following objective function

$$\text{maximize} \sum_{i \in F} \delta_i. \tag{12}$$

However, if demand i is *saturated*, where δ_i must be zero, its current allocated rate r_i should be reserved in this model, that means

$$\beta_i \geq r_i \quad \forall i \in F. \tag{13}$$

Using these constraints and the new objective function, we build the following model to find the unsaturated demands. In this model, the current allocated bandwidths are as input parameters and are represented by vector $\boldsymbol{r}$. The vector $\boldsymbol{\delta}$ obtained by solving the SATURATION model, specifies which pairs are saturated and which are not.

> **Model**:   SATURATION($\boldsymbol{r}$)
> **Objective**:   (12)
> **Subject to**:   (2)–(5), (7), (8), (11), and (13).

As explained above, in each iteration of the progressive filling algorithm, rates of unsaturated demands are grown equally. This is accomplished by replacing the objective function (1) and constraint (6) of STATICQRCA as follows. The new objective function is

$$\text{maximize } \gamma \tag{14}$$

and constraint (6) is converted to

$$\beta_i \geq \gamma \delta_i \quad \forall i \in F. \tag{15}$$

This means if demand i is not saturated, $\delta_i = 1$, its flow rate must be at least γ, which is the equal rate for all the unsaturated demands and is maximized through the objective function (14). Similar to the SATURATION model, we should maintain the current allocated rates for the saturated demands which is achieved by adding constraint (13) to this model. Therefore, in each iteration of the progressive filling algorithm, the following model is solved to equally grow flow rates of unsaturated demands, which are specified by $\boldsymbol{\delta}$.

> **Model**:   FAIRNESS($\boldsymbol{\delta}$)
> **Objective**:   (14)
> **Subject to**:   (2)–(5), (7), (8), (13), and (15).

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The SATURATION and FAIRNESS models are solved iteratively in the MAXMINFAIRCA algorithm to obtain the max-min fair rate allocation among demands. Pseudo-code of the algorithm is shown in Algorithm 2. In this algorithm, $\overline{0}$ and $\overline{1}$ are a vector with all coordinates equal to 0 and 1, respectively. This algorithm at the beginning, initializes vectors r and δ with proper values. Then in lines 3–6, it grows rates of unsaturated demands equally until there is an unsaturated demand, which is checked by $\delta > \overline{0}$; finally, in line 7, the algorithm finds new unsaturated demands.

Three points should be noted about the MAXTHROUGHPUTCA and MAXMINFAIRCA channel assignment algorithms. First, the worst case computational complexity of MAXMINFAIRCA is proportional to $O(|F|)$. However, in practice, the average case complexity is much lower. In our simulations for $|F| = 50$, the average number of iterations of the algorithm is about 2–3. Second, these algorithms solve the multi-commodity maximum flow problem in the context of *joint routing and channel assignment*. Their solutions provide both optimal routing, $f^i_{(u,v)} \quad \forall i \in F, \forall(u,v) \in E$, and channel assignments, $x^k_{(u,v)} \quad \forall k \in K, \forall(u,v) \in E$. We use only the channel assignment part, $\Psi = [x^k_{(u,v)}]_{\kappa \times m}$, in the static channel allocation schemes. Third, these algorithms were developed based on the fast switching capability assumption. Therefore, in the channel assignment obtained by them, each link may need to switch between multiple channels. In spite of this, these channel assignments are considered as static allocations because the *switching pattern* does not depend on the instantaneous actual traffic demands, and does not change over time.

8. SIMULATION RESULTS

This section is intended to answer the questions mentioned in Section 3.5 through extensive simulations. We study the effect of various parameters including the number of channels, the number of source-destination pairs, and traffic load on the performance and fairness of the dynamic and static channel allocation schemes.

Let $\mathcal{A}_i$ be the number of accepted demands with source-destination pair (s_i, d_i). We use the acceptance rate metric to measure the network performance, which is defined as

$$AR = \frac{\sum_{i \in \Delta} \mathcal{A}_i}{|F|}.$$

Fairness is measured in terms of Jain's fairness index [21], which is

$$FI = \frac{\left(\sum_{i \in \Delta} \mathcal{A}_i\right)^2}{|\Delta| \sum_{i \in \Delta} \mathcal{A}_i^2}.$$

Algorithm 2 : MAXMINFAIRCA(F)

1:   $r \leftarrow \overline{0}$ and $\delta \leftarrow \overline{1}$
2: **while** $\delta > \overline{0}$ **do**
3:     $\gamma \leftarrow$ FAIRNESS(δ)
4:     **for** each $i \in F$ **do**
5:       **if** $\delta_i = 1$ **then**
6:         $r_i \leftarrow \gamma$
7:     $\delta \leftarrow$ SATURATION(r)

Table II. Static Channel Allocation Schemes. $b_0 = 1$, $t_0 = 0$, and $e_0 = 1$.

Name	Channel Assignment	F Used in Channel Assignment
Static-Thr	MAXTHROUGHPUTCA	$\forall(s_i, d_i) \in \Delta \ \exists(s_i, d_i, b_0, t_0, e_0) \in F$
Static-MaxMin	MAXMINFAIRCA	$\forall(s_i, d_i) \in \Delta \ \exists(s_i, d_i, b_0, t_0, e_0) \in F$
Static-Uniform	MAXMINFAIRCA	$\forall(u, v) \in E \ \exists(u, v, b_0, t_0, e_0) \in F$

This parameter measures how fairly a resource allocation scheme accepts demands from different source-destination pairs. *Absolute fairness* is achieved when $FI = 1$, which implies that the same number of demands is accepted from all pairs. When all the accepted demands belong to only one source-destination pair, which means *absolute unfairness*, we have $FI = \frac{1}{|\Delta|}$.

8.1. Simulation Setup

We evaluated four channel allocation schemes. One of them, named **Dynamic**, is the dynamic scheme, which is implemented by the OQRCA algorithm. The others are static schemes, which are shown in Table II. **Static-Thr** and **Static-MaxMin** use the given set Δ and find the optimal static channel assignment for the set by MAXTHROUGHPUTCA and MAXMINFAIRCA, respectively. **Static-Uniform** is a special case of **Static-MaxMin** in which, it is assumed that no information is available about traffic pattern. This scheme assumes a uniform traffic pattern wherein all links have the same load. It optimizes the max-min fair *one-hop* capacity of the network by considering a demand $(u, v, 1, 0, 1)$ for each link $(u, v) \in E$.

We used a flow-level event-driven simulator developed in Java. Optimization problems were solved by ZIB Optimization Suite [43]. We carried out simulations in two topologies: Grid and Random. In the Grid topology, there were 25 nodes and distance between nodes in each row (column) was 200m. In the Random topology, 50 nodes were spread uniformly in $1000 \times 1000\text{m}^2$ area. In both topologies, $T_R = 200\text{m}$, $I_R = 400\text{m}$, $c = 100\text{Mb/s}$, $\kappa = 12$, and the number of radios per node is a uniform random variable in $\{2, \ldots, 5\}$. In each experiment, we generated a set of random source-destination pairs, $\Delta = \{(s_i, d_i)\}$, and a demand set $F = \{(s_i, d_i, b_i, t_i, e_i)\}$ where $(s_i, d_i) \in \Delta$, $b_i = 10\text{Mb/s}$, the demand arrival rate was a Poisson random variable with mean λ demands per minute, and the lifetime of the demands was exponentially distributed with mean 10 minutes. In each experiment, we used $|F| > 500$ demands, and there was an equal number of demands per source-destination pair. The results presented in the following subsections are the average of 10 experiments with different sets Δ and F.

In the following sections, in each topology, the **Dynamic** scheme is compared to the static schemes over a wide range of parameter settings. In each topology, we study the effect of the number of source-destination pairs, the network load (demand arrival rate), and the number of channels. Please note that the Grid and Random topologies are *not* compared to each other. Comparisons between the schemes in a topology are independent of the comparisons in the other topology. To carry out comprehensive comparisons in each topology, we simulated the schemes from lightly loaded regimes ($AR \sim 1.0$) to highly overloaded regimes ($AR \sim 0.2$). These regimes are obtained through appropriate setting of the parameters (λ, κ, $|\Delta|$) in each topology; obviously, since the underlying physical topologies are different, we needed to use different parameters for the Grid and Random topologies to generate the desired regimes in each topology.
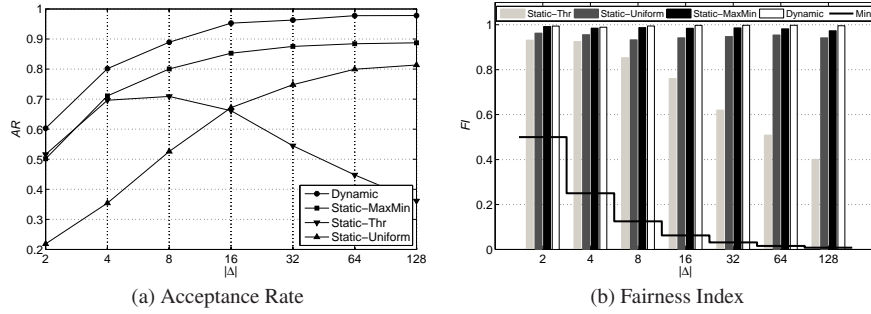
(a) Acceptance Rate

(b) Fairness Index

Figure 4. Acceptance rate and fairness index in the Grid topology versus the number of source-destination pairs. $\lambda = 7$ demands/min.
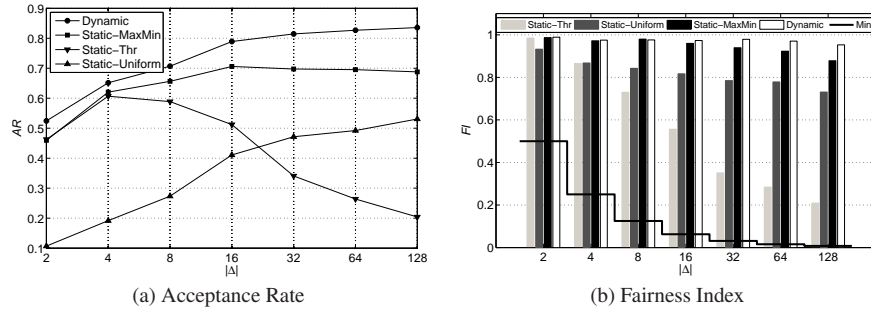

(a) Acceptance Rate

(b) Fairness Index

Figure 5. Acceptance rate and fairness index in the Random topology versus the number of source-destination pairs. $\lambda = 8$ demands/min.

8.2. *Effect of the Number of Source-Destination Pairs*

The dynamic channel allocation scheme does not use set Δ explicitly but the performance of the static schemes completely depends on it since they optimize channel allocation based on the set. The number of source-destination pairs, $|\Delta|$, has two effects. First, it influences load distribution in the network; for a given aggregate demand arrival rate λ, arrival rate of each source-destination pair is $\frac{\lambda}{|\Delta|}$. Second, it affects how network resources are allocated by the static schemes. In these schemes, network resources are reserved for every source-destination pair in the channel assignment phase; therefore, the number of pairs affects the amount of reserved resources for each source-destination pair.

Acceptance rate and fairness index of the simulated schemes in the Gird and Random topologies are depicted in Fig. 4 and Fig. 5, respectively. Note that in Fig. 4(a) and Fig. 5(a) the scale of the horizontal axis is logarithmic. In Fig. 4(b) and Fig. 5(b), "Min" is the minimum possible value of the fairness index, $\frac{1}{|\Delta|}$, corresponds to the absolute unfairness.

These results show the followings: (i) From the acceptance rate point of view, **Dynamic** outperforms the best static scheme, **Static-MaxMin**, about 10–15% in most cases. In Fig. 5(a), the gap between **Dynamic** and **Static-MaxMin** increases by increasing $|\Delta|$. This is due to the irregularity of the Random topology. When $|\Delta|$ is very small, the links in the center of this topology become bottlenecks and limit the maximum achievable performance gain. But in the case of a large $|\Delta|$, the links cause little effect on the acceptance rate since load is distributed throughout the network. Consequently,

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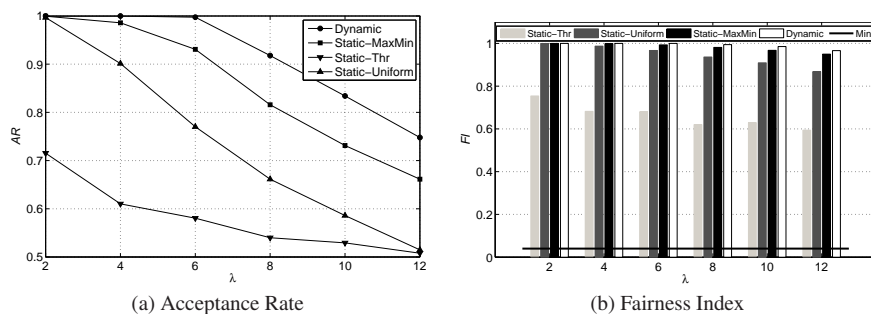(a) Acceptance Rate   (b) Fairness Index

Figure 6. Acceptance rate and fairness index in the Grid topology versus demand arrival rate. $|\Delta| = 25$.

in the latter case, the dynamic scheme can exploit available resources to improve the achievable performance gain. (ii) Acceptance rate is an increasing function of $|\Delta|$. Load distribution in the network, through increasing $|\Delta|$, avoids congestion and results in increase of acceptance rate. (iii) Achievable fairness is independent of the number of pairs; **Static-MaxMin** and **Dynamic** provide almost absolute fairness regardless of the number of source-destination pairs. (iv) The poor performance of **Static-Uniform** is caused by the uniform traffic assumption in this scheme. When there are very few source-destination pairs, there is a considerable difference between this assumption and the actual traffic pattern. Therefore, the channel allocation, which is optimized according to this assumption, is not suitable for the actual traffic pattern. (v) The unexpected behavior of **Static-Thr**, reduction of acceptance rate by increasing $|\Delta|$, is due to the resource reservation strategy by the scheme. Contrary to **Static-MaxMin**, this scheme does *not* guarantee a reserved resource for *every pair*. When there are many source-destination pairs, this scheme may not allocate any resource for some pairs in favor of allocating more resources to others that increase the aggregate network throughput. This can be verified by the fairness index; when this scheme gives low acceptance rates, it is also unfair. The small values of FI imply that the low acceptance rates are due to rejection of many demands from a subset of source-destination pairs. This subset is the pairs that the MAXTHROUGHPUTCA model has not reserved sufficient resources for them.

8.3. Effect of Network Load

Network performance depends on the load offered to the network; high loads lead to low acceptance rates. The load is determined by the arrival rate, lifetime, and required bandwidth of traffic demands. Since we have fixed the required bandwidth, $b_i = 10$Mb/s $\forall i \in F$, and the average lifetime, we control the offered load by arrival rate λ. Acceptance rate and fairness index of the channel allocation schemes versus demand arrival rate in the Grid and Random topologies are plotted in Fig. 6 and Fig. 7.

It can be seen from these figures that: (i) The **Dynamic** scheme improves acceptance rate about 10% in comparison to **Static-MaxMin** in both topologies when the networks are loaded moderately ($\lambda \geq 8$ in the Grid topology) or heavily. (ii) Fairness index decreases as demand arrival rate increases, which is more clear in the Random topology as depicted in Fig. 7(b). The reason is as follows. In the high demand arrival rates, network is overloaded, and its resources are not sufficient to accept all demands; so, resource-intensive demands are rejected. Whereas all demands request the same bandwidth 10Mb/s, they do not consume network resources equally. Resource consumption of each demand is proportional to the number of hops it traverses, which depends on the location of the source and destination
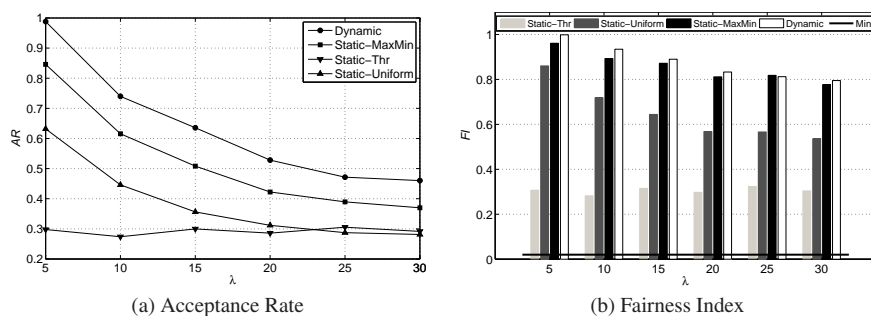
(a) Acceptance Rate

(b) Fairness Index

Figure 7. Acceptance rate and fairness index in the Random topology versus demand arrival rate. $|\Delta| = 50$.

of the demand. If source and destination are far away from each other, traffic demands from this source to the destination will be resource-intensive; hence, they are rejected with higher probability in overloaded regimes. This leads to the unfair acceptance rate among source-destination pairs. (iii) The poor performance of **Static-Thr** in Fig. 7(a) is due to the large number of source-destination pairs used in these simulations. Referring to Fig. 5(a), we see that $|\Delta| = 50$ leads to a low acceptance rate of **Static-Thr**.

8.4. Effect of the Number of Channels

Channels are the resources which our proposed schemes manage. Increasing the number of channels implies more resources and as a result gives better performance. We plotted acceptance rate and fairness index versus the number of available channels, κ, in Fig. 8 and Fig. 9 for the Grid and Random topologies, respectively. In these figures, the scale of the horizontal axis is also logarithmic. As we expect, acceptance rate is an increasing function of the number of channels.

Similar to the previous results, **Dynamic** outperforms **Static-MaxMin** about 10% in most cases. However, contrary to them, there are conditions, e.g., $\kappa \in \{2, \ldots, 8\}$ in the Grid topology, wherein **Static-Thr** has a satisfactory performance and even outperforms the other schemes. The reason is that network resources are very scarce in these conditions. Therefore, if a scheme accepts a resource-intensive demand, it cannot accept many subsequent demands because there are not sufficient resources to handle them. This is the behavior of **Dynamic** that attempts to accept every demand disrespect of its resource consumption. The low acceptance rate of **Static-MaxMin** in these conditions is due to the fact that this scheme distributes resources almost equally among source-destination pairs. When the network resources are very scarce, the allocated resources for each pair are such little that most demands are rejected. However, **Static-Thr** does not consider resource-intensive source-destination pairs and shares resources among a limited number of pairs that leads to a bit improvement in acceptance rate. There is another issue besides the low acceptance rate in these conditions; none of the schemes can provide good fairness as depicted in Fig. 8(b) and Fig. 9(b). The reason is that we explained in the previous section; the allocation schemes cannot accept the same number of demands from every source-destination pair because some of them are very resource-intensive. This issue becomes more significant when network resources are scarce.

In the Grid topology, Fig. 8(a), **Static-Uniform** is the worst scheme because demand arrival rate is very high, $\lambda = 20$ demands/min. It is straightforward to see in Fig. 6(a) that **Static-Uniform** is outperformed by the other schemes in high demand arrival rates.
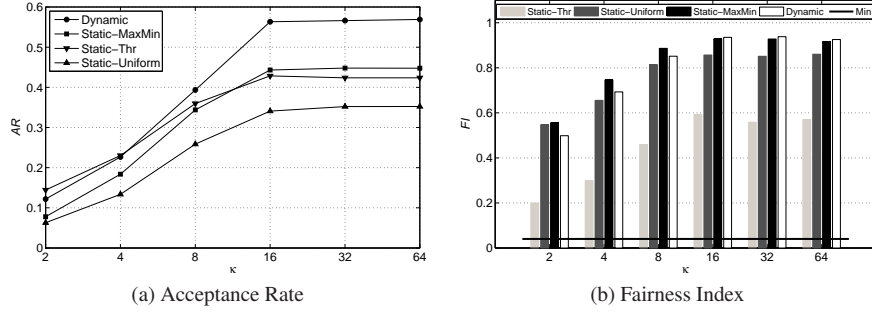
(a) Acceptance Rate   (b) Fairness Index

Figure 8. Acceptance rate and fairness index in the Grid topology versus the number of channels. $|\Delta| = 25$ and $\lambda = 20$ demands/min.

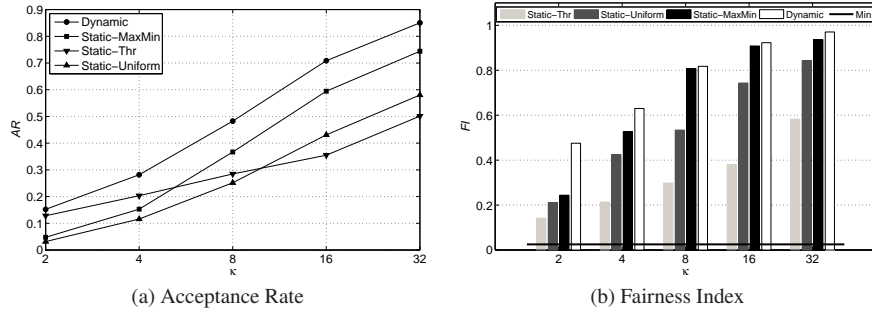(a) Acceptance Rate   (b) Fairness Index

Figure 9. Acceptance rate and fairness index in the Random topology versus the number of channels. $|\Delta| = 40$ and $\lambda = 15$ demands/min.

Resource allocation schemes cannot exploit all available channels due to two constraints: a limited number of radios in each node and the underlying network topology. At each node u, at most q_u channels are simultaneously usable. The network topology limits the amount of maximum possible flow per source-destination pair. These are the reasons that **Dynamic** cannot achieve higher acceptance rates by increasing κ beyond $\kappa = 16$ in the Grid topology.

8.5. Overhead

As mentioned before, the superiority of dynamic resource allocation schemes comes at the cost of updating network configuration over time. In this subsection, our goal is to measure the extra overhead caused by dynamic channel assignment in comparison to static channel allocation schemes.

There is an important point about the static schemes studied in this paper. Although channel assignment pattern is fixed in these schemes, routing changes over time. At the arrival time of each demand, these schemes may reroute all existing flows in the network to accept the new demand. In other words, if routing variables $f^i_{(u,v),j}$ and $f^i_{(u,v),j+1}$ are obtained by solving two instances of STATICQR corresponding to the arrival of jth and $(j + 1)$th demands, respectively, then in general $f^i_{(u,v),j} \neq f^i_{(u,v),j+1}$. The **Dynamic** scheme has extra overheads to update channel assignment in addition to routing.

Both routing and channel assignment are expressed in terms of attributes of links, $f^i_{(u,v)}$ and $x^k_{(u,v)}$.

Table III. Overhead of channel allocation schemes in term of the number of updated links.

Parameter Settings				Dynamic		Static-MaxMin
Topology	κ	λ	$|\Delta|$	Rerouting	Total	Rerouting
Grid	12	15	10	73.85	74.62	69.29
Grid	12	10	20	73.63	75.02	69.07
Grid	30	5	25	77.12	77.44	59.51
Random	12	5	30	185.89	188.63	88.26
Random	12	10	20	182.41	184.98	104.99
Random	40	15	20	206.52	208.26	150.15

Hence, the cost of updating network configurations, including signaling and processing overheads, is proportional to the number of links that their associated variables are updated. The average number of links updated by the **Static-MaxMin** and **Dynamic** schemes in various parameter settings are shown in Table III. In this table, column "Rerouting" is the average number of links that $f^i_{(u,v)}$ is updated, and column "Total" is the average number of links that $f^i_{(u,v)}$ **or** $x^k_{(u,v)}$ is modified. It can be seen that the difference between the numbers of updates due to rerouting can be quite big. For example, in the Random topology, the overhead of **Dynamic** is significantly more than **Static-MaxMin**. Comparing the "Rerouting" and "Total" subcolumns in the **Dynamic** column shows that dynamic channel assignment *by itself* does not increase the number of updated links significantly. In fact, the updated links through rerouting or channel reassignment are the same in most cases. Because when $f^i_{(u,v)}$ is modified, the aggregate load on the link changes according to (3), and consequently, $x^k_{(u,v)}$ is modified to maintain (2). The main overhead of the dynamic channel assignment is its effect on rerouting. When it is combined with rerouting increases degree of freedom that results in the high overhead of rerouting.

It must be noted that the overhead of practical resource allocation schemes can be considerably less than the overhead of **Dynamic** and **Static-MaxMin**. Because the STATICQR and STATICQRCA optimization models used in these schemes have not been designed to minimize the overhead. These models only find a feasible network configuration to accept a newly arrived demand, and the new configuration may need a lot of updates.

8.6. Concluding Remarks

Here, we summarize our observations in the previous subsections. The main results are the following.

- **Static-MaxMin** is far superior to other static schemes. This implies that availability of precise information about long-term steady state behavior of traffic pattern and maintaining fairness are crucial issues in static schemes.
- **Dynamic** in comparison to **Static-MaxMin** does not achieve any noteworthy fairness improvement independent of network and traffic parameter settings.
- **Dynamic** outperforms **Static-MaxMin** in most cases about 8–10%.
- When the network is heavily overloaded ($AR < 0.4$–0.5), all schemes are rather unfair.
- The performance gain of **Dynamic** becomes more significant when there are many source-destination pairs, especially in the Random network.
- When a network with scarce resources ($\kappa \leq 4$) is very heavily overloaded ($AR < 0.2$–0.3), static schemes perform as well as **Dynamic**.
- The overhead of the **Dynamic** scheme can be much more than **Static-MaxMin**; in our simulations in the Random topology, **Dynamic**'s overhead is about 2–2.5 times more than **Static-MaxMin**.

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9. CONCLUSIONS

In this paper, we quantified the maximum achievable performance gain and fairness enhancement by an *optimal* dynamic channel allocation scheme in comparison to *optimal* static schemes. The comparisons were carried out in the context of QoS provisioning. The dynamic scheme is indeed the online joint QoS routing and channel assignment algorithm. The static schemes are implemented by two separated algorithms: an off-line static channel assignment and online QoS routing. All these algorithms were developed based on MILP models. We developed three static schemes and compared them to the dynamic scheme. Simulations showed the following. First, static schemes achieve acceptable performance only if precise information is available about long-term traffic pattern, and the channel assignment is optimized for the pattern subject to max-min fairness constraint. Second, the dynamic scheme is superior (about 8–10%) to the max-min fair static scheme in most cases; however, both achieve almost the same fairness. Third, in the case of a heavily overloaded network with very scarce resources, static schemes are better solutions because their performances are comparable to the dynamic scheme and incur less overhead.

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