Cognitive Radio Resource Management Using Multi-Agent Systems

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***Abstract*—This paper investigates cooperative radio resource management for multiple cognitive radio networks in interference environments. The objective of this research is to manage shared radio resources fairly among multiple non-cooperative cognitive radio networks to optimize the overall performance. We emphasize the underlying predictability of network conditions and promote management solutions tailored to different interference environments. A multi-agent-system-based approach is proposed to achieve information sharing and decision distribution among multiple cognitive radio networks in a distributed manner. We address the distributed constraint optimization problem (DCOP) in cognitive radio networks and study the effectiveness of DCOP algorithms to find the optimal radio resource assignment through communications between distributed agents.**

***Keywords*—Spectrum management, distributed constraint optimization problem (DCOP), predictive models, third-party-based architecture**

I. Introduction

Cognitive radios [1] provide a potential solution for more efficient spectrum utilization. To achieve efficient spectrum utilization, a balanced and integrated communication system is required [2]. One solution is to incorporate spectrum management functionality with the software-defined radios attributes in communication systems. This paper provides an initial investigation into cooperative resource management for multiple cognitive radio networks. Interference from co-located, co-band, and non-coorporative wireless technologies is anticipated and is a component of the study presented. The objective of this research is to manage shared radio resources fairly among multiple non-cooperative cognitive radio networks to optimize the overall performance. We emphasize the underlying predictability of network conditions and promote management solutions tailored to different interference environments. A multi-agent-system-based approach is proposed to achieve information sharing and decision distribution among multiple cognitive radio networks in a distributed manner.

Cognitive radio resource management requires a tight coupling between the spectrum management functionality and the software-defined radios attributes, i.e., modes of operation supported by the physical layer. Wireless local area networks (WLANs) provide essential components for projected cognitive radio platforms. Since predictive models can be readily developed for current WLANs, they make an ideal hardware platform for developing our resource management strategy.

The rest of this paper is organized as follows. The proposed architecture for the distributed cognitive radio resource management is present in Section II. A centralized implement is presented in Section III and is used to illustrate the concept and provide a benchmark for the performance. A distributed implementation based on multi-agent-systems is outlined in Section IV, followed by the conclusions and future work in Section V.

II. Architecture of Cognitive Radio Resource Management Using Multi-Agent Systems

One application of cognitive radio resource management is the multi-domain WLAN environment. In recent years, many hot-spots are emerging and multiple WLANs are being deployed within small geographic vicinity. Different WLANs in a particular area may be deployed by different operators. In such a multi-domain environment, there is a growing interest in WLAN providers setting up reciprocal agreements so that mobile users may share the usage of multiple WLANs.

A multi-agent system-based approach is proposed to achieve information sharing and decision distribution among multiple WLANs in a distributed manner. WLAN providers may set up service-level agreements among themselves on how much data can be exchanged among agents. Compared to using a centralized controller, a multi-agent system-based approach is more scalable.

A. Multi-Agent-Based Architecture

We propose a resource management architecture for multiple WLANs using multi-agent systems, as shown in Fig. 1. Multiple WLANs are co-located within a particular geographic area. Communications inside the surrounding wireless personal area networks (WPANs) such as Bluetooth networks and wireless sensor networks (WSNs) generate interference to WLAN activities. Agents are located inside each access point (AP) and interact with other agents within its neighborhood. An agent's neighborhood consists of those agents with whom it has frequent interactions. These interactions include sharing of data and negotiating about resource assignments. Individual agents act as radio resource coordinators and cooperate with agents in their neighborhood to take care of resource management across multiple WLANs.

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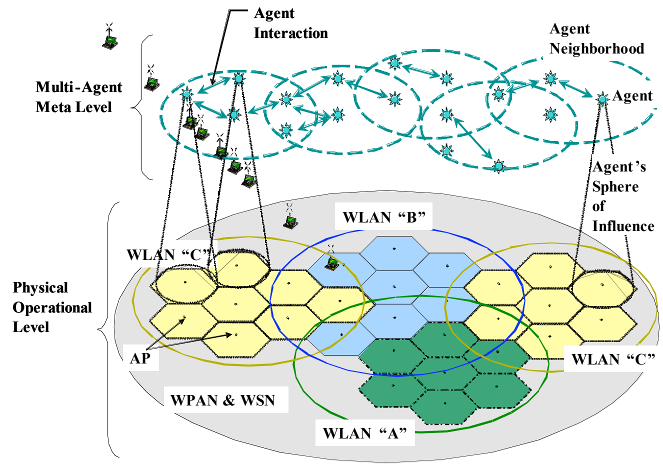

Fig. 1. Architecture of WLAN resource management using multi-agent systems.

Through agent coordination, providers may offer inter-WLAN roaming services to their subscribers as a value-added service feature. They can also support communications with better-quality signals since the impact of interactive interference can be globally balanced through multi-agent control. The functions related to user authentication, billing, security and privacy, and mobility management can also be implemented in agents. Within the multi-agent system, the agents are leveraged to fairly balance system-wide resources in order to accommodate more users with the least amount of cost.

The agent at each AP collects the statistics from the measured operational environment as well as its neighborhood and estimates the required parameters for optimizing system performance based on predictive models. The IEEE 802.11k task group [3] is developing a radio resource measurement extension to the IEEE 802.11 WLAN standard. As suggested by the IEEE 802.11k task group, the signal characteristics are obtained directly from WLANs. The data can be augmented by an additional sensing component to provide additional data specifically associated with WPAN interference sources in the environment. The agents use the measured data to generate local control decisions and try to optimize the performance of the entire WLAN system in a distributed fashion through agent interaction and coordination.

Agent interaction is an essential aspect of this architecture. Agent interaction occurs on the backbone network connecting all the APs. Therefore, the bandwidth requirement for agent interaction is not a critical issue. However, since multiple agents contribute to the control of optimal resource allocation across WLANs, they need to decide what information should be exchanged among neighbors, how often to exchange this information, and which neighbors should act as relay nodes for the data. When a control decision is made, an agent also needs to decide what actions its effector should take and how the control decision should be distributed to the desired area.

B. Multi-Agent-Based Architecture

Fig. 2 presents a block diagram of a general framework for physical environment prediction and resource management using agent technologies. The major functional blocks are: WLAN and WPAN cluster, RF environment sensing (RES), and agent operations which include predictive parameter estimation (PPE) and resource management optimization. They are explained in details as follows.

WLAN and WPAN Cluster: Each mobile station (MS) in WLANs operates within a dynamic RF environment comprising time-varying co-channel interference sources and time-varying interference sources from co-located WPANs. The agents inside each AP periodically collect measured statistics from the dynamic RF environment required for resource management.

RF Environment Sensing (RES): This block is used to provide estimates of the signal characteristics from both MSs within the WLAN cluster as well as potential interference sources within the operational environment. Part of the functions defined in this block can be provided by the specifications of IEEE 802.11k radio resource measurement. Statistics related to WPAN environmental interference levels should be provided from an additional sensing component inside each AP. It is important to remark that it does not imply measuring instantaneous small-scale multipath signal characteristics which are very time-sensitive. Instead, measurements would be targeted at capturing large-scale changes in signal characteristics due to variations in shadowing, MS mobility, interference sources, and interference locations. In other words, the RES needs to measure the factors which influence the resource management of the WLAN performance.

Agent Operation-Predictive Models for Parameter Estimation (PPE): Estimates of signal characteristics are input to the agent inside each AP. An agent also receives data from its neighborhood through agent interaction and coordination. The general concept for the PPE block is to use predictive models to generate parameter estimates required by the resource management optimization. The parameters to be estimated include:

- **Link Quality:** link quality between each MS and its AP.
- **Mobility Rate:** rate of changes in the expected link quality between each MS and its AP.
- **Energy Expenditure:** energy required to successfully transmit a packet between each MS and its AP.
- **Throughput:** throughput for each WLAN cell based on

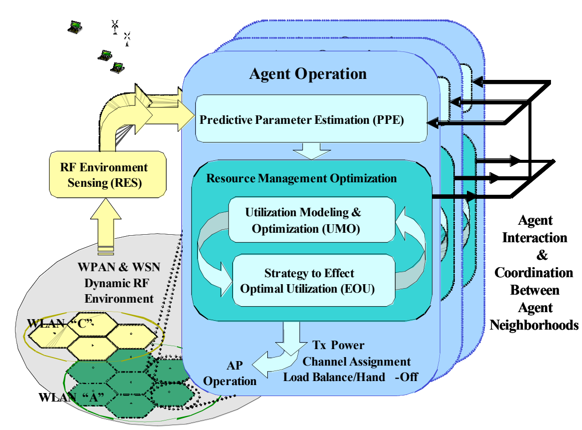

Fig. 2. Block diagram of physical environment prediction and agent operations.

the operational environment characteristics, current offered traffic, and projected offered traffic.

- **Latency:** expected time delay and the variance in the time delay between each MS and its AP.

Agent Operation-Resource Management Optimization: This block analyzes the parameter estimations and makes instructional decisions to optimize the overall WLAN performance based on designed optimization models. Instructional decisions include the optimal transmit power at APs, the optimal channel APs should operate in order to minimize interference levels and make the best use of overall resources, whether or not to accept association requests from specific MSs, whether to direct specific MSs to be associated to another AP for load balancing, and so on. These decisions are updated periodically in order to address changes in the traffic load and interference environment. They should target long-term performance improvement. The operational changes are downloaded to the WLAN cluster with the help of agent effectors and distributed to the neighborhood of agents through agent interaction and coordination.

The resource management optimization block includes two components:

- **Utilization Modeling and Optimization (UMO)**: This block finds the optimal utilization, i.e., the maximum allowable throughput, of each AP based on the environmental information agents possess. The decision of the optimal utilization is used by the EOU block (which is explained in the following) to generate specific strategies to achieve the optimal utilization at each AP.
- **Strategy to Effect Optimal Utilization (EOU):** Given the optimal utilization of each AP, instructional decisions are generated to achieve the optimal utilization while minimizing interference to the environment. Operational changes are negotiated within the agent's neighborhood and applied to the WLAN cluster. They are also fed back to the UMO block to update the optimal utilization decision.

III. Illustrative Example: Load Balancing in an Interference Constrained WLAN

In this section, we explain how to manage radio resource of multi-domain WLANs using a centralized approach. In the next section, a decentralized approach is adopted based on multi-agent systems. The goal of our work is to adaptively manage shared system-wide radio resources under time-varying network conditions among multiple WLANs. This radio resource management should incorporate the impact from the interference environment. Due to the co-location of WLANs such as the IEEE 802.11b and WPANs such as Bluetooth or the IEEE 802.15.4 low-rate WPAN (LR-WPAN) which operate in a shared spectrum, their communication activities interfere each other because of spectral overlap. Interference sources will impact mobile stations differently due to variations in RF path loss. These variations make it difficult and costly, in terms of network resources, to maintain performance requirements. Hence, it is imperative that the dynamic effects of interference be incorporated into network management and control decision-making.

Although a considerable amount of research on radio resource management in a single WLAN is proposed [4]-[7], cooperative resource management for multi-domain WLANs remains largely unexplored. Resource management schemes designed for a single WLAN cannot be directly applied to multi-domain WLANs because the interactive effect of inter-domain co-channel interference is not taken into consideration.

A. *Third-Party-Based Architecture*

We propose a third-party-based resource management architecture to facilitate the cooperative multi-domain resource management. A trusted third-party agent is needed who is independent from each network provider's financial interests. When a new WLAN is deployed, the WLAN provider does not need to set up direct service level agreements with all the other providers of the existing WLANs in the area. It only registers to the third-party agent. The third-party controller can collect information across multiple domains and send control signals back to each domain, thereby making radio resource management and other features possible [1].

A new entity, local network controller (LNC), is connected to all the APs of multiple WLANs, as shown in Fig. 3. WLANs under the control of an LNC form a WLAN cluster. The LNC acts as a radio resource coordinator across domains and takes care of issues related to inter-domain roaming and resource sharing within a WLAN cluster. As the number of domains in a WLAN cluster increases, the LNC can be built in a hierarchical structure to make it more scalable. As shown in Fig. 3, a global network controller (GNC) is connected to all LNCs supporting inter-WLAN-cluster roaming and resource sharing.

The LNC gathers the measured resource usage statistics from all the APs via Simple Network Management Protocol (SNMP) [8]. APs collect signal characteristics from client stations in each domain based on IEEE 802.11k specifications [3]. The measured data can then be used by the LNC to generate control decisions to optimize the performance of the entire WLAN cluster.

B. *Proposed Resource Management Scheme*

The goal of the proposed scheme is to minimize the total system cost by adjusting resource allocation in each domain. The cost is what the system needs to pay to support all the MSs to achieve performance requirements. It is related to the available radio resources for supporting the offered load in

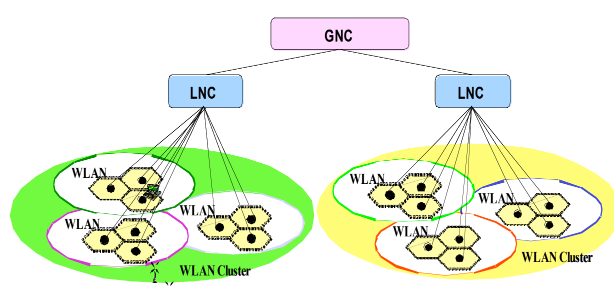

Fig. 3. Third-party-based multi-domain resource management architecture for WLANs.

each domain and mitigating interference from the operational environment. The LNC manages resource sharing across domains by controlling the maximum allowable throughput of each AP. When the maximum allowable throughput at an AP changes, the available radio resources of the cell is limited. Consequently, the cell utilization changes which leads to a different system cost. Therefore, minimizing the overall system cost is equivalent to finding the optimal allowable throughput at each AP. In addition, WPAN interference can adversely affect the WLAN performance by changing its resource utilization requirements and therefore needs to be considered. Moreover, due to the dynamics in the RF environment, signal characteristics, traffic load, and interference intensity are time-variant. As a result, the optimal resource allocation decision should be dynamically adjusted to reflect the influences of the time-varying environment.

The proposed resource management scheme includes three steps. First, based on the overall traffic load distribution at all the APs in a WLAN cluster, the impact of co-channel interference at each cell can be calculated. Then, by incorporating the impact of interference from other sources in the operational environment, the communication cost of the overall system can be derived which is a function of cell load, co-channel interference, and interference from other wireless services. Second, the LNC finds the optimal pattern of maximum allowable throughput at each AP in multiple domains. In other words, the LNC decides which AP should provide how much capacity to its users. This optimal throughput pattern results in the minimum system cost. Finally, the LNC sends control signals to APs to instruct them on how to update their allowable resources for users based on the calculated optimal throughput.

The multi-domain resource management issue can be formulated as an optimization problem. The LNC periodically optimizes the resource usage in each domain by minimizing the overall system cost function. The LNC not only finds the optimal throughput pattern for all the APs, but also determines the optimal capacity for each domain. After the LNC finds the optimal resource allocation, resources at each domain should be updated. Both the co-channel interference from other WLANs and the interference from co-located WPANs are considered during the optimization process. Therefore, the proposed multi-domain resource management scheme is able to minimize the co-channel interference across domains and mitigate other interference from the operational environment through fair resource allocation. Under the proposed scheme, resource utilization and co-channel interference can be adaptively balanced across the entire integrated system.

C. Performance Evaluation Using Simulations

We simulate a two-domain WLAN environment with IEEE 802.11b WLAN A and B co-located. Multiple Bluetooth nodes are also co-located with the two WLANs. Their communications interfere with each other. A two-state Markov traffic model is used for our simulation. There are two Pareto distributions involved in the model: one for the traffic load with a cutoff value at 6Mbps and the other for the HIGH/LOW state duration. The traffic is generated at both states with a burst threshold 100kbps, which means, when the generated traffic load is less than 100kbps, we assume the AP is at the LOW state. The Bluetooth traffic model is based on an ON-OFF Markov model and the traffic switches from an ON to an OFF state with probability 0.6.

Simulation results demonstrated that the proposed multi-domain cooperative resource management scheme is more cost-efficient for a WLAN/WPAN interference environment. The proposed scheme can save up to 99.8% and 47.3% cost compared to the scheme that each domain optimizes resource usage independently without the consideration of potential interference from co-located WPANs and the scheme that LNC is involved to help control the resource allocation in each domain but without the consideration of potential interference from co-located WPANs, respectively.

IV. MULTI-AGENTS – PROVIDING A DISTRIBUTED IMPLEMENTATION

We are interested in solving the resource allocation problem involving WLAN resource management in a decentralized fashion using multi-agent systems (MAS). As presented in the previous section, central to this process is balancing the traffic load between disparate WLANs. A mechanism for implementing load balancing is the handoff process of transferring the resource usage of an MS from one AP to another. This process can be triggered by two events: Type 1: An MS requests a handoff from one AP due to mobility requirements; Type 2: An AP, sheds or acquires additional load in order to balance the traffic load within its neighborhood set. We present a model based on multi-agent constraint optimization problem (MCOP) to optimize Type 1 handoffs in this paper in order to illustrate the approach.

A discrete multi-agent constraint optimization problem (MCOP) [9] is a tuple $\langle A, X, D, R\rangle$, where

- $A = \{A_1, \ldots, A_n\}$ is the set of agents interested in the solution,
- $X = \{X_1, \ldots, X_m\}$ is the set of variables; usually each agent A_i is assigned one variable,
- $D = \{d_1, \ldots, d_m\}$ is a set of domains of the variables, where each domain is a finite discrete set of possible values, and
- $R = \{r_1, \ldots, r_p\}$ is a set of relations where a relation r_i is a utility function which provides a measure of the value associated with a given combination of variables.

The objective of the MCOP is to find an assignment X^* for the variables X_i that maximizes the sum of utilities of the multi-agent system. DPOP [10], a distributed constraint optimization algorithm for general networks, uses dynamic programming for its utility propagation. DPOP has three phases: in phase 1, the algorithm performs a distributed depth first traversal of the general network to establish a pseudo-tree[1] [11] structure; in phase 2, the algorithm propagates utility

[1] A pseudo-tree of a graph G is a rooted tree with the same vertices as G and has the property that adjacent vertices from the original graph fall in the same

messages which contain utility vectors bottom-up along the pseudo-tree; in phase 3, the optimal value assignments are propagated top-down from the root node.

We map the WLAN resource allocation problem to a multi-agent distributed constraint optimization problem. Each AP is assigned an agent. However, at any point in time, only a subset of these agents will be involved in the resource-allocation process, which means that the multi-agent system is constructed dynamically. Periodically, each agent listens for event triggers. The frequency of event triggers can be an issue. If they occur too often, then the environment is too dynamic and a greedy reactive control would be preferable to planned deliberation, i.e., DPOP, as the latter uses up time only to have its results become obsolete prior to being applied to the intended environment, thus leading to instability. Each event trigger wakes up the corresponding AP agent and the multi-agent system initiates the resource-allocation process along with every other AP agent that has been awakened[2]. The variables belonging to each agent are AP recipient ids with associated handoff times. The domain for the variables is the set of APs in AP_X 's neighborhood set that are potential recipients of MS_i 's handoff. The recipient agents could include agents in MS_i 's immediate neighborhood as well as in its interference neighborhood.

Consider the following simple scenario with Type 1 event triggers. Suppose at time t_0, 3 APs are triggered by 4 MSs. Each trigger is represented as

$$MS_i : \; AP_x(t_1)\}\{AP_y(t_2)\},$$

where MS_i is the MS requesting a handoff; $AP_x(t_1)$ is the current handler of MS_i and t_1 is the estimate of the time by which the handoff has to occur; and $\{AP_y(t_2)\}$ is the set of destination APs in AP_X 's neighborhood set that MS_i could be handed off to and each AP_y has an associated time t_2, the estimate of the earliest time MS_i can be handed off to AP_y. The handoff duration time could also be incorporated as an additional parameter in each event trigger to represent the minimum requirement of the requested handoff. As depicted in Fig. 2, the utility function for the decisions is provided by the Utilization Modeling and Optimization (UMO) block. The following example gives an illustration of the even trigger explained above.

$$\begin{aligned}
&MS_1 : \; AP_1(t_1 = 10)\}\{AP_2(t_2 = 8)\} \\
&MS_2 : \; AP_2(t_1 = 6)\}\{AP_3(t_2 = 7)\} \\
&MS_3 : \; AP_2(t_1 = 32)\}\{AP_1(t_2 = 25), AP_3(t_2 = 30)\} \\
&MS_4 : \; AP_3(t_1 = 14)\}\{AP_1(t_2 = 7)\}.
\end{aligned}$$

branch of the tree. Pseudo-trees are used in search due to the relative independence of nodes lying in its different branches.

[2] If an AP has multiple event triggers at the same time, the corresponding AP agent will assign each MS a variable and solve the cumulative resource-allocation problem.

The vertices of the pseudo-tree constructed in the DPOP algorithm are AP_1, AP_2 and AP_3. The utility vectors of the leaves are determined by the utility function from the UMO and the optimal assignment of handoff destinations and timings is computed using the DPOP algorithm described above. The resource allocation process is triggered every time a new set of event triggers occurs. The DPOP algorithm provides the optimal solution within a bounded time, i.e., the algorithm is guaranteed to converge to the optimal solution.

V. Conclusion and Future Work

In this paper, we investigated how to dynamically manage shared radio resources fairly among multiple non-cooperative cognitive radio networks using multi-agent systems. We explained the components in our proposed architecture for the distributed cognitive radio resource management. We presented a centralized implement for multi-domain WLANs. We then outlined a decentralized implementation based on multi-agent systems and explained how to map WLAN resource allocation problem into a DCOP using multi-agent systems. We are currently studying the effectiveness of using DCOP algorithms to find the optimal radio resource management and comparing the performance of this distributed approach to that of the centralized approach.

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