Joint Revenue-based Call Admission Control and Routing in Wireless Mesh Networks

Nika Naghavi, Vasilis Friderikos, Hamid Aghvami
Centre for Telecommunications Research, King’s College London
nika.naghvai@kcl.ac.uk, vasilis.friderikos@kcl.ac.uk, hamid.aghvami@kcl.ac.uk

Abstract—Various algorithms have recently been proposed to enhance the Quality of Service (QoS) in Wireless Mesh Networks (WMNs). In this respect, we investigate joint Call Admission Control (CAC) and routing in order to provide quality of service (QoS) in wireless mesh networks. Joint association of each mesh client with a mesh access point and multi-hop backhaul routing to the Gateway, determine the availability of resources as to admit or reject a flow. We formulate a joint optimization problem, which maximizes the total revenue from all the carried connections in the network while taking into account the bandwidth constraints of access and backhaul links. In this regard, firstly we derive an optimal pricing policy that considers the complexity of the problem and the connection dropping probability. Then a CAC algorithm is presented using the pricing model. Due to its complexity, the proposed problem cannot be dealt with using the exact methods; therefore a sub-optimal solution is presented through incorporating the meta-heuristic search algorithm i.e batch based simulated annealing to the CAC algorithm.

Index Terms—Wireless Mesh Networks, Routing, Call Admission Control, Quality of Service

I. INTRODUCTION

Wireless mesh networks (WMNs) are multihop wireless networks consisting of mesh router and clients, able to provide wireless connectivity for a vast number of applications ranging from first mile Internet connectivity to backhaul support for cellular networks. In an infrastructure based WMNs, mesh routers form a backbone for mesh clients to be connected with minimal mobility. The mesh routers are normally equipped with multiple interfaces to connect to the other networks such as Cellular, Wi-Fi and WiMAX or wired connectivity to the Internet [1]. WMNs have the benefit of providing coverage in the areas that are difficult to reach or areas where deploying cables is either impossible or costly.

Call Admission Control (CAC) is a strategy for accepting, rejecting or negotiation connection to the network [2]. Admission control has been comprehensively studied in cellular networks. Most CAC schemes proposed for cellular networks are based on the concept of using guard channel information. A revenue-based CAC for wireless cellular networks, using channel reassignment is proposed in [3], where the study demonstrates the relationship between the number of guard channels, reassignments and total revenue.

In WMNs on the other hand, routing and CAC are strongly interrelated and would require a joint design scheme in order to optimize the performance of the system. A contention-aware admission control for multihop WLANs is proposed in [4], in which a contention graph is utilized to model the wireless interference in the network. A new flow can only be admitted if the total traffic on each maximal clique is not more than the available capacity in that clique. The capacity of a maximal clique is estimated as the saturation throughput. An admission control algorithm considering the connections’ rate and delay is proposed in [5]. In the proposed CAC scheme, first a tree-based topology connecting wireless backhaul nodes to the wired gateway is constructed, the admission decision is then carried out with the objective of revenue maximizing whilst taking into account the rate and delay of the connections.

A mobile agent (MA) based handoff approach for WMNs is suggested in [6]. In this scheme each mesh client is facilitated with an MA residing on its current router, which will move to a new mesh router and reserve resources in case of a hand over to a new mesh router. A proportional threshold structured optimal effective bandwidth CAC policy is implemented on mesh routers, which offers a higher priority to the hand over calls whilst providing the mesh clients with a high statistical effective bandwidth. In [7] optimization of association, backhaul routing and bandwidth allocation in WMNs is jointly addressed. The main objective of this work is to maximize the network throughput as well as assurance of a fair bandwidth allocation amongst all the mesh clients, considering the access and backhaul links capacity and taking the wireless interference into account. A revenue based connection admission control and routing, which is modeled as a semi-Markov decision process (SMDP) is addressed in [8]. It assumes k pre-computed paths for each origin-destination, and also resource reservations for classes or services possessing higher priority is embedded. However the admitting probability is used as the average reward criteria and the work does not delve into the effect of pricing model on the performance of the system such as total revenue gain or connection blocking probability.

In a single-hop WLAN, Access Points (AP) are directly connected to the wired backbone and the access link is most likely to be the bottleneck. In WMNS however, the traffic can be bottlenecked by either the access link or by the backhaul links. Thus this work primarily attempts to maximize the total revenue gained from the admitted connections whilst avoiding the bottlenecks in either the access or the backhaul links. Unlike the majority of the research in the context of CAC that consider maximizing the total revenue, congestion control and pricing separately [9], we present an optimal pricing scheme that takes both the blocking probability and total revenue into account. To this end, a joint CAC and routing algorithm

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are formulated using the proposed pricing policy. Routing and admission control are decoupled for further simplification purposes. A sub-optimal solution is obtained incorporating simulated annealing and we show that simulated annealing is capable of solving a complex CAC problem with difficult constraints. To the best of our knowledge this work is the first to consider the pricing policy, routing and admission control jointly in WMNs.

The rest of this paper is organised as follows. In section II the problem description, our routing algorithm and the proposed pricing scheme are detailed. Section III presents our proposed CAC problem formulation and explains the algorithms incorporated in finding the near-optimal solution. Numerical and simulation results are reported in Section IV, and finally section V concludes the paper by briefing the findings.

II. SYSTEM MODEL

In this work we formulate the joint admission control and routing as a Multiple Knapsack with Assignment Restrictions (MKAR) problem. Upon arrival of a request (i.e., flow), a decision as to which Mesh Access Point (MAP) to admit a flow and which shortest path to route a flow through should be made. This process is based on the available capacity in both the access link and the backhaul links. Jointly solving the admission control and routing in a wireless multihop environment, given a set of nodes and demands, is an NP-hard optimization problem [5]. Therefore, we decompose the problem into routing (path construction) and admission control, thus solving them separately. The goal is to associate each flow with an appropriate MAP which has enough capacity in both its access link and routing path from the gateway to accommodate that flow, in order to maximize the revenue from all the carried connections. In our model MAPs are considered as the knapsacks with a limited capacity and the flows as the items that need to be fitted in. The price associated with each flow is considered as the profit, and the bandwidth required by each flow is the weight of each item. Given that not all the flows are within the transmission range of all MAPs, a set of flows per MAP is defined, which is the same as a set of items being admissible to a specific knapsack.

An issue which has not been addressed in the literature is the economical side of the users’ management in CAC. Users’ reaction to the tariff proposed by the provider indicates that increased prices would result in fewer number of users, whilst also a low-priced tariffs lead to a low revenue, which would consequently affect the load on the network [10]. Since we have modeled our system as an MKAR, the correlation between the price and the bandwidth (rate) of each flow also needs to be considered, since this will change the hardness and complexity of the problem [11]. Our goal is to first find a pricing policy that maximizes the total revenue gain but which also takes into consideration the connection blocking probability and the hardness of the problem. Using this optimal pricing policy, the CAC algorithm is implemented. To this end, the above mentioned models are detailed as follows.

A. Network Model

We consider a wireless mesh network with m MAPs and n flows (or mesh clients) as a connectivity graph $G(V, L)$, where $V$ is a set of vertices (wireless nodes) and $L$ is the set of edges or transmission links that satisfy a pre-defined SINR threshold criterion. We assume that each of the wireless nodes use the same modulation scheme and transmit with the same fixed transmission power; thus a further assumption is that each node has an identical fixed transmission range of $r_{tx}$, which is a well-used assumption in wireless multihop networks [12][7].

A logical link between node $u$ and $v$ exists if the distance between them is less than or equal the $r_{tx}$:

$$L = \{(u; v)|u; v \in V \}$$

s.t. $u$ being in $r_{tx}$ of $v$ and vice versa. (1)

We can assume slow fading channel on the backhaul links due to end point being static. Let us define $C_j$ and $b(v)$ as the capacity of each MAP access link and each wireless node in the backbone respectively, where $j \in m = [1, 2, ..., M]$. Given $w_i$ and $p_i$, the bandwidth request of each flow $i \in n = [1, 2, ..., N]$ and the price associated with admitting the corresponding flow, we can construct $k = [1, 2, ..., K]$ shortest paths (sp) from each origin to the destination using the Dijkstra algorithm. Batch processing results in a significant degree of improvement regarding the admission control and revenue maximising as opposed to handling the flows individually. We assume that flows arrive according to a Poisson process with arrival rate $\lambda$, and we solve the optimisation problem for each batch. Processing a batch allows us to admit flows that lead to a higher revenue gain whilst not violating the capacity constraints, therefore meeting the QoS requirements [13].

In order to be able to define the problem in a mathematical programming setting, the following boolean variables are introduced, in which $sp$ denotes the calculated shortest path:

$D_{ij} = \begin{cases} 1 & \text{if flow } i \text{ is within transmission range of } MAP_j \\ 0 & \text{Otherwise} \end{cases}$ (2)

$sp^v(jk) = \begin{cases} 1 & \text{if } sp_k \text{ of } MAP_j \text{ passes through node } v \\ 0 & \text{Otherwise} \end{cases}$ (3)

$x_{ijk} = \begin{cases} 1 & \text{if flow } i \text{ is assigned to } sp_k \text{ of } MAP_j \\ 0 & \text{Otherwise} \end{cases}$ (4)

In equation (2) $D_{ij}$ is the transmission range Boolean variable, that shows which flows are within the transmission range of which MAPs. A $sp_k$ of a $MAP_j$ might share an intermediate node with another $sp$ of the same or a different $MAP$ and become a bottleneck. As stated before we are interested in routing the flows over one of the $k$ sps and therefore (3) and (4) exhibits whether a $sp_k$ passes through node $v \in V$ and the decision variable respectively. Any individual flow can only be admitted to one $sp_k$ of any $MAP_j$. 

A logical link between node $u$ and $v$ exists if the distance between them is less than or equal the $r_{tx}$: $L = \{(u; v)|u; v \in V \}$. s.t. $u$ being in $r_{tx}$ of $v$ and vice versa.
B. Routing Algorithm

As mentioned earlier, joint consideration of routing and CAC is an NP-hard problem which involves taking the wireless interference constraints into account. In our model routing paths are pre-constructed in a separate phase, the admission of demands is then carried out assuming that our environment is interference free. The assumption of an interference free environment and pre-computed paths [5] for each source-destination has also been adopted in [8].

Dijkstra’s algorithm manages to find the shortest path tree from a source node to every other node. The cost metric used here is the free path loss for the link \((i; j)\). The presented algorithm in this paper, manages to find \(K\) shortest paths for each source-destination pair based on the proposed algorithm in [14].

The \(K\) shortest paths constructed are not node-disjoint and they might share an intermediate node with any other shortest path in the topology. One of the primarily focuses of this work is to identify the bottlenecks in the system and in this regard a matrix of all \(sp-v\) can be constructed for the specific WMN topology, which is expressed by the boolean variable (3).

C. Price and Revenue Function

Next generation of wireless networks offer a vast range of multimedia services to the users; hence it is vital to design a call admission control algorithm that besides satisfying the users’ QoS requirements, aims at maximizing the revenue of the network operator. Pricing for different telecommunication services is a topic that has been widely studied in the literature and influences how QoS and Call Admission Control intertwine [9].

We use a similar pricing demand-function as the one in proposed in [15], which is detailed as follows:

\[
\lambda^{\beta} = a^{\beta} (p^{\beta})^{-e^{\beta}},
\]

where \(\lambda^{\beta}\) denote the arrival rate of class \(\beta\) traffic and \(p^{\beta}\) denotes the price associated with class \(\beta\) traffic. Also, \(a^{\beta}\) and \(e^{\beta}\) are the constants correlating the variables \(\lambda^{\beta}\) and \(p^{\beta}\). From equation(5), it can be immediately gathered that pricing a class of traffic determines the arrival rate of that class of service. The lower the price associated with a certain class of traffic, the more the arrival rate of that certain class of traffic. This assumption can result in a higher revenue gain but also low pricing can result in a highly congested network, with a high blocking probability [16]. In this work a static pricing proportional to the amount of bandwidth that a user requests is considered, as dynamic pricing might cause user dissatisfaction due to frequent changes in the price of the service[17].

In our proposed model \(p_i\) is the price associated with admitting flow \(i\). The total revenue that the operator gains is defined as follows:

\[
\sum_{j \in \Omega_i} \sum_{k=1}^{K} \sum_{i=1}^{N} x_{ijk} p_i
\]

where

\[
\Omega_i = \{ AP_j | D_{ij} = 1 \}
\]

As outlined before we have modeled our network as an MKAR problem, thus the correlation between the profit and weight also needs to be considered in this type of optimization problem and the complexity that this would impose on different instances of the problem. The computational experiments proposed in the literature commonly consider three main classes of randomly generated instances for 0-1 Knapsack Problems [11]:

1) Uncorrelated :
\[
w_i \text{ uniformly random in } [b,a]
\]
\[
p_i \text{ uniformly random in } [b,a]
\]
\[
C = \frac{1}{2} \sum_{i=1}^{N} w_i
\]

2) Weakly Correlated:
\[
w_i \text{ uniformly random in } [b,a]
\]
\[
p_i \text{ uniformly random in } [w_i - \delta, w_i + \delta]
\]
\[
C = \frac{1}{2} \sum_{i=1}^{N} w_i
\]

3) Strongly Correlated:
\[
w_i \text{ uniformly random in } [b,a]
\]
\[
p_i = w_i + \delta
\]
\[
C = \frac{1}{2} \sum_{i=1}^{N} w_i
\]

Stronger correlation between the profit and weight imposes more complexity and hardness in finding the optimal solution; therefore three factors should be considered in finding an optimal pricing policy: the total revenue of the operator, the blocking probability in the network and the complexity of the problem. We first solve the 0-1 Knapsack problem for these three instances for a maximum of 100 flows, a pricing policy that maximizes the revenue and at the same time does not result in a high blocking probability is chosen based on our simulation results.

III. PROBLEM DEFINITION

A. CAC Algorithm

In this section the joint routing and CAC algorithm is formulated as below:

Maximize
\[
\sum_{i=1}^{N} \sum_{j \in \Omega_i} \sum_{k=1}^{K} x_{ijk} p_i
\]

Subject to
\[
\sum_{i=1}^{N} \sum_{j \in \Omega_i} \sum_{k=1}^{K} w_i x_{ijk} \leq c_j
\]
\[
\sum_{i=1}^{N} \sum_{j \in \Omega_i} \sum_{k=1}^{K} sp^v(jk) w_i x_{ijk} \leq b(v), \quad \forall v \in V
\]
\[
\sum_{j \in \Omega_i} \sum_{k=1}^{K} x_{ijk} \leq 1, \quad \forall i
\]
\[
x_{ijk} \in \{0, 1\}, \quad \forall (i, j, k)
\]
\[
D_{ij} \in \{0, 1\}, \quad \forall (i, j)
\]
Constraints (7), (8) and (9) states that a flow \( i \) can only be admitted if there is enough capacity in the access link of the MAP \( j \) as well as the \( sp_k \) of the MAP \( j \). A set of MAPs per flow is defined as \( \Omega_i = \{AP_j | D_{ij} = 1 \} \), which shows the number of MAPs that a flow is within the transmission range of.

B. Near-optimal Solution

Our CAC problem formulated in the previous section can not be optimally solved, therefore by incorporating greedy call packing (GCP) algorithm and simulated annealing (SA) algorithm a near-optimal solution is obtained. The GCP is a heuristic that chooses the local optimum, assuming that this is the global optimum it progresses making one greedy choice after another, the details of which can be found in algorithm (1). In the first step, in order to produce good solution within a reasonable amount of computing time, an initial solution using the GCP algorithm is achieved, which is then followed by many iterations to modify this solution in order to find a more feasible solution. This is done through incorporating SA algorithm, which is a local search algorithm with the advantage of not becoming trapped in the local optimum. The name and inspiration of this algorithm comes from annealing in metallurgy in which the solid state metal is heated and slowly cooled down until it reaches a minimum energy crystalline structure [18]. At each iteration of the SA algorithm, the current solution and the new solution are compared. Better solutions are always accepted and non-improving solutions are accepted with the following probability \( p = \exp\left(\frac{-\Delta_L}{T}\right) \), which depends on a temperature parameter. By allowing worse or non-improving moves simulated annealing escapes from the local optima, but as the temperature decreased towards zero acceptance of non-improving moves decreases and the algorithm becomes similar to the greedy algorithm. The SA algorithm implemented here is based on the work proposed in [19] and is outlined in algorithm (2).

IV. PERFORMANCE EVALUATION

Our simulation scenario consists of a wireless mesh topology with a randomly placed MAPs and randomly distributed flows in a manner that each flow is within the transmission range of at least two MAPs. In our topology the backhaul is a 1 km\(^2\) rectangular area, containing three MAPs and one gateway; there are ten intermediate nodes (APs) that provide the backhaul routing. We use a uniform random generator to generate the bandwidth of the flows between 128Kbps and 4.096Mbps. Each backhaul link in the network has the equal capacity of 12Mbps and each access link has the total capacity of 30Mbps.

Once our topology was deployed using the Dijkstra algorithm \( k \) (\( k = 2 \) in our simulated scenario) shortest paths were constructed from each MAP to the gateway. This is shown in figure 1.

In the first set of simulation scenarios, 10-100 flows are considered and system performance in terms of blocking probability and total revenue for a single MAP is examined. Theses results are presented in figure 2, where the effect of pricing method on the revenue is obtained. From figure 2 it can be observed that on average the total revenue gained, using the uncorrelated class of random weighings, is much higher comparing to the other two classes. This is mainly because in the uncorrelated class a wider range for price exists as opposed to the weakly and strongly correlated classes, where the price ranges \( \pm \delta \) and \( \pm \delta \) from \( w_i \) respectively.

Figure 3 shows how the blocking probability can be affected by the price. The blocking probability of each sample against the number of flows using the three instances is plotted. From figure 2 and 3 it can be observed that in the scenario where there is no correlation between the price and the bandwidth the average blocking probability is the least. As can be seen from figures 2 and 3, the uncorrelated random class of weighing

\[
\begin{align*}
\text{Algorithm 1: Greedy Call Packing (GCP)}
\end{align*}
\]

1: Input: \( w_i, p_i, c_j \) and \( b(v) \)
2: for \( i = 1 \) to \( n \) do
3: \( G = \frac{p_i}{w_i} \)
4: end for
5: sort the flows so that \( G_1 > G_2 > \ldots > G_n \)
6: set \( L_t, Z_t \) and \( x_{ijk} \) to zero
7: for \( i = 1 \) to \( n \) do
8: find \( j \) for which \( D_{ij} = 1 \)
9: if \( L_{ij} + w_i \leq C_j \) then
10: find which \( sp_k \) has the available capacity
11: \( sp^V(j) = 1 \)
12: if \( w_i \leq b(v) \) then
13: \( L_{ij} = L_{ij} + w_i; Z_t = Z_t + p_j; x_{ijk} = 1 \);
14: \( b(v) = b(v) - w_i \);
15: end if
16: end if
17: end for
18: Output \( Z_t \) and \( x_{ijk} \)

\[
\begin{align*}
\text{Fig. 1. Topology of WMNs deployed in this work}
\end{align*}
\]
Algorithm 2 Simulated Annealing (SA)

1: select the initial solution : \( I_o = \{ijk \mid x_{ijk} = 0 \} \) and 
\( I_1 = \{ijk \mid x_{j} = 1 \} \) for \( j = 1, \ldots, M; i = 1, \ldots, n; k = 1, \ldots, K \), initial temperature \( t_o \), number of iterations per temperature \( tr \), cooling schedule \( D \) and final temperature \( t_f \).
2: \( t = t_o \)
3: repeat
4: set iteration counter \( no = 0 \);
5: choose \( h \in I_o \) randomly
6: find \( D_{bj} = 1 \)
7: if \( L_{t_j} + w_h \leq c_j \) then
8: find \( sp_{hj} = 1 \)
9: if \( w_h \leq b(v) \) then
10: \( I_o = I_o - h; I_1 = I_1 \cup h; b(v) = b(v) - w_h; \)
11: \( no = tr; \) goto cool
12: end if
13: end if
14: end if
15: choose \( k \in I_1 \) that is admitted to MAPs
16: find \( D_{bj} = 1 \)
17: if \( L_{t_j} + (w_h - w_k) \leq c_j \) then
18: find \( k \) and \( sp_{hk} = 1 \)
19: if \( w_h - w_k \leq b(v) \) then
20: \( \Delta = p_h - p_k; \)
21: if \( \Delta > 0 \) then
22: \( I_o = I_o - h \cup k; I_1 = I_1 \cup h - k; Z_t = Z_t + \Delta; \)
23: \( no = tr; \) goto cool
24: else
25: \( \Delta f = Z_t + \Delta; \)
26: if \( \) randomly distributed \( y \) in \( 0, 1 \) \( < \exp(\frac{-\Delta f}{t}) \) then
27: \( I_o = I_o - h \cup k; I_1 = I_1 \cup h - k; Z_t = Z_t + \Delta; \)
28: end if
29: else
30: end if
31: end if
32: else
33: if \( \) randomly distributed \( y \) in \( 0, 1 \) \( < \exp(\frac{-P_h}{t}) \) then
34: \( I_o = I_o \cup k; I_1 = I_1 - k; Z_t = Z_t - p_h; \)
35: \( no = tr; \) goto cool
36: end if
37: end if
38: \( no = no + 1; \)
39: until \( no = tr; \)
40: cool : \( t = t \times D; \)
41: until \( t < t_f \)

significantly outperforms the other two instances in both the total revenue gain and blocking probability, and therefore this pricing policy is chosen to be the optimal pricing policy and the rest of the simulation in this paper is based on this model. As mentioned earlier our objective is to maximize the total revenue that the network operator gains, and in this regard requests with higher price have more priority in terms of admission. In the strongly correlated instance, pricing is in a manner that the more bandwidth a flow is requesting the higher the price; therefore the request that have a higher price are first admitted and because these request require a large bandwidth they quickly use almost all of the capacity in the network resulting in a high blocking probability and a low total revenue gain. In the weakly correlated instance as well a higher price is associated to the requests with more bandwidth but not as high as the strongly correlated case, which results in a high blocking probability and a low total revenue gain.

After the network topology is deployed, using Dijkstra’s algorithm \( k \) shortest paths from each source-destination is computed. Using these pre-computed paths, the optimal solution using the exact method is achieved, the results of which is compared to the solution attained through the GCP and SA algorithms. As mentioned earlier we propose a batch processing CAC. In order to show that batch processing lead to a considerable degree of improvement in terms of revenue maximizing the optimal and GCP and SA results are compared to the on-line scheme, where flows are admitted individually. The results in figure 4 shows that batch processing results in a higher revenue gain comparing to the on-line scheme where the decision as to admit or reject is performed for each request independently as they arrive at the gateway. It can also be observed that SA algorithm outperforms GCP algorithm and it achieves a better near-optimal solution. This example also demonstrates that SA is capable of efficiently solving the complex CAC problem with difficult constraints and can be further adopted in scenarios with higher complexity i.e with more MAPs, flows and s; where an optimal solution cannot be achieved using the exact methods.

V. CONCLUSION

In this paper we formulate a joint admission control and routing in Wireless Mesh Networks as a Multiple Knapsack with Assignment Restrictions (MKAR) problem, which maximizes the total revenue from all the carried connections in the network while taking into account the bandwidth constraints of access and backhaul links. First, an optimal pricing policy that considers the complexity of the problem and the connection dropping probability is derived. Using this optimal pricing policy a sub-optimal solution is achieved through incorporating the meta-heuristic search algorithm Simulated Annealing to the CAC algorithm.

This work can be extended to decide dynamically if a newly arrived flow can be admitted without violating the QoS requirements. Another interesting dimension is to look into the inter-flow and intra-flow interference when constructing the shortest path from each source-destination. This requires
considering both the diversity of channel assignment and the link capacity.

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