Efficient Bandwidth Allocation in Wireless Community Networks

Fabio Martignon*, Stefano Paris†, Ilario Filippini‡ and Antonio Capone‡

*Lab. de Recherche en Informatique
Université Paris-Sud 11
fabio.martignon@lri.fr

†Dep. of Information Technology and Math. Methods
University of Bergamo
stefano.paris@unibg.it

‡Dip. di Elettronica e Informazione
Politecnico di Milano
{filippini, capone}@elet.polimi.it

***Abstract*—The network coverage and the number of residential users that a network operator may serve through a Wireless Mesh Network can be significantly increased by subleasing the available bandwidth to a subset of customers.**

In this paper we propose an innovative mechanism to allocate the available bandwidth of a wireless network operator to those customers who are willing to pay the higher price for satisfying their bandwidth demand. We formulate the allocation mechanism as a combinatorial truthful auction and further present a greedy algorithm that finds efficient allocations even for large-size, real scenarios, while maintaining the truthfulness property.

Numerical results show that the greedy algorithm represents an efficient and practical alternative to the combinatorial auction mechanism.

***Index Terms*—Bandwidth Auctions, Mechanism Design, Wireless Community Networks.**

I. Introduction

Wireless Mesh Networks (WMNs) have been accepted as a new communication paradigm able to provide a cost-effective means to deploy all-wireless network infrastructures [1]. Several network operators have started using the WMN paradigm as a valuable mechanism to provide broadband Internet access to remote areas, where the low return on investments cannot cover all costs to deploy more expensive wired solutions. However, the maintenance costs of the wireless devices, mainly due to the low channel reliability, might still limit the diffusion of this technology.

With the aim of further reducing the overall costs to provide broadband Internet access to residential users in both metropolitan and remote areas, and thus maximizing their profit, network operators have been fostering the deployment of Wireless Mesh Community Networks (WMCNs) [2]. In WMCNs, a group of independent mesh routers owned by different individuals forms a WMN in order to share their broadband connectivity, which may be available only to a part of them and with different bandwidths.

In this context, we envision a marketplace scenario where a network operator may lease the bandwidth of its access network to a subset of customers in order to increase the network coverage of its WMN and provide access to residential users through *third party* mesh client devices. The customers who manage these mesh clients pay the network operator to exploit the access bandwidth, while they are rewarded directly by the residential users they serve. Note that both the network operator and the customers[1] gain from this agreement, since the former can lease the bandwidth of its WMNs saving management and maintenance costs, while the latter can earn money by subleasing the purchased bandwidth to other residential users. Finally, the residential users that would not have been covered by the network operator because of low payoffs obtain a better Internet service.

In order to be an attractive solution, the aforementioned bandwidth market managed by the WMN operator needs convincing allocation and payment mechanisms that should act as incentives for customers to participate and subscribe to the service. One of the main problems that might discourage residential users and the WMN operator from participating is the possibility that even few dishonest customers misbehave. Specifically, from a residential user's perspective, the customer can provide a smaller bandwidth than the one promised. In this case the residential user can cancel the subscription and/or react to unsatisfied QoS guarantees. From an operator's perspective, the scenario is even more complex, since a customer could strategically bid false offers, thus manipulating the market as it prefers, in order to pay a lower price or rule out honest customers. These adversarial behaviors reduce the operator's revenue.

In this paper we present a mechanism targeted for the network scenario described above, which is resilient against any actions attempted by selfish customers aimed at manipulating the bandwidth market. To meet this latter requirement, we design an optimal truthful auction that forces each customer interested in leasing the available bandwidth to bid its real valuation of the required bandwidth demand.

The approach consists in finding the optimal set of customers to be accepted by the operator (auction winners), whose traffic demands can be routed through the WMN, and the corresponding prices they have to pay for the leased service, which constitute the operator revenue. The optimal allocation and the pricing together make the auction truthful.

Since finding such optimal allocations is an NP-hard problem, we have also designed a greedy algorithm which implements the auction and, although not being optimal, still guarantees that bidding its real valuation is the best strategy

[1] The customers are residential users that operate the mesh client devices.

for each participating customer.

Several research works investigate the use of auction theory to design efficient mechanisms for resource allocation, in which true and fair collaboration emerges as the best rational strategy for all selfish participants. They are reviewed in the next section. However, existing solutions do not accurately capture the main features of wireless multi-hop networks, and do not take into account the high computational time to carry out the auction. The main contributions of this paper are:

- We propose and analyze an innovative marketplace for the allocation of the WMN's available bandwidth to those customers who are willing to pay more for sharing their bandwidth with final users.
- We propose a combinatorial truthful auction that maximizes the revenue of the WMN operator, which is resilient against any market manipulation.
- We design a greedy algorithm to efficiently compute customer allocations and payments, which still guarantees that participating customers bid their real valuations.

Experimental results show that the proposed greedy algorithm performs close to the optimal auction, even in large scale, realistic scenarios, thus representing an efficient yet truthful alternative mechanism to the combinatorial auction.

The rest of this paper is structured as follows: Section II discusses related work. Section III presents the communication and network models considered in our work. Section IV formulates the combinatorial auction as an optimization model, while Section V illustrates the greedy algorithm that we propose to efficiently compute the solution. Section VI provides a numerical evaluation of the proposed framework. Finally, conclusions are discussed in Section VII.

II. Related Work

Auction theory has been used to design efficient allocation mechanisms in several network contexts.

With the upcoming generation of cognitive radio networks, market-based auctions have been extensively studied as an efficient mechanism to dynamically sublease the unexploited licensed spectrum to secondary users and increase the revenue of the spectrum owner [3], [4], [5], [6], [7].

Auction theory has been exploited to design innovative traffic engineering techniques and routing protocols, both to enhance the utilization of unused network paths and force the collaboration of intermediate relaying nodes [8], [9], [10], [11], [12], [13].

Ad Hoc-VCG [8] is a routing protocol based on the VCG (Vickrey-Clarke-Groves) auction, which guarantees that each intermediate node is refunded at least the true cost incurred to relay packets. The Commit algorithm [9] further develops this approach assuring that even the source node behaves correctly. The performance of the previous incentive-based schemes are analytically evaluated by Jaramillo et al. in [10]. The analysis of their basic properties led to the design of DARWIN, a new protocol robust to imperfect measurements and collusion attacks. In [11], [12] the truthful pricing mechanism proposed by Vickrey, Clarke, and Groves is used to solve a broad class of problems concerning the non-cooperative behavior of intermediate nodes. Zhong et al. in [13] exploit two solution concepts defined in game theory to consider also the collusion among network devices, showing that even if Group Strategy-proof Equilibrium cannot be satisfied at routing level, their proposed solutions reach Strong Nash Equilibria among network nodes, which are robust to deviations of any component of the colluding group.

Works sharing a similar approach to the solutions described in this paper have been recently proposed [14], [15]. In particular, Jain et al. in [14] present a mechanism for per-link bandwidth allocation of end-to-end paths in wired network, whereas Fu et al. in [15] design an auction-based stochastic game for resource allocation of virtual operators in wireless cellular networks. However, these works do not accurately capture the main features of wireless multi-hop networks, and do not take into account the very large computational time needed to solve the considered auction in realistic network scenarios.

III. System Model

This section presents the communication and network models considered in our work, as well as the definitions and assumptions we adopt in the design of our auction mechanisms.

Let us refer to the Wireless Mesh Network (WMN) scenario illustrated in Figure 1, where the WMN is managed by a single operator that leases the available bandwidth of the mesh access points to secondary (customer) mesh clients.

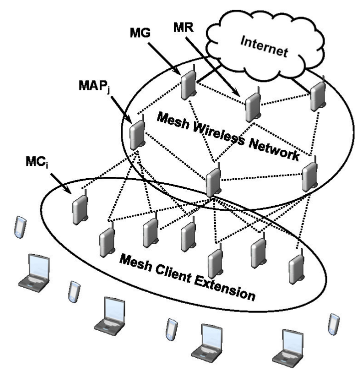


Fig. 1: Wireless Mesh Network scenario considered in this work.

The mechanism we propose allocates the available bandwidth of the access network established by Mesh Access Point (MAPs). More specifically, the WMN operator leases the available bandwidth provided by its MAPs to secondary Mesh Clients (MCs) that in turn may eventually sublease it to other clients.

Each buyer [2] i has a bandwidth demand d_i that he wishes to satisfy by transmitting to one of the mesh access points that cover it with their wireless signal. We assume, without loss of generality, that the term d_i accounts for the traffic demand of both the downlink and uplink, since the wireless resource is a

[2]In this paper we use interchangeably the terms *buyers* and *mesh clients*, while we use the term *seller* to refer to the *wireless mesh network operator*.

half-duplex channel. To satisfy such demand, each buyer bids an offer b_i for its bandwidth demand to the WMN operator. This latter decides which MCs are served, and the price that winners have to pay to exploit the available bandwidth.

We further assume that MAPs use orthogonal channels; therefore, the different subsets of MCs assigned to each MAP do not interfere with each other.

We observe that the transmission rate and the channel utilization required to satisfy the WMN's demand depend, clearly on device technologies, but in particular on the distance between the mesh client and the mesh access point to which it is connected; hence, the allocation mechanism influences the number of mesh clients that have the opportunity to exploit the available bandwidth. Therefore, the aim of the operator is to increase its revenue by allocating the available bandwidth of its mesh access points to those mesh clients that are willing to pay the highest price for the channel utilization. To this end, we design a truthful auction that, in addition to maximize the revenue of the WMN operator, prevents market distortion by forcing every mesh client to bid its true valuation, $v_i = b_i$.

Each mesh client i submits its bid in the form (b_i, d_i), where b_i represents the price that the buyer i is willing to pay for its bandwidth demand d_i. The operator turns the demand d_i into a vector of channel utilizations, $\overrightarrow{o_i} = \begin{bmatrix} o_{i1} & o_{i2} & \dots & o_{ij} & \dots & o_{im} \end{bmatrix}$, where each pair (i, j) refers to a possible allocation of MC i to MAP j, whereas m represents the number of MAPs in the network. Channel utilizations are computed as follows:

$$o_{ij} = \frac{d_i}{r_{ij}^{(max)}} \tag{1}$$

where the element o_{ij} represents the channel utilization perceived by MAP j when it satisfies the demand of MC i, and it is computed as the ratio between the required bandwidth demand d_i and the maximum achievable transmission rate of the wireless link that might connect MC i and MAP j, $r_{ij}^{(max)}$. Note that this latter value can be easily obtained from the MAC layer through a scanning of the wireless channels, which is performed periodically by all network devices.

Let us denote by p_i the price paid by user i when its demand is satisfied. Then, the utility of user i is defined as the difference between its private valuation v_i and the price paid to exploit the bandwidth p_i, according to the following expression:

$$u_i = \begin{cases} v_i - p_i & \text{if } i\text{'s demand is satisfied} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

Obviously, when the demand of mesh client i is not satisfied, its utility is null, since both the paid price and its valuation are null.

We further assume that the MN operator has only a limited and imperfect knowledge about the real valuation that mesh clients are willing to pay for satisfying their traffic demand. According to the Meyerson's proposal [16], we therefore model the operators uncertainty about the real value of any mesh client i as a continuous probability distribution over a finite interval $F(x)$, with related density function $f(x)$, and we optimize over the virtual valuation of customer i as defined in Equation (3) to design a revenue-maximization truthful auction.

$$\phi_i(v_i) = v_i - \frac{1 - F(v_i)}{f(v_i)}. \tag{3}$$

Finally, the mechanism illustrated in [16] shows that such auction can be implemented by assigning the items to the customers with the highest virtual valuations ϕ_i, provided they are not negative. The payment rule is: the winners pay the smallest value b_k that would result in their winning, that is, the bid (thus the valuation v_k, as it is a truthful auction) of the first excluded customer. If the first excluded customer has a valuation v_k such that $\phi_k(v_k) < 0$, then the winner pays $b_r = \phi^{-1}(0)$, that is, the bid whose corresponding virtual valuation is 0. The value b_r is like a *reservation price* for the auctioneer, since he does not sell anything for bids below this value.

IV. Truthful and Optimal Bandwidth Allocation

This section presents the combinatorial auction mechanism we propose to allocate the available access bandwidth of a WMN operator and maximize its expected revenue. We formalize the optimal and truthful auction mechanism in two steps. First, we present an Integer Linear Programming (ILP) model which gives the optimal allocation for the optimal auction. Then, we describe the algorithm that, exploiting the allocation of the ILP model, makes the auction truthful. This algorithm computes the price paid by MCs in such a way that the optimal strategy for each mesh client i is to bid its real valuation v_i.

Let $\mathcal{N}$ denote the set of mesh clients (MCs), $\mathcal{M}$ the set of mesh routers (MRs), and $\mathcal{L}$ the set of wireless links (j, k) among MRs j and k such that the two MRs are in their reciprocal radio range. In particular, let us define $\mathcal{M}_{C,i}$ as the set of MRs operating as MAPs that are in the radio range of MC i and $\mathcal{G}$, $\mathcal{G} \subset \mathcal{M}$, as the set of MRs that act as gateways for the WMN to the wired backbone.

We can now introduce the decision variables used in our ILP model. Binary variables x_i, $i \in \mathcal{N}$, indicate which MCs win the auction, i.e., the buyers whose demands are satisfied by the allocation mechanism ($x_i = 1$ if the demand of MC i is satisfied, 0 otherwise). Binary variables y_{ij}, $i \in \mathcal{N}, j \in \mathcal{M}_{C,i}$, provide the assignment of MCs to MAPs ($y_{ij} = 1$ if MC i is assigned to MAP j, 0 otherwise). The last set of binary variables w_{jk}, $(j, k) \in \mathcal{L}$, defines which wireless links of the operator's WMN are established to route MC demands towards mesh gateways ($w_{jk} = 1$ if a wireless link between devices j and k is active, 0 otherwise). Finally, let variables f_{jk}, $(j, k) \in \mathcal{L}$, denote the traffic flow routed on link (j, k) and f_j, $j \in \mathcal{G}$, the traffic flow routed to the wired connection (note that this value is null for mesh routers that do not act as gateways).

Given the above definitions and notation, the combinatorial auction problem can be stated as follows:

$$\max \sum_{i \in \mathcal{N}} \phi_i(b_i) \cdot x_i \tag{4}$$

$$\text{s.t.} \sum_{j \in \mathcal{M}_{C,i}} y_{ij} = x_i \qquad \forall i \in \mathcal{N} \tag{5}$$

$$\sum_{\substack{i \in \mathcal{N}: \\ j \in \mathcal{M}_{C,i}}} y_{ij} o_{ij} \leq 1 \qquad \forall j \in \mathcal{M} \tag{6}$$

$$\sum_{\substack{i \in \mathcal{N}: \\ j \in \mathcal{M}_{C,i}}} d_i y_{ij} + \sum_{\substack{k \in \mathcal{M}: \\ (j,k) \in \mathcal{L}}} (f_{kj} - f_{jk}) = 0 \qquad \forall j \in \mathcal{M} \setminus \mathcal{G} \tag{7}$$

$$\sum_{\substack{i \in \mathcal{N}: \\ j \in \mathcal{M}_{C,i}}} d_i y_{ij} + \sum_{\substack{k \in \mathcal{M}: \\ (j,k) \in \mathcal{L}}} (f_{kj} - f_{jk}) = f_j \qquad \forall j \in \mathcal{G} \tag{8}$$

$$f_{kj} + f_{jk} \leq w_{jk} c_{jk} \qquad \forall (j,k) \in \mathcal{L} \tag{9}$$

$$f_j \leq C \qquad \forall j \in \mathcal{G} \tag{10}$$

$$f_{jk}, f_q \geq 0 \qquad \forall (j,k) \in \mathcal{L}, q \in \mathcal{G} \tag{11}$$

$$x_i, y_{ij} \in \{0,1\} \qquad \forall i \in \mathcal{N}, j \in \mathcal{M}_{C,i} \tag{12}$$

$$w_{jk} \in \{0,1\} \qquad \forall (j,k) \in \mathcal{L} \tag{13}$$

The objective function (4) maximizes the expected revenue of the WMN operator obtained from the bandwidth auction.

Constraints (5) provide full coverage of all the mesh clients that win the auction. More specifically, if a mesh client i wins the bandwidth auction, then it must be associated only to one mesh access point among the set of those that cover it. Constraints also ensure that only the mesh clients that win the auction can be assigned to a mesh access point. Constraints (6) prevent the allocation of an overall bandwidth demand that cannot be satisfied by a mesh access point.

Constraints (7) and (8) define the flow balance at node j. The term $\sum d_i y_{ij}$ accounts for the total traffic that is assigned to mesh access point j, while the terms $\sum f_{kj}$ and $\sum f_{jk}$ represent the total incoming and outgoing traffic, respectively. The term f_j represents the traffic sent by gateway mesh routers to the wired backbone.

The set of constraints (9) ensures that the total traffic routed on a link established between two devices j and k does not exceed its capacity, denoted by c_{jk}, while (10) represent the capacity constraints for the wired backbone.

Note that in multi-channel multi-radio WMNs the intra-flow and inter-flow interference can be ignored, since wireless interfaces with directive antennas can be tuned to different channels according to an optimization strategy in order to reduce interference effects on the backbone link capacity.

Finally, constraints (11) ensure the positiveness of the flow variables, while (12) and (13) ensure the integrality of the binary decision variables.

Having defined the ILP model representing the optimal auction, we now illustrate the algorithm that forces mesh clients to bid their real valuation.

Algorithm 1 describes the steps performed by the WMN operator to auction its available bandwidth. The algorithm receives as input the parameters which describe the network topology and mesh client bids; these latter are composed of the required demand d_i and the offered value b_i. It produces as output the allocation of mesh clients to mesh access points, y_{ij}, as well as the price p_i paid by each winning mesh client, x_i, to exploit the required bandwidth.

Algorithm 1: Optimal and Truthful Bandwidth Auction

Input : $\mathcal{N}, \mathcal{M}, \mathcal{G}, \mathcal{L}, d_i, b_i$
Output: x_i, p_i, y_{ij}
1 Compute channel utilizations o_{ij};
2 Compute virtual bids $\phi_i(b_i)$;
3 $x_i \Leftarrow$ Solve the ILP model (4)-(13);
4 **foreach** $i \in \mathcal{N}$ **do**
  if $x_i = 1$ **then**
    $\tilde{p}_i \Leftarrow \max_{x_{-i}} \sum_{h \neq i} x_h b_h - \max_x \sum_{h \neq i} x_h \cdot b_h$;
    $p_i \Leftarrow \max\{\phi^{-1}(0), \phi^{-1}(\tilde{p}_i)\}$;
  else
    $p_i \Leftarrow 0$;
  end
end

The algorithm proceeds in 4 steps. In step 1 and 2, the user demands are transformed into equivalent channel utilizations, and virtual valuations are computed using both the bid actually offered by the buyers and valuation distribution function $F(x)$. Step 3 consists in solving the ILP model to find the allocation that maximizes the expected revenue. Finally, in step 4, the operator computes the prices paid by the winners, which, according to Myerson [16], guarantees a truthful auction.

V. Greedy and Truthful Bandwidth Auction

The optimal auction problem described in the previous section is NP-Hard, since the well known Knapsack problem can be reduced to it in polynomial time. For this reason, in the following we present a greedy algorithm to solve efficiently (i.e., in polynomial time) the bandwidth allocation problem preserving the *truthful* property.

The greedy auction is summarized in Algorithm 2, and it is composed of two main phases: (1) the *allocation* phase, which allocates mesh client demands in descending order of the virtual valuation per channel utilization until the available bandwidth of the entire network is exhausted, and (2) the *payment* phase, which establishes the price paid by each winner based on the first mesh client whose demand is not satisfied. This latter is also referred to as *critical mesh client* and its offered bid b_c as *critical value*. Furthermore, the value o_{cj_c} represents the lowest channel utilization among the links that the critical mesh clients can establish with the set of its covering MAPs to satisfy its traffic demand.

Algorithm 2: Greedy Bandwidth Auction

Input : $\mathcal{N}, \mathcal{M}, \mathcal{G}, \mathcal{L}, d_i, b_i$
Output: x_i, p_i, y_{ij}
1 $(x_i, y_{ij}) \Leftarrow$ Greedy_Allocation_Phase($d_i, \phi_i(b_i), o_{ij}$) ;
2 **if** $\phi_c(b_c) \leq 0$ **then**
  $p_c \Leftarrow \phi^{-1}(0)$;
else
  $p_c \Leftarrow \phi^{-1}(b_c)$;
end
foreach $i \in \mathcal{N} : x_i = 1$ **do**
  $p_i \Leftarrow \frac{p_c}{o_{cj_c}} \sum_{j \in \mathcal{M}_i} o_{ij} y_{ij}$;
end

Note that the truthful property guaranteed by the payment scheme proposed for Algorithm 1 is no longer true if the combinatorial auction is not solved to the optimality but approximated [17]. For this reason, we have modified the payment scheme of the greedy algorithm, so that revealing the true valuation is the dominant strategy for all the customers who participate to the approximated bandwidth auction.

Our greedy allocation scheme, which is detailed in Algorithm 3, sorts the list of possible MC-MAP allocations in non increasing order of submitted virtual valuation per channel utilization, $\frac{\phi_i(b_i)}{o_{ij}}$. Then, each element of the sorted list is allocated only if its demand, or equivalently its channel utilization, can be satisfied by the corresponding MAP and routed towards any mesh gateway. Thus, $FeasibleSolution(\tilde{x}, \tilde{y}, \tilde{d})$ verifies if the additional bandwidth demand of MC i assigned to MAP j can actually be routed through the WMN backbone towards mesh gateways, without violating the link capacities. To this end, we develop an efficient procedure to compute the maximum flow that can be routed over the wireless backbone using the well known push-relabel algorithm [18].

Algorithm 3: Greedy Allocation Phase (Step 1 of Alg. 2)

Input : $d_i, \phi_i(b_i), o_{ij}$
Output: x_i, y_{ij}
Initialize: $o_j = 1, \forall j \in \mathcal{M}$;
$L \Leftarrow Sort\Big((i,j) \in \mathcal{N} \times \mathcal{M}_i, \frac{\phi_i(b_i)}{o_{ij}}, \text{“}non-increasing\text{“}\Big)$;
while $L \neq \emptyset$ **do**
  $(i,j) \Leftarrow Next(L)$;
  if $o_j - o_{ij} \geq 0 \wedge FeasibleSolution(\tilde{x}, \tilde{y}, \tilde{d}) \wedge \phi_i(b_i) \geq 0$ **then**
    $x_i \Leftarrow 1,\ y_{ij} \Leftarrow 1$;
    $o_j \Leftarrow o_j - o_{ij}$;
    $RemoveAll(i, L)$;
  end
end

Note that MC i might be satisfied by multiple MAPs $j \in \mathcal{M}(i)$; however, once its demand is satisfied, all entries in the list representing the possible allocations are removed by the function $RemoveAll(i, L)$. Throughout the iterations of Algorithm 3, the total utilization of each MAP (o_j) is updated and verified in order to keep the sum of allocated demands within the bandwidth limit of the access network formed by MAPs.

We observe that Algorithm 2 implements a truthful auction. We do not give here a full proof due to space constraints. However, to have a sketch, observe that the allocation and refinement phases satisfy the monotonicity property (recall that the bids are sorted in non-increasing order of their bid per channel utilization), and there exists a critical value which determines if the MC demand is satisfied or not. Therefore, a WMN operator can efficiently compute a solution for the auction problem, being assured that all MCs reveal the true valuation for their bandwidth demand.

VI. Numerical Results

In this section, we illustrate the numerical results obtained solving optimally the bandwidth allocation auction and using the greedy algorithm detailed in previous sections.

Experimental Methodology. In our simulations, we consider typical WMCN topologies composed of 30, 60, and 120 mesh devices randomly scattered over an area of $1000 \times 1000 m^2$. The ratios between the three different devices was fixed to 1:2 and 1:3 for MGWs:MRs and MGWs:MAPs, respectively.

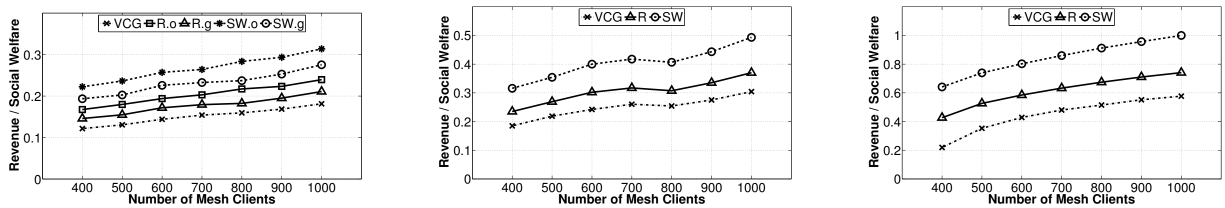
In all the topologies, we vary the number of MCs, which participate to the bandwidth auction, from 400 to 1000. The bandwidth demands and bids are uniformly distributed in the range $[1, 9]$ Mbps and $[10, 30]$ monetary units (e.g., US dollars), respectively.

The channel capacity of both access and backbone links was defined according to the reception sensitivity of the Wistron CM9 commercial wireless cards (based on Atheros chipset). The path loss necessary to evaluate the sensitivity of the receiving node was computed according to the Friis propagation model.

In order to gauge the performance of the proposed greedy algorithm (Section V) with respect to the optimal solution (Section IV), we consider as performance metrics the *Revenue* ($\sum_{i \in \mathcal{N}} p_i \cdot x_i$), the *Social Welfare* ($\sum_{i \in \mathcal{N}} b_i \cdot x_i$), and the number of *Winners*. For each network scenario we performed 10 independent measurements, computing very narrow 95% confidence intervals. For the sake of clarity, the revenue and the social welfare have been normalized with respect to the maximum value measured in the network topology composed of 120 mesh devices (about 12500 monetary units).

Performance Evaluation. Figure 2 shows the performance metrics measured in the network topologies composed of 30, 60, and 120 backbone mesh devices as a function of the number of MCs, using the allocation mechanisms discussed in previous sections. The curves identified with “R.o” and “R.g” represent the solutions obtained using Algorithms 1 and 2, respectively. The curves “SW.o” and “SW.g” show the Social Welfare computed as the sum of the bids b_i submitted by the MCs selected as winners by the corresponding algorithm. Finally, the remaining curve identified with “VCG” represents the revenue of solutions obtained by modifying Algorithm 2 in order to maximize the Social Welfare. Note that, due to the high computational complexity, we were able to solve the auction problem optimally only for the network scenario composed of 30 mesh devices. Nevertheless, even in this simple scenario, the maximum computational time we measured to solve the problem on a Pentium 4 3.0 Ghz and 2 GB of RAM was approximately equal to 43 hours, while with the greedy algorithm we solved a 120-device scenario in few minutes.

As illustrated in Figure 2(a), the additional information provided by the virtual bids permits to increase the operator’s expected revenue with respect to a mechanism which exploits only the MC bids.We can further notice that the auction implemented by the greedy algorithm well approaches the optimal revenue, and therefore it represents an effective and efficient solution for the computation of the prices paid by the MCs. In addition, the Social Welfare is always higher than the revenue earned when using Algorithms 1 and 2. Indeed, this value represents an ideal upper bound to the revenue, since it can be achieved only assuming that all mesh clients behave honestly, submitting the price they are willing to pay for their



(a) $\mathcal{M} = 30$ (b) $\mathcal{M} = 60$ (c) $\mathcal{M} = 120$

Fig. 2: Revenue and Social Welfare measured as a function of the number of mesh clients in scenarios with 30, 60, and 120 mesh devices.

bandwidth demands, even if it is not the best strategy. On the contrary, we underline that the proposed solutions *assure* that *all* mesh clients bid truthfully their valuations, because it is their best strategy. The achieved revenue is approximately equal to 75% of the Social Welfare.

Greedy solutions illustrated in Figures 2(b) and 2(c) confirm the trends observed for the network scenario composed of 30 mesh devices. Note how increasing the number of mesh clients guarantees higher revenues. This is due to the effect of the competition: only mesh clients offering more will be accepted.

Figure 3 shows the number of winners selected by Algorithms 1 and 2 as a function of the number of mesh clients that participate to the auction for the bandwidth allocation. It can be observed that the greedy algorithm satisfies a number of mesh clients very close to the value obtained using the optimal allocation algorithm (see the curves identified by labels "30.o" and "30.g"). In particular, the greedy algorithm leads to a performance gap always lower than 10%, for instance sizes when both algorithms can be run. The figure illustrates also the number of winners selected in the network scenarios composed of 60 and 120 mesh devices. As expected, the higher is the number of mesh devices, the higher is the available network bandwidth and the greater is the number of mesh clients satisfied by the allocation algorithm implementing the auction.

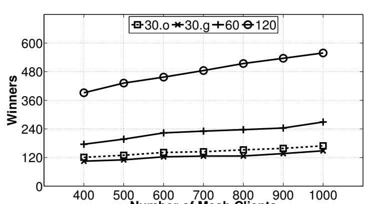


Fig. 3: Number of winners as a function of the number of mesh clients in scenarios with 30, 60, and 120 mesh devices.

VII. Conclusion

This paper proposed two effective mechanisms to allocate the available bandwidth of a wireless network operator to those customers who are willing to pay the higher price for satisfying their bandwidth demand. We first formulated the allocation mechanism as a combinatorial auction, which guarantees that all customers reveal their real valuation of the required bandwidth. Then, we proposed a greedy algorithm that finds efficient allocations in polynomial time even for large-size, real network scenarios, while maintaining the truthfulness property.

Numerical results show that the greedy algorithm performs very close to the optimal auction, thus representing an efficient and practical alternative for solving the auction.

Acknowledgment

This work has been partially funded by Italian PRIN 2009 project GATECOM (GATEway-based architecture for content-centric COMmunity networking) and the PRIN 2008 project PEPPER: Privacy and Protection of Personal Data.

References

[1] I. F. Akyildiz, X. Wang, and W. Wang. Wireless Mesh Networks: a Survey. *Computer Networks*, 47(4):445–487, 2005.

[2] Nandiraju, N. and Nandiraju, D. and Santhanam, L. and He, B. and Wang, J. and Agrawal, D.P. Wireless Mesh Networks: Current Challenges and Future Directions of Web-In-The-Sky. *IEEE Wireless Communications*, 14(4):79–89, 2007.

[3] X. Zhou, S. Gandhi, S. Suri, and H. Zheng. eBay in the Sky: Strategy-proof Wireless Spectrum Auctions. *ACM MobiCom*, pages 2–13, 2008.

[4] X. Zhou and H. Zheng. TRUST: A General Framework for Truthful Double Spectrum Auctions. *IEEE INFOCOM*, pages 999–1007, 2009.

[5] J. Jia, Q. Zhang, Q. Zhang, and M. Liu. Revenue Generation for Truthful Spectrum Auction in Dynamic Spectrum Access. *ACM MobiCom*, 2009.

[6] G.S. Kasbekar and S. Sarkar. Spectrum Auction Framework for Access Allocation in Cognitive Radio Networks. *ACM MobiHoc*, 2009.

[7] S. Sengupta and M. Chatterjee. An Economic Framework for Dynamic Spectrum Access and Service Pricing. *IEEE/ACM Trans. on Networking*, 17(4):1200–1213, 2009.

[8] L. Anderegg and S. Eidenbenz. Ad hoc-VCG: a Truthful and Cost-efficient Routing Protocol for Mobile Ad hoc Networks with Selfish Agents. *ACM MobiCom*, pages 245–259, 2003.

[9] S. Eidenbenz, G. Resta, and P. Santi. The COMMIT Protocol for Truthful and Cost-efficient Routing in Ad hoc Networks with Selfish Nodes. *IEEE Trans. on Mobile Computing*, 7(1):19–33, 2008.

[10] J. Jaramillo and R. Srikant. DARWIN: Distributed and Adaptive Reputation Mechanism for Wireless Ad hoc Networks. *ACM MobiCom*, pages 87–98, 2007.

[11] W. Wang and X.Y. Li. Low-Cost Routing in Selfish and Rational Wireless Ad hoc Networks. *IEEE Trans. on Mobile Computing*, 5(5):596–607, 2006.

[12] Y. Wu, S. Tang, P. Xu, and X.Y. Li. Dealing With Selfishness and Moral Hazard in Non-Cooperative Wireless Networks. *IEEE Trans. on Mobile Computing*, 9(3):420–434, 2009.

[13] S. Zhong and F. Wu. On Designing Collusion-Resistant Routing Schemes for Non-Cooperative Wireless Ad hoc Networks. *ACM MobiCom*, pages 278–289, 2007.

[14] R. Jain and J. Walrand. An Efficient Mechanism for Network Bandwidth Auction. *IEEE NOMS*, pages 227–234, 2008.

[15] F. Fu and U.C. Kozat. Wireless Network Virtualization as A Sequential Auction Game. *IEEE INFOCOM*, pages 1945–1953, 2010.

[16] R.B. Myerson. Optimal Auction Design. *Mathematics of Operations Research*, 6(1):58–73, 1981.

[17] D. Lehmann, L.I. Oćallaghan, and Y. Shoham. Truth Revelation in Approximately Efficient Combinatorial Auctions. *Journal of the ACM (JACM)*, 49(5):577–602, 2002.

[18] A.V. Goldberg and R.E. Tarjan. A new approach to the maximum-flow problem. *Journal of the ACM (JACM)*, 35(4):921–940, 1988.