Overview of Cross-Layer Optimization Methodologies for Cognitive Radio

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Abstract **— This paper presents a short overview of some cross-layer optimization methodologies for cognitive radio. Cognitive radio is a relatively new paradigm that pursues the goal of optimizing network resources or satisfying user/application preferences, in an intelligent manner. Cross-layer design and cognitive techniques are combined in order to achieve optimization goals, thus becoming one of the focal points of interest for the wireless networks research community. Even though there are still open issues in these research areas, as well as in the pertinent practical implementations, cognitive radio promises to become a cornerstone of future wireless communication networks.**

Keywords **— Cognitive radio, cross-layer design, optimization methodologies, system modelling.**

I. Introduction

COGNITIVE radio (CR) using the principles of cross-layer optimization has gained a significant attention of research community in the last few years. Starting with the initial objective of efficient radio spectrum utilization this new paradigm has evolved to encompass also general objectives of network usage optimization and/or satisfying user requirements based on application preferences. Obviously, these are complex tasks that often require interventions in the radio system itself with new architectural concepts, introducing notions of reconfigurability, new interfaces, cognitivity and artificial intelligence, as well as optimization algorithms. This paper attempts to provide an introductory overview of some CR concepts, considered to be important for new researchers in this exciting field of wireless communications.

The paper is organized as follows. Chapter II provides short overview of the CR basics and Chapter III presents cross-layer design principles. System modelling is subject of Chapter IV, while Chapter V presents some optimization methodologies. Finally, Chapter VI gives the conclusions.

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II. The Basics of Cognitive Radio

There are different definitions on what a CR presents.

J. Mitola III in his pioneering work, [1], has defined the term cognitive radio for wireless devices and networks, associating it with computational intelligence about radio resources and related communications, in order to detect user communication needs and provide most appropriate radio resources and wireless services.

The author in [2] gives a more specific definition of CR that takes into account that cognitive radio is aimed at improved utilization of the radio spectrum, while [3] lists also other viewpoints on CR considered by some organizations as SDR Forum, [4], and standardization bodies as IEEE Standards Coordinating Committee 41, [5].

Even though it is difficult to strictly define common denominators of different CR viewpoints, one can list the following characteristics frequently attributed to a CR:

- *Environment awareness* - the CR can „sense" and probably even model the communication environment it is operating in, by measuring, for example, the packet-error-rate, delay, received signal strength, etc.
- *Reconfigurability* – it can reconfigure system parameters at different layers of the protocol stack (e.g. physical, MAC, network, transport)
- *Multiradio* – different radio technologies and bands can be made available to the CR (e.g. IEEE 802.11b, GPRS, GSM, etc), with emphasize on efficient spectrum usage
- *Decision making* based on optimization principles – an „intelligent" part of the radio can make decisions based on available knowledge on external (environmental) parameters, current system configuration, measurements of the degree of meeting certain objectives and historical data.
- *Learning* – the „intelligent" part of the CR can learn based on past experiences by first recognizing recurrent contexts and patterns (e.g. daily traffic patterns at certain location, mobility patterns etc).

The cognitive entity as part of a CR is presented in the research work under different names, e.g. as a Cognitive Engine [6], Cognitive Radio Engine [7], Cognitive Resource Manager [8], etc, sometimes denoting different concepts. Cognitive entities can be centralized or distributed in every node of the network. A cognitive network in [9] is defined as a network of nodes with cognitive functionality. Authors in [10] have shown the potential of teamwork and collaboration in cognitive wireless networks.

The cognitive radio, apart from the features listed above, frequently includes some cross-layer design, shortly presented in the following chapter.

III. CROSS-LAYER DESIGN

The traditional OSI reference model defines a strictly layered protocol stack, where each layer interacts only with the adjacent layers and adequate protocols are designed for the separate layers. This design has shown to work relatively well for the wired communication systems, but wireless systems are different because the wireless medium is a multi-access medium and its features can significantly vary over time as result of limited resources (channels) available for transmission, small-scale channel variations due to fading, scattering and multipath propagation, and large-scale channel variations depending on user location and interference levels from the surroundings, [11]. Therefore, the concept of cross-layer design (CLD) has been introduced and extensively researched in the last years. The CLD concept allows protocols at nonadjacent layers to exchange parameters inherent for their layers, [12]. This is usually done in order to increase system performance by obtaining a global view on the radio system and its environment.

There are many design choices that can be made with CLD:

- which layers will be chosen to exchange parameters
- which parameters will be selected to be most influential (largely depending on the performance optimization problem in question)
- how will be the cross-layer interactions performed (e.g. [12] classifies the interactions in three categories – direct communication between layers, a shared database across the layers or trough completely new abstractions)

The extreme cross-layer design takes a revolutionary approach by replacing the traditional layered structures completely, for task or application-specific implementations [11], [13].

Fig. 1 lists some relevant parameters for cross-layer optimization. This list is not exhaustive but gives some examples of candidate parameters.

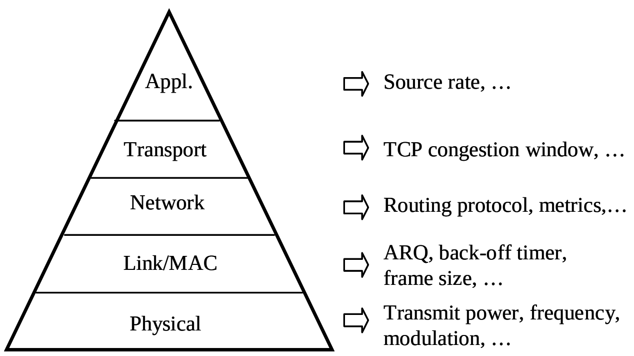

Fig. 1. Some relevant parameters that can be provided by different layers, for cross-layer design and optimization.

An interesting approach to cross-layer design is presented in [14], where authors argue that fuzzy logic is an effective means for representation of cross-layer information (parameters) and the implementation of optimization strategies in CLD. By keeping technology-specific information within each layer while representing cross-layer information using generic status (fuzzy) variables they try to create a modular, scalable and simple CLD-based architecture.

There are, of course, many other CLD proposals based on specific information exchange between certain layers tailored to satisfy some performance objectives – references [13], [15] and [16] give a good overview of some proposals.

The authors of [17] have shown with examples based on simulation studies that unintended cross-layer interactions can actually have an adverse effect on the overall system performance. Therefore, “spaghetti designs” should be avoided and a *holistic approach* for CLD should be pursued.

Even though there is no final cross-layer architecture and design adopted yet, it is generally believed that the advantages of CLD shown in recent research work, combined with cognitive approaches, make it to be one of the cornerstones of future cognitive radio real-world implementations.

IV. SYSTEM MODELLING

The purpose of cross-layer optimization is to determine the values of design parameters that will optimize (maximize or minimize) an *objective function*, which defines the ultimate goal. The objective function (sometimes also referred to as fitness function, utility function) will depend on whether the optimization is *user-centric* or *network-centric*, [18]. User-centric optimization focuses on the transmission strategy adaptation at the user side, while network-centric one strives to improve the network utility ([18] and references therein). Often, *application-layer utility* is used as performance metric and optimization goal, which can use other attributes such as throughput or latency, depending on the application, [19], [20]. Clearly, for real-time applications delay is a critical requirement, for bandwidth-intensive applications it is the throughput, while for sensor networks battery consumption should be minimized.

In [20] utility is defined as a quantitative, numerical expression of the quality of connection measured at application layer. In general, the utility will depend on parameters that can be configured locally (Fig.1) and some stochastic variables used to model end-to-end connection (e.g. SNR, bit-error-rate, etc). Therefore, the problem of optimization is basically a numerical optimization problem that in cognitive wireless networks can be solved by machine learning techniques, [20]. The optimization problem in case of cognitive wireless radio with CLD is complex, due to:

- existence of many parameters that can be tuned in a cognitive radio, which makes the search (configuration) space very large,
- deriving analytical expressions for the objective as function of the channel conditions is very

challenging, since these functions are non-deterministic and non-linear, [21], [22],
- wireless channel conditions might be changing,
- real cognitive wireless networks require to perform multi-objective optimization, often with conflicting goals, [22], [8].

The authors of [23] have identified and compared two types of models for performance characterization: *analytical models* used to derive objective functions and *black-box models* used to predict output values of the system.

Analytical models are widely present in the research work. For example, in [24] a relation for BER (Bit-Error-Rate) objective function of AWGN (Additive White Gaussian Noise) channel is given for different modulation schemes as well as a multi-objective function problem solution through weighted sum approach. In [25], see also [7], the cognitive engine deals with maximization of noisy channel capacity for which an analytical model for AWGN channel is presented. An application-oriented objective function for video-streaming over wireless networks is employed in [26], where an analytical model for average PSNR (Peak Signal-to-Noise Ratio) of all users is derived.

On the other hand, the authors of [23] stress the advantages of the *black-box models* and show the applicability of Multilayer Feedforward Neural Networks with good modelling accuracy for this purpose. They also list and shortly discuss some other black-box models, for example Hidden Markov Models, linear models and regression techniques for non-linear modes.

V. Optimization Methodologies

The CR has to perform optimizations in an intelligent, cognitive way, dealing with many input parameters, often satisfying multiple objectives in the conditions of changing characteristics of the wireless channel. Therefore, powerful optimization techniques combined with machine learning approaches are promising candidates for optimization methodologies, [20]. A good overview of cognitive techniques for cross-layer optimization is given in [15]. Four optimization methods have been selected to be shortly presented in this paper, due to their capability for fulfilling specific optimization tasks.

A. Simulated Annealing

Simulated annealing (SA) and genetic algorithms (GA) can deal with multidimensional optimizations where traditional numerical methods might not be fast and scalable enough if applied to the full dataset, [27]. Simulated annealing, see for example [28] and [29], belongs to the random (adaptive) search algorithms where a random walk through the solution space governs the search towards an optimal solution. It mimics the natural processes of controlled cooling of a material. SA algorithm frequently avoids local minima by accepting, with some probability, also changes in the search space that worsen the objective function score. This probability is proportional to the "temperature" control parameter that decreases as the algorithm proceeds. There are also adaptations that improve the performance of the algorithm, (e.g. [30]). The advantage of SA is that it is a simple and highly efficient method for finding the optimal or acceptably good solution, which can be combined with other methods to improve the final result. However, initial parameters of the algorithm should be carefully chosen for an effective search.

B. Genetic Algorithms

Genetic algorithms belong to the heuristic stochastic optimization and global search methodologies, based on the principles of natural selection (see for example [31]). There are many variations of GAs but the common ingredients of them are: "chromosomes" representing radio parameters in case of CR, genetic operators of crossover and mutation, evaluation function to determine the "score" i.e. fitness of a chromosome, and selection function that chooses the chromosomes that will survive to the next generation based on their scores. Thus, at each step the algorithm selects chromosomes from the current population that will serve as a base (parents) to create chromosomes of the next generation (children). Crossover function combines two parent chromosomes to form children for the next generation. Mutation function makes changes to individual parents to form children. There are many choices that control the performance of a GA, e.g. the selection, crossover, mutation function, initial population. The choice of initial population of chromosomes is very important for fast convergence of the algorithm - [32] proposes a specific method for this purpose.

The benefit of using GAs for solving optimization and control problems in CR area has already been shown by many researchers (e.g. [22], [24], [33], etc).

C. Neural Networks

Artificial neural networks (NN) offer an effective data modelling mechanism able to model complex (linear and non-linear) input/output relationships and to learn these relationships by training (see for example [34]). Frequently used for this purpose is a Multilayer Feedforward NN (MFNN), a supervised network that requires a known desired output in order to learn. Learning in this case is a process of determining the optimal combination of network weights (internal parameters) so that the network approximates a given function (input/output relationship). Training algorithms that are frequently used are, for example, gradient descent back-propagation (GDBP), conjugate GDBP, Levenberg-Marquardt algorithm, etc. In some cases also GAs can be used to train the neural network. Common issues with NN modelling are designing the network (e.g. number of layers), initializing the weights, defining the learning rules, avoiding local minima, "overfitting".

The learning capability of a MFNN in cognitive radio has been shown, for example, in [23], where it is used for real-time modelling based on measurements.

D. Fuzzy Logic

In fuzzy logic (FL) the degree of truth of a statement is not crisp, similarly to the degree of membership within a set in fuzzy set theory. FL is based on reasoning close to humans which make decisions based on often imprecise and approximate input information. It uses the important notions of membership functions, linguistic variables, a rule base and an inference procedure. For a more elaborated view on FL and fuzzy set theory see, for example, [35].

Fuzzy logic is a promising research topic for cross-layer optimization in wireless networks. For example, in [36] it has been used for specific cross-layer design, while in [14] it is shown how it can be used for generic knowledge representation of cross-layer information and building controllers in CR.

VI. Conclusions

There is still a way to go for the cognitive radio to reach standard implementations and get to the commercial market, but research community is on the right track. There is a tremendous work performed in the broad area of cross-layer optimization involving different methodologies, already delivering promising results that have to be worked-out and channelized through the standardization bodies.

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