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# NASCOR: Network Assisted Spectrum Coordination Service for Coexistence between Heterogeneous Radio Systems*

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**SUMMARY** This paper presents the design and proof-of-concept validation of a novel network-assisted spectrum coordination (NASCOR) service for improved radio coexistence in future shared spectrum bands. The basic idea is to create an overlay network service for dissemination of spectrum usage information between otherwise independent radio devices and systems, enabling them to implement decentralized spectrum coexistence policies that reduce interference and improve spectrum packing efficiency. The proposed method is applicable to unlicensed band and shared spectrum systems in general (including femtocells), but is particularly relevant to emerging TV white spaces and cognitive radio systems which are still in need of scalable and accurate solutions for both primary-to-secondary and secondary-to-secondary coordination. Key challenges in enabling a network layer spectrum coordination service are discussed along with the description of our system architecture and a detailed case-study for a specific example of spectrum coordination: client-AP association optimization in dense networks. Performance gains are evaluated through large-scale simulations with multiple overlapping networks, each consisting of 15–35 access points and 50–250 clients in a 0.5×0.5 sq.km. urban setting. Results show an average of 150% improvement in random deployments and upto 7× improvements in clustered deployments for the least-performing client throughputs with modest reductions in the mean client throughputs.

*key words:* *heterogeneous radios, spectrum coordination, secondary-to-secondary coexistence*

## 1. Introduction

This paper describes the design and proof-of-concept validation of a novel network-assisted spectrum coordination (NASCOR) service for improved radio coexistence in future shared spectrum bands. The goal of this work is to advance the state-of-the-art in dynamic spectrum access (DSA) technology [2]–[4] by taking advantage of ubiquitous Internet connectivity at wireless devices. The basic idea is to create an overlay network service for dissemination of spectrum usage information between otherwise independent radio devices and systems, enabling them to implement decentralized spectrum coexistence policies that reduce interference and improve spectrum packing efficiency. The method described here is applicable to unlicensed band and shared spectrum systems in general (including femtocells), but is particularly relevant to emerging TV white spaces [5], [6] and cognitive radio systems which are still in need of scalable and accurate solutions for both primary-to-secondary

and secondary-to-secondary coordination.

The NASCOR approach described here is a network assisted spectrum coordination service which deals directly with radio heterogeneity and operates in a completely distributed manner. We believe that network assistance is quite feasible given the fact that the vast majority of wireless systems are connected to the Internet. Creation of a standardized network service (initially as an overlay on IP) is expected to provide significant benefits for spectrum allocation over other techniques such as centralized spectrum servers [7], [8] or radio-based local common control channels [9], [10]. This is because the network inherently has a global view of all connected devices and can thus enable large-scale and effective coordination by disseminating radio usage information across the entire geographic region of interest. A network service for spectrum has the advantage of enabling completely decentralized action at radio devices which are connected to this service, avoiding the need for centralized decision with relatively static policies. While the use of the wired infrastructure has been suggested in literature, it was proposed only as a medium for communication [11]. In contrast, the fundamental shift that we suggest is including the network as an integral entity in the distributed decision making process. The distinct advantages of using network layer information about heterogeneous radio devices enables a range of feasible coexistence solutions that neither require common physical channels nor rely on sophisticated sensing architectures.

Realizing a network-enabled heterogeneous spectrum allocation services involves several key challenges. First, the architecture must be generic enough to accommodate the full range of wireless devices that work with different radio standards. Second, the design should include a physical world model that is robust to inaccuracies in location information or radio propagation modeling and at the same time, can be improved gradually through actual measurements from devices in the field. Third, the network based spectrum service protocols used should scale well across both numbers of devices and geography. The overlay network service involves knowledge of geographic location of devices and their supporting routers and collected spectrum information must be routed efficiently to the appropriate set of network addresses in the region of interest to avoid flooding the whole network with excessive control traffic. The final technical challenge is that of designing completely decentralized spectrum coordination algorithms which prevent interference and achieve efficient spectrum packing across

various realistic wireless device density and usage scenarios.

While the inter-network cooperation enabled by NASCOR can be used for optimizing several different spectrum usage parameters such as channel selection, rate allocation, power control, and back-off windows, in this paper, we focus on a specific use case of client-AP associations: given a set of APs that a client can potentially connect to, selecting the best AP so as to maximize the sum utility of all the clients across all the network. Due to its direct impact on both the client experience (in terms of throughput) as well as the network performance (in terms of traffic load), this problem has been approached through both centralized network utility maximization framework [12], [13] and game-theoretic formulations [14]. In particular, we follow the proportional fairness framework developed in [12] for the basic intra-network optimization of AP selection and enhance it to incorporate NASCOR-enabled inter-network cooperation.

In the following section (Sect. 2), we provide further details on the proposed NASCOR system architecture followed by a description of the key enabling technologies mentioned above (Sect. 3). Next we present a detailed use-case of NASCOR in the context of client-AP association optimization in Sect. 4. Simulation results from this use-case are presented in Sect. 5, and finally concluding remarks are provided in Sect. 6.

## 2. System Architecture

The basic design goal of NASCOR is to create network support for facilitating seamless communication and information dissemination required for heterogeneous co-existence. The system consists of in-network Spectrum Gateways (SGs) that connect between themselves and to all the wireless devices in the region through overlay network as shown in Fig. 1. The overlay spectrum coordination network is defined by two protocol interfaces: the R-interface for spectrum use updates from the radios and spectrum occupancy

maps from the SGs; and the N-interface for aggregated spectrum updates between SGs. The Spectrum Gateways get updates about spectrum usage from the wireless devices (e.g. current frequency band in use, power level, time duty cycle, data rate, etc.) and releases the overall spectrum occupancy map to the devices upon request†. The SGs also relay aggregated spectrum usage updates to neighboring SG peers since devices in radio range might be served by different SGs. A key feature of this architecture is that spectrum updates from a wireless device are disseminated to only those geographic neighbors which affect, or are affected by, the transmissions of the sending station. This is done using a region-of-interest based geo-routing protocol as explained in Sect. 3.3. This ensures that each wireless entity acquires the local visibility needed for it to determine a suitable set of spectrum access parameters. Wireless devices receiving the regional spectrum map then execute a completely decentralized spectrum coordination algorithm which determines radio parameters to be used. The distributed algorithm may be a simple non-adaptive one, or may include adaptation to changing device density and traffic patterns.

## 3. Technical Challenges

In this section we discuss four key technical problems to be solved in the design of any co-existence solution and provide details of how NASCOR addresses each of them.

### 3.1 Characterization of Radio Interference

A basic problem to be addressed is that of characterizing the interference impact of multiple radio technologies using a small number of key parameters. Standard parameters which can be used are frequency band, power, modulation type, time duty cycle and data rate. The goal is to use these

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†Spectrum usage of non-compliant devices for e.g. microwave oven, cordless phones, etc. is ascertained by participatory sensing as described in Sect. 3.2
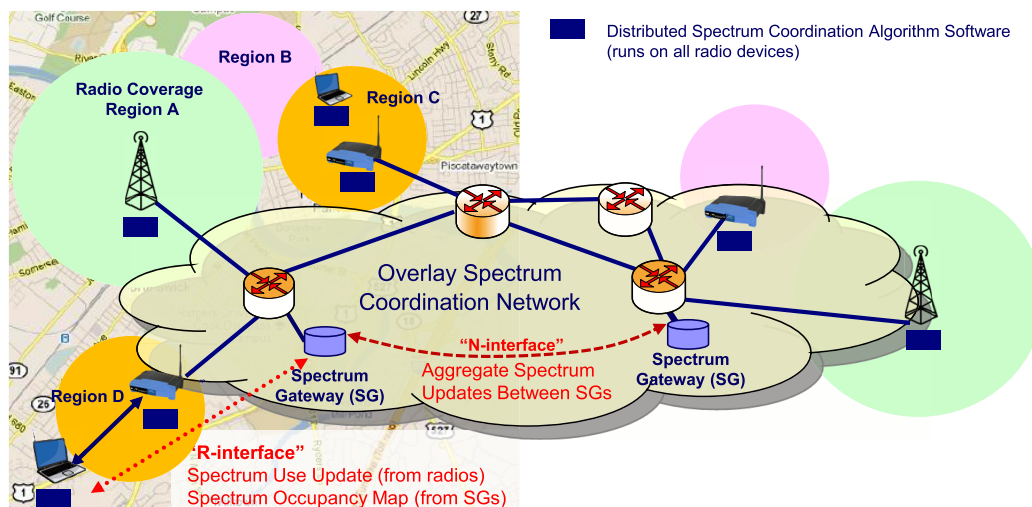


**Fig. 1** System architecture for network assisted spectrum coordination service.

(a) Topology for interference measurements



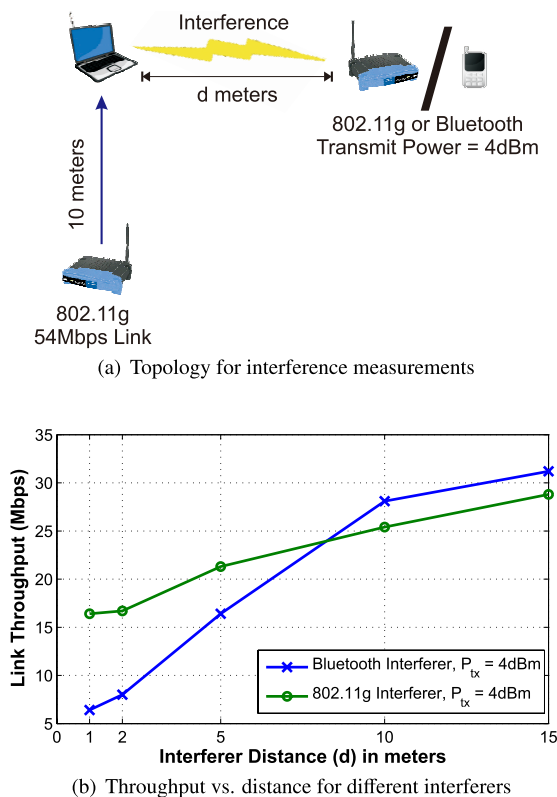(b) Throughput vs. distance for different interferers

**Fig. 2** Topology and the impact on throughput for 802.11 vs. Bluetooth interference.

declared radio parameters to accurately compute the effect of interference at other nodes in the region. Typically this is done using something like a "contributed SINR" model. However, there are limitations to such schemes due to intrinsic PHY signal and MAC protocol differences - see for example the result of an interference experiment we carried out recently using a mix of WiFi and Bluetooth radios [15] (Fig. 2).

In NASCOR, we use a unified method of interference characterization based on impact on throughput rather than interference power. In this scheme, the system starts with a Basic Set (BS) which contains impact on throughput values precomputed from emulation experiments for different type of devices, power levels, average duty cycles, distance and possibly other standard specific parameters. However since interference impacts also depend on non-measurable parameters such as relative location inside a building, presence of foliage and ambient noise, each network also maintains an Acquired Set (AS) of locally collected impact on throughput values by leveraging the visibility offered at the wired-end of the network. Advancements in reinforcement learning [16] can be used to determine the confidence level in the acquired set and the decision thresholds to select between the two set.

## 3.2 Improving Location and Propagation Measurements

Accurate information about a wireless device's geo-location and the applicable radio propagation characteristics are key requirements for co-existence calculations in heterogeneous radio environments. However due to high building penetration loss of GPS signals and inherent errors in parameterizing the propagation loss, achieving high accuracy for these two inputs is a challenging problem. In our network assisted model, co-operation of co-located devices can be utilized to enable terrestrial localization. To determine its location $L_x$, a home AP $X$ sends out *assist request* messages to a set of neighboring devices who have their own location information, e.g. fixed outdoor devices, $N_1, N_2, \ldots, N_p$. The neighboring base stations reply with their location and transmission characteristics (power, operating frequency and an identifiable signature) for their downlink transmissions scheduled over a horizon of time $T_h$. By correlating the received power with the signal signatures obtained, $X$ can utilize received signal strength indicator, time (difference) of arrival or angle of arrival ranging modalities to estimate $L_x$ relative to the locations of the neighbors. Since the method does not rely on specific physical signals to be transmitted by neighboring devices but only uses already scheduled transmissions, bandwidth and power overhead is asymptotically kept at zero.

To capture the location-specific characteristics of the propagation loss, NASCOR includes a participatory sensing mechanism with which peer radios near an area of interest provide an estimate of the environmental effects on propagation through long term averaged measurements. A mobile device, $X$, planning to operate at a location $L_t$ after time $t$, queries the system for the estimation of interference at $L_t$. Using the aggregated participatory measurements recorded over time, the service returns a set of parametric results to $X$. While most location services only model 2-dimensional space, the congested multi-storied structure of urban environments can cause uncorrectable errors for the interference management algorithms. With participatory sensing, it is possible for us to extend our service to 3-dimensional space where estimation of location $L_t = (x, y, z)$ is done in 3-D coordinate system.

## 3.3 Spectrum Coordination Protocol

In our architecture, the gateway routers which directly connect to the base stations/home APs run an evolved flavor of geocast routing [17] which store the information about the region of operation of each network that they support. As illustrated in Fig. 3, the source $X$ of any spectrum management message, signs it using $\{L_x, r_x\}$ where $L_x$ is the geo-location of $X$ and $r_x$ is the radius of operation obtained by equating: $PL_x(r) = P_{x,max} + G_x - S_{x,min} - N$, where $PL_x(.)$ is the appropriate indoor/outdoor pathloss model used, $G_x$ and $P_{x,max}$ are the antenna gain and maximum transmit power of $X$ respectively, $S_{x,min}$ is the minimum received power re-
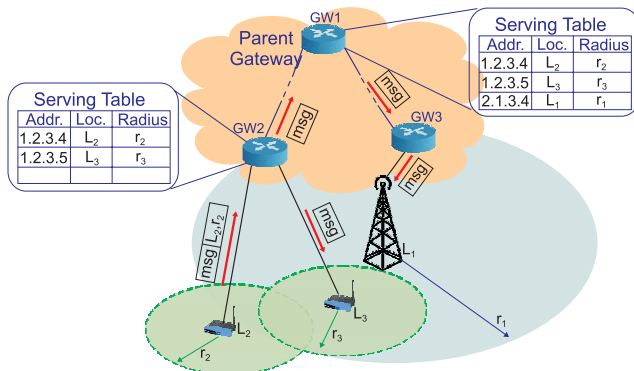
**Fig. 3** Network support for neighbor selection.

quired for operation and $N$ is the noise floor. Each router stores the list of $\{L_i, r_i\}$ pair for each of the network that it supports either directly or through a child router. Upon receiving this message, the NASCOR router checks to see if the source region in the message overlaps with any of its networks and passes the message to all overlapping networks. It further routes the message to its parent NASCOR router (using IP tunneling if there are other routers on the way that do not support this feature) which then sends it to other routers connected to it using a similar overlap search. Note that the calculation of the radius of operation can be based on simple first-order assumptions and need not be precise since it only determines the recipients of the message, not the action that they take. To ensure that all neighboring devices which can find use for a certain spectrum management message receive it, the constants in the equation above can be set conservatively so as to broaden the radius; this can result in some extra devices receiving the message but it can be discarded based on their local observations.

The key advantage of using this network service model for neighbor communication is the resulting simplicity on the source side. Each device or network need not store the states for all of its interfering networks nor keep track of networks joining and leaving in its neighborhood.

### 3.4 Distributed Co-Existence Algorithms

The main challenge in designing a co-existence scheme is to take into account the wide variability in the set of adaptable parameters that different devices have. The NASCOR architecture provides a means for supporting different granularities of coordination while leaving the final task of deciding the optimal spectrum access parameters up to the individual devices/networks. Each device $\{X\}$, in our system sends out a periodic update about its spectrum usage including the type of device, transmission power, operating frequency and bandwidth, average duty cycle and average packet error rate. Using the area of interest based geo-routing protocol, as described Sect. 3.3, this information is routed to the set of devices which are affected by or affect the transmissions of $X$. Here we describe three sets of algorithms which makes use of the neighboring spectrum usage with increasing granularity:

- **Non-adaptive parameter selection (NAPS):** With the NAPS algorithm, a device/network upon initialization requests the current set of neighborhood spectrum usage from its serving NASCOR router. By aggregating the spectrum usage messages received, the routers maintain a snapshot of current usage and send it to any requesting device. The device/network uses this neighborhood information along with the basic set of Impact of Throughput values for each transmission in range and selects an optimal operating point. Under the NAPS scheme, co-existing devices determine the spectrum access parameters only on initialization or when a measurable indicator of the quality of service falls below a set threshold. This algorithm is intended for low-cost devices with simple radio architecture.

- **Adaptive Parameter Selection (APS):** Devices using this approach initialize their parameters in the same manned as NAPS but also request the connected routers for periodic spectrum usage updates provided by its radio neighbors. Local estimates of spectrum congesting derived from performance parameters such as packet error rate reported by neighboring devices can then be used, for example, in controlling the backoff algorithm, bandwidth modification or transmit power control.

- **Global Coordinated Resource Packing (GCRP):** The NASCOR architecture also provides a mechanism for direct exchange of coordination messages between different devices in radio range. From the list of spectrum usage updates received by a device, it identifies a set of suitable candidates for GCRP and sends out coordination messages containing requests for power, frequency of operation or bandwidth modification. This leads to an iterative algorithm which tries to find the spectrum access parameters which corresponds to more globally optimal resource packing between co-existing radios. An example usage scenario for GCRP would be the backup channel list exchange among neighboring WRANs following the 802.22 standard, which ensures low likelihood of identical operating channel selection [18].

## 4. Cooperative Optimization of Client-AP Association

In this section, we present a detailed use-case of the NASCOR platform for the optimization of client-AP associations in WiFi networks. Some results from this study have been previously presented in [1]. In a WiFi deployment with multiple access points, optimizing the way each client selects an AP from amongst the available choices, has a significant impact on the realized performance. When two or more such multi-AP networks are deployed in the same region, APs from different networks can cause severe interference to one another. In order to show the use of network-
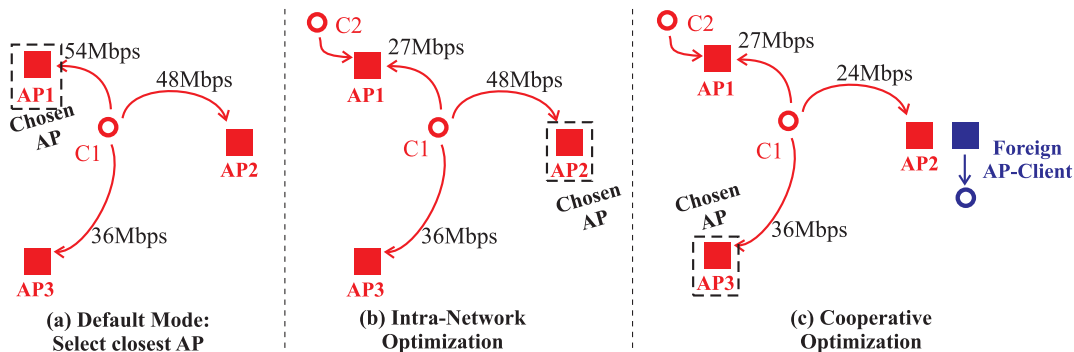
**Fig. 4** Qualtitative example of why cooperation is needed: (a) Default mode chooses the least distance AP, (b) Intra-network optimization selects least crowded AP if their distance to the client are comparable, (c) Cooperative optimization selects AP with least internal and external interference.

assisted coordination described in Sect. 2, we study how *inter*-network interference effects the *intra*-network association optimization and propose a cooperative optimization scheme to mitigate the interference.

In order to alleviate this inter-network interference, we propose a back-end *operational cooperation* between the networks: each network periodically shares the information about the location and operating channels of its APs with all other networks operating in the same area through NASCOR. Note that clients belonging to one network cannot join other networks in this model. Within the scope of the traffic model described in Sect. 4.2, this form of information exchange followed by *intra*-network optimization is the same as a global optimization considering all APs of all networks as being controlled by a single entity. This follows from the fact that for certain problem formulations, the interference terms in the intra-network problem can be summarized and substituted using the information received from neighboring networks. To the best of our knowledge, such forms of cooperation between multiple managed WiFi networks has received very little attention with only some recent works in the related area of cellular networks [19].

### 4.1 Motivating Example

Figure 4 shows an illustrative example of cooperation gain. Client $C1$ is in communication range of three APs of the same network; and the default 802.11 rule as shown in Fig. 4(a) is to choose the closest AP (here $AP1$), which gives the highest rate to the client. However, if there is another client $C2$ attached to $AP1$, $AP1$ has to divide its downlink transmission time between the two clients, as in Fig. 4(b). Assuming proportional fair scheduling, the real throughput that $C1$ gets from $AP1$ is only 27 Mbps. Intra-network optimization through a central controller (e.g., Aruba WLAN controllers [20]) can identify this load imbalance and connect $C1$ to $AP2$ instead and allow the client to get a throughput of 48 Mbps. In doing so, the network controller assumes that $AP2$ has sole control of the channel. However in a multi-network setting, a foreign network may have a nearby AP that shares $AP2$'s channel. CSMA contention

**Table 1** Definition of parameters.

| Symbol | Meaning |
|---|---|
| $N$ | No. of WiFi networks |
| $U_i$ | Set of clients in network $i$ |
| $A_i$ | Set of access points in network $i$ |
| $R_{cs}$ | Carrier sense radius (equal for all APs) |
| $R_{int}$ | Interference radius (equal for all APs) |
| $B_{ik}$ | Set of co-channel foreign APs within $R_{cs}$ of $k$th AP of $i$th network |
| $C_{ik}$ | Set of co-channel foreign APs outside $R_{cs}$ but within $R_{int}$ of $k$th AP of $i$th network |
| $\eta_{ik}$ | Number of clients connected to the $k$th AP of $i$th network |
| $r_{ij}(k)$ | Wireless PHY rate obtained by the $j$th client of $i$th network when connected to the $k$th AP of that network |
| $x_{ij}(k)$ | Association indicator between the $j$th client of $i$th network and its $k$th AP (value = 0 or 1) |
| $p_{ij}(k)$ | Fraction of time the $j$th client of $i$th network gets from its $k$th AP |

leads to approximately equal time share between the two APs, leading to an actual throughput of only 24 Mbps for $C1$ if connected to $AP2$, as shown in Fig. 4(c). Cooperative optimization incorporates the effect of APs of other networks and thus connects $C1$ to $AP3$ leading to a throughput of 36 Mbps.

### 4.2 System Model

We consider a system with $N$ independently operated WiFi networks with $U_i$ and $A_i$ denoting the set of clients and APs in the $i$th network respectively. Table 1 summarizes the notations we use in this paper. Binary variables $x_{ij}(k)$ indicate the connection state between the $j$th client and $k$th AP of the $i$th network (1 is connected, 0 if not), while $p_{ij}(k)$ denote the fraction of time provided by the AP to the client. Similarly, $r_{ij}(k)$ denotes the effective bit rate received by the client. Note that while the bit rate values primarily depend on the physical distance between the AP and the client, other factors such as collision induced retransmissions and nature of the rate selection algorithms also impact the bit rate values. In order to make the problem tractable, we only include the distance-dependent component, and in particular,

assume $r_{ij}(k)$ to be a step-wise function of the distance between the client and the AP in our simulations. Since air time fraction and rate are relevant only for clients connected to an AP, $p_{ij}(k) = 0$ and $r_{ij}(k) = 0$ whenever the corresponding $x_{ij}(k) = 0$. Thus the $j$th client of the $i$th network has an effective downlink rate of $\sum_{k \in A_i} r_{ij}(k) x_{ij}(k) p_{ij}(k)$.

As is common in commercial WLAN controllers [20], each AP employs a proportional fairness policy. Ignoring the protocol overheads and assuming equal priorities for all clients, proportional fairness translates to equal time share between clients in multi-rate WLAN [21]. Thus for the $k$th AP of the $i$th network, each of its $\eta_{ik}$ clients receive a fraction $1/\eta_{ik}$ the APs airtime. We focus on downlink traffic which forms the majority of WiFi data transmission [22] and assume clients always have pending data requests at the AP. This assumption simplifies the estimation of the client rates significantly and is valid in hot-spot deployments where the number of clients is large enough that each client cannot receive its maximum desired data rate.

In order to account for the inter-network interference, we denote the set of co-channel foreign APs within carrier sense range of the $k$th AP of $i$th network as $B_{ik}$ and those outside carrier sense but within interference range (potential hidden nodes) as $C_{ik}$. Each AP has to participate in CSMA and thus shares the channel with co-channel APs within its carrier sense radius. We assume that within each network, frequency planning is such that no two APs within carrier sense distance are assigned the same channel. Thus the $k$th AP of the $i$th network has to share its channel with $|B_{ik}|$ other APs, bringing its share of the channel access time fraction to approximately $1/(1 + |B_{ik}|)$ [23]. Further we model the hidden node interference (interference from APs outside the carrier sense range but with signals still strong enough to affect ongoing transmissions) by lowering the channel access time further. We introduce a parameter $\alpha \in [0, 1]$ which captures the average effect of hidden node interference per interferer. The channel access time fraction for the $k$th AP of the $i$th network is thus also reduced by a factor of $1/(1 + \alpha |C_{ik}|)$. Note that an exact model of hidden node interference has been the subject of several past studies [24], [25], and usually requires aggregate interference power calculations which makes the resulting optimization problem extremely intractable. As such, we take a pragmatic approach towards capturing the effect of hidden terminals through the use of the parameter $\alpha$ - a value of 1 implies a hidden node has as much impact on the throughput of a given node as another node within carrier sense range, while a value of 0 implies that the hidden node has negligible impact. In practise, the choice of the $\alpha$ parameter can either be made through probe experiments during the deployment stage or be pre-set to the values derived through testbed measurements [24]. $\alpha$ values in the (0.2, 0.6) range satisfy most of our past experiments on the ORBIT testbed [26].

The objective of the intra-network association optimization, given such a model, is to optimize the set of $x_{ij}(k)$ variables for maximum utility which we choose to be one

which results in proportional fairness. The choice of log(.) or proportional fair utility function is a de facto standard in the current EV-DO, 3G cellular systems, as well as in emerging 4G systems based on LTE and WiMAX and has been shown to provide a good balance between resource utilization and fairness of allocation [12], [13], [27]. For cooperative optimization, each network first ascertains the values of $|B_{ik}|$ and $|C_{ik}|$ for each of its APs through periodic message exchange with other networks. This information is then used to formulate a similar optimization problem as in the case of intra-network optimization. Note however, that by including the hitherto unknown interference components, the cooperative problem formulation now matches the real interference scenario.

### 4.3 Problem Formulation and Solution

#### 4.3.1 Individual Network Optimization

The intra-network non-cooperative optimization problem formulation is similar to the description in [12]. Since $x_{ij}(k)$ equals 1 only if client $j$ is associated with AP $k$ and channel access time is equally divided between clients connected to an AP, the association optimization within network $i$ can be denoted by:

$$
\begin{aligned}
\text{Maximize:} \quad & \sum_{j \in U_i} \log \left( \sum_{k \in A_i} r_{ij}(k) x_{ij}(k) p_{ij}(k) \right) \\
\text{subject to:} \quad & p_{ij}(k) = \frac{1}{\sum_{j' \in U_i} x_{ij'}(k)} \qquad \forall k \in A_i, j \in U_i \\
& \sum_{k \in A_i} x_{ij}(k) = 1 \qquad \forall j \in U_i \\
& x_{ij}(k) \in \{0, 1\} \qquad \forall k \in A_i, j \in U_i
\end{aligned}
$$
(1)

Here the first constraint models the proportional fairness policy of each AP and makes the problem non-linear in $x_{ij}(k)$ while the second constraint along with the binary constraint restricts each client to connect to exactly one AP. Note that the $p_{ij}(k)$ in (1) is not the actual time fraction that the client would receive as it does not capture the effect of foreign APs. But without any cooperation, each network has no idea about the number/location of such APs and thus uses this value. Reference [12] shows an efficient approximation algorithm to solve this NP-hard non-linear integer problem for a slightly different problem formulation. This method first requires converting (1) to a relaxed discretized linear program without the integrality constraint on $x_{ij}(k)$, i.e., each client is allowed to connect to multiple APs simultaneously. Then the rounding process described by Shmoys and Tardos for the generalized assignment problem [28] is used to arrive at binary values. This polynomial time 2-approximate rounding algorithm thus results in a total utility bounded below by that of the optimal assignment scaled down by a factor of $2 + \epsilon$.

### 4.3.2 Cooperative Optimization

Extending the above formulation based on the assumptions of equal time sharing MAC and availability of $|B_{ik}|$ and $|C_{ik}|$ values, the global association optimization problem can be written as:

$$
\text{Maximize:} \quad \sum_{i=1}^{N} \sum_{j \in U_i} \log \left( \sum_{k \in A_i} r_{ij}(k) x_{ij}(k) p_{ij}(k) \right)
$$

$$
\text{subject to:} \quad p_{ij}(k) = \frac{1}{\sum_{j' \in U_i} x_{ij'}(k)} \cdot \frac{1}{(1+|B_{ik}|)(1+\alpha|C_{ik}|)}
$$

$$
\forall k \in A_i, j \in U_i, i \in [1,N]
$$

$$
\sum_{k \in A_i} x_{ij}(k) = 1 \qquad \forall j \in U_i, i \in [1,N]
$$

$$
x_{ij}(k) \in \{0,1\} \qquad \forall k \in A_i, j \in U_i, i \in [1,N]
$$

$$(2)$$

The constraints in (2) are a simple extension to those in (1) Note here that the first term in $p_{ij}(k)$ is directly dependent on the optimization variables $x_{ij}(k)$. However $|B_{ik}|$ and $|C_{ik}|$ are only dependent on the relative placement of co-channel APs of different networks and are thus constants given a certain topology. So once each network $i$ knows about the $|B_{ik}|$ and $|C_{ik}|$ values for each of its AP $k$, it can individually solve the association problem. This joint problem can be solved using the same technique as the individual network optimization.

## 5. Simulation Results

Here we present results from detailed analytical simulations that show the benefit of inter-network cooperation through NASCOR for the specific use-case of client-AP association optimization. We compare three association schemes to quantify the gains of cooperation -

- Least Distance: Each client connects to the closest AP of the same network (benchmark case).
- Intra-Network Optimization: Each network optimizes the association pattern of its clients.
- Cooperative Optimization: All networks share information for optimizing the client association.

Note that in all the three cases we assume that the clients belonging to a network can only connect to APs from that network. The discretized linear program was solved using the open source *lpsolve* solver [29]. All the results presented are averaged over 10 simulation runs. We present results for two deployment scenarios: random deployment and clustered deployment as follows.

### 5.1 Random Deployment

Multiple overlapping networks are considered in a $0.5 \times 0.5$ sq.km area, which reflect deployment scenarios in urban hot-spot networks, multi-tenant buildings, or airports. Each network has a variable 15–25 APs placed at uniformly randomly selected points. While there is a minimum separation of 50 meters between two APs of the same network, there is no such restriction for APs of different networks. Reasonable frequency planning is assumed - each AP chooses one of the three orthogonal channels in the 2.4 GHz range to minimize the number of co-channel APs. However due to dense deployment of multiple overlapping networks, choosing a completely isolated channel is seldom possible. The carrier sense and interference range thresholds of all devices are set to 215 meters and 250 meters respectively as per the specifications in [30]. Within each network, a planned deployment model is assumed - under this assumption, it is ensured that two APs from the same network which are within interference range are not on the same channel. Clients are placed at random within the area with the total number of clients of each network set as a parameter. The physical data rates $r_{ij}(k)$ are selected based on the distance between the client $j$ and AP $k$, also from [30]. The value of the interference scaling parameter $\alpha$ is taken as 0.5. Figure 5 shows an instance of the random AP and client placement.

Figure 6 shows the cumulative distribution of the client throughputs for all the clients in the system for the topology shown in Fig. 5. The plot shows that while intra-network optimization improves fairness in client throughput, its effect is limited due to the presence of APs of another network. Cooperative optimization more than doubles the 10 percentile throughput from 230 kbps to 550 kbps compared to least distance scheme and shows a 77% gain when compared to the same metric in intra-network optimization. Since the cooperative optimization problem (2) decouples into separate problems for each network, utility of each network is individually maximized.

Figure 7 further dissects the comparison between intra-network and cooperative optimization schemes. In this figure, clients are arranged in the increasing order of the throughput they get through intra-network optimization.
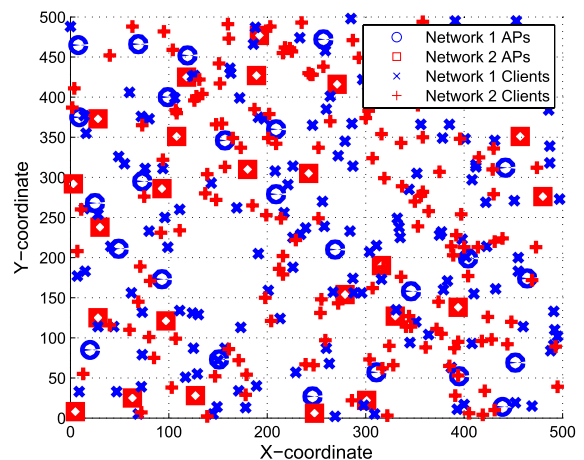


**Fig. 5** Topology showing an instance of 2 networks, 25 APs per network and 150 clients per network at random points.
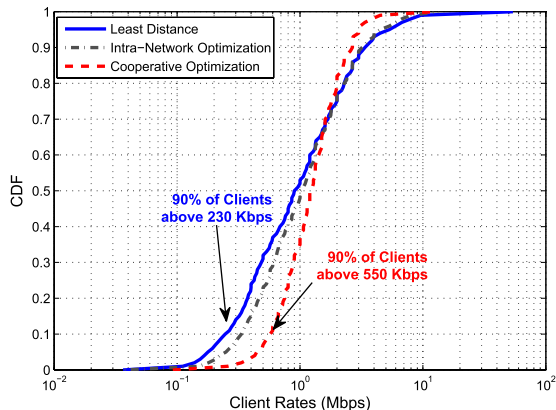
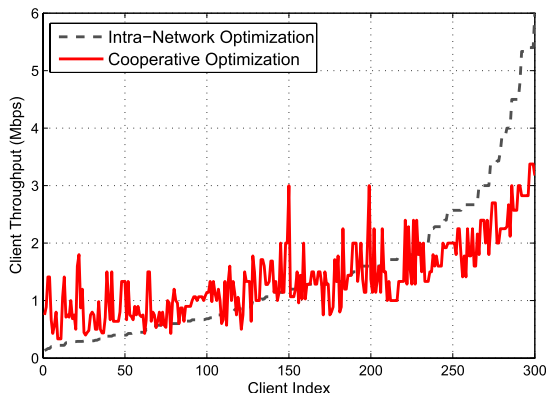**Fig. 6** CDF of client throughputs for all clients. $N = 2$, $|A_i| = 25$, $|U_i| = 150$.



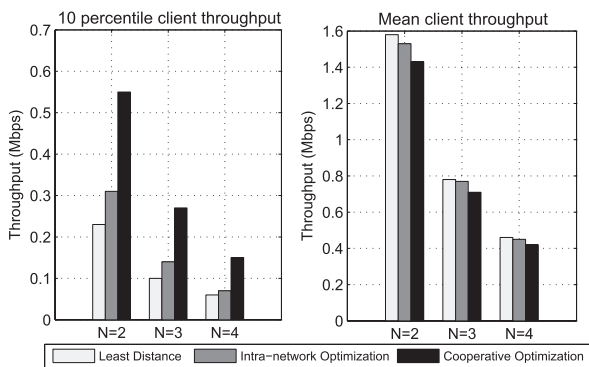**Fig. 7** Per-client comparison between intra-network and cooperative optimization schemes.



**Fig. 8** 10 percentile and mean client throughput values for varying $N$ with $|A_i| = 25$, $|U_i| = 150$.

The key observation here is that almost all lowest throughput clients are better off after cooperative optimization, while the accompanying loss in throughput is inflicted primarily on the clients with high throughputs.

Figure 8 shows the 10 percentile and mean throughput values for simulations with $N = \{2, 3, 4\}$, 25 APs, and 150 clients. We note that in each of the cases, the 10 percentile throughputs improve by 140–170% with a small 8–

**Table 2** 10 percentile and mean client throughput values for varying number of APs and clients with $N = 3$.

| | | 10 %ile throughput(Mbps) | | | Mean throughput(Mbps) | | |
|---|---|---|---|---|---|---|---|
| $|A_i|$ | $|U_i|$ | Least Dist. | Intra Optim. | Coop. Optim. | Least Dist. | Intra Optim. | Coop. Optim. |
| 15 | 150 | 0.09 | 0.13 | 0.19 | 0.7 | 0.66 | 0.62 |
| 25 | 150 | 0.1 | 0.14 | 0.27 | 0.78 | 0.77 | 0.71 |
| 35 | 150 | 0.11 | 0.14 | 0.31 | 0.85 | 0.85 | 0.77 |
| 25 | 50 | 0.21 | 0.33 | 0.64 | 1.95 | 2.17 | 2 |
| 25 | 150 | 0.1 | 0.14 | 0.27 | 0.78 | 0.77 | 0.71 |
| 25 | 250 | 0.07 | 0.09 | 0.17 | 0.49 | 0.47 | 0.43 |

10% decrease in the mean throughput. The achievable mean throughput naturally goes down with increasing $N$ due to sharing of the spectrum between a larger number of users. Table 2 shows the effect of variations in the number of APs and clients per network for the case of $N = 3$. The key observation here is that the percentage gain brought about due to cooperation increases with AP density, but decreases with client density. The insight from these trends suggests that higher AP densities lead to greater uncertainties that each network has to cope with and thus the information sharing becomes more valuable. However, under a capacity limited regime with large number of users, since all APs are heavily crowded, the relative gain of shifting clients from one AP to another reduces.

### 5.2 Clustered Deployment

Clustered deployments, characterized by a large number of APs placed in a targeted small region are commonly used to serve public places with very high number of peak users, e.g., waiting rooms, mall entrance, etc. In order to study the effects of such topology-specific interference patterns, we considered a clustered topology with two networks. APs of the first network are clustered in three rectangular regions of size $200 \times 200$ meters each, while the second network still has a random AP deployment. All other access parameters remain the same as in the random deployment case. Figure 9 shows the CDF of the client throughputs for each network. We observe that since network 1 APs are strongly clustered, the relative effect of network 2 APs on its performance is minimal. Hence cooperative optimization does not improve the client throughputs for this network. Conversely, network 1 clusters strongly effect the performance of network 2, thus cooperating between the two networks leads to large gains for network 2.

### 5.3 Comparison with *Access Coordination*

A simple alternative cooperation scheme in a multi-network scenario is *access coordination* in which two or more networks agree to allow each others' clients to access their networks. Each client can now connect to the nearest AP of any network. In order to compare the operational cooperation scheme proposed in this paper with an access coordination scheme, we reuse the topology in Fig. 5 but allow clients to connect to APs in either network. Figure 10 shows
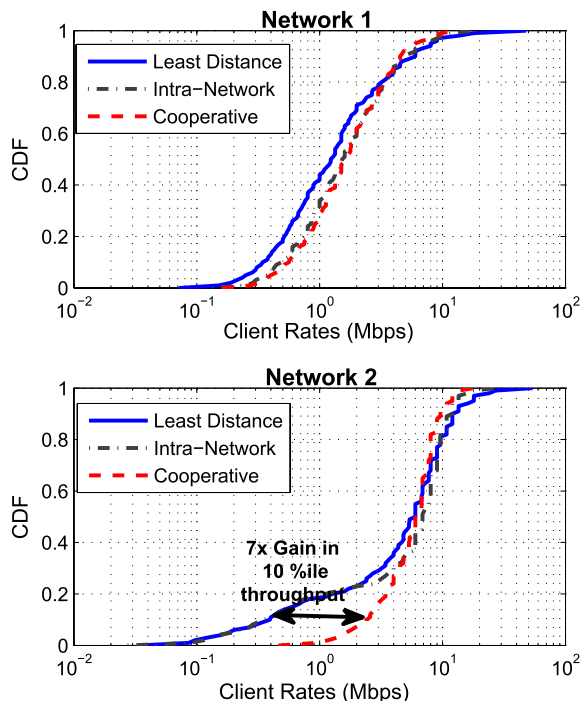
**Fig. 9** CDF of client throughputs for network 1 (clustered APs) and network 2 (randomly deployed APs). $|A_i| = 25, |U_i| = 150$.
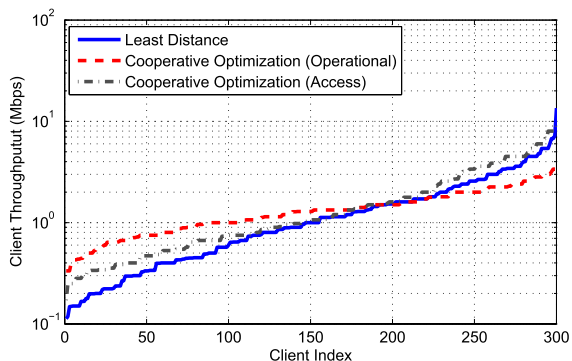


**Fig. 10** Throughput of each client for different association schemes (sorted).

the throughput of each client under the three association schemes with the client indices arranged in the order of increasing throughput. We note that, access cooperation leads to a decrease in the shortest distance between an AP and a client and thus gives higher throughput for almost all clients. However, since access to more APs does not solve the load balancing problem, operational cooperation results in better performance for more than 2/3rd of the lowest throughput clients.

## 6. Conclusions

This paper has presented a novel network-assisted approach for dynamic spectrum coordination, intended for application to emerging white space and cognitive radio scenarios. Key design components necessary to implement the

proposed NASCOR architecture have been described and validated. Detailed simulation results were presented for a specific dense WiFi deployment scenario demonstrating significant performance gains from coordination between co-located networks. Based on the results obtained so far, we believe that network assisted techniques represent a promising approach for achieving high efficiency dynamic spectrum access systems in the future. We note that the IETF has recently initiated standardization of an interface for access to a spectrum database (PAWS [31], and it may be appropriate to consider further extensions to this or other networking standards to provide support for distributed inter-network spectrum coordination as well. In our future work, we intend to further develop the details of the protocol framework outlined in this paper and build a proof-of-concept prototype using software-defined radio (SDR) and software-defined network technologies as the foundation.

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