Designing a Self-Optimization System for Cognitive Wireless Home Networks

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***Abstract*—In this paper, we describe the design and implementation of an extensible and flexible self-optimization framework for cognitive home networks that employs cognitive wireless networking and agent-based design principles. We provide a "first-principles" derivation of its architecture based on a careful analysis of user requirements on wireless home networks (WHNs), state the related design objectives and constraints, and address those in the context of present-day and emerging radio platforms. We utilize the cognitive resource manager as an architecture of the individual agents. This architecture serves as a "constraint that de-constrains," i.e., it allows achieving high system flexibility, while providing structural constraints to ensure robustness. We show that the designed system is capable of solving complex utility maximization problems constrained with user, operator, and regulatory policies in the crowded ISM bands. The system successfully operates on an extensible parameter configuration space across multiple protocol layers. For example, the prototype employs diverse optimization algorithms, and can also benefit from radio environment map information on primary transmitters propagated through the integrated policy mechanism. The proposed system delivers both efficient and robust radio resource management, and enables comfortable WHN experimentation by providing extensibility of sensory inputs, actuation parameters, and optimization algorithms.**

***Index Terms*—Wireless home networks, self-optimization, cognitive radio, cognitive resource management, radio environment map.**

I. Introduction

THE POPULARITY of wireless communications systems for home networking is rapidly growing along with the user demand for diverse high quality telecommunications services. In 2020, the number of devices for home usage equipped with Wi-Fi interfaces is expected to exceed 1.5 billion units in terms of PCs and tablets alone, with more than half of mobile traffic being offloaded over Wi-Fi as well [1]. The increasing adoption of wireless interfaces creates new usage models, like wireless content sharing and streaming between home media appliances. This also results in dense and poorly predictable wireless home environments. Wireless interference is already becoming an increasingly serious problem, and the utilization of especially ISM spectrum bands is constantly increasing [2]. However, current network management solutions do not sufficiently assist non-professional users to efficiently setup and maintain wireless home networks. For example, Wi-Fi networks are often configured to operate on a single fixed channel that is selected at system startup or at periodic intervals, and route all the traffic through an Access Point (AP). These are clearly sub-optimal solutions in a dynamic environment. The emergence of small cells and 5G system deployments and alternative wireless access technologies such as mm-Wave solutions will further complicate the management and optimization of home networks.

The increasing complexity of future wireless networks makes self-organization an important networking requirement. Self-organization can be achieved through a system that *autonomously manages wireless home networks fulfilling changing user needs in dynamic operational conditions*. Preferably, this system should be *minimally complex* and provide high levels of *flexibility and evolvability* to incorporate the likely short- and long-term changes in user demands, operational environment, and list of desired services or applications. In this article we derive from first principles a design of a self-optimizing framework for wireless home networks, called Home Cognitive Resource Manager (HCRM), and evaluate the resulting prototype implementation. The framework primarily focuses on radio-resource management aspects of the network control, also employing cross-layer adaptation, utility-based reasoning, and complying to policy regulations that, among others, are also derived using radio environment maps (REMs) [3], [4]. The HCRM design aims to serve as "constraint that de-constrains" [5] the self-optimization process, allowing for both robust and efficient stakeholders service, as well as easy system extensibility and upgrade possibilities. We apply the HCRM in this paper specifically on Wi-Fi networks due to their dominance in present-day deployments,

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availability of mature platforms for prototyping, and since ISM bands due to their complex usage patterns and several coexisting wireless technologies provide the most challenging environment for testing any self-optimizing systems. However, we strongly emphasize that our framework is generic and other wireless technologies can be incorporated with ease. In particular, any new wireless technology needs to simply implement an instance of a generic interface (the Unified Link-Layer API, or ULLA, described in more detail in the following section) while the rest of the HCRM design and implementation is entirely generic.

We demonstrate that exploitation of the chosen architectural principles leads to an efficient, robust, and flexible system. The HCRM is comfortable to the end users, accommodates for operator demands through policy constraints, and addresses the network complexity and the evolvability issues. The latter aspect is approached through the modular and extensible design that enables consideration for alternative optimization algorithms, as well as flexible definition of sensory inputs and actuation state spaces defined over multiple protocol stack layers utilizing various degrees of cooperation between nodes. It should be noted that this article integrates and significantly extends our earlier results on self-organization for home networks presented in [6]–[8], especially in the domains of architecture and design, as well as model based radio-resource management.

There have been a number of interesting self-management approaches for wireless environments [9], [10] and, specifically, for wireless home networks [11], [12]. However, these either have a different focus, do not consider the dynamic spectrum allocation aspects, or just present a certain resource allocation scheme, e.g., [13], without addressing the system-wise aspect of the problem. The work on virtualization of wireless interfaces, e.g., presented in [14] and [15], has not been incorporated as part of a complex self-management system until recently within the same context as our present work [16]. The relevant focus of the cognitive wireless networking is the consideration for flexible radio resource management architectures, e.g., [17]–[20]. However, this research rarely considers the wireless home domain explicitly with its specific requirements. In particular, unlike for cellular and corporate wireless deployments, in home deployments no expertise is usually available from users, the boundaries between "administrative domains" of users are very strict, solutions should be of very low complexity due to cost reasons, and nevertheless provide full automation. From this field we adopted the Cognitive Resource Manager architecture [17] as a starting point for our work.

This article is further organized as follows. In Section II we describe the design of the HCRM, discuss the high level requirements for the system together with their mapping to the lower-level system-specific objectives, and derive the HCRM design based on agent-based approaches and cognitive resource manager architectural principles [17]. Section III provides detailed description of the arising system design. In Section IV we discuss selected evaluation results. Finally, Sections V and VI draw some conclusions with explicit summary of the lessons learned from working on the HCRM, and discuss applications of the developed technologies to other wireless systems as well.

II. Deriving Design

We begin by stating the main requirements and constraints imposed on a WHN self-optimizing system. Then using two foundational architectural constructs, which we argue to be applicable to our application area, we derive the final system design.

A. Challenges and Constraints

We proceed by stating the main requirements and constraints imposed on such systems as the HCRM, both summarized in Table I. Wireless home networks are deployed in individual apartments, and consist of a home gateway (that can be incorporated into an access point), and multiple clients that might require either Internet and/or ad-hoc connectivity (Fig. 1). Typically the same spectrum is shared not only between multiple users of one network, but also between different WHNs and other technologies. This applies especially to ISM bands, but also other emerging shared frequency bands such as the 3.5 GHz band in the USA. In this context, the suboptimality of the strictly layered TCP/IP stack without cross-layer optimization capabilities, the imperfectness of software and hardware, and non-professional users with the lack of expert support contribute to the WHN challenges.

Typical stakeholders of a home network deployment are users, network and service providers. In shared frequency bands further licensed or license-exempt users might also need to be considered. In this work we focus only on their technical goals, without explicit consideration for socio-economical aspects. The objectives of a network provider can be approximated as a trade-off between efficient usage of wireless resources, e.g., spectrum, and provision of high quality of service to users to guarantee their satisfaction. Individual users aim to maximize performance provided by a network that can be perceived through Quality-of-Experience (QoE) metrics, while complying to external (operator) constraints. These stakeholders operate on dynamically changing objectives, that should be accurately conveyed to the system to achieve the best performance provided that the imposed overhead and complexity are tolerable [21]. We chose to lower the corresponding complexity by the decomposition of objectives into two classes: global, slow varying, goals expressed using *policies*, and local, more rapidly evolving aims captured by *utility functions* stated on the per flow basis. Policies represent a set of rules, constraints and preferences imposed by different network stakeholders, including regulatory bodies and contractual partners in spectrum sharing agreements. Utilities on the per flow basis reflect stakeholders satisfaction from the network performance as a function of such Key Performance Indicators (KPIs) such as transport or MAC layer throughput, delay, packet delivery ratio, jitter, or wireless driver (buffer) load. It is important to highlight that global goals affect local objectives. For example, explicit prioritization between utilities imposed by the policies decreases network complexity, and therefore, increase its robustness.

TABLE I
SUMMARY OF THE HIGH-LEVEL SYSTEM REQUIREMENTS

By operators	By users	Additional requirements
- Efficient use of network resources - User satisfaction - Compliancy to constraints and policies - Robustness to changes in the operational conditions	- Max. of QoE and robustness in expected operational conditions - Predictability and stability of performance - Indications of changing goals and constraints - Minimal involvement, i.e., maximal automation	- Minimal complexity - Evolvability and flexibility - Operation of COTS (Commercial Off-The-Shelf) hardware and Windows OS - Experimentation platform for self-optimization in WHNs - Policy conflict handler

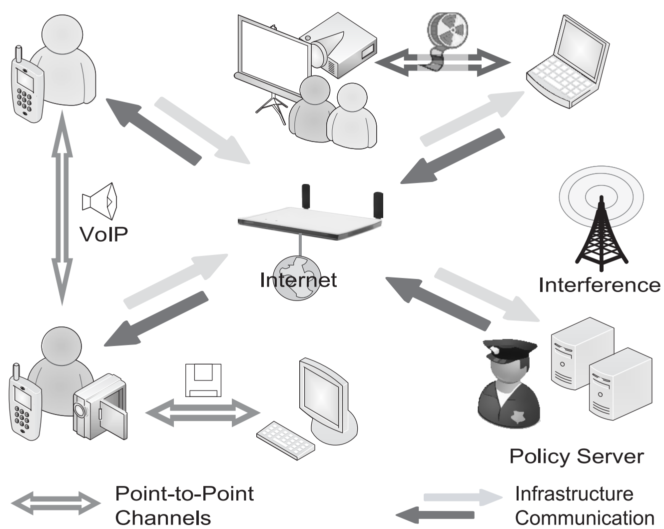


Fig. 1. A wireless home network scenario (from [7]).

The overall system utility can be seen as a result of a trade-off between its *efficiency*, which can be seen as absolute displayed performance for a given set of resources, and *robustness*. Robustness is a measure of performance variability as a result of changes in the system or its operational environment [5], including the considerations for critical system failures as a result of a software or hardware malfunctioning. Networks that directly provide services to users, in contrary to many machine-to-machine networks, need to be consistent in displayed performance trends over long periods of time. Robustness can often be improved by duplication of functionalities at different parts of the system at a price of additional overhead, e.g., via the re-transmission mechanisms both with the 802.11 MAC and the TCP transport protocols.

Any system design needs to deal with the challenge of choosing the type and the amount of input information that can be efficiently utilized by its algorithms. This leads to performance maximization at the price of acceptable overhead and minimal increase of complexity (to lower the emergent risks). For flexibility we exposed the HCRM to a wide variety of inputs through a set of unified interfaces. However, the amount and rate of querying is decided by the particular HCRM self-optimization algorithms. The HCRM gathers information on the performance of a WHN in terms of KPIs. It also can observe the spectrum conditions. The inner state of a node also requires monitoring as it might be altered by management entities external to the HCRM. For instance, it can be affected by hardware or software updates, the rate adaptation mechanisms of IEEE 802.11 or LTE wireless interfaces, and so on. The HCRM nodes may exchange information and take cooperative actions. Furthermore, the goals and constraints are another category of inputs.

The HCRM software should be *evolvable* to support changes in the specification of the optimization task of the system. This includes, among others, support for changes in available hardware or software. Therefore, the HCRM is additionally required to support new sources of information on the radio environment (such as various types of spectrum sensing devices), as well as increasing the range of configuration options available on the wireless platforms.[1] We also provide support for expansion of the protocol parameters and their value ranges considered by the system. As an example, we choose two promising non-standard inputs. First, we experiment with application layer re-configuration. Second, we consider the effect of an adjustable transmission bandwidth as enabled by recent Wi-Fi and 3GPP standards. Additionally, we show how the HCRM can benefit through policy mechanisms from the models and data derived from a radio environment map updated at runtime.

The requirements for evolvability and adaptability imply that the HCRM should also be able to vary its optimization logic. This effectively means that the system has to solve a *meta-optimization task*. Meta-optimization implies that the optimization process can be decomposed and organized hierarchically to be performed by simpler optimization modules, while still achieving satisfactory performance. Alternative ways to optimization are also accessed in meta-optimization. In networking, meta-optimization is almost inevitable if both control and data planes are being optimized and these processes affect each other. Many of the well-known networking architectural concepts, such as cognitive wireless networking, require meta-optimization especially if one considers not only the stage of network exploitation, but also its design and planning.

[1] In our experimental work reported later in this article we use software defined radio boards as examples of such new technologies, but in future home deployments these would be replaced, for example, by upcoming IEEE 802.11 extensions for improved measurement and configuration fidelity, or similar extensions provided by future 5G based home networking solutions.

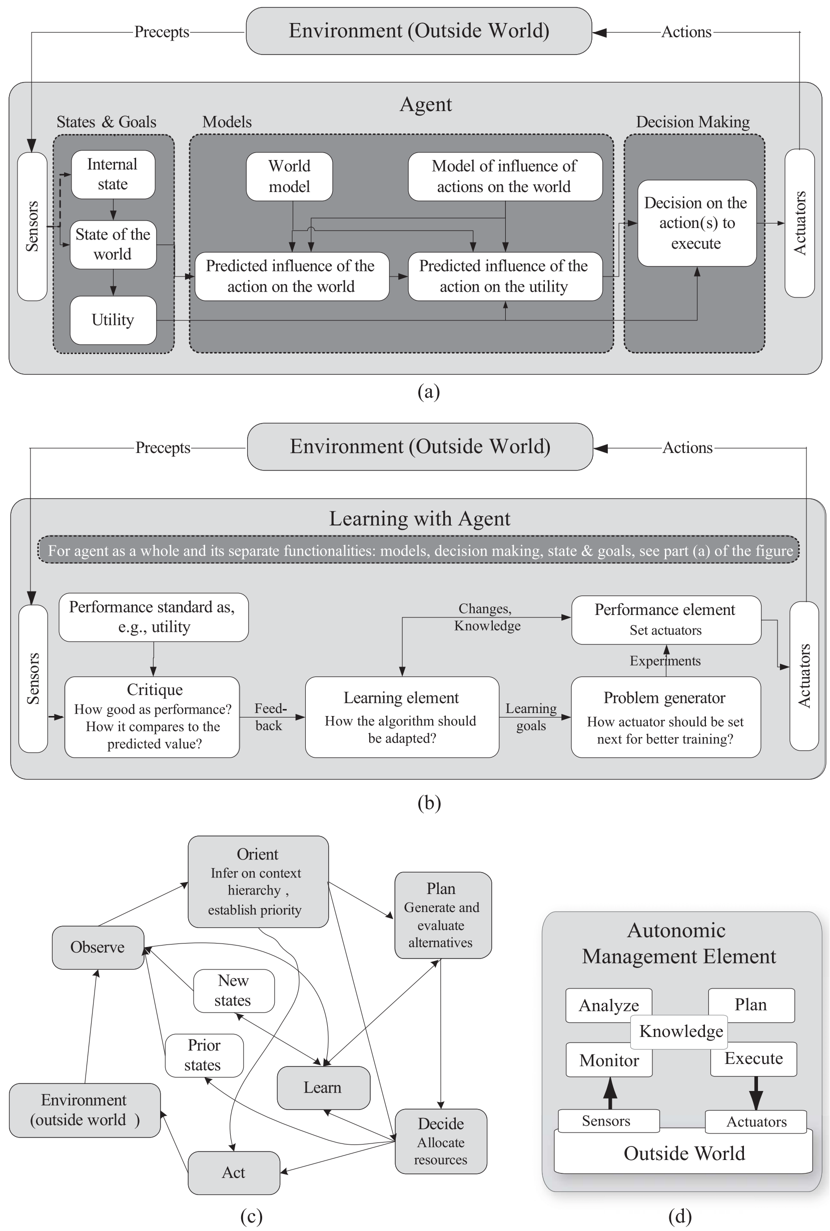


Fig. 2. Sample control loops for self-management: (a) Generalized representation of an (intelligent) reflex agent, (b) a learning agent, (a,b) are extended from [22], (c) Cognitive Radio Cycle, adapted from [23], (d) an autonomic element, after [24]. An agent as a whole or its internal modules can incorporate learning functionalities to adapt their behavior. The figure shows that the different control loops have a lot in common, and, therefore, they can be adopted in common, e.g., agent-based, design practices.

Finally, we note that radio resource management systems that aim at flexibility of their operational logic typically operate on a *hybrid solution state space*, with actions on networks being primarily parameter-based, and the composition of optimization logic being component-based. The first analysis for the need of a hybrid solution state space for wireless TCP/IP networks was to the best of our knowledge suggested by Mähönen *et al.* [17] (though not explicitly formulated in these terms). The HCRM belongs to the class of such systems and, therefore, should be effective on the hybrid state space.

B. Finding an Appropriate Architecture

In this section we argue that *agent-based* design principles provide the most natural foundation for the HCRM architecture. We begin by providing a concise overview of agent-based system design, and then show how the *CRM* architecture [17] from the area of cognitive wireless networking can be used as the basis for the core HCRM agent that resides on any WHN node.

1) Agent-Based Approach: Feedback loops lie at the core of many proposals for self-management, such as knowledge plane [25], cognitive wireless networking [20], [23], autonomic [24], and self-organized networking, Fig. 2c-d. The concept of agents that basically implement feedback loops was independently introduced in multiple research fields, e.g., artificial intelligence (Fig. 2a-b), software engineering, and game theory.

In cognitive wireless networking the role of learning is widely discussed and compared to traditional decision-making techniques that rely on pre-determined (trained) models. This discussion maps to the field of artificial intelligence, where distinction is usually made between *learning* agents that, as the name implies, adapt and learn the optimum behavioral strategy, and *reflex* agents that act according to pre-defined models, Fig. 2a-b (see [22] for further discussion). Learning agents are typically more complex and provide increased fragility/robustness risks, as compared to the traditional reflex agents. Reflex agents can be built upon the results obtained by the learning agents codified in models of different types. In networking one of the downsides of learning agents is that if they rely on active probing, they can considerably lower the quality of experience of active users during probing periods. Therefore in our work we implement as part of the prototype both the learning and the reflex optimizing agents.

The concept of an agent from artificial intelligence maps well to its notion in software engineering. Generally, a software agent is a module or a program that acts on behalf of a user or another agent. Software agents are reactive, autonomous, persistent (i.e., can self-execute if a set of conditions are reached), and capable of coordination and communication with other agents. These characteristics distinguish agents from other software constructs, such as services, components, and objects [26]. In our work we realize major functionalities of the HCRM as agents.

In general we argue that it is beneficial to take an agent-based goal-oriented view [26] when designing self-optimizing systems. As we show below this approach allows mapping of initial requirements to desired system behaviors, understanding their interfacing, and deciding which of those functionalities can be enclosed as agents, thus enabling autonomous system behavior. It is important to note that although agents may potentially add to the system's flexibility and enable it to react on external events more efficiently, their poor structuring might increase, rather then decrease, system's complexity leading to undesired behavior, such as deadlocks or oscillations.

We emphasize that we consider a multi-scale modular agent design, where simple agents can be parts of more complex ones, performing for them specified functionalities. The main element of our system is a HCRM agent that runs on each node of a network. It is further decomposed into a number of interacting agents and supporting components, which depending on the active decision strategy take semi-distributed or centralized solutions. Before deriving the design of these agents, we briefly discuss the CRM architecture that is in the core of the HCRM agent.

2) The CRM Architecture: Self-management and especially self-optimization on lower protocol layers for wireless network is often studied as part of cognitive radio (or cognitive wireless networks) research. Cognitive Resource Manager (CRM) [17] is one of the suggested alternatives [18], [27] to classical resource management architectures for flexible realization of self-optimization. The CRM architecture implements Mitola's cognitive cycle [23]. It achieves a good balance between being generic in component structure and accommodating for wireless field specifics, such as explicitly considering the interactions with layered protocol stacks or the external policy

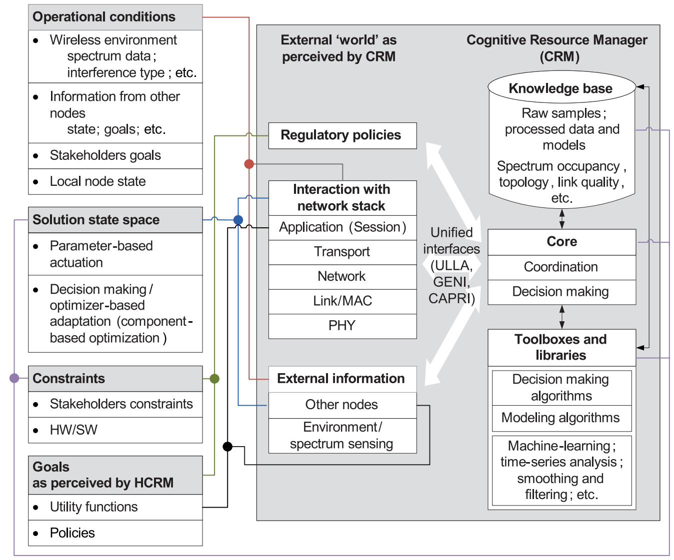


Fig. 3. Overview of the Cognitive Resource Manager (adapted from [17]) and mapping of this architecture to the main variables constituting the HCRM design task.

entities. Fig. 3 displays a slightly adapted version of the CRM architecture, and shows relations between major parameters of the HCRM design task (operational conditions, constraints, solution state space, goals) and the CRM. As we see, the main components that should be considered in the HCRM design map quite directly to the elements of the CRM architecture, which indicates appropriateness of this architecture. Additionally, the CRM is already structured as an autonomous entity. It is split into a number of interacting components, and defines a set of unified interfaces for communication with its environment. Therefore, it is straightforward to do an agent-based decomposition of the CRM.

The original CRM architecture distinguishes three interfaces, CAPRI, ULLA and GENI [16], for interaction with the protocol stack and user space applications. It also foresees the existence of external policy entity that contain regulatory constraints to the system. The CRM also defines a block for cooperation with other nodes, and a sensory block to obtain spectrum information from the environment. Internally, the architecture is split into three modules. The core coordinates all the activities, obtains sensory data, and decides on actions to be taken. The knowledge base is a collection of data and models required for decision making. The toolbox and libraries module contains algorithms required for the perception and the modeling of the operational environment, and establishing causal relations between an actuation state space and sensory inputs. It also can accommodate for optimization/decision making algorithms. Therefore, the CRM is designed to have a hybrid actuation state space which fits to one of our key requirements. The architecture can be also represented as a set of core coordinating agents, interface-providing agents, agents for cooperation between nodes, and, finally, learning agents that employ particular toolbox algorithms. This maps well to the classification of software agents suggested by Nwana [28].

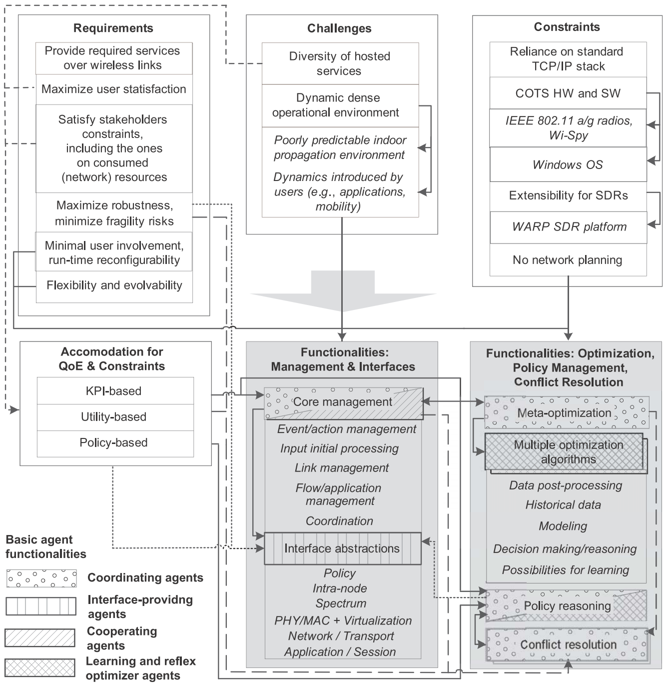


Fig. 4. Illustration how major requirements to the WHN self-optimizing system are used to derive the HCRM functionalities. The functionalities that are viable to realization as particular types of agents are pattern-coded. The intuition for developing separate control loops for them, is the necessity to independently interact with the environment and other system modules.

We conclude that the CRM can be adopted as the functional architecture for the HCRM agents residing on network nodes. Its structure and interface definition may serve as an architectural constraint that defines the backbone for autonomous resource management in WHN environment, thus, in the end de-constraining and opening possibilities for efficient and flexible self-optimization.

C. Functionalities and Architectural Decomposition

There exist multiple architectural approaches for decomposing a system. One could apply, for example, the RCS (Real-time Control System) architectural approach [29] or goal-oriented requirements engineering [30]. We utilize the general principles common to these approaches such as minimal component interdependency, clear goal statement, straightforward information flow, and simplicity of interfaces. Based on the requirements to the HCRM formulated above we continue the design by defining the major system functionalities and, if appropriate, mapping those to agents, as summarized in Fig. 4. To enable rapid software implementation we define the major relations between the HCRM functionalities, as well as their hierarchy. The major functionalities (core management, interfacing, optimization, conflict resolution, and policy reasoning) can be realized as agents, as they all encapsulate well-defined functions, and it is beneficial for them to act asynchronously at different time-scales. Moreover, the first two functionalities directly correspond to the core and the interfacing blocks of the CRM, and the others jointly map to the toolbox and the knowledge base.

We address the goal of performance maximization by expressing concretely the objectives of network stakeholders. For assessing network performance in terms of QoE we choose to use KPI-dependent *utility functions*. We also directly use selected KPIs to improve the response time of the system and avoid critical system failures. For example, in our implementation in the case of a sudden strong interference on a channel its traffic is immediately moved to the interference-free control channel. Simultaneous use of both utilities and selected KPIs adds redundancy into the HCRM improving its robustness, without increasing overhead as these inputs have to be reported to the system anyway. We use *policies* to express rules imposed on the system by various stakeholders. Generally network policies tend to have a hierarchical structure that depends on relations between network stakeholders. For example, FCC regulations apply to all wireless networks operating in the USA, while operator policies apply to only their networks. Further spectrum sharing contracts might impose constraints that apply to two or more networks. In our system policies can be defined either centrally or locally. A policy framework is a centralized entity that, for example, can restrict usage of a certain bandwidth. Applications and user priorities are examples of policies that locally affect utility functions.

The HCRM supports both cooperative and non-cooperative node behavior (for centralized decision on channel usage), as though all nodes are sharing the control channel and therefore can exchange information, global data exchange can create considerable overhead in large networks. For instance, it is often better to centrally decide on employed transmission frequencies, and determine how to share this capacity locally between the involved nodes.

The support for multiple radio-access technologies, cross-layer optimization, and additional spectrum sensing enables the reconfigurability of the network, thus contributing to the goals of performance improvement and efficient resource usage. This flexibility can be realized through definition of *unified protocol interfaces* and *virtualization* of network adapters. These functionalities are also required to ensure *minimal user involvement* and enable evolvability of the HCRM. The *meta-optimizer* functionality that enables execution of diverse optimization algorithms also contributes to the above goals.

The *core manager* addresses the robustness of the system by incorporating key functionalities realizing fail-safe system performance. For instance, it bootstraps and maintains data flows and links, and ensures temporary movement of the flows to the control channel during reconfiguration actions. We decided to introduce a control channel on which an access point operates as part of our solution, as that is an effective way to improve the robustness of CSMA/CA-based wireless networks. The control channel also serves as a backup for the data traffic and ensure continuous, though not quality-wise optimal, user connectivity. The assumption of a control channel availability is valid as at homes almost all the nodes have both full time AP connectivity, and can be equipped with multiple radio interfaces for simultaneous maintenance of both infrastructure and ad-hoc point-to-point links. In future applications of HCRM Wi-Fi based control channel can further

TABLE II
SUMMARY ON CONFLICT RESOLUTION IN THE HCRM

Module	Incoming events with priorities		Behavior
Policy Reasoner	Policy changes	High	Resolve conflicts within local policy configurations (typically using the local and the server ontology reasoners). Forward the corresponding actions that the HCRM is required to perform internally to the core manager.
Core Manager	1. Policy changes from the policy reasoner 2. Critical events 3. Data inputs (e.g., KPIs) and utilities 4. Actions from the meta-optimizer	High Normal Low Same as the driving events	All events are forwarded to the meta-optimizer for decisions on re-configuration. If there is a policy-related conflict or critical system events, such as detection of link failures, or detections of new flows, all the related traffic is moved to the control channel. Further actions on this traffic are invoked by the meta-optimizer.
Meta-optimizer	Same as for the core manager	Same as for the core manager	The meta-optimizer reacts on the events according to their priorities. If a higher priority event appears while the other event is being handled, the latter is canceled. Event of the same priority cannot be serviced before execution of the previous one is acknowledged by the core manager. The LIFO servicing principle applies.

be supplemented with 4G/5G-based one on most foreseen hardware platforms.

Both the meta-optimizer and the core manager are complex agents that perform multitude of functionalities, and incorporate other agents in their designs. For example, the core manager requires separate threads to effectively interact with the TCP/IP stack, the control channel, the meta-optimizer, the policy server, and perform critical event handling and utility assessment. The meta-optimizer incorporates components for data storage, and hosts individual modeling and optimization modules, some of which are instantiated as agents.

The robustness of the HCRM can be further improved through *conflict resolution*. Conflicts can occur due to, e.g., statement of competing goals or race conditions arising due to contradictory decisions reached within the network. Our system handles conflicts at the policy reasoner, the core manager, and the meta-optimizer (Table II). Conflicts in the HCRM are solved based on the priorities of the events incoming into the system and its modules.

There is an obvious trade-off between efficiency, flexibility and robustness offered by the HCRM. We address it by allowing developers/users of the HCRM to decide on the *size of the state space*, the *complexity of the optimization algorithms*, and the *alignment of objectives and information sharing* between nodes within the same home network or even separate networks. The latter decision defines the amount of cooperation required and centralization between nodes. For our system this is done using a common control channel. For data transfer it is done primarily using the point-to-point links, as those typically provide higher performance, until their inter-node distances are too large, or the interference levels are high. The HCRM establishes ad-hoc links and redirects traffic between ad-hoc and a control channel links as part of the optimization.

III. IMPLEMENTATION ARCHITECTURE

Based on the analysis from the previous section, we derived the component-wise design of the HCRM which is depicted in Fig. 5a. We designed HCRM interfaces to abstract away differences between protocols of the same families enabling homogeneous interaction format with other protocols, external devices and nodes [16]. Their sensory inputs are the KPIs, and actuators are protocol settings and overall management of data flows and ad-hoc wireless links. Monitoring of both low and high layer KPIs allows for adequate and rapid reaction by the HCRM to performance changes. For example, low-layer KPIs, such as the link load, allow quick detection of unfavorable channel conditions. However, if the high-layer utility-based metrics indicate user satisfaction with current performance then no actions are taken, especially if their costs are high. The example in our implementation is channel switching that can take up to few seconds. Two of the HCRM interfaces are of particular interest. The *virtual driver wrapper*, called OneIP, minimizes user involvement in network interface configuration, as it abstracts them through a single IP address and enables automatic adjustment of the corresponding MAC/PHY parameters. The *Common Application Requirement Interface (CAPRI)* [31] allows expressing the Quality-of-Experience requirements provided by the applications and their data flows, using dynamically updatable utility functions that are expressed as combinations of KPIs. CAPRI is logically placed on the session layer, as this layer can be perceived as another hourglass waist besides the IP layer of the TCP/IP stack. The CAPRI interface is also used to adjust the setting of individual applications, if the latter supports this option. The spectrum sensing functionality is accessed through another interface that provides data in a unified format from a number of external devices, such as commercially available from MetaGeek low-cost Wi-Spy spectrum analyzers [32] or SDR platforms, for instance USRP series of boards from National Instruments and Ettus Research. Combination of the spectrum sensing interface and the virtual driver wrapper perform the role of the ULLA interface of the CRM architecture [16].

Policy-based reasoning is introduced on examples of spectrum and preferential policies, which allow setting user and application priorities, and regulate usage of frequency bands up to the per-device, user, application and time-of-the-day granularity [33]. Policy constraints impose restrictions on certain optimization states, e.g., that involve channels forbidden to transmission. Policy preferences that set user/application

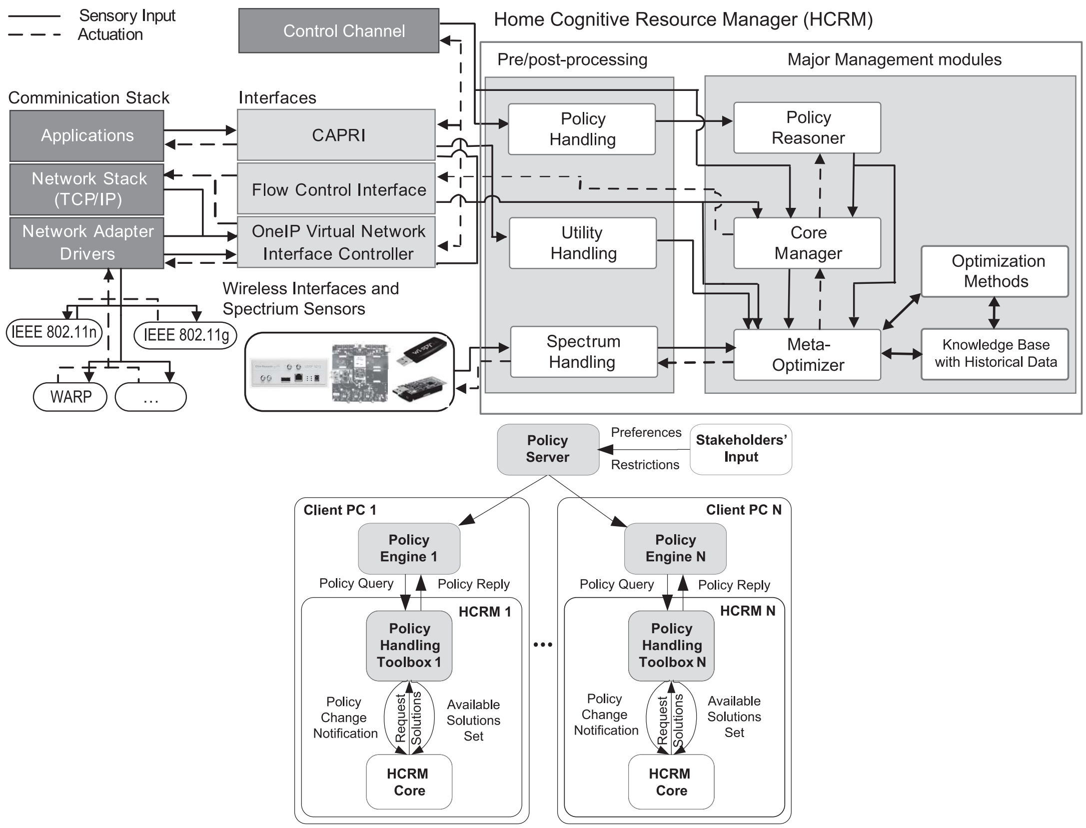


Fig. 5. Illustration of the HCRM design aspects. Panel at the top shows the HCRM agent design, which displays major internal agents and their interactions via specially developed interfaces. Panel at the bottom overviews the HCRM policy framework that includes the central server, the locally residing engines and toolboxes.

priorities are used to modify application utility functions to accurately express objectives of the stakeholders. Policy reasoning is realized using three main building blocks shown in Fig. 5b. These are (a) the centralized server that is the repository of all policies updatable by both local and external stakeholders, (b) the ontology-based policy reasoner, based on a HCRM agent, analyzes incoming policy updates for integrity, and (c) the related module that forwards policy updates to the core manager of the HCRM so that it can take the corresponding actions, e.g., move the traffic from the forbidden bands to the control channel. We use CoRaL as an ontological basis for policy reasoning [34]. In our implementation we demonstrate both the effect of the manually set policies, but also of the automatically derived ones, see Section IV-C. The latter are the result of the work of the REM system that is continuously updated with realtime sensory readings from a channel utilized by a primary (high-priority) transmitter. This data is then processed to derive the policy on usability of a primary channel that depends on the activity of the primary nodes and their distance from the HCRM agents.

The *core manager* is one of the main agents of the HCRM. This complex agent ensures the robustness of HCRM against critical failures and provides its skeletal functionalities. The agent detects new application flows, and establishes and manages ad-hoc point-to-point links. It handles both periodic and asynchronous commands between the protocol stack, other HCRM nodes, spectrum analyzers, the policy framework and the meta-optimizer. For example, it detects new applications and initializes the configuration of their data flows, monitors status of available wireless interfaces, and performs seamless channel handovers. This is done by either moving data flows directly between ad-hoc links, or through the control channel if a new point-to-point link is to be built, which requires some time. The ad-hoc links are handled using a sub-module, the link manager, that performs handshakes and probes for stable links. The core manager also filters out the control traffic on which the optimization actions are not viable. It can detect critical events related to ad-hoc links and data, e.g., breaking of a link (no data received) or data flow cancellation, react on them, and signal to other agents. Actions and events triggered by this agent are assigned a high priority, the next after policy-based decisions, as they influence not only the performance, but the very network connectivity.

The *meta-optimizer* agent is an event-driven component that enables hybrid optimization. It is modular in design and is capable of dynamically invoking different algorithms to change its functionality. It also stores historical data, and maintains queues and corresponding support modules to address conflicts that might arise while deriving optimization decisions. The overview of the meta-optimizer is given in Fig. 6. Additionally, this agent supports dynamic adjustment of the configuration options of the protocol parameters that might change, for example, due to executed optimizers and operational conditions. The corresponding class hierarchy allows not

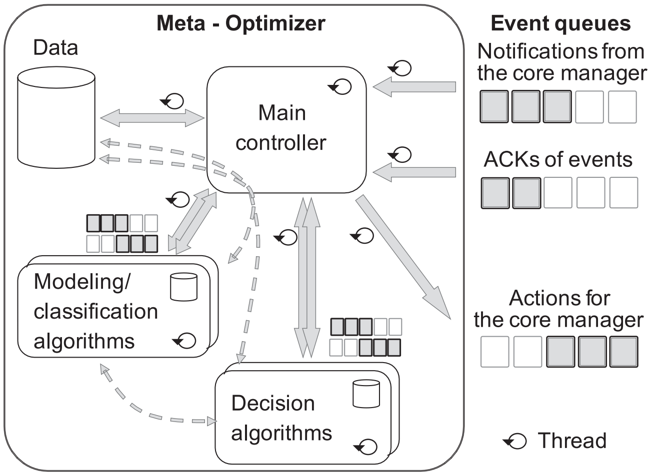


Fig. 6. Overview of the meta-optimization agent.

only to restrict a certain parameter state from being used, e.g., due to changes in a spectrum policy, but also to update the number of states that certain parameters can take at runtime.

The optimization-related functionality is split into two parts: *modeling/classification* and *decision-making*. The classification or modeling modules establish the "model of the world" that the decision making algorithm utilizes to determine optimization actions. The results of modeling and classification of sensory inputs are also used to invoke optimization algorithms. For example, clustering of the utility values to determine is the utility is low or high is done by the modeling entities. This classification is required to, for example, determine worsening of the network performance that directly lead to execution of an optimizer. From our experience we noticed that the logical division of an optimizer into modeling and decision making should not always be followed too literally, as many algorithms integrate modeling, classification and decision-making functionalities as they are designed to work with only certain models or information representations. Therefore, we also support a possibility for designing dedicated optimization algorithms that integrate combinations of the above functionalities, and directly operate on raw data inputs.

The meta-optimizer is notified with three classes of events: *new data*, *policy adjustments*, and *critical system changes*. New data is forwarded to the selected optimization algorithm, which then either suggests some re-configuration actions, or updates models, or does nothing. Policy changes affect the actuation state space. Policy and critical changes events, such as a detection of a new data flow, or an update on spectrum availability, force the meta-optimizer to invoke the fastest and most robust algorithms, such as simple decision trees, to arrive to the optimization solutions as fast as possible.

Software-wise classes realizing optimization algorithms are inherited from a common class, which is also a parent to the meta-optimization entity. This allows the meta-optimizer to invoke optimization algorithms in a unified manner, and for them in turn to access (but not modify) the required data though the interface provided by the meta-optimizer. This class structure allows separate optimizers to serve as agents that are initialized using a thread pool of the meta-optimizer, or being incorporated into this module as part of its reasoning routine. (The latter option is especially useful for fast robust decision-tree/reflex algorithms.) Such approach ensures minimal duplication of information, enables component reuse, while avoiding data management conflicts. For example, if any optimizing agent suggests new data for the meta-optimizer, it generates an event, and it is the latter that accesses it and stores information in the database.

The meta-optimizer went through multiple re-design cycles. It started from the state of being a simple large decision tree with multiple flags to switch between different options that, for e.g., enable inter-node collaboration or restrict the option of the transmission bandwidth adaptation. This implementation allowed to test and partially enhance the rest of the HCRM modules. In parallel we developed the more complex agent which is described below that complies to the main principles of the CRM architecture and satisfies the requirements to the HCRM state above. We believe that the current design is sufficiently good for most applications. However, it lacks the support of reacting to incoming events at very high rates and can give no hard realtime guarantees, as this module is realized in the user space on non real-time OS. It also has only limited support of the decision-making directly on the radio hardware, and requires exploitation of flexible SDR frameworks, such as TRUMP [35], with related experiments are reported in Section IV-A.

A. Selected Subcomponent Designs

In this section we further discuss the algorithmic design of selected HCRM modules that we believe to be of independent interest. The first of these is the *Radio Environment Map* (REM) module, that constructs spatial predictions of quantities such as signal strengths or SINR values based on measurements conducted by the network nodes. The second is a time-domain prediction module that utilises *Hidden Semi-Markov Models* to estimate the activity patterns of several transmitters based on power measurements alone. The outputs of these modules are used by our policy reasoning framework as illustrated in the following section, as well as other optimization components (such as enhanced MAC modules in the case of time-domain predictions).

1) Radio Environment Map Construction: An important development in the area of cognitive wireless networking has been the introduction of Radio Environment Maps (REMs) [3] — which can be thought of as knowledge bases that store and processes spectrum and protocol data. Gathered information and resulting models can be utilized by both human operators as well as autonomous radio resource management systems. Two examples of popular REM applications are identification of coverage holes in wireless networks, as well as capturing and characterization of network activity conducted by primary nodes.

In the context of wireless home networks information provided by REMs in conjunction with policy-based administration allows for light inter-network administration of WHNs that may even belong to different operators. One option is to enforce *prioritized coexistence*, *primary-secondary sharing* scheme, or *licensed share access*, where individual networks have prioritized, but not exclusive, access to a particular frequency band [36]. Such approaches enable both deployment of optimal primary channel allocation schemes, and accommodation for peak loads though exploitation of neighboring (secondary) spectrum. In this section we briefly outline the design of our REM module, which solves diverse spatial estimation problems based on data obtained from other modules. The REM module itself is entirely general, and can be used on any spatially indexed measurement data obtained by the HCRM. For more details and performance evaluation results on the REM design used here we refer the reader to [37]. Further information on the theoretical foundations of the estimation problems involved can be found from [38] and [39].

We begin by formally expressing the coverage estimation problem our REM module needs to solve. Let D denote the region over which we seek to estimate the coverage area of a wireless system through measurements. This coverage area for a *random field* or spatial stochastic process $Y(\boldsymbol{x})$ ($\boldsymbol{x} \in D$) of received signal strength or SINR is the *excursion set* [38]

$$D_{\mathrm{CA}} \equiv \{\, \boldsymbol{x} \in D \mid Y(\boldsymbol{x}) \geq \theta_{\mathrm{S}} \,\}, \tag{1}$$

where θ_{S} is a technology or policy specific threshold. When using the REM module to optimize network coverage θ_{S} would typically be the receiver sensitivity with the given modulation and coding scheme, or the target SINR for the given quality of service, whereas for policy applications θ_{S} would typically be selected to be the signal strength threshold defining the *protected zone* of a primary transmitter or licensed user. As D_{CA} is completely determined by $Y(\boldsymbol{x})$, coverage estimation can be done by estimating the value of $Y(\boldsymbol{x})$ for all $\boldsymbol{x} \in D$ based on some possibly noisy and unreliable measurements related to Y.

Assume now that the HCRM has obtained a vector of measurements $\boldsymbol{Z} \equiv \big(Z(\boldsymbol{x}_1), \ldots, Z(\boldsymbol{x}_n)\big)'$, which are related to the underlying true signal strength or SINR $Y(\boldsymbol{x})$ by the inclusion of an additive error of the form $Z(\boldsymbol{x}) \equiv Y(\boldsymbol{x}) + \varepsilon(\boldsymbol{x})$. Here $\varepsilon(\boldsymbol{x})$ includes both location independent as well as location dependent terms, including receiver noise, effects of antenna directionality, multipath fading, and so on. We further assume that $Y(\boldsymbol{x})$ has the form

$$Y(\boldsymbol{x}) = \boldsymbol{t}(\boldsymbol{x})'\boldsymbol{\alpha} + \nu(\boldsymbol{x}), \tag{2}$$

where $\boldsymbol{t}$ are *covariates*, $\boldsymbol{\alpha}$ are coefficients to be estimated, and ν is assumed to be a random field with zero mean and spatial covariance function

$$C(\boldsymbol{x}, \boldsymbol{y}) = \mathrm{Cov}(\nu(\boldsymbol{x}), \nu(\boldsymbol{y})). \tag{3}$$

Covariates can be used to encode further information on transmitters and the propagation environment available to the HCRM, such as number of walls between the transmitter and the measurement location or the distance between them. Then the coefficients $\boldsymbol{\alpha}$ correspond to wall losses, path loss exponents, and so on. The covariance function must be estimated from the data. We do this by fitting the *exponential covariance model*

$$C(\boldsymbol{\tau}; \boldsymbol{\beta}) = \beta_0 + \beta_1 \exp\left(\frac{-\|\boldsymbol{\tau}\|}{\beta_2}\right), \tag{4}$$

where $\boldsymbol{\tau} = \boldsymbol{x} - \boldsymbol{y}$, β_0 accounts for variance arising from measurement inaccuracies, short-range variations, or superimposed noise, β_1 controls the variance of Z, and β_2 is the *range parameter*, determining the correlation distance of the model.

Combining these assumptions we obtain the model $\boldsymbol{Z} = \boldsymbol{T}\boldsymbol{\alpha} + \boldsymbol{\delta}$, where $\boldsymbol{T}$ consists of known covariates at different measurement locations (if any), and $\boldsymbol{\delta} = \boldsymbol{\nu} + \boldsymbol{\epsilon}$ is a zero-mean random process. Denoting $(\boldsymbol{C})_{ij} \equiv C(\boldsymbol{x}_i, \boldsymbol{x}_j)$, the covariance matrix $\boldsymbol{\Sigma}$ of $\boldsymbol{\delta}$ can be written as $\boldsymbol{\Sigma} = \boldsymbol{C} + \boldsymbol{V}$, where $\boldsymbol{V}$ is a diagonal matrix. The coverage estimation problem is now equivalent to finding an estimate $\widehat{Y}(\boldsymbol{x}_0)$ at every location $\boldsymbol{x}_0 \in D$ for which measurements are not directly available. The "best" such estimate in the sense of being both unbiased and having the minimal estimation variance is given by the conditional expectation $\widehat{Y}(\boldsymbol{x}_0) = \mathbb{E}\{Y(\boldsymbol{x}_0) \mid \boldsymbol{Z}\}$. In general conditional expectation is unfortunately intractable, but if the underlying random fields are assumed to be Gaussian the resulting predictor has simple form given by

$$\widehat{Y}(\boldsymbol{x}_0) = \boldsymbol{t}(\boldsymbol{x}_0)'\widehat{\boldsymbol{\alpha}} + \boldsymbol{c}(\boldsymbol{x}_0)'\boldsymbol{\Sigma}^{-1}(\boldsymbol{Z} - \boldsymbol{T}\widehat{\boldsymbol{\alpha}}), \tag{5}$$

where the estimator $\widehat{\boldsymbol{\alpha}}$ for the coefficients is given by

$$\widehat{\boldsymbol{\alpha}} = \left(\boldsymbol{T}'\boldsymbol{\Sigma}^{-1}\boldsymbol{T}\right)^{-1}\boldsymbol{T}'\boldsymbol{\Sigma}^{-1}\boldsymbol{Z}, \tag{6}$$

and $\boldsymbol{c}(\boldsymbol{x}_0) \equiv \big(C(\boldsymbol{x}_0, \boldsymbol{x}_1), \ldots, C(\boldsymbol{x}_0, \boldsymbol{x}_n)\big)'$. Further, even if the assumption of Gaussianity does *not* hold, the resulting predictor is the best possible linear one. This is exactly the *kriging estimator* of spatial statistics (see [39] for detailed derivation and discussion).

We use the above estimating equations whenever sufficient number of measurements are available to robustly estimate the covariance function. In the bootstrapping phase this might not be the case, in which case we provide the users of the REM data options of either not obtaining any predictions at all unless they can be robustly made, or provide predictions with an *a priori* covariance function that can be configured as part of the system settings.

2) Time-Domain Estimation of Transmitter Activity Patterns: The HCRM needs to perform optimization decisions based on, for example, signal strength measurements that represent aggregate power in a given frequency band. In order to enable more fine-grained decision making based on such measurements we have designed a temporal prediction module that attempts to further disaggregate such data to estimate the activity patterns of *individual* transmitters. This module utilizes *Semi-Markov ON/OFF process* as the foundation of its estimation framework as described in [40] and references therein. It uses the following transmission model. Each transmitter at any given time is either active (ON state) or inactive (OFF state). If active, the transmitter is assumed to send signals (almost) continuously at constant power. The durations of these ON/OFF periods are presumed to follow general distributions that are independent of each other.

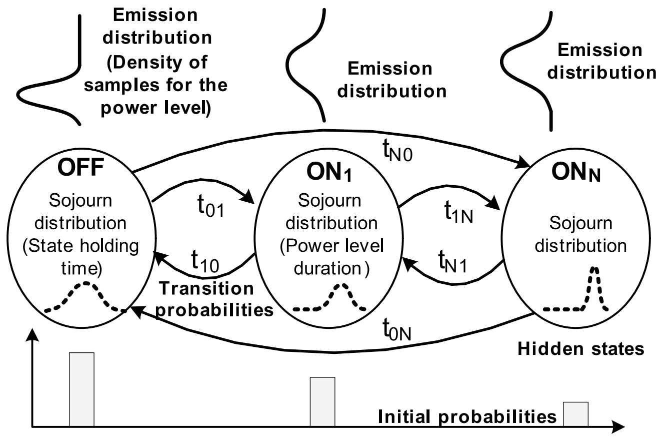


Fig. 7. An example Hidden Semi-Markov model. The figure shows three states of the HSMM corresponding to the OFF activity state of the network and two ON states that are characterized by different power levels.

If the states of the different transmitters were directly observable, the estimation of the ON and OFF distributions would easily be solved using standard statistical techniques, and the state of the individual transmitters would be directly available to us. In practice this occurs only if there is a single or one dominant transmitter that can be reliably distinguished from ambient interference and noise [41]. However, especially in indoor scenarios, fast fading and complex propagation environment often cause the measured received power from an active transmitter to fluctuate heavily, signals can often disappear into the noise and interference for short periods of time, and there might be several transmitters of comparable contributions to the received aggregate power present. We overcome these challenges by considering *Hidden* Semi-Markov Models (HSMMs) [42].[2] The true state of the system is still assumed to follow a Semi-Markov ON/OFF process (or in the case of multiple transmitters, a product of such processes), but instead of making observations on the underlying process directly, we assume that we observe at given times a received sum power that is random with distribution depending on the actual state.

The general structure of the employed HSMM is illustrated in Fig. 7. The model requires specification of a) *number of states* in the HSMM graph, b) *initial probabilities* of states, c) *transition probabilities* between states, d) *sojourn times* spent in each of the states (corresponding to the ON/OFF state durations for a single transmitter case), and e) the *emission distributions* of the received power conditional on the state of the system [43].

For the initial classification of the power levels we use a simple density-based threshold detection algorithm (described in [40]). The number of states of the HSMM is set to be equal to the number of resulting power classes. The statistics of these power classes are used to initialize the emission distributions. Initial state probabilities and transition probabilities between all HSMM states are initially set to be equal. The first zero of the autocorrelation function of the received power was used to determine initial values for the parameters of the sojourn distributions. We applied the gamma distribution as main parametric model for the sojourn time distributions due to its flexibility. For estimating the parameter values of both emission and sojourn distributions as well as the state transition probabilities *Expectation Maximization (EM)* is used by the module [42]. In particular, we use the implementation of [44] specifically developed for estimating hidden Semi-Markov models.

As the output of the module other HCRM components obtain the distributions of expected power levels (in particular expected interference power *per transmitter*), ON/OFF period durations, and the estimated states of the individual transmitters obtained from a Viterbi algorithm as described in [43]. This data is especially useful for optimizing medium access control protocols as discussed in our performance evaluation section below.

[2]This method was first applied on the empirical data for the offline activity patter estimation in [41]. However, there the reported difference between the spectrum power samples corresponding to ON/OFF levels was high and, therefore, the challenge for the states estimation was minimal.

IV. Performance Evaluation

In this section we describe example results obtained from the HCRM implementation. We focus on the experimental setup shown in Fig. 8. We provide results from three scenarios. The first one is running reflex agents based on the pre-determined decision tree (reflex) algorithms. The other demonstrates integration with a radio-environment map backend through the policy mechanism. The third, providing an example of Hidden Semi-Markov Model (HSMM) based learning agents, shows how the HCRM can successfully operate on complex optimizers and non-COTS hardware.

The last two scenarios aim at demonstrating the extensibility and the flexibility of the HCRM. They are both concerned with the primary nodes that do not belong to the HCRM network and impose strict non-interference demands on the other lower priority networks, to which our system belongs. In contrary to the first four-node deployment, the last scenarios involve only two nodes and the external primary interference. For clarity we also chose to experiment only on channel settings (including both bandwidth and central frequency) for these scenarios.

A. Implementation Details

The HCRM prototype provides wireless connectivity in an optimized way with enhanced capability to withstand interference and contention. The system dynamically establishes adaptive point-to-point connections between HCRM nodes while maintaining connectivity to the AP. We use the AP-based communication as the control channel, which is enabled by the installation of a second wireless interface card on each node or connection to a WARP board via an Ethernet interface. The continuous performance of the network during re-configuration phases is ensured by using the control channel as the relay point.

We implemented the HCRM on a Windows platform using low cost COTS hardware such as basic Wi-Fi adapters and Metageek Wi-Spy spectrum analyzers [32]. In order to perform MAC parameter and channel width adaptation on COTS hardware, we use NETGEAR WAG511 32-bit PCMCIA NICs

Fig. 8. Example deployment of the HCRM running at the IEEE DySPAN conference.

(Atheros chipsets 5211 and 5212) [45] and a customized device driver, allowing significant flexibility. Each node is equipped with two wireless interfaces and, typically, an external spectrum sensor.

Some of the modules we experiment with are realized in R in contrary to the main HCRM code that is based on C++. Therefore, we developed additional TCP socket-based interfaces between the HCRM meta-optimizer and these components. Additionally the second HSMM-based algorithm uses WARP boards for building ad-hoc links. In order to use WARPs we have extended the core manager and the virtual driver to support Ethernet as secondary interface for point-to-point link establishment. This improvement allows the HCRM to interact with any SDR platform that can communicate to the host PC via Ethernet, ensuring high data rate, and low delay communication.

The parameters adapted during the autonomous resource management process are the central channel frequency and channel width (realized as suggested in [46]), traffic redirection and traffic shaping using Class-Based Queueing (CBQ), and data rate adaptation for selected applications. When WARP platforms are used as secondary interfaces on the MAC/PHY layer we perform high rate dynamic channel switching. The influential KPIs are throughput, link load, packet error rate, spectrum power for a certain frequency range (RSSI samples), and the resulting utilities. Additionally, nodes exchange their configuration data in a limited manner for more efficient decision making, e.g., to find a common transmission channel.

B. Scenario With Reflex Agents on the COTS Hardware

First to test the overall HCRM system we set a test network consisting of four nodes organized into pairs that transmit variable multimedia and download data in the same radio range, see Fig. 9. Operating on the 2.4 GHz ISM band the network is prone to external interference. In this scenario we use IEEE 802.11g cards and commercial Wi-Spy spectrum analyzers.

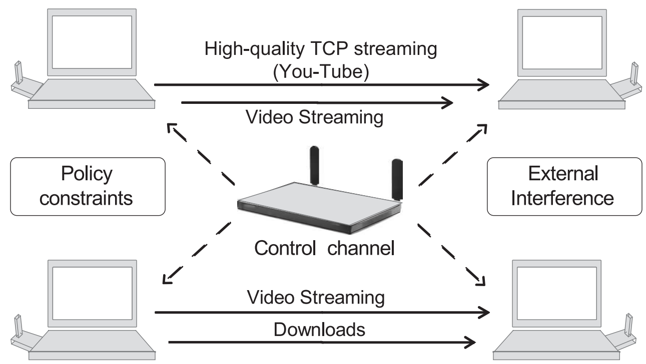


Fig. 9. Scenario with COTS hardware (Wi-Fi and WiSpy spectrum sensors) running the reflex agents.

The scenario aims to show that the HCRM can indeed perform the declared functionalities of ad-hoc point-to-point link setups, seamless handovers, inter-node communication, effective interference avoidance and parameter-based protocol stack optimization.

First we tested the HCRM acting on the set of configuration parameters that by default are supported by the Windows OS and the COTS Wi-Fi drivers and interface cards, even without presence of the sensing devices. The HCRM performed as we expected, executing all of the above actions according to the defined algorithms, and gaining significant performance advantage over standard home Wi-Fi deployments. We skip reporting of these results as this scenario has a lot in common with the more interesting setup discussed below, which allows the HCRM to benefit from spectrum sensing, channel bandwidth flexility, reconfigurability of applications and utility-based reasoning.

The HCRM executes two simple decision tree algorithms, realized as agents, that run in parallel threads at the meta-optimizer. They utilize pre-defined thresholds that were obtained as results of extensive measurements. These agents perform optimization based on utility metrics or low-level KPIs. First, utility-based optimization operates the moving

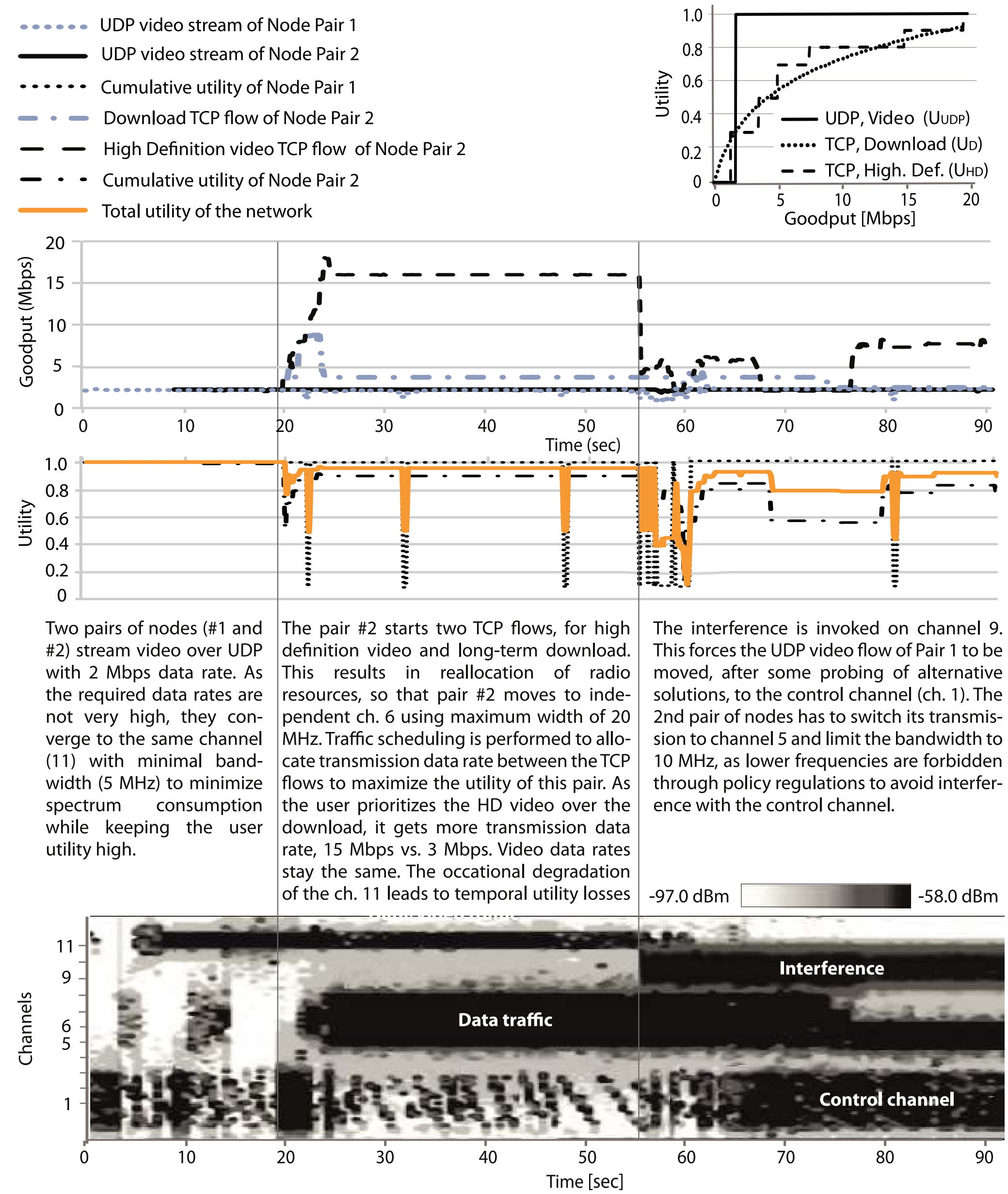


Fig. 10. Performance of four node network in the dynamic environment with changing number of applications. The figure displays (from top) the goodput achieved by the data flows, the overall network utility and the individual utility functions of the nodes, and the waterfall spectrogram of power distribution in the 2.4 GHz band[1,2]. Utilities as functions of throughput for applications executed in the reflex agents scenario are shown in the top right corner of the figure.

averages of the utilities of separate data flows and combines them in a weighted way according to user preferences as indicated through policies. Performance changes are indicated by significant drops in the observed utility or timeouts in probes if operational conditions have improved and, for example, higher data rates are feasible for an application [31]. The purpose of the second agent is to react fast to critical levels of observed KPIs, primarily the link load. This algorithm aims to take actions based on momentary (very few) readings. It can, for example, avoid data losses by moving traffic to the control channel from the point-to-point link in cases of very high sudden interference, which cannot be done rapidly using utility based estimates as those rely on averages over several samples. This algorithm operates on very conservative thresholds in order not to overreact and cause too frequent reconfigurations, as well as not to interfere with the utility-based decisions.

Fig. 10 illustrates this scenario and explains the HCRM's actions by showing the annotated graphs of goodput and the waterfall spectrogram of energy distribution over 2.4 GHz ISM band. The overall normalized network utility, due to the policy-based application priorities, is

$$\begin{aligned} U_{\mathrm{N}} &= U_{\mathrm{pair1}} + U_{\mathrm{pair2}} \\ &= \big((U_{\mathrm{HD}} + 6U_{\mathrm{D}} + 3U_{\mathrm{UDP}})/10 + U_{\mathrm{UDP}}\big)/2, \end{aligned}$$

where U_{HD} is the utility function of high definition video over TCP in form of the step function, U_{UDP} is the utility of the streaming video over UDP with maximum datarate of 2 Mbps, and U_{D} is the logarithmic utility function of the download application.[3] Channel 1 is used as the control channel, and it is forbidden (through policies) to establish ad-hoc links on the involved frequencies. We use VLC video streaming application running over UDP [47], and TCP-based data traffic generated using iperf [48].

On the right side of spectral diagram of Fig. 10 we observe that the first pair of nodes starts the video transmission, which is moved after intermediate probing from the control channel to the Channel 11, as the one that has the least amount of interference. The channel width is assigned to be 5 MHz, as it is enough to accommodate the 2 Mbps data rate required by the video. Later the second pair of nodes also starts a low quality video transmission. According to the secondary goal pursued by the network regarding efficient utilization of network resources, the second pair of nodes co-locates its transmission with the first pair on Channel 11. At the time slot 2 the second pair of nodes is introduced with two additional TCP transmissions, one with higher priority than the other. The HCRM of the transmitting node detects that more bandwidth is required due to degradation in utility, and decides to move transmission to non-overlapping Channel 6 and allocate it a wider bandwidth. First the bandwidth of 10 MHz instead of 5 MHz is probed, which is subsequently increased further to 20 MHz. This HCRM also adapts the application data rate of the low priority TCP-based traffic via the CAPRI interface. In the time slot 3 we introduce interference created by a noise generator [49] on Channel 9. All the HCRMs detect the interference by evaluating the link load and the packet error rates. As the result, the first pair of nodes decides to move, after some unsuccessful probing, to the control Channel 1. The second pair of nodes switch to Channel 5, shrink their bandwidth due to the policy regulations (not to overlap with the control channel) and further reduce the allowable data rate for low priority TCP traffic this time executing CBQ option as no further data rate reduction option are supported by the application.

It should be noted that both channel expansion/shrinking and channel switching are made automatically by HCRM without user intervention and kept transparent for upper layer applications as well. The optimization performed by HCRM does not break any connection at the application level. Short-term reductions in utility for the first pair of nodes are the result of wireless channel variations, and these interruptions are too short to invoke such optimization actions as channel switching. The slow performance of the system is explained by hardware constraints of the utilized wireless cards on establishing the ad-hoc connections specially in poor environmental conditions, and not by the additional delay introduced during HCRM decisions. More modern wireless cards can switch ad-hoc channels with much higher speeds thus overcoming this deficiency in our prototype.

Our experiments show that the HCRM is successful in autonomously handling dynamic variations in external interference patterns and changes in the mixture of applications executed by the nodes, without breaking any data flow connections and maintaining high network utility.

[3]We emphasize that the HCRM performs optimization on *arbitrary* utility functions specified by the applications and users through the CAPRI interface. The specific utility functions and coefficients in their combination used in this section are specific examples used to illustrate the HCRM operation.

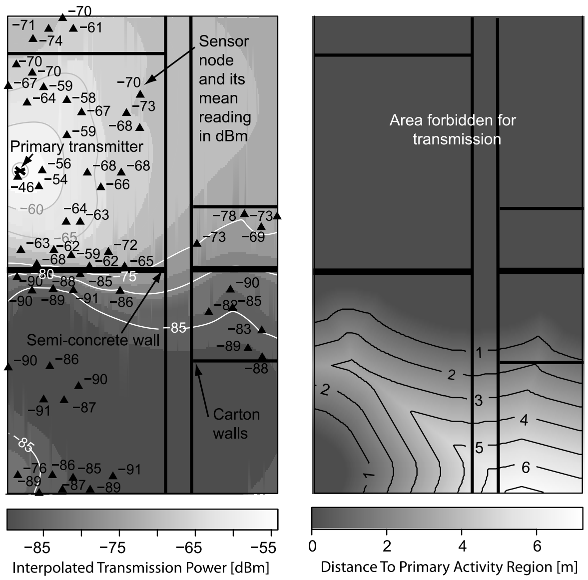
C. Radio-Environment Map Based Spectrum Management

In this subsection we demonstrate how prioritized coexistence can be incorporated in the HCRM resource management through the integration of REM data with the policy engine. To obtain real spatial spectrum occupancy data on the 2.4 GHz ISM band we utilize the indoor spectrum sensing testbed [50] with the sensory information obtained online from 58 geo-located TelosB nodes, the physical layer of which complies to the IEEE 802.15.4 standard. This data goes into the REM system, which uses stochastic interpolation techniques to establish the spectrum coverage map of the indoor environment. Further, the interpolated data is clustered and the distance map is constructed to establish the distance to the primary coverage area, when power is above a predefined threshold (see Figure 11a). This information is then propagated through the policy framework to the HCRM, which based on the location information of its own nodes, determines if transmission is allowed at this channel. In other words, the REM information allows to determine if a HCRM node is at the safe distance from the primary network to avoid interference. As REM information is updated periodically HCRM nodes can also detect the inactive periods of the primary nodes and utilize the respective frequencies even if they are in the inference range when the primaries are active. We have implemented the entire REM/policy/HCRM processing chain and successfully tested it also in the demonstration setup as shown in Fig. 11. Here the REM system takes inputs from sensors deployed under the tables (with only one being shown in the figure), and based on these values as well as power and distance threshold controlled by the GUI restricts the transmission of the two HCRM nodes on the Wi-Fi channel 1 of the 2.4 GHz ISM band.

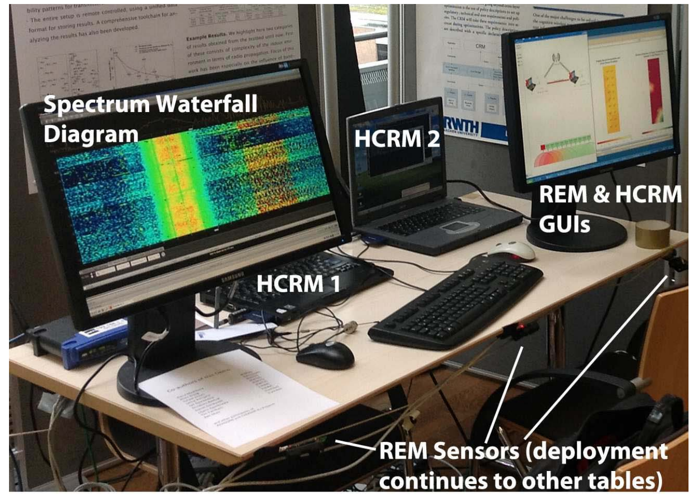
The REM-oriented case study allowed us to demonstrate that the HCRM is flexible and easily extensible system for which, due to the carefully interface and policy language design, new parts can be integrated in just few hours (as was in our case). Moreover, experimentation with the REM interpolation techniques, especially kriging [51], one more time demonstrated pros and cons of different learning techniques. On one hand the ability to learn online the model guiding the interpolation (the spatial correlation model known as the semivariogram) allows the REM/HCRM system to operate flawlessly in different deployment sites (the demonstration location and our office). On the other hand, these calculations caused observable computational delays which were considerably reduced once the spatial correlation model was fixed after the initial training phase.

D. Estimating and Exploiting Network Activity Patterns With HSMMs and WARPs

In this subsection we discuss the design and implementation of an optimization learning agent based on information on

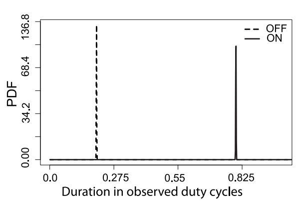


(a) Visualization of sample REM outputs.

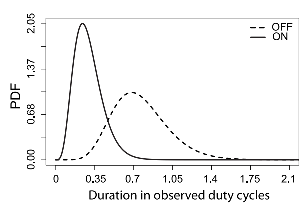


(b) Demonstration setup with HCRMs utilizing REM.

Fig. 11. Figure (a) displays a sample REM in a scenario with a single primary beaconing access point being deployed on the Wi-Fi channel 2 of the 2.4 GHz ISM band in the indoor office deployment of 12×20 m. Kriging interpolation results on the geo-located sensor measurements, and the following distance mapping from the interpolated power spectrum that is cut on the propagated signal level of -85 dBm are shown. The distance from the restricted zone does not exceed 7 m. Therefore, the secondary HCRM nodes can transmit only in the lower part of the deployment if the policy distance value is above 7 m. The right figure shows the REM/CRM setup at the demonstration venue.



(a) Fixed duration of ON and OFF periods



(b) Duration of ON and OFF periods strongly overlap

Fig. 12. The estimated PDFs of the sojourn distributions of sample durations as estimated by the proposed HSMM algorithm for fixed and variable duty cycles.

network activity patterns. It uses the temporal prediction module based on Hidden Semi-Markov Models discussed above as the source of this information, and provides long-term guidance for the decentralized spectrum-agile MAC protocol [52] which runs on WARP SDR boards [53] that serve as alternative secondary wireless interface in our implementation. In this scenario we do not use additional sensing devices. All estimations of spectrum conditions is done by the WARP boards.

The original spectrum agile MAC protocol [52] already shows efficient run-time self-optimization behavior based on short-term temporal dynamics of the spectrum. Performance of this MAC protocol can be further improved by providing a long-term guidance on the likely behavior of the channels. The models derived by the temporal prediction framework or the extracted duty cycle information is forwarded to the MAC protocol. Based on this data and the estimated ON/OFF states, the protocol adjusts its sensing and transmission patterns.

Our experimentation with HSMM-based techniques have demonstrated that direct utilization of information on the distribution of ON/OFF period lengths is useful when one can reason on them with a high level of certainty (Fig. 12a for the extreme case of such behavior). Otherwise exploitation of information on duty cycles is enough to provide good performance, as it still allows on a coarse level to determine less busy channels with longer average OFF-period, while avoiding uncertainties connected with direct exploitation of ON/OFF distributions (Fig. 12b). In both cases training of the HSMMs is useful as it allows with higher degree of certainty to cluster signals levels into the ON/OFF states than simple threshold-based methods, as HSMMs are capable to take the historical information into account [40]. Overall, as successfully demonstrated at [8], and shown in Fig. 13, the proposed algorithm can be employed online to enhance MAC performance for a selected set of scenarios. As we see even if primary, not to be interfered, transmissions are almost simultaneous on Channels 1 and 11, still both of these channels are utilized to minimize the times when the data has to be forwarded through the control channel at 5 GHz ISM band. The algorithm takes advantage of the small differences in the transmission schedules of the primary transmitters. For example, the top panel shows that the transmission from Channel 1 is preemptively moved to Channel 11 before the primary interfere becomes active. Channel 6 is almost never used due to high duty cycle of the encountered interference there. The downside of the proposed optimization algorithm is its computational intensity primarily caused by the online training of the HSMMs. To a large extend this load can be reduced if the primary nodes show stable behaviors that can be studied and modeled in the pre-exploitation, training phase, of the HCRM, which includes training of the proposed optimization algorithm as well.

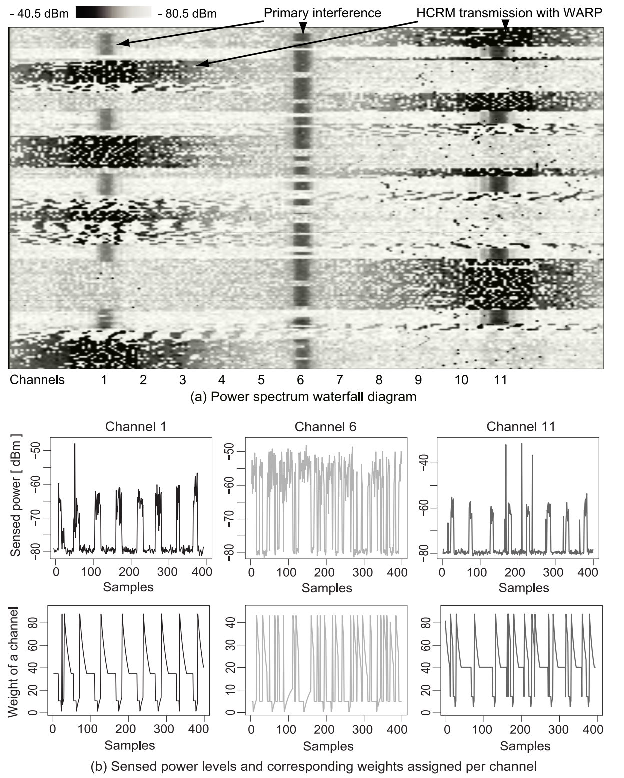


Fig. 13. Illustrating the performance of a MAC protocol running on WARP boards that utilizes the developed ML algorithm for ON/OFF network activity estimation based on HSMMs. (a) Temporal behavior of the primary and secondary HCRM nodes, (b) Example sensing for Channels 1, 6 and 11 and the resulting weighing of these channels.

V. Discussion

Before concluding the paper we briefly summarize the key lessons learned during the development of the self-optimization system for wireless home networks. We believe these observations to be both relevant and important when applying cognitive wireless networking principles also for other emerging network types, such as dense femtocell deployments and LTE-U deployments.

Software development aspects: Our experience with the HCRM confirmed the main principles of software design. We encountered recursiveness in the HCRM development lifecycle in application to the whole system and its individual modules. Clear interface abstraction and careful class hierarchy design also fully payed off. For instance, in the early development stage we had to urgently adjust a module so that its interfaces got altered, as a result we spent considerable time developing additional function wrappers. On the contrary, extension of the HCRM to support the WARP SDR platform enabled by the virtual driver interface happened fast and painlessly. Similarly the well-defined policy language and the corresponding framework allowed us very quick integration with the REM system within just a few hours.

We believe that application of the *optimization-based agent-centric view* on the HCRM design helped to uncover and explain some hidden design risks (e.g., robustness considerations, conflict resolution mechanisms) compared to the initial perception of the task of the WHN system design. Our prototype fulfills the main design goal of providing an extensive autonomous resource management framework for wireless home networks. However, we are not completely satisfied with the built system, as it is somewhat bulky and, maybe, its implementation is quite complex at places. We plan to revisit the design of the system when developing efficient self-optimized femtocell solutions following the same design and architectural principles as presented in this article. During the implementation of the HCRM we also encountered that the problem of conflict resolution is much more complex and interesting than we had expected, and definitely requires additional research.

External hardware and software impact: The HCRM required alterations due to limitations or unexpected behavior of the COTS hardware (unstable ad-hoc link setup process for example) and features of Windows OS (e.g., there is no standard interface from which to obtain information about packet drops occurring in low layer protocol buffers/queues). Clearly Windows, being a non real-time OS, also cannot provide latency guarantees on reaction of the system on incoming events. Therefore, we encountered the emergent risks caused by external hardware and software components. Those could be accommodated in the optimization mechanisms either through thorough testing in case of reflex solutions or by introducing hidden influence factors in the structure of learning agents. Additionally, it is also possible to hierarchically structure the HCRM and, in particular, the meta-optimizer agent to invoke some of the optimization algorithms on SDR platforms, thus providing a tighter control over MAC/PHY mechanisms.

Reflex and learning agents: Our experience when developing the HCRM confirms that reflex agents are more efficient than learning agents in cases when a network operates in a small range predictable operational conditions. However, the learning components become increasingly important in cases when they could be used as training mechanisms to shape the reflex algorithms. In these terms the CRM architecture as opposed to traditional radio resource management architectures shows its power, especially if it is extended with appropriate update and module loading mechanisms. However, the trade-offs between efficiency of simple resource management solutions, which have careful modular design and could be easily upgraded, and more complex cognitive approaches that are more flexible at the runtime and more optimal control over the network at the price of greater complexity have to be studied still. We believe that a careful consideration should be paid to system design to address the issues of maintainability and extensibility of both physical components and functionalities of the system keeping in mind the clear trade-offs between system performance, complexity and robustness.

VI. Conclusion

In this article we discussed the design and implementation of a self-optimizing resource management system for wireless home networks, called the Home Cognitive Resource Manager (HCRM). The HCRM provides high and robust performance according to the requirements of multiple stakeholders in a dynamic environment. At the same time the framework allows experimentation with new SDR platforms and optimization algorithms, including machine learning approaches some of which we have explored in this article. The system design, based on a combination of an agent-based approach and the CRM architecture, is highly suitable for the development of evolvable self-optimized systems, especially the ones falling in the domain of cognitive wireless research.

We strongly believe that the technologies discussed in this article can be used and adapted to form a solid basis for cognitive resource management solutions in other wireless networks as well. The most straightforward applications would be towards other small cell networks, such as residential and enterprise LTE femtocell networks. At the level of abstraction on which the HCRM operates the key resource management concerns are quite similar, differences between the systems arising mostly from the differences in physical and MAC layers of the protocol stack. The same applies to other emerging wireless access technologies as well, in particular future 5G and next-generation Wi-Fi technologies. Therefore, in order to apply HCRM on such systems what is needed is an implementation of the ULLA interface for the said technologies. Designing such implementation does require some care due to the extremely large number of potential tunable parameters the LTE PHY could expose. Instead, the ULLA implementation should abstract away the parameters that are already controlled by the LTE stack in short (resource block level) time scales, and focus on exposing parameters mostly related to the operations and management level interfaces. Most important of these include the channel configuration used, UE association rules, etc. The rest of the HCRM implementation could then be applied practically unmodified.

Many of the individual components developed for the HCRM could also be applied in conjunction with other resource and spectrum management solutions, especially in frequency bands on which multiple wireless technologies need to coexist. Most important examples of such bands are the 5 GHz ISM band (which is becoming more diverse with the introduction of LTE-U), and the recently introduced 3.5 GHz Citizens Broadband Radio Service (CBRS) [54]. On such bands first of all the REM coverage estimation component could be used to obtain measurement-based estimates on actual coverage areas and — more importantly — spatial interference footprints of the different transmitters. The time-domain HSMM estimator can further be used to map power measurements to individual transmitters, making construction of individual interference maps on per transmitter/technology/band basis possible. Such more refined information could both be used to improve the robustness of protecting incumbents on shared bands from interference, and also to improve spectral efficiency of the different new technologies sharing the band by providing more accurate propagation and interference estimates. Another set of frequency bands with such applications are the sub-1GHz frequencies used by the various IoT radio technologies, especially ones with long range such as LoRa [55]. IoT applications have traditionally very low duty cycles, making interference assessment without including temporal component highly ineffective. Incorporating HSMM activity models would again allow more precise quantification of expected performance by estimating which transmitters are expected to be active simultaneously.

Finally, the interface technologies (ULLA, GENI and CAPRI) used between the HCRM, applications, and the rest of the protocol stack could be employed in other wireless systems as well to simplify their architectures. In particular, employing ULLA and GENI could help simplify management of heterogeneous wireless systems and increase their portability. Interesting application areas include spectrum access systems (SASs) in the CBRS context as well as integrated management solutions for LTE-U and Wi-Fi access networks that we foresee emerging in the near future especially in the enterprise wireless networking context.

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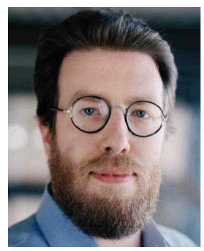

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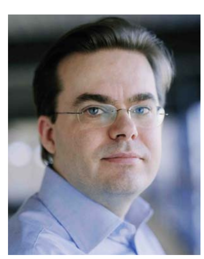

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