Application of Artificial Intelligence to Wireless Communications

Abstract

The paper sketches the overall theory, design, and implementation of a cognitive engine and the enabling technology of cognitive radio. The cognitive engine presented here provides a general framework to build and test cognitive engine algorithms and components such as sensing technology, optimization routines, and learning algorithms. The cognitive engine platform allows easy development of new components and algorithms to enhance the cognitive radio capabilities. The paper includes discussions of both theory and implementation of the cognitive engine. The need for and implementation of all of the cognitive components is strongly featured as well as the specific issues related to the development of algorithms for cognitive radio behavior. The theoretical work also investigates the use of learning to enhance the cognitive engine's capabilities through feed-back, learning, and knowledge representation.

Keywords: cognitive radio, wireless communications, artificial intelligence, genetic algorithms

1.Introduction:

1.1 Cognitive Radio:

A cognitive radio is a wireless communications device capable of sensing the environment and making decisions on how to use the available radio resources to enable communications with a certain quality of service. The definition of cognitive radio has been under debate since its introduction. In particular, much of the early work in cognitive radio deals with the concept of DSA, that is, dynamically selecting frequency channels to enable spectrum sharing and reuse. While this is one of the applications of cognitive radio, it is certainly not the only one. The other aspects of cognitive radio develop more of a service-oriented view of communications whereby the entire communications system is adapted to offer better quality of service. The service model extends beyond the DSA model by looking at the system performance and not just the slice of spectrum allocated.

1.2. Cognitive Engine:

The cognitive engine, the intelligent system behind the cognitive radio, combines sensing, learning, and optimization algorithms to control and adapt the radio system from the physical layer and up the communication stack. The cognitive engine presented here provides a general framework to build and test cognitive engine algorithms and components such as sensing technology, optimization routines, and learning algorithms. The cognitive engine platform allows easy development of new components and algorithms to enhance the cognitive radio capabilities.

2 .Literature Survey:

2.1 Cognitive Engine:

The cognitive engine (CE) design serves two simultaneous objectives:

1. Develop and apply cognitive radio algorithms
2. Deploy cognitive radio functionality

A cognitive radio is a flexible and intelligent radio capable of creating any waveform and using any protocol supported by the radio hardware and software. Waveforms consist of all of the parameters that define the way in which the radio transmits and receives information, including transmitter power, operating frequency, modulation, pulse shape, symbol rate, coding, etc. Protocols are the rules by which network nodes transfer information. A cognitive radio develops waveforms and chooses protocols in real-time using artificial intelligence. These actions require three components:

1. Perception: Sensors that collect data on both external factors (channel conditions, other radios, regulations, user needs) and internal factors (waveform capabilities, available computational power, remaining battery power).
2. Conception: An intelligent core that learns and understands how to combine knowledge from the sensing mechanism to aid the adaptation mechanism.
3. Execution: An optimization and adaptation mechanism that alters the radio's behavior.

The cognitive engine is a separate system within the total solution, which relies on information from the user, radio, and policy domains for instructions on how to best control the communication system. This structure works well as a generalized architecture as it makes no recommendations about how the cognitive engine (and therefore the rest of the cognitive radio) should behave while still mapping the interactions of the rest of the systems. The communications system itself is shown as a simplified protocol stack, again showing the independence of the cognitive engine from the overall system. There are three input domains that concern the cognitive radio:

1. User Domain: The user domain tells the cognitive engine performance requirements of services and applications. Service and application requirements are related to the quality of service measures of a communications system. As each application requires different QoS

concepts like speed and latency, this domain sets the performance goals of the radio.

2. The external environment and RF channel provide environmental context to the radio's transmission and reception behavior. Different propagation environments cause changes in performance of waveforms and optimal receiver architectures. A heavy multipath environment requires a more complex receiver than simple line of sight only or log-normal models. The external radio environment also plays a significant role in performance and adaptation. This environmental information helps provide optimization boundaries on the decision making and waveform development.
3. Policy Domain: The policy domain restricts the system to work within the boundaries and limitations set by the regulatory bodies as interpreted by the policy engine. The policy environment might determine a maximum amount of power a radio can use in a given spectrum or other spectrum rights as compared with other users.

It includes a central component called the Cognitive Controller that acts as the system kernel and scheduler to handle the input/output and timing of the other attached components. The other major components include:

- **Sensors:** collect radio/environmental data
- **Optimizer:** given an objective and environment, create an optimized waveform
- **Decision Maker:** coordinate information and decide on how to optimize and act
- **Policy Engine:** enforce regulatory restrictions
- **Radio Framework:** communicate with the radio platform to enable new waveforms and pull information for the sensors
- **User Interface:** provide control and monitor support to the cognitive engine

Each component is launched as a separate process that interfaces and exchanges data between processes through some generic interface (i.e., sockets).

The architecture is designed around two important aspects. First, it allows development, testing, and launching of each component separately for low coupling between processes. This aspect also enables distributed processing, where different components can reside on different processors or hosts with little change in behavior. Second, this architecture enables the testing of different types of algorithms and processes to realize different components. Many different sensors may be defined for different purposes by different people and easily fit into the system, or different optimization functions may be developed and compared. Through this architecture, both research and development are encouraged.

2.2 Artificial Intelligence:

Successful cognitive radios are aware, can learn, and can take action for any situation that might arise. Applications range from voice communications under low power conditions, communications in high interference zones, to more complex, critical, and hostile military networks of interoperating vehicles and soldiers with many different network needs. A radio must respond to any of these scenarios and adapt its many different parameters that define the radio's waveform and protocols. These radios do not just require learning; instead, they need highly sophisticated learning and decision making capabilities. Successful applications of AI are often limited to narrowly defined, well bounded applications. While waveform adaptation is a bounded problem, the technical demands for intelligence in a radio exceed those normally associated with successful applications of classic artificial intelligence techniques such as expert systems or neural networks. Waveform optimization requires stronger reasoning capabilities and the potential to create and test new design solutions.

Information and knowledge are both important concepts for a cognitive radio. Information is data of the environment collected through the available sensors. Information can include such items as position, interference, battery life, or performance analysis. The information collected from the sensors feeds both the learning and the optimization routines to help them make decisions. Knowledge is a concept developed from information. Knowledge is a useful representation of the information that says something about what the information means. The sensors might provide the cognitive radio with time and position information, but the radio needs to know what that information might mean about potential use patterns and known problems, such as areas of outage or high interference during a daily commute.

More information is good, but only if the cognitive engine can transform the information into usable knowledge. Some sensors might provide a lot of information such as ambient temperature, but if the models used to make decisions do not use that information, the sensor adds no useful knowledge to the system. On the other hand, sophisticated sensors that provide information about interference power over a wide bandwidth can find immediate use by a cognitive radio seeking access to a particular amount of spectrum.

3. Methodology

3.1 Artificial Intelligence:

The next few sections highlight different artificial intelligence techniques that use information to make knowledgeable decisions in the cognitive radio.

3.1.1 Neural Networks

Neural networks are among the oldest form of AI in computer science, starting with the mathematical formulation by McCulloch and Pitts **[21].** They have come and gone as a fad over the decades, but recent advances, both hardware and software, enable their use in more applications. Of particular importance to cognitive radios, neural networks provide a means for signal and modulation detection and classification.

The use of neural networks in modulation classification has since become as well-accepted technique using both time-based statistics **[22]** and frequency analysis **[23]** inputs.

Neural networks are really just glorified signal processing elements that perform simple operations on data. However, the collection of artificial neurons and clever learning algorithms allow networks to build and adapt to represent and process data in interesting ways. In signal classification, they take multiple noisy input items and provide highly accurate (when built correctly) answers to the type of modulation represented.

3.1.2 Hidden Markov Models (HMM)

In some circles, Hidden Markov Models (HMM) **[25]** might be considered artificial intelligence, though I certainly would not categorize them as such. A HMM is a processing tool that uses past data to help predict future actions.

Channel modeling has extensively used Markov models in research. Probably the most famous is the two-state Gilbert-Elliot model **[26]** that describes a channel as in either a good state or bad. When in one state, there is a probability of either staying in that state or moving to the other state. The channel properties determine the type of transition probabilities. Researchers have developed other, more extensive models, and **[27]** provides a good comprehensive overview of these.

The idea of developing such a model lends itself to cognitive radios. The idea was to use the HMMs as a sensor to understand the channel behavior in a cognitive engine, though the research was not taken much farther in this direction.

3.1.3 Fuzzy Logic

Fuzzy logic is a famous technique that started during the early development of artificial intelligence [**31, 32**]. Because it deals extensively with uncertainty in decision making and analysis, it has great potential for application to cognitive radio. However, only a little work has so far been published in the field, notably by Baldo and

Zorzi **[33].** Their implementation suggests some interesting applications, and the discussion points out larger uses than the specific application of adapting the TCP layer used in the paper. A problematic aspect of this work is the amount of domain-specific rules required. All implementations of AI require domain information, but fuzzy logic must establish a rule related to the specific situation in which it is used and recalls some of the limitations of expert systems, though still far more flexible and powerful. Fuzzy logic has potential in either specific problem solving areas or as a subset or part of a cognitive radio.

3.1.4 Evolutionary Algorithms

The basic principles, as discussed throughout, are that the large search space involved in optimizing a radio are more complex than many search and optimization algorithms can handle. Among those algorithms that are suited to the task, evolutionary, specifically genetic, algorithms offer a significant amount of power and flexibility. Cognitive radios are likely to face dynamic environments and situations as well as radio upgrades due to advancing technology, so genetic algorithms are particularly applicable.

Since then, Newman, *et al.* **[39]** have also contributed significantly to the use of genetic algorithms for cognitive radios. Newman's work has developed a single, linear objective function to combine the objectives of BER minimization, power minimization, and throughput maximization.

3.1.5 Case-Based Reasoning

The final traditional AI technique to discuss here is case-based reasoning (CBR) **[41].** CBR systems use past knowledge to learn and improve future actions. In these systems, a case-base stores actions and receives inputs from a sensor. Those inputs help find the action in the case-base that best fits the information received by the sensor. As mentioned previously, an optimization routine could, instead of designing a new waveform, select a waveform from a pre-defined list. CBR is a method used to make the associations. Although this may sound like an expert system, CBR systems generally provide learning and feedback to continuously and autonomously improve their performance. As information is received and actions taken, the results can help the system improve its response the next time.

Another contribution from **[39]** develops a similar idea in the experiments they run using previous knowledge to seed the next run of the genetic algorithm. The cognitive radio remembers solutions found for one particular problem to apply to the next problem to initialize the population with known successful chromosomes. The population seeding in **[39]** resembles the case-based decision theory work. Their seeding concept uses a factor to calculate the expected change in the environment between runs of the genetic algorithm to provide context for how successful a new chromosome might be with respect to the new environment.

3.2 Genetic Algorithms for radio optimization:

In their most simplistic form, genetic algorithms (GA) are single-objective search and optimization algorithms. Common to all GAs is the chromosome definition: how the data are represented; the genetic operations of crossover and mutation; the selection mechanism for choosing the chromosomes that will survive from generation to generation; and the evaluation function used to determine the fitness of a chromosome. All of these operations are described in **[34].**

A genetic algorithm encodes a set of input parameters that represent possible solutions into a chromosome. The evaluation stage develops a ranking metric of chromosome fitness for each individual, which then determines their survival to the next generation. Optimization progresses through finding genes that provide higher fitness for the chromosome in which it is found. The fitness calculation is often done through some absolute metric such as cost, weight, or value by which the algorithm can rank the success of an individual. Selection is the technique by which more fit individuals are selected for survival to reproduce for the next generation while less fit chromosomes are killed off. An algorithm terminates when it reaches a desired level of fitness in the population, a single member exceeds a desired fitness, the fitness plateaus for a certain number of generations, or through a simple criteria based on a maximum number of generations. The algorithm then takes the most fit individual of the last generation as the solution.

3.2.1 Wireless System Genetic Algorithm

The wireless system genetic algorithm (WSGA) is a MOGA designed to optimize a waveform by modeling the physical radio system as a biological organism and optimizing its performance through genetic and evolutionary processes. In the WSGA, radio behavior is interpreted as a set of PHY-layer parameters as traits or genes of a chromosome. Other general radio functional parameters (such as antenna configuration, voice coding, encryption, equalization, retransmission requests, and spreading technique/code) are also identified as possible chromosome genes for future growth as the SDR platforms develop to support each of these traits. Expansion of PHY-layer parameters is a horizontal growth while the MOGA method can also extend vertically to higher layers such as the MAC or network layer. Extension to the higher layers will require proper understanding of the objective function analysis of these layers, the genetic representation of the adjustable parameters, and the available communications platform capable of reconfiguration in the layers.

The WSGA uses a Pareto ranking selection method similar to**,** but with a few adjustments. First, the WSGA awards points for every objective an individual wins. By doing this, the algorithm has a bit more granularity in how it ranks individuals, especially when two objectives are directly competing, such as BER and power. With these two objectives, the only way to improve or dominate another solution is through a change in the modulation since power and BER are direct trade-offs, so inferiority does not properly allow these objectives to be compared. Second, the WSGA ranks members by the number of members the individual dominates in each objective to make a maximization problem (whereas Fonseca and Fleming rank the individuals by how many members dominate them and thus perform a minimization problem).

Crossover and mutation are simple implementations of these mechanisms. The WSGA uses one crossover point chosen as uniform random numbers with a static probability of crossover occurring. Mutation is also a single point operation chosen from a uniform random number with a static probability of crossover occurring. Future enhancements to the WSGA can include adaptive adjustment of crossover and mutation probabilities as well as the population size during the optimization process for higher convergence efficiency and accuracy.

The WSGA provides a waveform optimized to a single radio node. For the new waveform to be of any use, all other nodes on the network must also use the new waveform.

3.3 Decision Making with Case Based Learning:

Decision making is a complex part of the cognitive radio design. A cognitive radio uses environmental and behavioral information about a radio performance or user requirements to make decisions on how to adapt. Decisions can include what parameters to adapt, if adaptation is required, or even the method by which to adapt.

3.3.1 Case-Based Decision Theory

The decision making theory is largely derived from the case-based decision theory (CBDT) work of Gilboa and Schmeidler [14]. CBDT uses past knowledge to make decisions about future actions. Case-based decision theory is closely related to CBR **[41],** and to avoid arguing semantics between the two techniques, I like to think of this generically as case-based learning.

Formally, case-based learning defines a set of problems $q \in P$, a set of actions $a \in A$, and a set of results $r \in R$. A case, c, is a tuple of a problem, an action, and a result such that $c \in C$ where $C = P \times A \times R$. Furthermore, memory, M, is formally defined as a set of cases c currently known such that $M \subseteq C$.

When the environment or user's needs change as observed by a sensor, the new information is modeled as a new problem, p. The sensors could indicate a change in the interference environment, a new propagation channel, or a change in the application of the radio requiring different QoS needs. The cognitive engine must then determine the action, a, to take in response. The case-base system analyzes the new problem against past cases in memory to determine the similarities between the new problem and past problems as well as the utility of the past actions. Utility refers to how successful an action was at responding the problem. The action defined by the current cognitive engine is the waveform to use in the current situation. As the cognitive engine processes and learns, it populates the knowledge base with more cases and actions that better reflect the environment to help make better choices. This technique is similar to an expert system that learns autonomously.

A similarity function defines how similar two cases are and is represented by equation 3.1. The similarity function is any function that provides some measure of how close two problems are to each other where 0 represents no similarity while 1 represents a perfect match.

$$s : P \times P \rightarrow [0,1] \quad (3.1)$$

The utility analysis of the past cases is represented in equation 3.2, which is any function that produces some real-valued result measuring the utility of the action.

$$u : R \rightarrow < \quad (3.2)$$

Case analysis comes down to which case is both most similar to the new problem as well as how successful the action was in the past. The decision maker then uses a final decision function to decide which case to use. The simplest implementation is a similarity-weighted decision function as shown in equation 3.3. A particular case may be very similar but might have performed poorly in the past, so a less similar but better performing case is selected instead.

$$U(a) = s(p,q)u(r) \text{ where } \quad (q,a,r) \in M \quad (3.3)$$

This equation is only one decision function used to make the decision. The challenge of this technique is to create effective similarity, utility, and decision functions that best represent the types of information received through the sensors.

3.4 Cognitive Engine Architecture with CBDT

The cognitive engine uses case-based decision theory to augment the optimization process. Instead of relying on pure optimization alone, the case-base helps prime and direct the optimization with learned experience. Likewise, instead of basing all decisions on past actions from the case-base, the optimization process allows on-line learning to build knowledge. The case-base and optimization routines work together to enable learning and adaptation in the cognitive engine.

The case-base holds past cases, actions, and results of the actions. In the cognitive radio, the case represents some model of the environment, such as a sequence of meter readings or an interference map. The action for a given case is in the form of the waveform created to meet the case's needs. The results, then, are a measurement of how well the action performed.

To develop the performance measurements, the cognitive engine uses the results of the optimization process and analyzes how closely those results match to the actual performance of the radio. The optimization process develops the waveform based on a set of mathematical models in the form of objective functions. The results of the objective functions are calculated performance measures of the waveform. When the waveform is then used in the environment, the resulting performance may differ from the calculated performance. This difference relates to the utility of the waveform.

3.5 Cognitive Radio Networking and Rendezvous

A final challenge to enable the cognitive radio system's basic functionality is the ability to transmit the cognitive engine's information and solutions among the nodes operating on the network. A farther enhancement to the cognitive radio design is not only to distribute the waveform information, but also the use of the network nodes to enhance the optimization process. Each cognitive radio in a network has the ability to cooperatively optimize through the use of distributed and parallel processing. I end this chapter by addressing some of the very basics of these techniques with respect to enhancing the genetic algorithm.

3.5.1 Waveform Distribution and Rendezvous

The simplest approach to enabling communications among cognitive radio nodes is through a static control channel. When one radio develops a new waveform for the network to use, the conditions of the channel might allow for continued communications where the new waveform represents an enhancement to the current communications capabilities. Under this condition, the radio can simply pass the new waveform to the radio nodes using the current channel. This method is a form of *in-band signaling* and can use a different logical control channel over the same physical channel to send configuration information. This type of control information is commonly used in home networking systems like IEEE 802.11, where connection and configuration data use the same frequency channel but a simpler, more robust modulation scheme.

On the other hand, *out-of-band signaling* uses a separate physical channel to communicate control information, a concept commonly used in cellular communications systems. The control channel is defined to use simple, robust waveforms on which all nodes are capable of communicating. In the worst case, if the cognitive radio nodes loose communications, they can revert to the control channel and wait for the new waveform information and then reestablish communications. The use of a control channel is also used to begin communications when a node wants to join a network that might be using any waveform or any frequency. The control channel allows the new node a way to communicate with the network and initialize communications. This concept is often referred to as *rendezvous*: the method by which a radio hails and enters a network.

Static control channels, while easily implemented, are problematic because they are easily jammed and rendered useless. More innovative ideas involve dynamic control channels, which still require coordination among the nodes to determine where the control channel is. A few proposals have been shown recently that remove the control channel from the rendezvous model and instead use physical layer descriptors to identify radios and enable rendezvous. Sutton, *et al.* shows the use of embedded cyclostationary signatures in OFDM-based systems that can identify a network and coordinate access. Because the signature is embedded in each OFDM symbol transmitted, the system does not need to transmit particular frames or switch channels to enable the network identification and coordination. Horine proposes a technique to search for clear channels, transmit a beaconing signal, and wait for a response while other radios scan for the particular beacon. The beacon is shaped in frequency to identify the node or network. Unfortunately, since the detection is based on FFT amplitude, there is no offered explanation of how the approach will work in multipath or fading channels.

3.5.2 Cognitive Radio Networks

The static control channel and push method used in the cognitive engine implementation are used currently for lack of a better solution. This method also ignores the possibility that a waveform created by one radio does not work for another radio. In a heterogeneous network, some nodes may be incapable of using the particular waveform. Even if all nodes are capable of using the specified waveform, other aspects of the waveform may perform badly for certain nodes. For example, a hidden node to the cognitive radio designing the waveform might be in close proximity to another node on the network. The new waveform is good for the designing node cases interference to the other nodes.

Research in cognitive networks, such as the work by Thomas, *et al.* [**96, 97**], attempts to address this issue by looking at the end-to-end performance. From this perspective, the cognitive network uses objective functions that optimize with respect to the network performance. In [**96**], they use a game theory approach to optimize an ad hoc network with respect to power and channel control. Game theory has been widely studied for wireless network optimization to look for optimal states for all nodes, or a *Nash equilibrium*. Neel provides an extensive discussion and analysis of game theory for cognitive radio [**98**].

3.5.3 Distributed AI

Another benefit from looking at the whole network instead of the single node adaptation is to take advantage of the available processing power capabilities of each node. Parallel processing has often been used advantageously in computer science, and with the move towards multicore processors, it is likely a subject that will continue to receive attention. Some algorithms have shown themselves to be easily separable for processing portions on different processors, and genetic algorithms are among these.

When applying a parallel genetic algorithm to an on-line learning system such as a cognitive radio, however, there are many questions that need to be addressed. The parallel GA's have some form of migration, or sharing, of population members to perform the global analysis of the results to find a solution. The implementation of the migration should be designed to consider network overhead required. Another issue is that cognitive radio networks these are dynamic where nodes can come and go at random. Most parallel GA's are studied under the assumption that the network of processing elements was established for this task. Instead, a parallel GA in a cognitive radio network performs the parallelization as a secondary process of the communications network. The algorithm must be implemented with respect to the dynamics of the networks and robust against the loss of processing nodes. Distributed AI offers significant potential to improve the global solutions and reduce the time and power required by any individual node, but these are some of the issues around which such a distributed system must be implemented.

4.Conclusions:

The paper presented an analysis and implementation of a cognitive engine, the enabling technology of cognitive radio. It presented a brief but important treatment of using the cognitive engine as part of a network of cognitive radios and some considerations for what information can be distributed to all nodes on a network. Through the development of the distributed cognitive engine, it provided a system that can be extended, enhanced, and made useable for future applications and radio systems.

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