A Survey of Artificial Intelligence for Cognitive Radios

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***Abstract*—Cognitive radio (CR) is an enabling technology for numerous new capabilities such as dynamic spectrum access, spectrum markets, and self-organizing networks. To realize this diverse set of applications, CR researchers leverage a variety of artificial intelligence (AI) techniques. To help researchers better understand the practical implications of AI to their CR designs, this paper reviews several CR implementations that used the following AI techniques: artificial neural networks (ANNs), metaheuristic algorithms, hidden Markov models (HMMs), rule-based systems, ontology-based systems (OBSs), and case-based systems (CBSs). Factors that influence the choice of AI techniques, such as responsiveness, complexity, security, robustness, and stability, are discussed. To provide readers with a more concrete understanding, these factors are illustrated in an extended discussion of two CR designs.**

***Index Terms*—Artificial intelligence (AI), cognitive engine (CE), cognitive radio (CR).**

I. Introduction

WITH roots arguably tracing back to early cellular systems and personal communication systems, cognitive radio (CR) research has greatly expanded since the concept was first formalized in the late 1990s [1]. The assumption of CR or CR-like capabilities formed the basis for the Federal Communications Commission's tentative approval for unlicensed devices to operate as secondary users in the TV spectrum (the so-called "white space") [2], the Office of Communications (OFCOM)'s plans for the digital dividend [3], and the plans for future U.S. military networks [4]. CR has been proposed for a wide range of applications such as automated interoperability for public safety systems [5], cognitive networking [6], spectrum markets [7], femtocells [8], self-organizing networks, cooperative relaying and networks [9], smart grid communications [10], and vehicular networks [11]. CR promises to dramatically improve spectrum access [12], capacity [13], and link performance [14] while also more closely tying the behavior of the network to the needs of the user [1].

While all of these applications are recognized as in the domain of "CR," there is much disagreement on exactly what is and what is not a CR, with seemingly everyone having their own definition (e.g., see [1] and [15]–[19]). Nonetheless, the following attributes are commonly expected from a CR and form a baseline set of assumptions for the remainder of this paper.

1) Observation: Collect information about the operating environment, capability, and characteristics of the radio.
2) Reconfiguration: Change the operation parameters of the radio.
3) Cognition: Understand the environment and capability of the radio (awareness), make informed decisions on actions (reasoning), and learn the impact of these actions on the performance of the radio, as well as the performance of the network in which the radio is embedded (learning).

These three attributes can be embodied in a common element known as a cognitive engine (CE). This paper defines a CE as an "intelligent" agent that manages the cognition tasks in a CR, where intelligence denotes behavior that is consistent with a specified goal [18]. The CE can be implemented as an independent entity interacting with the radio transceiver [e.g., reconfigurable radio transceiver implemented with software-defined radio (SDR)] or as a collection of interacting entities with each entity fulfilling a specific role. Given the input from its environment or user (observation), the CE analyzes and classifies the situation and determines the appropriate response to the stimulus (cognition) and carries out the decision (reconfiguration). As an example, this response can be adapting radio parameters such as the channel coding scheme, the modulation scheme, and the operation frequency, given user requirements, current environment conditions, and previous experiences at the CE.

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How to implement the various aspects of a CE is an active area of research in which considerable attention is given to each of these three attributes. This paper focuses on the practical issues associated with realizing cognition in a radio, which we view as an application of artificial intelligence (AI) to the radio domain, while only considering the aspects of observation and reconfiguration as needed for clarity. Specifically, this paper surveys the state of the art in the use of AI in CR to ascertain available choices for implementing a practical CR and the relative merits of various proposed techniques in differing applications. This paper takes the following structure. Section II reviews AI techniques proposed for use in a CE and presents examples of their applications. Section III discusses practical issues with CR, such as convergence time, implementation complexity, stability, and how to handle multiple coexisting AIs, perhaps within a single CE. Section IV reviews two CEs developed using different AI techniques. Finally, Section V concludes with some observations on the different AI techniques.

II. Artificial Intelligence Techniques for Cognitive Radio

Awareness, reasoning, and learning are the basic components of a CR discussed in this paper. Despite various definitions of these terms, in this paper, awareness refers to the process of extracting the information regarding environment and radio itself for a specific purpose. Reasoning is defined as the process of finding an appropriate action in response to a particular situation with a system target (e.g., maximum operating lifetime, maximum robustness, and lowest cost communications) based on the user application quality-of-service (QoS) requirement [e.g., latency and bit error rate (BER)] and willingness to share resources and collaborate with other devices in the network. Learning is defined as the process of accumulating knowledge based on the observed impact upon applying the action. Typically, these processes complement each other to improve the operation of the CR process as a whole. In other words, awareness, reasoning, and learning in a CR interact and influence each other. Among these three, awareness is the starting point of a CR process and is the foundation of learning and reasoning. Learning can improve reasoning by enriching the knowledge or experience used in reasoning process. Powerful reasoning can improve the efficiency of learning by providing good examples for learning in return. This section presents some AI techniques that have been proposed throughout the literature as possible candidates for CR. They are presented in the order of historical development. The discussion on general AI and its applications is out of the scope of this paper, on which abundant information may be found in [20], which is the website provided by the Association for the Advancement of Artificial Intelligence.

A. ANN

The first artificial neural was presented by the neurophysiologist W. McCulloch and the logician W. Pits in 1943 for the study of the human brain. The idea of artificial neural network (ANN) was then applied to computational models. Modeled on a nerve plexus, an ANN is nothing more than a set of nonlinear functions with adjustable parameters to give a desired output [21]. Different types of ANNs are separated by their network configurations and training methods, allowing for a multitude of applications. However, they are all comprised of neurons interconnected to form a network. Each artificial neuron usually produces a single output value by accumulating inputs from other neurons. While there are many types of ANNs available in the literature, only those most common and applicable to CR are presented here.

1) MLPN: Multi-layer linear perceptron networks (MLPNs) are comprised of layers of neurons, each being a linear combination of the previous layer's outputs. Generally, the weights for the linear combination are randomly chosen before training and can be updated using several methods such as back propagation (BP) [21], a genetic algorithm (GA), or combinations of methods. The performance of such training algorithms is dependent upon the size of the network and its application. Hybrid training methods can be used to extract the best features from each, such as pretraining a network with a GA and then refining the output using BP.

2) NPN: By introducing nonlinearity into the network through perhaps squaring the inputs, or cross-multiplying two inputs, the network can be customized to fit the sample set. Although multilayer nonlinear perceptron networks (NPNs) can provide highly flexible and dynamic results, their network configuration must often reflect the data that they represent. Furthermore, BP for training the weights in the neurons may be slow to converge, requiring significant processing time to achieve precise results [21].

3) RBFN: Similar to NPN, radial basis function networks (RBFNs) have a built-in distance criterion with respect to a center (a radial nonlinear function) in its hidden layer. This transformation has the advantage of preventing the network from settling into local minimals, which is a common problem with perceptron networks. The function itself is usually Gaussian, but Euclidean distance and others have also been used [21]. Training is often implemented with the gradient descent method.

4) Application of ANN to CRs: Because of their ability to dynamically adapt and be trained at any time, ANNs are able to "learn" patterns, features, and attributes of the system they describe. The term "learn" refers to the fact that the neurons are stored in computer memory, the outputs of which can systematically be adjusted to yield a new result for a new situation and remember the results. The attributes can be highly nonlinear, complex, and numerous, yet ANNs can be constructed by only a few examples, thus reducing the complexity of the solution. For this reason, they have long been used to describe functions, processes, or classes that are otherwise difficult to analytically formulate. Therefore, ANNs can be used not only to classify or recognize received stimuli but to assist in the solution adaptation process as well.

The ANN has been adopted in spectrum sensing for CR [22]–[24]. In [22], Fehske *et al.* develop an ANN-based signal classifier utilizing the extracted cyclostationary signal features. The combination of cyclostationary analysis and ANN provides efficient and reliable signal classification and reduces the online processing time by performing a significant amount of

TABLE I
CHARACTERISTICS OF METAHEURISTIC TECHNIQUES

Decision Process	Key Benefits	Drawbacks
Classical Techniques	Provides globally optimal solutions for class of convex optimization problems; Convergence properties are well-analyzed.	Could yield sub-optimal (non-desirable) solutions for ill-behaved functions; Branch-and-bound, clustering and multi-start techniques that enhance performance need access to global information in addition to being computationally intensive.
Genetic Algorithms	Well-investigated for wireless applications.	Convergence has not been fully investigated; Efficiency depends on proper parameter selection
Simulated Annealing	Asymptotically converges to globally optimal solution with probability 1; Easy to implement.	Convergence rate can be slow; Only converges to a global optimal as time goes to infinity for a finite search space.
Tabu Search	Easy to implement	Efficiency depends on proper parameter selection;
Ant Colony Optimization	Can easily adapt to changes in real-time	Inferior to simulated annealing for local searches

computation offline. In [23], Cattoni *et al.* use the ANN to classify different IEEE 802.11 signals (the complementary code keying signal and the orthogonal frequency-division multiplexing signal) based on the frequency features. In [24], Zhu *et al.* evaluate an ANN-based spectrum sensing algorithm for wireless mesh networks. The simulation results show that the ANN-based algorithm achieves better performance in accuracy and speed than the Bayesian-based algorithm.

The ANN has also been used for radio parameter adaptation in CR [25]–[27]. In [25], Reed *et al.* develop a CR testbed using Tektronix test equipment as RF hardware and a personal computer running Open Source SCA Implementation (OSSIE [28], [29]) for different waveforms. The ANN determines radio parameters for given channel states with three optimization goals, including meeting the BER, maximizing the throughput, and minimizing the transmit power. In [26], Hasegawa *et al.* propose an ANN-based distributed optimization algorithm for large-scale cognitive wireless clouds, which consists of many heterogeneous terminals and networks.

Baldo and Zorzi propose to use the ANN to characterize the real-time achievable communication performance in CR [30]. Since the characterization is based on runtime measurement, it provides certain learning capability that can be exploited by the CE. The simulation results demonstrate good modeling accuracy and flexibility in various applications and scenarios.

In addition, the ANN has been used for pattern classification in a pattern-based transmission for CR [31], [32], where the transmission bit string is mapped to a signal pattern at the transmitter, and the received pattern is classified and mapped back to a bit string at the receiver using the ANN.

B. Metaheuristic Algorithms

Explicit relations between the parameters of a CR and the desired performance metrics are usually not available. Therefore, search algorithms based on mathematical relations cannot be applied to find the optimal parameters with respect to the performance metrics. Instead, metaheuristic algorithms [33] can be applied to computationally hard problems to search through the solution space while learning and establishing the requisite relationships. Although the term "metaheuristic" was probably first mentioned in 1986 [34], it can be traced back to earlier work on stochastic optimization methods in the 1950s [35]. Several selected metaheuristic algorithms are presented here, and their relative merits are summarized in Table I.

1) Evolutionary Algorithms/GAs: GAs [36], which are a particular class of evolutionary algorithms, draw their inspiration from genetic evolution and natural selection of species in nature.

The definitions of chromosomes and fitness functions are fundamental to the description of a GA. Chromosomes are abstract representations of candidate solutions. A fitness function, which is closely correlated with the objective of the algorithm or optimization process, quantifies the desirability of the solution. Candidate solutions are evaluated on the basis of the values they generate for the fitness function (called fitness levels), which characterize the performance of candidate solutions. An ideal fitness function should lend itself to fast computation, since it takes several evaluations to produce a single generation and several generations to produce a useful result. A GA maintains a population of candidate solutions for a given problem. The fitness of the population is evaluated, and multiple individuals (based on fitness levels) are selected to form a new population by "reproduction" (combination of candidate solutions) and "mutation" (incorporation of some new solution trait to the current solution). This new population then becomes the current population for the next iteration (or generation). In this process, "unfit" elements eventually die out and are replaced by solution offspring with increased fitness levels.

2) SA: Simulated annealing (SA) [37] is a simple approach for global optimization in a large search space. SA is motivated by the annealing process in metallurgy: a process involving controlled slow cooling of a heated melt to reduce or remove defects and achieve perfect crystallization of the material.

At each step, the SA algorithm considers some neighbors of the current state s and probabilistically decides to either move the system to state s' or stay in state s. The probabilities are chosen so that the system ultimately tends to move to states of lower energy. Typically, this step is repeated until the system reaches a state that is good enough for the application or until a given computation budget has been exhausted. The local search space size is usually a function of the current energy level or, sometimes, the time from start. This way, the algorithm initially wanders in a broad area of the search space containing good solutions, ignoring small features of the energy function, and as it moves toward lower energy regions, the search space becomes narrower and narrower.

3) TS: Tabu search (TS) [38] enhances the performance of a search method by using a memory structure.

The basic elements of TS are memory structures called Tabu list. The list ensures that a recent move is not repeated or reversed. TS uses memory in different ways to guide the search procedure and the role of memory can change as the search proceeds. When the search procedure is in some region with more acceptable solutions, it might be more advantageous to intensify or focus the search. Such intensification can be carried out by prioritizing solutions that have common features with the current solution. This can be done with the introduction of an additional term in the objective function that penalizes solutions far from the present one. At other times, it might be useful to spread the exploration space of the search algorithm, and this can be done by diversification. As before, diversification can be achieved by introducing an additional term in the objective function that penalizes solutions that are close to the present solution. Dynamic weights are attached to the intensification and diversification terms such that intensification and diversification phases alternate during the search.

4) ACO: Ant colony optimization (ACO) [39] is inspired by the behavior of ants in finding shortest paths from their colonies to food sources.

Ants initially randomly wander and, upon finding food, return to their colony while laying down pheromone trails. Upon finding a pheromone trail, other ants follow this trail rather than randomly wandering. Thus, a successful pheromone trail (a trail that leads to food) is continually reinforced. Furthermore, the pheromone trail starts to evaporate over time. Hence, the pheromone trail is more attractive if the time taken to travel the path is shorter as this gives the pheromone lesser time to evaporate. The ants are thus successful in finding the shortest path to a food source. ACO mimics this ant behavior with "simulated ants" walking around a graph representing the problem to solve and finding locally productive areas. ACO algorithms search in parallel over several constructive computational threads based on local problem data and a dynamic memory structure containing information on the quality of the previously obtained result. These algorithms thus combine *a priori* information about the structure of a promising solution with *a posteriori* information about the structure of previously obtained good solutions.

5) Application of Metaheuristic Algorithms to CR: The metaheuristic techniques presented here can not only be used for reasoning or finding the optimal solution with objective/utility function but can also be used for learning with the aid of training examples when the relationship between parameters and a desired performance measure is not well understood. The objective of learning is to identify a hypothesis or a rule set from the search space that maximizes the fit of the training examples to the target concept or, in other words, to identify a hypothesis set or a set of rules that is consistent with the training examples. Although the characteristics of each search algorithm are different, as can be seen in Table I, a common challenge in the application of metaheuristic techniques is the formulation of extensive examples for target scenarios.

Among the various metaheuristic algorithms, the GA has been widely adopted to solve multiobjective optimization problem and dynamically configure the CR in response to the changing wireless environment [14], [40]–[46]. In [14], Rondeau *et al.* apply the GA to adapt the radio parameters of an SDR to the changing radio environment. In their implementation, the fitness function dynamically links and weights different objects according to the link conditions and user-application requirements. In [40], Newman *et al.* design a GA-based CE to control the radio parameters for single-carrier and multicarrier transceivers. This paper derives a set of fitness functions to guide the search direction of the GA and investigate the tradeoff between the convergence time and the size of the GA search space. In [41], Hauris uses the GA to adapt the parameters of CRs on autonomous vehicles. These autonomous vehicles form a geographically varying dynamic wireless network for communication and information sharing among the vehicles and the base station (BS). In [42], Park *et al.* validate the applicability of GA-based radio parameter adaptation for the cdma2000 forward link in a realistic scenario with Rician fading. In [43], Thilakawardana and Moessner investigate a GA-based cell-by-cell dynamic spectrum-allocation scheme achieving better spectral efficiency than the fixed spectrum-allocation scheme. A new solution-encoding technique is proposed to reduce the GA convergence time. In [44], Kim *et al.* implement a software testbed for CR with the spectrum-sensing capability and a GA-based CE to optimize radio parameters for dynamic spectrum access (DSA).

C. HMM

The hidden Markov model (HMM) was first introduced in the late 1960s. It is a convenient and mathematically tractable statistical model to describe and analyze the dynamic behavior of a complex random phenomenon [47] that can be modeled as a Markov process with observable and unobservable states. The HMM generates sequences of observation symbols by making transitions from state to state, one symbol per transition. However, the states are hidden, and only the output is observable. In general, a real-world process can be expressed as a random process producing a sequence of observation symbols or patterns with hidden parameters generating the observables. The symbols or patterns may be discrete or continuous depending on the specific processes.

An HHM can completely be specified in a compact form $\lambda = (\mathbf{A}, \mathbf{B}, \pi(1))$, where $\mathbf{A}$ is state transition probability matrix of dimension $N \times N$, $\mathbf{B}$ is the observation symbol probability matrix of dimension $K \times N$, $\pi(1)$ is the initial state probability vector of dimension $N \times 1$, N is the number of states, and K is the number of distinct observation symbols per state.

1) Three Basic Problems for an HMM: There are three key problems associated with an HMM in real-world applications [47].

1) Evaluation or recognition problem: Given the parameters of the model λ, compute the probability of a particular observation sequence. The forward–backward algorithm solves this problem.
2) Decoding problem: Given the parameters of the model λ and the observation sequence, find the sequence of hidden states that best explains the observation sequence. The Viterbi algorithm solves this problem.

3) Training or learning problem: Given an observation sequence, find the most likely set of state transition and observation symbol probabilities. In other words, this estimates an HMM λ using an observation sequence. This problem is the subset of expectation–maximization. The Baum–Welch algorithm solves this problem.

2) Application of HMM to CR: An HMM can be built for a specific system to explain and characterize the occurrence of the observed symbols or patterns. This model can then be used to identify the sequences of observations with the same pattern by choosing the model that would most likely produce the observed sequences. Therefore, an HMM can be used as an observation process of the CE to recognize or classify received stimuli and can achieve awareness. In addition, since it can reproduce the training sequences, it can be used for prediction. Furthermore, learning can be accomplished by creating new models.

HMMs have been applied to CR research. Rondeau *et al.* propose to model the wireless channel online using an HMM for CR [48]. The HMM is trained using the GA with data from a broadband channel sounder in a line-of-sight additive white Gaussian noise channel.

HMMs have also been used for spectrum sensing in CR [49], [50]. In [49], Kim *et al.* propose to use the HMM to process signal cyclostationary features for primary signal detection in CR. The HMM-based spectrum sensing approach can detect and classify signals at low SNRs with only limited information on signal bandwidth. In [50], Ghosh *et al.* validate the existence of a Markov chain model for wireless channel utilization with real-time measured data in the paging band and formulate the spectrum-sensing problem using an HMM.

In addition, HMMs have been used for spectrum occupancy prediction [51], [52]. In [51], Akbar *et al.* develop an HMM-based DSA algorithm where the HMM models and predicts the spectrum occupancy of the licensed radio bands for CR networks. This paper shows that the HMM-based DSA algorithm can achieve significant signal-to-interference ratio improvement compared with the traditional carrier-sense-multiple-access-based approach.

D. RBS

In a rule-based system (RBS), rules are extracted from a specific application area (automatically or manually) and used in decision making for that domain. It is a natural way of encoding a human expert's knowledge in a narrow area into an automated system. The idea of RBS was used in the development of DENDRAL: one of the oldest expert systems, which was developed in 1964. A typical RBS consists of the following fundamental elements [53].

1) Rule base: This contains a list of permanent rules.
2) Inference engine (IE): This infers information or takes action based upon the input and the rule base.

Rules are usually expressed in the following form [53]:

$$\text{IF } conditions \text{ THEN } actions.$$

The input is tested against the conditions, and the actions are taken if the conditions are satisfied. In general, the order in which the rules are executed is not critical to the final result, as long as all rules are executed [53]. This is different from most procedural programs where the order is important.

1) Operation of the IE: Generally speaking, there are two broad sets of IEs: forward chaining and backward chaining [53]. In a forward-chaining IE, new data trigger rules whose conditions are met, and conclusions are drawn based on these rules. Conclusions can further trigger other rules to generate new conclusions. This process continues until no more rules can be triggered. In other words, a forward-chaining IE is data driven. On the contrary, a backward-chaining IE is goal driven. In a backward-chaining IE, a particular goal is set to be proved, and rules whose conclusions match the goal are identified. The conditions of those rules are then set as goals for new rules. This process continues until no new conditions are identified.

2) Application of RBS to CR: The most significant advantage of an RBS is its simplicity. A radio can deduce actions for an input quickly using an RBS. Given the proper domain knowledge, the rule base can automatically or manually be built. During the rule-derivation process, relevant and irrelevant features can be handled differently for a rule. However, this process is usually tedious for a complex domain. The accuracy of the RBS depends on the completeness and accuracy of the underlying rule base. If the domain is not perfectly understood, the RBS might return inappropriate responses. This is often the case for some CR applications such as DSA. One possible solution to this issue is to assign certainty values to rules [53] and make use of statistical tools such as Bayesian analysis. Although this approach leads to a less rigorous conclusion, it could provide a good guess for situations that are not perfectly understood. Another choice can be to combine the RBS with the case-based system and make use of experience to compensate for the inaccuracy in the RBS.

The rule-based reasoning CE (RBR-CE) has been designed for CR [54]–[56]. In [54] and [55], Reed *et al.* design and evaluate an RBR-CE for IEEE 802.22 wireless rural area network (WRAN) applications. The developed RBR-CE can achieve similar performance to the CE based on the GA with a lower computational complexity. In [56], Clancy *et al.* develop an RBR-CE using predicate calculus, focusing on a generic CR architecture enabling learning in the reasoning process. The learning results are expressed in predicate calculus and can therefore be used in the CE. The operation of the CE is demonstrated for capacity maximization and DSA problems.

Fundamental to any rule-based reasoning system is the generation of the rule database. In [57], Weingart *et al.* develop a systematic method to derive the rule database through automatic experiments over a vast parameter space using statistical analysis of variance and design of experiments. Important parameters across the protocol layers and relationships between parameters and performance metrics are identified and modeled through the experiments. Based on the extracted rules, optimal configuration can be drawn for specific channel conditions and application requirements.

E. OBS

Although “ontology” was not deliberately defined in computer science until the early 1990s by Gruber [58], it has been used in the AI community since the 1980s. An ontology is an “explicit,” “shared,” and “formal” representation of a set of concepts within a domain and relationships among these concepts [59]. As a formal representation, the ontology becomes machine understandable. In addition, the ontology needs to be accepted or shared in a community to make it useful. In ontology-based systems (OBSs), the ontology is used to reason about the attributes of the domain of interest.

An ontology usually includes the following basic components [59]:

1) classes: a set of objects in the modeled domain;
2) instances: individuals belonging to classes in the modeled domain;
3) attributes: properties of objects;
4) relations: links between various entities.

1) Ontology Languages: An ontology is expressed using an ontology language to facilitate machine processing. A number of ontology languages have been developed for various ontologies. Here, we focus on web-based ontology languages due to the immense impact of the World Wide Web. There are three major web-based ontology languages.

1) XML Topic Maps [60]: This is an ISO standard that allows relations among any number of entities.
2) Resource Description Framework (RDF) [61]: This is a World Wide Web Consortium standard that only allows relations between two entities.
3) Web Ontology Language (OWL) [62]: This is a World Wide Web Consortium standard that only allows relations between two entities. It is an extension to RDF.

Note that RDF and OWL are fundamental technologies for semantic web, which is a web of data (computer manipulatable) instead of a web of documents (human readable) [63].

2) Application of OBS to CR: Using ontology languages, an OBS is able to logically deduce facts. A radio equipped with an OBS can understand the capability and characteristics of itself and other radios using logic deduction. This understanding, as well as the understanding of the environment, helps the radio to deduce optimal operating parameters. Note that the logic derivation in the IE might be impractically long [62]. For example, the time requirement of OWL-Full, which is the most sophisticated level of OWL, is undecidable, which means that some derivation cannot be completed within a finite amount of time.

Ontology language has been investigated for CR development [64], [65]. An important example is the Defense Advanced Research Projects Agency’s next-generation (XG) policy language framework [64]. This framework is based on an extensible ontological framework to facilitate future extension of spectrum rules and related concepts. It allows both regulatory and system policies to be expressed and enforced. A good tutorial on the properties of a formal language for CR is provided in [65]. Kokar *et al.* start the investigation with the OWL and extend the capability of the OWL as the areas that the OWL cannot support are identified. This paper concludes that a good language for CR should be able to express rules, introduce new functions, and specify radio behaviors.

In [66], ontology-based reasoning (OBR) is used to achieve self-awareness and interoperability among SDR nodes. With an example on radios negotiating an equalizer training sequence structure, the authors show that self-awareness can improve the interoperability of SDRs. OWL is used in the OBR.

In addition to self-awareness and interoperability, OBR is also used to apply spectrum policy to DSA [67], [68]. A prototype framework is built for CR using OBR [67], [68]. Ontologies and rules are combined to achieve a knowledge-driven differential-response capability, which, as defined by the authors, is the capability of reasoning about a failure in an attempt and identifying alternative actions to satisfy the goal using knowledge of radio technology, policy, goals, and other contextual information. In other words, the CE learns from its failures and avoids the same failures in the future.

F. CBS

The case-based system (CBS) can trace its roots to the work of Schank on the model’s of dynamic memory in the early 1980s. It is an AI area that focuses on using previous similar experiences or cases to guide the problem-solving process and to obtain a solution [69]. In a CBS, a solution to the new problem is created by selecting the cases that are most relevant to the problem, narrowing down the selected cases to a single case, and adapting this case to fit the current scenario. Adapting the parameters of the case can be viewed as an optimization problem. The purpose of the initial similar case retrieval is to allow the optimization process to begin at a point closer to the goal in a search space by finding similar cases. This reduces the time and processing needed to optimize the parameters for which the system is looking. Upon new solutions obtained from case adaptation, the case database is updated with the new cases.

The characteristics of CBS [69] include the capability to solve problems within partially understood domains, the capability to provide a unique explanation, and the close resemblance to actual human reasoning process. One of the key issues of CBS is that the performance relies on previous cases. If previous cases have been incorrectly solved, it is possible for mistakes to propagate onto new cases. In addition, for a complex domain where the system requires a large case database to represent its characteristics, populating and searching such a case database can be time consuming and sometimes difficult. In this case, integration with other techniques such as an RBS may be necessary to improve the performance and reduce the time to build and search the case database.

1) Modules in a CBS: In general, a CBS may contain the following functional modules [69].

1) Case representation and indexing module: Format the input information such that it can be understood by other modules of the system.
2) Case selection and retrieval module: Search the case database, and obtain cases that satisfy the request under certain criteria.

3) Case evaluation and adaptation module: Evaluate the performance of the retrieved case for the new problem based on some criteria, and modify the case if its performance is not satisfactory.
4) Case database population and maintenance module: Populate the initial case database, insert new cases, update existing cases, and remove redundant cases in the case database as necessary.

2) Application of CBS to CR: Given the currently observed environment and radio objectives, a CR can use a CBS to determine an acceptable solution (action) for the current environment based on the existing case in a case database. As a case database may not include all possible situations a CR may encounter in operation, a CR needs to learn new cases when it encounters new situations, generate new actions for the new situations, and update the case database with the new cases. These are the general tasks of the CBS or case-based reasoning (CBR) in a CR.

CBR has recently been investigated for CE design [70]–[72]. In [70] and [71], Reed *et al.* design a CBR-based CE (CBR-CE) to obtain radio parameters for IEEE 802.22 WRAN applications. The performance of the CBR-CE is evaluated under various radio scenarios and compared to several multiobjective-optimization-only algorithms, including the hill-climbing search (HCS) and a GA. The simulation results show that the CBR-CE can achieve comparable performance with less complexity after appropriate training/learning. The learning process of the CBR is also simulated and discussed. In [72], Khedr and Shatila design a CE using CBR and fuzzy logic to determine the channel type (flat fading versus frequency-selective fading and fast fading versus slow fading) for WiMAX systems.

In [73], Le *et al.* propose a CE architecture and the use of CBR in a CE. The functionalities of the building blocks in the cognition cycle and the CE are discussed, including environmental awareness, case-based learning, multiobjective optimization, and hardware-portable interface. The implementation of the building blocks is also suggested.

III. Practical Issues and Interactions of Cognitive Engines

A. Implementation of a Single CE

ANNs are mathematical emulations of biological neural networks, which are used primarily for nonlinear pattern matching and statistical modeling. They are able to describe complex relationships between multidimensional data sets and are trainable online to contend with fluctuations in trends. ANNs are excellent candidates for classification. However, there is little theory to link the particular application with the required network size or the specific type of network. Furthermore, overtraining a network to recognize only the initial data set is a possible problem.

Metaheuristic or search algorithms are very efficient when the rules to be learned are in the form of searching for a set of parameters that optimize a given performance metric. Furthermore, the effectiveness of the algorithms can itself be improved by using the algorithms in conjunction with learning mechanisms such as prior knowledge-based learning (as is done in Soar,[1] and Prodigy [74]) and inductive learning, where new search rules are formulated on the basis of training examples and/or patterns observed in previous iterations of the search. The biggest challenge for metaheuristic search algorithms is the formulation of the hypothesis space. By definition, these techniques only try to find the best hypotheses from the search space and cannot create new hypotheses beyond the search space. Hence, the formulation of a comprehensive search space that includes all possible hypotheses or relationships between contributing factors is extremely critical to the performance of these algorithms.

An HMM-based approach can analytically model a complicated stochastic process using the observation sequence. Both classification and predication can be achieved using an HMM. However, the development of an HMM requires a good training sequence, and the training process can be computationally complex. Other AI techniques such as GA are used to improve the model training efficiency [48]. In addition, an RBS and a CBS can help the HMM to determine the required observation duration.

The most significant advantage of an RBS is that it is simple to understand and that it can tackle unforeseen scenarios. An RBS also has the ability to include only relevant features while formulating a rule. However, the rule-derivation process could be tedious, and it requires perfect domain knowledge, which may not always be available. In practice, an RBS can be combined with a CBS and an OBS to better deal with an unfamiliar domain. Without characterization and abstraction of radio scenarios, the number of rules in the knowledge base could be prohibitively large for implementation. A tradeoff has to be made between the levels of abstraction and the details of the solutions for adaptation [55].

An OBS provides a good approach to enable the radio to understand the characteristics, capabilities, and constraints of itself and others in the radio environment. In addition, this understanding can further be used in its logical deduction. One challenge for the OBS lies in the development of ontology. This process usually requires perfect domain knowledge and extensive processing. In addition, the logic-derivation process using the ontology can sometimes be time consuming [62]. To improve the efficiency and robustness of an OBS, a CBS and an RBS can be incorporated to gather effective experience and to reduce the workload of the logic deduction.

Similar to the human learning and reasoning process, a CBS can develop as it operates. This characteristic is particularly appealing to CR design, as a CR needs to be able to operate in an unfamiliar environment. On the other hand, appropriate training of the CBS before deployment can reduce the processing time and improve the robustness of the system [71]. In addition, prior knowledge about the expected deployment environment can help to reduce the size of the case database, to accelerate the case retrieval time, and, more importantly, to reduce the impact of irrelevant patterns.

These preceding tradeoffs are summarized in Table II.

[1]http://sitemaker.umich.edu/soar/home.

TABLE II
COMPARISON OF DIFFERENT AI TECHNIQUES

Algorithm	Strengths	Limitations	Options
Artificial neural network (ANN)	Ability to describe a multitude of functions Conceptually easy to scalable Excellent for classification Can identify new patterns	Training may be slow depending on network size Possible over training No theory to link application with required network	Can use other learning techniques in the training phase (i.e., GA) Can be combined with RBS
Metaheuristic algorithms	Excellent for parameter optimization and learning involving relationship between parameter values Can use other learning techniques in the training phase (i.e., GA)	Formulation of rule space is difficult when learning or optimization is not restricted to parameter values	Can be used in conjunction with RBS Learning can also be used in the search process
Hidden Markov model (HMM)	Can model complicated statistical processes Good for classification Easily scalable Can predict based on experiences	Requires good training sequence Computationally complex	Based on previous knowledge, CBS and RBS can help HMM determine the observation duration for a specific application and overcome issues with new situations
Rule-based system (RBS)	Simple implementation Ability to tackle unforeseen situations Ability to include only relevant features while formulating a rule	Tedious rule derivation process Requires perfect domain knowledge which is not always available	Can be combined with CBS and OBS to better deal with unfamiliar domain
Ontology-based system (OBS)	Ability to logically deduce Ability to understand the capabilities and characteristics of its own and others	Requires perfect domain knowledge to develop ontology Low efficiency for sophisticated ontology and ontology language	Can be combined with CBS and RBS to improve efficiency and robustness
Case-based system (CBS)	Close to human reasoning Can work in a chaotic situation with lots of variables Allows fast acquisition of knowledge Allows learning in the absence of domain knowledge	Relies solely on previous case Requires large case memory Might include irrelevant patterns	Can be combined with RBS and OBS to yield a more robust problem solving system that does not rely solely on experience

B. Coexistence of Multiple CEs

As highlighted by the movement toward cognitive femtocells, centralized control of hundreds and thousands of clusters adapting in real time quickly becomes infeasible. Therefore, we can expect that there will be numerous CEs, each controlling a subset of all adaptive radios. Further simplifications could be made if instead of implementing a single CE process that manages all aspects of a radio's (or subnet's) behavior, several quasi-independent processes could be used to manage different aspects of the system's behavior, e.g., different processes for spectrum utilization, transmit power, group membership, and routing. Likewise, independent processes could be used to make different observations (e.g., location, presence of a primary user, and link states elsewhere in the network), to guide radio behavior (e.g., ascertaining policy and user objectives), and to differentiate radios in the network. Thus, rather than realizing a CE as a singular AI, computational considerations dictate the deployment of multiple AIs, each controlling their own domain but influenced by the choices of the other AIs in the radio or network.

Therefore, whether we consider each device in a wireless network to be controlled by a singular autonomous CE or we consider the adaptations of each device to be jointly determined by several CEs distributed across the protocol stack or we consider multiple devices controlled by a single CE in a cognitive network [6], it is clear that the deployment of CR will introduce countless situations where the performance (and, thus, the choices of each CE) is influenced by the choices of the multitude of other CEs in the environment. These interactions can easily spawn an infinite sequence of adaptations that never converge, can yield an unstable network whose behavior radically changes with small changes in the environment, or can produce a network with decidedly suboptimal performance (e.g., a tragedy of the commons [75]). Examples of this unstable behavior arising from even simple cognitive processes are illustrated in [13] and [76]. The analysis and design of networks with numerous interactive processes is further complicated by market realities where platform and process implementations will vary by vendor. Thus, it is insufficient to design an AI process for a CE that only considers the behavior of the AI in isolation.

While these interactions makes CR networks much more complex to analyze and design, the interaction of multiple networked AIs has a natural analog—the interaction of multiple (somewhat) networked natural intelligences we call human society—that can be drawn upon to guide the practical design of coexisting AIs. Informally extending back to the dawn of human history and, more formally, since the 18th (Waldgreave), 19th (Cournot), 20th (Zermelo) centuries, depending on the desired level of formalism, game theory has provided a collection of models and analytical techniques that permit the prediction of likely outcomes of the interactions of intelligent decision makers. Generally, the basic model of these interactions—a game—consists of at least a set of players, which correspond to the intelligent decision makers, sets of available adaptations for each player, and a set of preferences over the possible outcomes from these interactions (usually expressed as *utility functions*—analogous to the objective or cost functions discussed in Section II). The analogy between the AIs in CR networks and the natural intelligences in human society was so clear that, almost immediately after the term CR was publicly coined, papers were written suggesting the use of game theory in the design and analysis of the interactions of CRs [77]. By leveraging analysis techniques from game theory, CE researchers are able to predict the likely operating states for interacting CR AIs as the points from which no CE would choose to unilaterally adapt away from lest its own performance suffers (points called Nash equilibria) and to characterize convergence and stability properties of complex networks of CEs [76].

Furthermore, by drawing on the relatively rich body of literature game theory has developed for humans, CR researchers have identified numerous game models that allow for the researchers to shape the way their AIs will interact in the field. This includes

1) supermodular games as applied to distributed power control [78];
2) supermodular games for beamforming and power control in multiple-input–multiple-output systems [79];
3) repeated games with punishment to encourage the forwarding of packets [80];
4) auction theory for power control and resource allocation [81];
5) potential games as applied to distributed spectrum management [13];
6) potential games as applied to routing algorithms [82];
7) potential games for topology control algorithms [83];
8) stochastic games with strategic learning applied to spectrum management [84].

In general, these game models are adopted because they yield the desired behavior when CEs interact in the desired domain but also dictate what properties the AIs must adopt to ensure the networked deployment achieves the desired results. For instance, cognitive processes designed assuming interactions that can be modeled as a supermodular game (loosely, a game with strategic complementaries between players) require the AIs to exhaust its search space so that each adaptation is individually "optimal" to ensure convergent behavior. While this may not be practically achievable in the general case, it has been proven to be quite doable for various power control applications [78]. Likewise, when the interactions can be modeled as a potential game (a game where there exists an emergent function that monotonically increases with every unilateral selfish adaptation by an AI), there are virtually no further restrictions on the design of cognitive processes—only informed selfish unsynchronized behavior is required. However, ensuring that the AIs satisfy the requisite conditions for a potential game is not as readily done as in other game models [76].

IV. Case Study

This section presents CE development efforts by researchers at Wireless @ Virginia Tech as a case study for applying AI techniques to CR. Two design examples are presented: one using an ANN and the other using CBR. The first example uses ordinary laboratory testing equipment to build a fast CR prototype. It also proves that, in general, an AI technique (e.g., an ANN) can be chosen to accomplish complicated parameter optimization in the CR for a given channel state and application requirement. The second example builds upon the observation from the first one and develops a refined CE framework and process flow based on CBR. The CBR-based framework can better facilitate the interaction among awareness, reasoning, and learning in the CR.

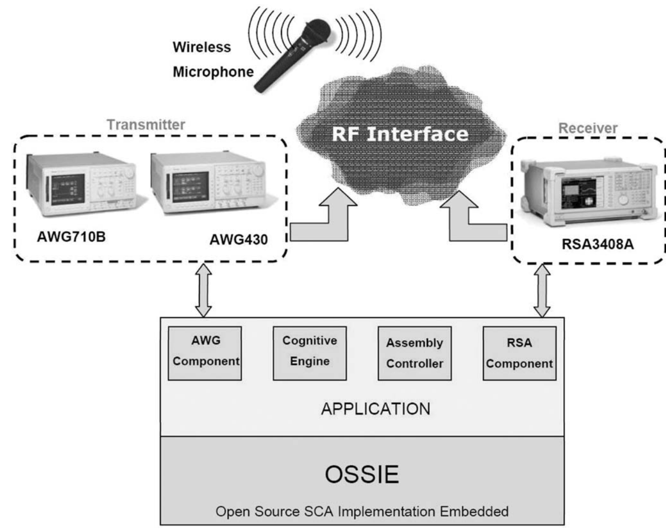

Fig. 1. Block diagram of the CoRTekS.

A. ANN-Based CE Development

As a proof of concept, a CR testbed, i.e., the Cognitive Radio Tektronix System (CoRTekS), has been developed by researchers at Wireless @ Virginia Tech [25]. The block diagram of this testbed is shown in Fig. 1. It consists of a transmitter [Tektronix arbitrary waveform generators (AWGs), a mixer, filters, an amplifier, and an omnidirectional antenna], a receiver [Tektronix real-time spectrum analyzer (RSA) and an omnidirectional antenna], and a personal computer (on which the SDR and CE run).

The CE controls the transmitter and receiver by determining the best set of radio parameters for the given channel state and application requirement. An image is transmitted over the air where potential interference exists. As shown in Fig. 2, the image is successfully received with the current channel condition and radio parameters.

As the first attempt at CE implementation, a classic AI technique, i.e., ANN, has been chosen to drive the CE. In the CE, a MLPN ANN assists in deciding the parameters to be used in the next block of transmissions. The CE uses the ANN to determine how closely a set of parameters meet a set of goals and then chooses the set of parameters that maximizes the utility functions. The radio can change the modulation type, transmission power, and frequency to minimize interference, avoid the channels that primary users use, and optimize three main goals: meeting the QoS (BER), maximizing the throughput, and minimizing the transmit power. Periodically, the CE retrains the ANN based on decisions it has made and results observed. Gradually, the ANN learns a better parameter set for a given situation by drawing relationships between radio parameters and system performance.

To protect primary users while the CR operates, spectrum sensing and policy are enforced in the testbed. Spectral information shown in Fig. 2 indicates the available spectrum, the detected interference, and the current spectrum usage. On

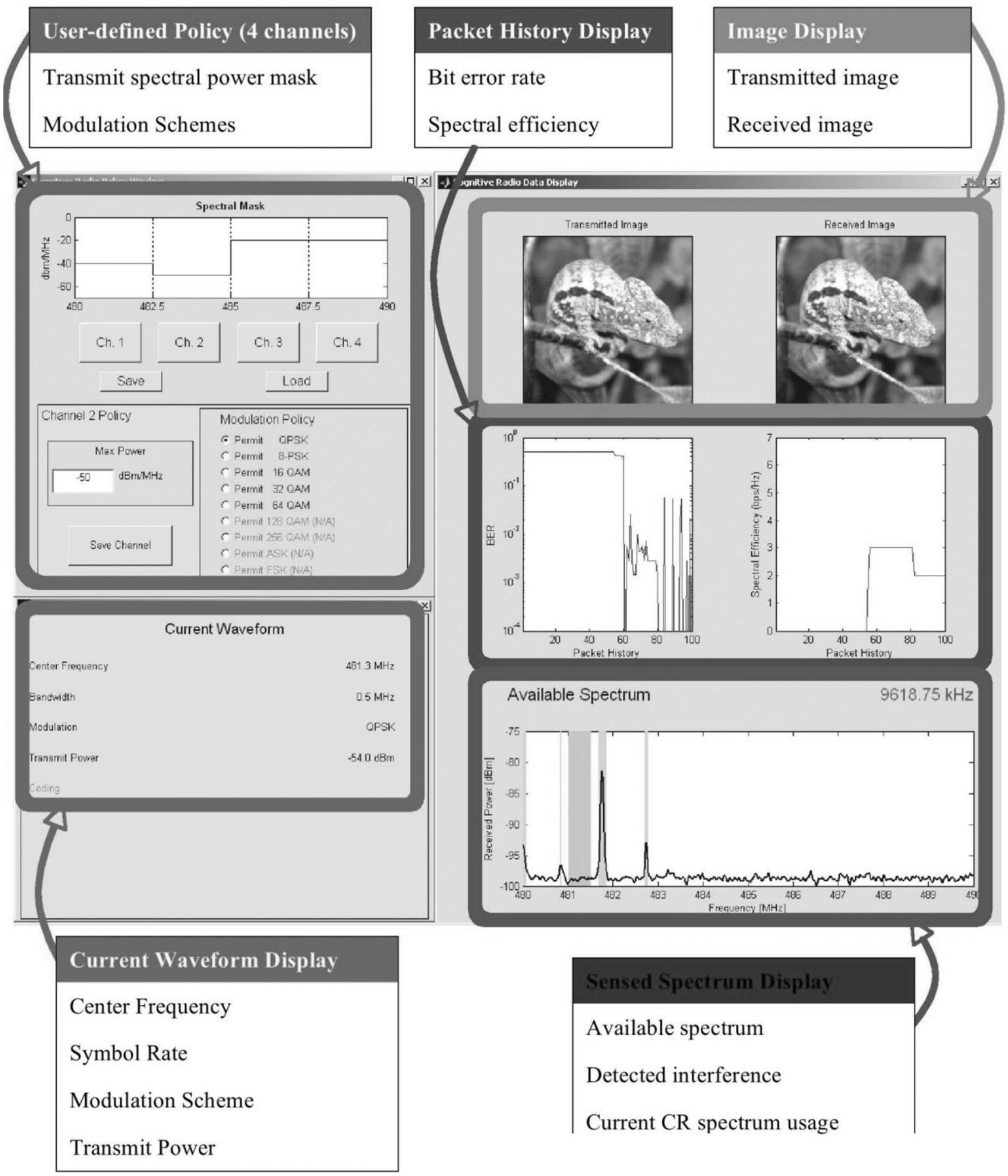

Fig. 2. Screen shot of the CR testbed.

the other hand, active policies, as demonstrated in Fig. 2, include the transmit spectral power mask and allowable modulation schemes. Each solution adopted by the radio, e.g., the waveform (radio configuration such as operating frequency, bandwidth, modulation scheme, channel-coding scheme, and transmit power) used in the screen shot, complies with both policies.

B. CBR-Based CE Development

After the validation of the feasibility of applying AI techniques in CE design, further efforts were taken to investigate the architecture of the CE and the performance of different AI techniques. Due to the inherent structure and flexibility of a CBR system, various AI techniques can be employed in different modules of a CBR system to tailor the CE to a specific application. A CBR-based CE has been developed for IEEE 802.22 WRAN applications. This work has been reported in [71] in detail. Here, we review the architecture of the CE and the observation based on this development.

An architecture of the CE is shown in Fig. 3 [71]. The CE consists of three major processes:

1) orientation: maps the current scenario (e.g., primary user detected) to a state vector that the optimizer (e.g., CBR) can understand;
2) reasoning and learning: develops and optimizes the solution (e.g., a case in the CBR case database) to the current problem under the policy;
3) solution mapping and validity checking: maps the solution to a specific action and validates it against the policy and regulation before it is applied to the radio.

Furthermore, a CBR-based framework has been proposed for the IEEE 802.22 WRAN applications, as in Fig. 4 [71]. The arrows and the number markups in Fig. 4 indicate a general processing flow of the CE. The CBR-CE is designed in modules

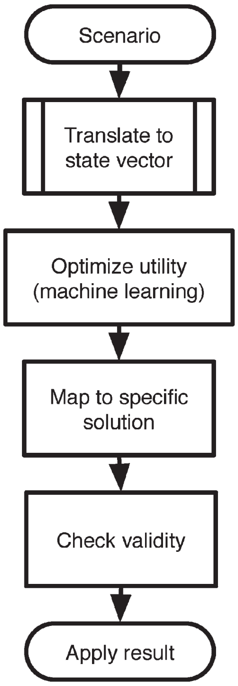

Fig. 3. Architecture for a CE.

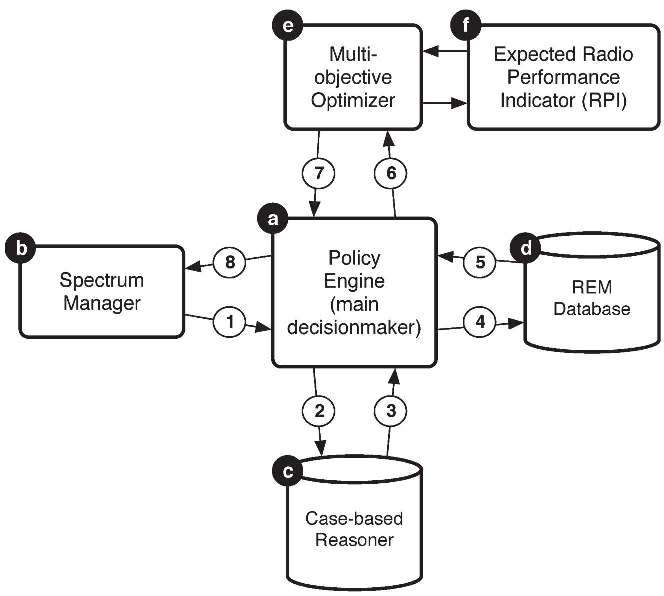

Fig. 4. Framework of the CBR-CE for the WRAN application.

with well-defined interfaces so that each module can properly pass on the necessary information. This modular approach makes it easier to replace any functional block with an equivalent processing element. This approach also makes the framework useful for testing and evaluating different algorithms.

The functionalities of the modules in this proposed framework are described as follows.

1) Spectrum manager (SM): This module monitors the radio environment, interfaces with the physical radio hardware, and allocates resources according to the solution received.
2) Policy engine (PE): This module interprets policies, including standards, regulations, and customer specifications, to guide the operation of the CBR. It checks the legitimacy of a candidate solution before returning this solution to the SM.
3) CBR: This module provides candidate solutions based on the request from the PE module.
4) Radio environment map (REM) database: This module stores scenario-specific parameters about the system, such as geographic features, network and service availability, spectrum information, radio location and activities, policies, and experiences [55].
5) Multiobjective optimizer (MOO): This module adapts parameters at the physical and medium access control layers based on the solution provided by the CBR. The algorithms investigated include the HCS, the GA, and a combination of HCS and GA. Note that other algorithms can be added to the MOO. The algorithms can also be combined to achieve a better balance between performance and the execution time.
6) Expected radio performance indicator (RPI): This module evaluates the anticipated performance for a given solution before applying it in the real environment. The result is used in the MOO to determine whether the QoS requirements are satisfied and whether further optimization is necessary.

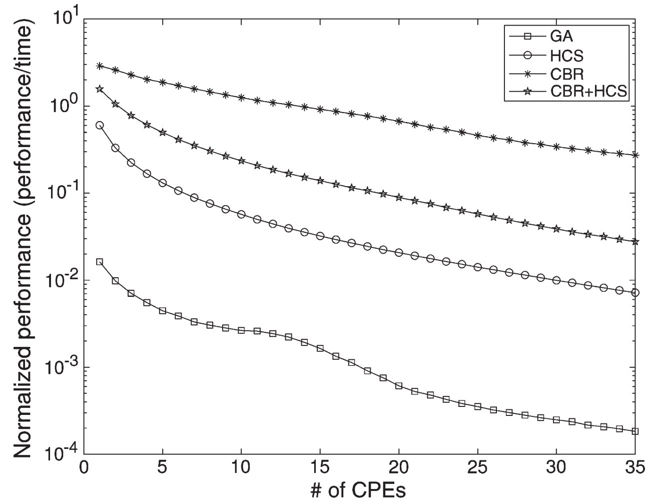

Fig. 5. Performance comparison of different CEs.

Using the framework in Fig. 4, we emulate the operation of a CR BS and customer premise equipment (CPE). A GA-based CE (GA-CE), an HCS-based CE (HCS-CE), a CBR-CE, and a CE based on the combination of CBR and HCS (CBR + HCS-CE) are used to find the optimal radio configurations for specific channel conditions and application QoS requirements. In the simulation, a BS allocates resources to multiple CPEs with different QoS requirements. The complexity of the problem depends on the number of CPEs, as do the execution time and the performance. The simulation results we obtained (see Fig. 5) indicate that a tradeoff between CE performance and execution time needs to be explored for specific applications. In this figure, the performance of each CE is normalized by its corresponding execution time for different numbers of CPEs. For the IEEE 802.22 WRAN applications where the response time of the CE is critical, a CBR-CE with or without MOO (CBR + HCS) provides a sound balance between the achieved performance and the execution time. The detailed discussion and more results can be found in [71].

C. Observations From the Case Study

The examples studied earlier show that although various AI techniques can be used for a particular application, a CE must carefully be designed, observing the tradeoff between performance and complexity determined by the application requirement.

Another important observation is that training and learning is necessary for the CE to achieve acceptable performance. In the ANN-based CE, it takes a significant amount of cases (simulated or measured) to train the ANN. Similarly, after appropriate training, the CBR-CE performs well for new scenarios. In addition, the designed CBR-CE is capable of performing real-time learning.

V. Conclusion

AI techniques lie at the heart of CR, and understanding the tradeoffs in the selection and design of AI processes is critical to a successful CR design. This paper has reviewed several AI techniques—ANNs, metahueristic algorithms, HMMs, RBSs, OBSs, and CBSs—that have been proposed to provide the cognition capability in a CE. While we have seen that AI techniques have been applied to numerous CR applications [2]–[14], many implementations remain rudimentary, perhaps due to the interdisciplinary nature of the field and perhaps because products are just beginning to appear.

We have seen that the appropriateness of AI techniques varied by application and implementation. The decision in choosing one or some AI techniques over other techniques in CE design needs to be made based on the application requirement, considering the tradeoffs among response time, processing complexity, training sample availability, robustness, etc. In addition, the learning capability of the AI technique needs to be considered and exploited in designing a CE as learning is critical to the performance of autonomously deployed CRs.

Additionally, we have noted that the design of AI processes should consider how the processes perform when deployed in the context of other AI processes and not just performance in isolation. While game theory provides an approach to make this problem analytically tractable, any analysis must begin with knowledge of the expected operation of other AIs that may be encountered, which is problematic, assuming different implementations from different vendors and if the AI processes self-direct their evolution. Thus, developing an inter-CE (and, thus, inter-AI) etiquette that is robust to variances in AI implementations will be important to the success of large-scale deployments of CRs. Ultimately, the implications of the etiquette will need to flow down all the way to the choice of performance metrics that guide the AI processes' decisions [85].

Our experience suggests that, for a robust CE, different AI techniques should be used to complement their relative strengths and weaknesses. A CE needs to be tailored for the desired application by identifying and appropriately combining different reasoning/learning AI algorithms. Attractive combinations that we have found include combining CBS, OBS, and RBS or combining HMMs with GAs or RBS. Given that the best combination of AI techniques varies by application, CE designs should accommodate mechanisms to change AI combinations as applications change. If the use of a single AI technique is required, we feel that the modularity of CBR comes closest to achieving the cognitive capabilities and application flexibility while still maintaining suitability for real-time systems.

In addition to the choice of AI techniques, the CE training process is crucial to performance. Training could be hastened by using cooperative training techniques, but to limit potential security vulnerabilities, these sources should be authenticated, and externally learned behaviors should be evaluated against self-generated field measurements.

Last but not least, although secondary spectrum access enabled by DSA has received the most interest in the CR community and arguably does not require AI, we believe that the greatest payoff from CR will come from the ability to support self-organizing networks that can continuously improve the management of heterogeneous network elements and radio resources far beyond what the CR's designers could conceive. To achieve this goal, the application of AI techniques to CR will need to be further refined and extended to a metacognitive process. Learning how to design radios that learn is a journey of exploration that has just begun.

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References

[1] J. Mitola, III, "Cognitive radio for flexible mobile multimedia communications," in *Proc. IEEE Int. Workshop MoMuC*, San Diego, CA, Nov. 15–17, 1999, pp. 3–10.

[2] Fed. Commun. Comm., FCC Adopts Rules for Unlicensed Use of Television White Spaces, Nov. 8, 2008. [Online]. Available: http://hraunfoss.fcc.gov/edocs_public/attachmatch/DOC-286566A1.pdf

[3] QinetiQ, Cognitive Radio Technology a Study for Ofcom—Volume 1, Feb. 12, 2007. [Online]. Available: http://www.ofcom.org.uk/research/technology/research/emer_tech/cograd/

[4] R. Lo, "Moving towards cognitive netops," in *Proc. JSTeF 3*, San Diego, CA, Jan. 26–29, 2009.

[5] W. Lane, Topic 9: Cognitive Radio Potential for Public Safety. [Online]. Available: http://www.fcc.gov/pshs/techtopics/techtopic9.html

[6] R. Thomas, "Cognitive networks," Ph.D. dissertation, Virginia Polytech. Inst., State Univ., Blacksburg, VA, Jun., 2007.

[7] D. Niyato and E. Hossain, "Spectrum trading in cognitive radio networks: A market-equilibrium-based approach," *IEEE Wireless Commun.*, vol. 15, no. 6, pp. 71–80, Dec. 2008.

[8] Ubiquisys, Ubiquisys and Percello Unveil Next Generation Femtocell Platform, Jun. 22, 2009. [Online]. Available: http://www.ubiquisys.com/ub3b/pressreleases.php?id=115

[9] C. Lu, F. H. P. Fitzek, and P. C. F. Eggers, "A cooperative scheme enabling spatial reuse in wireless networks," *Wireless Commun. Mag.*, vol. 15, no. 6, pp. 457–471, Sep. 2007.

[10] P. Greenis, "Smart communications for smart grids," in *Proc. Nanotech Conf. Expo*, Houston, TX, May 3–7, 2009.

[11] J. Neel and A. Amanna, "Introduction to cognitive radio technology for transportation systems," in *Proc. SDR Forum Workshop Smart Commun. Transp. Syst.*, Houston, TX, Jun. 18, 2009.

[12] M. McHenry, NSF Spectrum Occupancy Measurements Project Summary, Aug. 15, 2005. [Online]. Available: http://www.sharedspectrum.com/?section=nsf_measurements

[13] J. Neel, "Synthetic symmetry in cognitive radio networks," in *Proc. Forum Tech. Conf. Product Expo. SDR*, Denver, Co, Nov. 5–9, 2007.

[14] T. W. Rondeau, B. Le, C. J. Rieser, and C. W. Bostian, "Cognitive radios with genetic algorithms: Intelligent control of software defined radios," in *Proc. Forum Tech. Conf. SDR*, Phoenix, AZ, Nov. 15–18, 2004, pp. C-3–C-8.

[15] "Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies," Notice of Proposed Rulemaking and Order, Washington, DC: Fed. Commun. Comm., Dec. 2003.

[16] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[17] IEEE, Standard Terms, Definitions, and Concepts for Spectrum Management, Policy Defined Radio, Adaptive Radio, and Software Defined Radio. [Online]. Available: http://grouper.ieee.org/groups/emc/emc/ieee_emcs_-_sdcom/P1900-1/IEEE%20P1900-1%20Draft%20-%20Current.doc

[18] SDR Forum, Cognitive Radio Work Group. [Online]. Available: http://www.sdrforum.org/pages/aboutTheForum/currentProjects.asp

[19] IEEE Std. 802.22 Working Group on Wireless Regional Area Networks. [Online]. Available: http://www.ieee802.org/22/

[20] AAAI, Artificial Intelligence Topics. [Online]. Available: http://www.aaai.org/AITopics/pmwiki/pmwiki.php/AITopics/HomePage

[21] S. Haykin, *Neural Networks: A Comprehensive Foundation*. Upper Saddle River, NJ: Prentice-Hall, 1999.

[22] A. Fehske, J. Gaeddert, and J. H. Reed, "A new approach to signal classification using spectral correlation and neural networks," in *Proc. 1st IEEE Int. Symp. New Frontiers DySPAN*, Baltimore, MD, Nov. 8–11, 2005, pp. 144–150.

[23] A. F. Cattoni, M. Ottonello, M. Raffetto, and C. S. Regazzoni, "Neural networks mode classification based on frequency distribution features," in *Proc. 2nd Int. Conf. CrownCom*, Orlando, FL, Aug. 1–3, 2007, pp. 251–257.

[24] X.-L. Zhu, Y.-A. Liu, W.-W. Weng, and D.-M. Yuan, "Channel sensing algorithm based on neural networks for cognitive wireless mesh networks," in *Proc. 4th Int. Conf. WiCOM*, Dalian, China, Oct. 12–14, 2008, pp. 1–4.

[25] J. H. Reed *et al.*, "Development of a Cognitive Engine and Analysis of WRAN Cognitive Radio Algorithms—Phase I," Wireless @ Virginia Tech, Virginia Polytech. Inst. State Univ., Blacksburg, VA, Dec. 2005.

[26] M. Hasegawa, T. Ha Nguyen, G. Miyamoto, Y. Murata, and S. Kato, "Distributed optimization based on neurodynamics for cognitive wireless clouds," in *Proc. IEEE 18th Int. Symp. PIMRC*, Athens, Greece, Sep. 3–7, 2007, pp. 1–5.

[27] Z. Zhang and X. Xie, "Intelligent cognitive radio: Research on learning and evaluation of CR based on neural network," in *Proc. ITI 5th ICICT*, Dhaka, Bangladesh, Dec. 16–18, 2007, pp. 33–37.

[28] Wireless @ Virginia Tech, OSSIE: Open Source SCA Implementation—Embedded. [Online]. Available: http://ossie.wireless.vt.edu/trac/wiki

[29] C. R. A. Gonzalez, C. B. Dietrich, F. E. Kragh, S. Sayed, H. I. Volos, J. D. Gaeddert, P. M. Robert, and J. H. Reed, "Open-source SCA-based core framework and rapid development tools enable software-defined radio education and research," *IEEE Commun. Mag.*, vol. 47, no. 10, pp. 48–55, Oct. 2009.

[30] N. Baldo and M. Zorzi, "Learning and adaptation in cognitive radios using neural networks," in *Proc. 5th IEEE CCNC*, Las Vegas, NV, Jan. 10–12, 2008, pp. 998–1003.

[31] B. Ustundag and O. Orcay, "Pattern based encoding for cognitive communication," in *Proc. 3rd Int. Conf. CrownCom*, Singapore, May 15–17, 2008, pp. 1–6.

[32] O. Orcay and B. Ustundag, "Pattern recognition in cognitive communication," in *Proc. 23rd ISCIS*, Istanbul, Turkey, Oct. 27–29, 2008, pp. 1–6.

[33] C. Blum and A. Roli, "Metaheuristics in combinatorial optimization: Overview and conceptual comparison," *ACM Comput. Surv.*, vol. 35, no. 3, pp. 268–308, Sep. 2003.

[34] F. Glover, "Future paths for integer programming and links to artificial intelligence," *Comput. Oper. Res.*, vol. 13, no. 5, pp. 533–549, May 1986.

[35] H. Robbins and S. Monro, "A stochastic approximation method," *Ann. Math. Stat.*, vol. 22, no. 3, pp. 400–407, 1951.

[36] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Reading, MA: Addison-Wesley, 1989.

[37] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," *Science*, vol. 220, no. 4598, pp. 671–680, May 1983.

[38] F. W. Glover and M. Laguna, *Tabu Search*. Boston, MA: Kluwer, 1997.

[39] M. Dorigo and C. Blum, "Ant colony optimization theory: A survey," *Theor. Comput. Sci.*, vol. 344, no. 2/3, pp. 243–278, Nov. 2005.

[40] T. R. Newman, B. A. Barker, A. M. Wyglinski, A. Agah, J. B. Evans, and G. J. Minden, "Cognitive engine implementation for wireless multicarrier transceivers," *Wireless Commun. Mobile Comput.*, vol. 7, no. 9, pp. 1129–1142, Nov. 2007.

[41] J. F. Hauris, "Genetic algorithm optimization in a cognitive radio for autonomous vehicle communications," in *Proc. Int. Symp. CIRA*, Jacksonville, FL, Jun. 20–23, 2007, pp. 427–431.

[42] S. K. Park, Y. Shin, and W. C. Lee, "Goal-Pareto based NSGA for optimal reconfiguration of cognitive radio systems," in *Proc. 2nd Int. Conf. CrownCom*, Orlando, FL, Aug. 1–3, 2007, pp. 147–153.

[43] D. Thilakawardana and K. Moessner, "A genetic approach to cell-by-cell dynamic spectrum allocation for optimising spectral efficiency in wireless mobile systems," in *Proc. 2nd Int. Conf. CrownCom*, Orlando, FL, Aug. 1–3, 2007, pp. 367–372.

[44] J. M. Kim, S. H. Sohn, N. Han, G. Zheng, Y. M. Kim, and J. K. Lee, "Cognitive radio software testbed using dual optimization in genetic algorithm," in *Proc. 3rd Int. Conf. CrownCom*, Singapore, May 15–17, 2008, pp. 1–6.

[45] Z. Zhang and X. Xie, "Application research of evolution in cognitive radio based on GA," in *Proc. 3rd ICIEA*, Singapore, Jun. 3–5, 2008, pp. 1575–1579.

[46] Y. Liu, H. Jiang, and Y. Q. Huang, "Design of cognitive radio wireless parameters based on multi-objective immune genetic algorithm," in *Proc. WRI Int. Conf. CMC*, Kunming, China, Jan. 6–8, 2009, pp. 92–96.

[47] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proc. IEEE*, vol. 77, no. 2, pp. 257–286, Feb. 1989.

[48] T. W. Rondeau, C. J. Rieser, T. M. Gallagher, and C. W. Bostian, "Online modeling of wireless channels with hidden Markov models and channel impulse responses for cognitive radios," in *Proc. IEEE MTT-S Int. Microw. Symp. Dig.*, Fort Worth, TX, Jun. 6–11, 2004, pp. 739–742.

[49] K. Kim, I. A. Akbar, K. K. Bae, J.-s. Urn, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," in *Proc. 2nd IEEE Int. Symp. New Frontiers DySPAN*, Dublin, Ireland, Apr. 17–20, 2007, pp. 212–215.

[50] C. Ghosh, C. Cordeiro, D. P. Agrawal, and M. B. Rao, "Markov chain existence and hidden Markov models in spectrum sensing," in *Proc. IEEE Int. Conf. PerCom*, Galveston, TX, Mar. 9–13, 2009, pp. 1–6.

[51] I. A. Akbar and W. H. Tranter, "Dynamic spectrum allocation in cognitive radio using hidden Markov models: Poisson distributed case," in *Proc. IEEE SoutheastCon*, Richmond, VA, Mar. 22–25, 2007, pp. 196–201.

[52] C.-H. Park, S.-W. Kim, S.-M. Lim, and M.-S. Song, "HMM based channel status predictor for cognitive radio," in *Proc. APMC*, Bangkok, Thailand, Dec. 11–14, 2007, pp. 1–4.

[53] J. Paine, Expert systems. [Online]. Available: http://www.j-paine.org/students/lectures/lect3/lect3.html

[54] J. H. Reed *et al.*, "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms—Phase II," Wireless @ Virginia Tech, Virginia Polytech. Inst. State Univ., Blacksburg, VA, Dec. 2006.

[55] Y. Zhao, J. Gaeddert, L. Morales, K. Bae, J.-S. Um, and J. H. Reed, "Development of radio environment map enabled case- and knowledge-based learning algorithms for IEEE 802.22 WRAN cognitive engines," in *Proc. 2nd Int. Conf. CrownCom*, Orlando, FL, Aug. 1–3, 2007, pp. 44–49.

[56] C. Clancy, J. Hecker, E. Stuntebeck, and T. O'Shea, "Applications of machine learning to cognitive radio networks," *IEEE Wireless Commun.*, vol. 14, no. 4, pp. 47–52, Aug. 2007.

[57] T. Weingart, D. C. Sicker, and D. Grunwald, "A statistical method for reconfiguration of cognitive radios," *IEEE Wireless Commun.*, vol. 14, no. 4, pp. 34–40, Aug. 2007.

[58] T. R. Gruber, "Toward principles for the design of ontologies used for knowledge sharing," *Int. J. Human-Comput. Stud.*, vol. 43, no. 5/6, pp. 907–928, Nov./Dec. 1995.

[59] N. Guarino, "Formal ontology in information systems," in *Proc. FOIS*, Trento, Italy, Jun. 6–8, 1998, pp. 3–15.

[60] XTM, XML Topic Maps (XTM) 1.0. [Online]. Available: http://www.topicmaps.org/xtm/
[61] W3C, Resource Description Framework. [Online]. Available: http://www.w3.org/RDF/
[62] W3C, OWL Web Ontology Language Overview. [Online]. Available: http://www.w3.org/TR/owl-features/
[63] W3C, W3C Semantic Web Activity. [Online]. Available: http://www.w3.org/2001/sw/
[64] BBN Technol., XG Policy Language Framework - Request for Comments, Apr. 2004. [Online]. Available: http://www.autonomic-communication.org/web/bodies/DARPA_XG_rfc_policylang.pdf
[65] M. M. Kokar and L. Lechowicz, "Language issues for cognitive radio," *IEEE J. Sel. Areas Commun.*, vol. 97, no. 4, pp. 689–707, Apr. 2009.
[66] J. Wang, M. M. Kokar, K. Baclawski, and D. Brady, "Achieving self-awareness of SDR nodes through ontology-based reasoning and reflection," in *Proc. Tech. Conf. Product Expo. SDR*, Phoenix, AZ, Nov. 15–18, 2004.
[67] J. D. Poston, W. D. Horne, M. G. Taylor, and F. Z. Zhu, "Ontology-based reasoning for context-aware radios: insights and findings from prototype development," in *Proc. 1st IEEE Int. Symp. New Frontiers DySPAN*, Baltimore, MD, Nov. 8–11, 2005, pp. 634–637.
[68] A. Ginsberg, J. D. Poston, and W. D. Horne, "Toward a cognitive radio architecture: Integrating knowledge representation with software defined radio technologies," in *Proc. MILCOM*, Washington, DC, Oct. 23–25, 2006, pp. 1–7.
[69] J. L. Kolodner and D. Leake, "A tutorial introduction to case-based reasoning," in *Case-Based Reasoning: Experiences, Lessons and Future Directions*. Cambridge, MA: MIT Press, 1996, pp. 31–65.
[70] J. H. Reed *et al.*, "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms—Phase III," Wireless @ Virginia Tech, Virginia Polytech. Inst. State Univ., Blacksburg, VA, Dec. 2007.
[71] A. He, J. Gaeddert, K. Bae, T. R. Newman, J. H. Reed, L. Morales, and C. Park, "Development of a case-based reasoning cognitive engine for IEEE 802.22 WRAN applications," *ACM Mobile Comput. Commun. Rev.*, vol. 13, no. 2, pp. 37–48, Apr. 2009.
[72] M. Khedr and H. Shatila, "Cogmax—A cognitive radio approach for WiMAX systems," in *Proc. IEEE AICCSA*, Rabat, Morocco, May 10–13, 2009, pp. 550–554.
[73] B. Le, T. W. Rondeau, and C. W. Bostian, "Cognitive radio realities," *Wireless Commun. Mobile Comput.*, vol. 7, no. 9, pp. 1037–1048, Nov. 2007.
[74] T. M. Mitchell, *Machine Learning*. New York: McGraw-Hill, 1997.
[75] G. Hardin, "The tragedy of the commons," *Science*, vol. 162, no. 3859, pp. 21 243–21 248, Dec. 1968.
[76] J. Neel, "Analysis and design of cognitive radio and distributed radio resource management algorithms," Ph.D. dissertation, Virginia Polytech. Inst. State Univ., Blacksburg, VA, Sep. 2006.
[77] J. Neel, R. Buehrer, J. Reed, and R. Gilles, "Game theoretic analysis of a network of cognitive radios," in *Proc. 45th IEEE Int. MWSCAS*, Stillwater, OK, Aug. 4–7, 2002, pp. 409–412.
[78] E. Altman and Z. Altman, "S-modular games and power control in wireless networks," *IEEE Trans. Autom. Control*, vol. 48, no. 5, pp. 839–842, May 2003.
[79] Y. Zeng and Z. Zhang, "Joint transmit beamforming and power control in multi-user mimo downlink using a game theoretic approach," *J. China Univ. Posts Telecommun.*, vol. 14, no. 2, pp. 14–18, Jun. 2007.
[80] V. Srivastava and L. DaSilva, "Game theoretic analysis of a network of cognitive radios," in *Proc. IEEE ICC*, Istanbul, Turkey, Jun. 11–15, 2006, pp. 3850–3855.
[81] J. Huang, Z. Han, M. Chiang, and H. V. Poor, "Auction-based distributed resource allocation for cooperation transmission in wireless networks," in *Proc. IEEE GLOBECOM*, Washington, DC, Nov. 26–30, 2007, pp. 4807–4812.
[82] T. Roughgarden, "Routing games," in *Algorithmic Game Theory*. Cambridge, U.K.: Cambridge Univ. Press, 2007, pp. 31–65.
[83] R. G. R. Komali and A. MacKenzie, "Effect of selfish node behavior on efficient topology design," *IEEE Trans. Mobile Comput.*, vol. 7, no. 9, pp. 1057–1070, Sep. 2008.
[84] M. van der Schaar and F. Fu, "Spectrum access games and strategic learning in cognitive radio networks for delay-critical applications," *Proc. IEEE*, vol. 97, no. 4, pp. 720–740, Apr. 2009.
[85] Y. Zhao, S. Mao, J. O. Neel, and J. H. Reed, "Performance evaluation of cognitive radios: Metrics, utility functions, and methodology," *Proc. IEEE*, vol. 97, no. 4, pp. 642–659, Apr. 2009.

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