Cognitive Engine Implementation for Wireless Multicarrier Transceivers

Tim R. Newman, Brett A. Barker, Alexander M. Wyglinski, Arvin Agah, Joseph B. Evans, and Gary J. Minden

Information and Telecommunication Technology Center

The University of Kansas, Lawrence, KS 66045

Email: newman@ittc.ku.edu

Abstract

This paper presents a genetic-algorithm driven, cognitive radio decision engine that determines the optimal radio transmission parameters for single and multicarrier systems. Determining the appropriate radio parameters given a dynamic wireless channel environment is the primary feature of cognitive radios for wireless communication systems. Genetic algorithms (GA) are designed to select the optimal transmission parameters by scoring a subset of parameters and evolving them until the optimal value is reached for a given goal. Although there have been implementations of GA-based single carrier cognitive radio engines, the performance of these algorithms has not been thoroughly analyzed nor have the fitness functions employed by the algorithms been explored in detail. Multicarrier systems are common in today's communication environment, thus cognitive techniques that account for only single carrier systems neglect the practical issues of multiple carriers. A set of accurate single carrier and multicarrier fitness functions for our GA implementation that completely control the evolution of the algorithm have been derived. The performance analysis results illustrate the trade-offs between the convergence time of the GA and the size of the GA search space.

Index Terms

Cognitive Radios, cognitive techniques, genetic algorithms, transceiver optimization, multicarrier modulation.

Manuscript submitted May 1, 2006. This work was supported by the National Science Foundation (NSF) through awards ANI-0230786 and ANI-0335272. This work is also supported by BBN Technologies, through the ADROIT project.

I. Introduction

Cognitive radio technology is receiving significant attention as an approach to alleviate the apparent scarcity of available radio spectrum [1]–[4]. Cognitive radios encompass all the reconfigurable attributes of a conventional software-defined radio (SDR) while possessing the ”intelligence” to automatically adapt operating parameters based on learning from previous events and current inputs to the system. The momentum of research efforts, due in part to the current spectrum scarcity problem, as well as a Department of Defense initiative [1] to develop a flexible software radio approach for war fighter communications, has yielded numerous initiatives and programs by researchers in academia [5] and industry [6]. The resulting plethora of cognitive radio solutions range from cognitive radio components and radio network testbeds [5] to complete radio systems [2].

Much current cognitive radio development is focused on providing dynamic spectrum access solutions [3], [4], [7], where unlicensed transmissions operate across licensed spectrum while not interfering with incumbent users. With current regulatory requirements based on assigning fixed allocations of spectrum to the highest bidding operators, and with the demand for additional transmission bandwidth increasing for both existing and new wireless applications, there exists an apparent shortage of spectrum for expansion [4]. Nevertheless, several measurement studies have shown that spectrum usage is sparse in both time and frequency [8]. Thus, dynamic spectrum access provides radios with the ability to detect the spectrum usage and determine what to do if the target frequency band is in use. The major technical issue is how to reliably determine if the target spectrum is occupied by an incumbent transmission or another unlicensed user [3], [7], [9]–[11].

Research done at Virginia Tech has also developed a genetic algorithm engine for cognitive radios [12], [13]. Their simulation results validate that their genetic algorithm implementation does in fact change the transmission parameters to different settings, based upon a set of objectives. The work presented in this paper goes beyond just demonstrating that the genetic algorithm outputs a selection, but also provides the numerical analysis of the relationships between the environmental parameters and the transmission parameters. We provide the derivation of the equations representing these relationships and use them as the fitness functions for the genetic algorithm. As we will also show in the following sections, the methods used to place importance factors on the various radio objectives are also different.

This paper focuses on the technical issues that exist once multiple radios are simultaneously communicating and channel problems become the source of communication errors, i.e., after spectrum assignments have been determined. Cognitive radios should not only be capable of adapting to the frequency spectrum being used around it, but also the channel conditions that could possibly prevent it from effectively communicating in the available bandwidth. This work focuses on the adaptation of radio parameters to the prevailing channel conditions for both single carrier and multicarrier systems. The traditional fine-grained adaptation of specific parameters, e.g., equalizer coefficients [14], power levels [15], modulation schemes [16], are common in today's radio systems. Cognitive radios go beyond this with more comprehensive techniques. In this context, autonomous radio parameter adaptation involves having an artificial intelligence (AI) system decide on the values of the radio parameters in order to create the intended communications environment. Therefore, the AI system constitutes the core controller for a cognitive radio system, and the selection process of an AI can substantially affect the performance of the system. Thus, it is important to understand the available AI methods and their suitability under various operating conditions.

This paper presents a genetic algorithm (GA) driven cognitive engine implementation for single carrier and multicarrier systems. Although there have been implementations of single carrier GA-based cognitive radio engines, the performance of these algorithms has not been thoroughly analyzed nor have the fitness functions employed by the algorithms [2] been explored in detail. We derive a set of fitness functions that guide the search direction of the GA to an optimal set of transmission parameters given a set of goals and the controllable transmission parameters. We then demonstrate the trade-off between the size of the search space and the convergence time of the GA to the optimal parameter set.

II. COGNITIVE RADIO PARAMETERS

In developing a cognitive radio control system, several inputs must be defined. The accuracy of the decisions made by an AI method is based upon the quality and quantity of inputs to the system. A primary feature of cognitive radios is the ability to adapt to the surrounding environment. This feature defines a critical input to the system - a representation of the environment. In order for the system to make decisions about a certain output, the current wireless environment

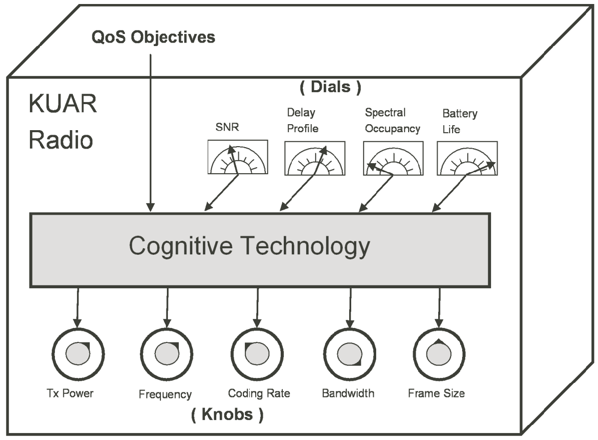

Fig. 1. Cognitive Radio Illustration

must be modeled internally. This model is created using environmentally-sensed data received by the system using an external sensor.

Several devices exist to detect characteristics of the wireless environment. The DARPA XG program has introduced hardware for sensing environment characteristics, including spectrum usage [10]. This information is useful if the radio is trying to maximize spectral efficiency. Other sensors may detect important characteristics such as, the current noise floor, or determine the bit-error-rate (BER) of the current running configuration. In the following sections, we will propose a list of environmentally-sensed parameters that will be used to aid in the decision making process of the cognitive controller.

Another important set of inputs to any AI method are the decision variables. In the cognitive radio case, these variables represent the transmission parameters that can be controlled by the system. Once the virtual channel environment is created, a set of decision variables are applied to the fitness function and an approximation of how well they meet a set of quality of service (QoS) goals is returned based upon the virtual environment. The end result is a quantification of how well a sample set of transmission parameters achieves the set of QoS goals. The AI can use this scalar approximation to evolve the system to an optimal set of transmission parameters. Fig. 1 depicts a cognitive radio and several example transmission parameters and environmentally sensed parameters represented as the ”‘knobs”’ and ”‘dials”’ of the radio.

In addition to the environmental data used to model the wireless channel and the transmission parameters, several objectives must also be determined to define how the system should operate. The objectives of the system are the road map for determining the fate of the system. They allow the controller to steer the system to a specific QoS state. This research defines three objectives that represent common wireless radio goals. Section II-C covers the selection process of these three objectives.

A. Decision Variables

Cognitive radios become possible when the components within the radio permit the modification of the control parameters. These control parameters are set by the cognitive component once an optimal decision has been formulated using the AI technology. Generating fitness functions to be used by evolutionary algorithms requires defining a specific list of decision parameters that must be available to the system. These decision parameters are equivalent to the control parameters made available by the software radio components. The term *decision variables* will be used in this paper to refer to the list of parameters that are used to control the individual radio components.

Defining a complete list of decision variables to generate a generic fitness function usable by all radios is not possible. Radios are developed independently, each possessing a unique list of parameters used to control them. A goal of this paper is to define a decision variable list large enough to guarantee that a majority of parameter sets for cognitive radios will include the set defined in this work.

The decision variables selected for this work are radio parameters that would commonly be adjusted on the order of several minutes to adapt to the channel environment. This work intentionally does not focus on parameters that change on the order of hours, such as transmission formats (e.g. OFDM or CDMA), encryption (e.g. WEP or PGP), or error control types (e.g. Turbo or convolutional coding). Restricting our focus to parameters that may change on a sub-second level, such as transmit power, does not provide enough flexibility when controlling a radio system. Thus, when defining our list, we make a compromise between the large time scale, system-level parameters and the small time scale, transmission-level parameters. The three parameters used as transmission parameters in this paper to generate a fitness function is shown in Table I.

TABLE I

TRANSMISSION PARAMETER LIST

Parameter Name	Symbol	Description
Transmit Power	P	Raw transmission power
Modulation Type	MT	Type of modulation
Modulation Index	M	Total number of symbols in a constellation

B. Environment Parameters

Environmental variables inform the system of the surrounding environment characteristics. These characteristics include: internal information acquired using sensors within the cognitive radio, and external information from local cognitive radios within the same network. Both types of information can be used to aide the cognitive controller in making decisions. These variables are primarily used as inputs to the fitness function. The complete list of environmental parameters used in this paper as inputs to the fitness function is shown in Table II.

TABLE II

ENVIRONMENTALLY SENSED PARAMETER LIST

Parameter Name	Symbol	Description
Bit-Error-Rate	BER	Percentage of bits that have errors relative to the total number of transmitted bits.
Signal-to-Noise Ratio	SNR	Ratio of the signal power to the noise power.
Noise Power	N	Magnitude in decibels of the noise power.

The BER parameter represents the current operating BER of a specific modulation type. This value depends on several channel characteristics, including the noise level and transmit power. The SNR represents the ratio of the signal power to the noise power in decibels. The noise power parameter informs the system of the approximate power of the noise in decibels.

C. Fitness Objectives

In a wireless communications environment, there are several desirable objectives that the radio system may want to achieve. This works defines three objectives for the fitness function in order to lead the system to an optimal state. The three objectives are given below in Table III.

TABLE III

COGNITIVE RADIO OBJECTIVES

Objective Name	**Description**
Minimize Bit-Error-Rate	Improve the overall BER of the transmission environment.
Maximize Throughput	Increase the overall data throughput transmitted by the radio.
Minimize Power Consumption	Decrease the amount of power consumed by the system.

Minimizing the BER is an extremely common communications goal. This objective represents minimizing the amount of errors relation to the amount of bits being sent. In general this objective represents improving the communications quality of the radio. Maximizing the throughput deals with the data throughput rate of the system. Emphasizing this objective, the overall system throughput should be increased. The power consumption objective is, as expected, used to direct the system to a state of minimal power utilization. This objective introduces interesting trade-offs between several other objectives. A trade-off analysis between minimizing BER, maximizing throughput, and minimizing power consumption is discussed in Section V.

Using the objectives in Table III as sole inputs to the fitness functions will not suffice. It is ambiguous to have the system minimize power consumption while also minimizing BER. Thus, the objectives must also contain a quantifiable rank representing the importance of each. This will allow the fitness function to characterize the trade-offs between each objective by ranking the objectives in order of importance. Several approaches exists for determining the preference information of a set of objectives [17]. This research uses a weighted, aggregate sum approach where each objective receives a weight representing its importance. This method is detailed in Section IV.

III. Genetic Algorithm Overview

Genetic algorithms are a class of artificial reasoning whereby the search is performed in a manner similar to genetic evolution. In general, solutions to a problem set are represented by binary strings. These strings then are allowed to act in a manner similar to genetic growth; strings which are considered ’good’ split and recombine with other good strings to form new solutions, while ’poorer’ strings are allowed to ’die’ out of the solution set. This decision is made by the fitness function which inputs the parameters and outputs a score based on the specific goals of the radio. Strings undergo a process called mutation, i.e., a random flipping of bits, to help prevent local minimization from occurring. Genetic algorithms are typically used as a method of problem optimization [8], [18], [19]. However, given its random nature, fast computation time, and ability to spontaneously generate unique solutions, genetic algorithms are an appealing candidate for cognitive radios. Input and output parameters can easily be mapped to a binary form and the size of the genetic population is customizable to space available within any given configuration [19]. Genetic algorithms are used mainly when the search space is too large to be simply brute force search to determine the optimal parameter set. In this paper we choose to use only two parameters, modulation type and transmit power. An actual communications system would have more output parameters than modulation and transmit power, and these parameters alone do not create a sufficiently large population to perform evaluations of the genetic algorithm without other mechanisms. To solve this problem we simply increase the resolution of the parameters. Increasing the resolution of the parameters provides the GA with more combinations and thus a larger search space. The effects of the search space size on the GA convergence size is discussed in detail in Section V.

A. *Other AI Methods*

Several other potential artificial intelligence (AI) methods can be implemented in a cognitive radio engine. Before we discuss the implementation of the GA and the fitness functions, a brief technical overview of several traditional cognitive methods is presented. Although these cognitive methods have been employed in numerous applications, the following overview will investigate them within a cognitive radio framework. The approaches covered briefly include: rule-based systems [20], [21], cased-based reasoning [22], fuzzy logic [23], [24], and neural network [25]. Rule-based systems are derivatives of knowledge-based systems, where instead of representing knowledge as declarative logical statements, knowledge is manipulated by a simple ”if-then-else” implementation. While easy to implement, rule-based systems suffer from poor adaptability: situations encountered that are not within the rule set can cause severe degradation in answer quality [20], [21]. One means of dealing with this drawback in rule-based systems is to incorporate fuzzy logic. Fuzzy logic systems allow decisions to be made using parameters that are not exact and may be noisy [23], [24]. However, the main advantage to fuzzy systems is merely this mapping of input values to discrete internal values. An alternative technique to rules is neural networks [25], which tries to solve large, complex problems by analyzing information in a manner similar to neurons of the human brain. Neural networks have the advantage of not needing a large database of storage when implemented. However, the inability to track why a specific decision is made by a neural network system is an unattractive attribute. Case-based reasoning systems (CBR) are widely used for systems with a large amount of space to store a history of cases [22]. CBR systems match the current situation with similar previous cases in order to use similar outputs. The major concern with CBR systems is the space requirement needed to provide an optimal case database size. Determining if the final case selected actually performed well will require a feedback loop from the receiver to score how well the parameter set in fact performed.

IV. Multiple Objective Fitness Functions

A. Overview

In general, a multi-objective fitness function problem can be presented as trying to determine the correct mapping of a set of m parameters to a set of n objectives. This can be seen algebraically as:

$$\vec{y} = \langle f_1(\vec{x}), f_2(\vec{x}), f_3(\vec{x}), \dots f_m(\vec{x}) \rangle \tag{1}$$

subject to

$$\vec{x} = \langle x_1, x_2, x_3, \dots x_n \rangle \in X$$

$$\vec{y} = \langle y_1, y_2, y_3, \dots y_m \rangle \in Y$$

where x is the set of decision variables and X is the parameter space, and y is the set of objectives with Y as the objective space. In practical problems, such as the problem investigated

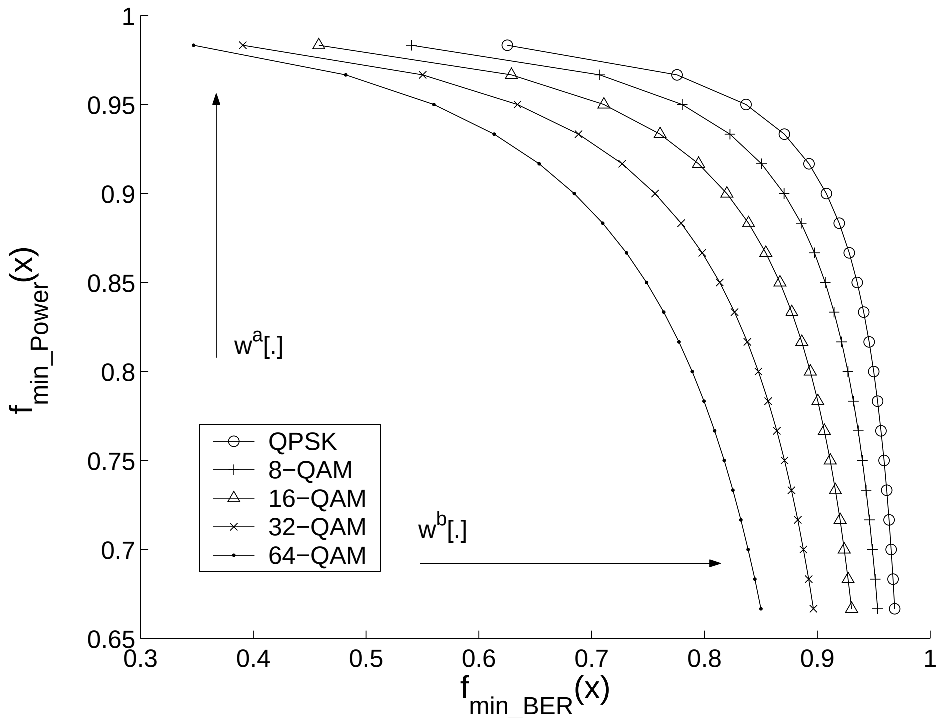

Fig. 2. Search Direction Example

in this paper, the objectives under consideration might conflict with each other. For example, minimizing power and minimizing BER simultaneously creates a conflict due to the single parameter, transmit power, affecting each objective in a different way. Determining the optimal set of decision variables for a single objective, e.g. minimize power, often results in a non-optimal set with respect to other objectives, e.g. minimize BER and maximize throughput. The optimal set for multiple objective functions lie on what is known as the Pareto optimal front. This front represents the set of solutions that cannot be improved upon in any dimension. The solutions on the Pareto front are optimal and co-exist due to the trade-offs between the multiple objectives. A graphical example of a Pareto front, using a simple cognitive radio parameter scenario is shown in Fig. 2.

The x-axis in the figure represents the score of the single objective fitness function for minimizing BER in the case of several modulation types, while the y-axis is the score for the single objective fitness function for minimize power. The parameter *x* represents the decision variable vectors used as inputs to the fitness functions. In this simple case, transmit power and modulation were used as decision variables. For each curve, as the fitness score for minimize power decreases, the score for the minimize BER objective increases. This trade-off represents the core of the multiple objective optimization problem. The QPSK curve represents the Pareto front, because no parameter set on that curve can be improved upon to gain a better objective score in respect to both objectives. The other modulation curves represent the dominated solutions to the bi-objective optimization problem.

B. Preference Information

In practice, the fitness function must be able to guide the system to one optimal parameter set. A cognitive radio must perform an action based on a single set of parameters, which should be selected from the Pareto front according to some preference information. Preference information is used to rank the objectives in order to help the fitness function guide the evolutionary algorithm to one optimal solution.

In addition to needing preference information for each objective, the scalarization of the objective vector is also necessary. Evolutionary algorithms need scalar fitness functions that provide a single scalar value for the given parameter set. In many optimization problems, when no global criteria for the parameters exist, objectives are often combined, or aggregated, into a scalar function. This aggregation optimization method has the advantage of providing a single scalar solution for the fitness function. As a result, this requires no extra interaction with the evolutionary algorithm to determine the optimality of a given parameter set.

There have been several approaches to the optimization of aggregated functions. A simple weighted sum approach is presented in [26]. The weighted sum approach attempts to minimize the sum of the positively normalized, weighted, single objective scores. In [27], target vector optimization was developed. Target vector optimization requires a vector of goal values. The optimization is driven toward the shortest distance between any candidate solution and the goal vector. Goal attainment was also studied by Wilson and MacLeod in [28]. The importance weighting methods used by the researchers at Virginia Tech place a numerical value on each objective representing how much importance the system should place on each objective. Their weights range from between 0 and 255, with 0 being no importance and 255 being the most important.

This research proposes to use the simple weighted sum approach. The weighted sum approach method suits the cognitive radio scenario well since it provides a convenient process for applying weights to the objectives. Changing the objective direction of the fitness function requires only a simple change of the weighting vector. This enables a simple interface for a higher level controller to modify the primary objective of the radio. The interface could be used by a human to change the weights manually or by an automated controller that monitors the internal radio state and adjusts the weights to change the objective state of the radio. For example, a radio in default mode may be operating so as to ensure the best throughput possible while not caring much about minimizing power. However, assuming this is a battery powered radio, the system may sense low power in the battery and modify the objective weights to emphasize minimizing power.

We define a multiple objective fitness function of the parameter set solution x by the following weighted sum of N objectives:

$$f(x) = \sum_{i=1}^{m} w_i f_i(\vec{x}) \tag{2}$$

with w_1,...,w_n satisfy the following constraints:

$$\begin{aligned} W &= [w_1, w_2, \ldots w_n] \\ w_i \geq 0 \;\; &\text{for} \;\; i = 1, 2, \ldots, n \\ w_1 + w_2 + \ldots + w_n &= 1 \end{aligned} \tag{3}$$

When the weighting for each objective is constant, the search direction of the evolutionary algorithm is fixed. This is the intended property when trying to find a single optimal solution for a given environment. However, changing the objective weighting means the fitness function will immediately start steering the evolutionary algorithm to a new solution. For example, take the case in which a radio is operating in a maximize throughput mode. In this mode, the fitness function will give higher scores to parameter sets providing a high throughput, e.g. large signal constellation size. Suppose that the radio then detects low battery power. At this instance, it changes the objective weighting to reflect an emphasis on minimizing power. Once the weights change, the fitness function will instantly start giving higher scores to parameter sets which provide for lower power transmission, e.g. lower transmit power. This is the primary attribute that allows the objective weighting to dictate the goal state of the radio. It also allows for a dynamic system to instantly switch operating goals by simply modifying the objective weighting vector.

Fig. 2 gives a graphical representation of the previous example. The search direction $w^a[.]$ corresponds to a minimized power weight vector in the 2-D objective space. The search direction $w^b[.]$ corresponds to a minimized BER weight vector in the 2-D objective space. As the objective space increases, so does the dimension of search space for a solution.

V. Parameter Trade-off Analysis

A. Single Objective Goals

The weighted sum approach allows us to develop a single objective function for each objective and combine them to create a multiple objective function. To develop the single objective functions, we must determine the dependence relationship between each objective and the set of parameters defined in Section II-A. The complete table of relationships is displayed in Table IV.

TABLE IV

Objective and Parameter Relationships

Objective Name	**Related Parameters**
Minimize Bit-Error-Rate	P,N,MT,M
Maximize Throughput	P,MT,M
Minimize Power Consumption	P

This method differs from the methods of other cognitive radio work because we restrict our weights to sum to 1. This normalization makes the weighting of the objective more intuitive for both a human and the cognitive system. When using a normalized system, there is no ambiguity about how much importance is given to an objective. Non-normalized systems can cause confusion when placing importance because there is no reference when determining the objective importance. For example, if we are using a non-normalized system with values between 0 and 255, and we place a value of 255 on all objectives. There is no way for the system to understand how this is different if we place values of 128 on all objectives. In both cases the objectives are weighted equally. Using a normalized system removes this ambiguity.

The weighting constraints imposed on the individual weights, each single fitness function score, must be normalized to the same range. Otherwise, if fitness function A outputs scores from ranges [0,1] and fitness function B outputs scores from [0,x] where $x > 1$, then the global fitness function would show a bias to function B due to the larger output range. The outputs of the functions developed in this research are all normalized to the range [0,1].

For each single objective function, the inputs for the function must be the parameters corresponding to the objectives in Table IV. Deriving the relationships between each objective and its parameters is the ultimate objective of this research, and will require analysis of the closed form solutions of each parameters and the potential range of values.

The trade-off analysis has been done using a set of objectives and parameters presented earlier. Using this analysis, we created several single objective functions for both single carrier and multicarrier cognitive systems. For a single carrier system, the functions using the previously defined parameters are:

$$f_{min\_ber} = 1 - \frac{P}{P_{max}} \quad (4)$$

$$f_{min\_power} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(P_{be})} \quad (5)$$

$$f_{max\_throughput} = \frac{\log_2(M)}{\log_2(M_{max})} \quad (6)$$

where P is the transmit power of the single carrier, P_{max} is the maximum available transmit power, M is the modulation index, M_{max} is the maximum modulation index, and P_{be} represents the probability of a bit error or BER for a given modulation scheme and a given channel type. In this investigation, we assume the possible modulation types include QAM, PSK, and FSK. To apply this work to practical systems, we must determine the BER for each modulation. The following equations describe the BER of QAM, PSK, and FSK, using a gray-coded bit assignment and assuming an AWGN channel model.

For a BPSK signal constellation, the BER is defined as [29]:

$$P_{be} = \mathrm{Q}\left(\sqrt{\frac{P}{N}}\right) \quad (7)$$

Whereas for M-ary PSK the BER is given as [29]:

$$P_{be} = \frac{2}{\log_2(M)}\mathrm{Q}\left(\sqrt{2 * \log_2(M) * \frac{P}{N}} * \sin\frac{\pi}{M}\right) \quad (8)$$

For M-ary QAM, the BER is defined as [29]:

$$P_{be} = \frac{4}{\log_2(M)}(1 - \frac{1}{\sqrt{M}})\mathrm{Q}\left(\sqrt{\frac{3 * \log_2(M)}{M-1}\frac{P}{N}}\right) \tag{9}$$

For a multicarrier system with N subcarriers, the objective functions are defined as:

$$f_{mc\_min\_ber} = 1 - \frac{P_i}{N * P_{max}} \tag{10}$$

$$f_{mc\_min\_power} = 1 - \frac{\log_{10}(0.5)}{\log_{10}(\overline{P_{be}})} \tag{11}$$

$$f_{mc\_max\_throughput} = \frac{\log_2(M)}{\log_2(M_{max})} \tag{12}$$

where P_i is the transmit power on subcarrier i, N is the number of carriers, $\bar{P_{be}}$ is the average BER over N channels, and P_{max} is the maximum possible transmit power for a single subcarrier.

B. Multiple Objective Goals

The weighted sum approach allows us to combine the single objective functions into one single multiple objective function. Eq. (2) shows that each objective is multiplied by a weight w_i and summed together to give a single scalar value for approximating the value of a parameter set. For the single objective equations, we form the multiple objective functions for both single and multiple carriers below:

Single Carrier:

$$f_{single} = w_1 * (f_{min\_ber}) + w_2 * (f_{min\_power}) + w_3 * (f_{max\_throughput}) \tag{13}$$

Multicarrier:

$$f_{multi} = w_1 * (f_{mc\_min\_ber}) + w_2 * (f_{mc\_min\_power}) + w_3 * (f_{mc\_max\_throughput}) \tag{14}$$

The weight vector W determines the search direction for the evolutionary algorithm and must conform to the constraints given in Eq. (3). We have defined several example weight vectors representing common scenarios in which a cognitive radio may be placed. Each weight vector shown in Table V emphasizes different objectives causing an evolutionary algorithm using this fitness function to evolve toward solutions pertaining to the specific objective.

Using these example weight vectors and a genetic algorithm engine, we have generated genetic algorithm convergence results, along with the statistics representing the average final decision output by the GA. These results are presented in Section VII.

TABLE V

EXAMPLE WEIGHTING SCENARIOS

Scenario	**Weight Vector [w_1,w_2,w_3]**
Low Power Mode (minimize power)	[0.80, 0.05, 0.15]
Emergency Mode (minimize BER)	[0.15, 0.80, 0.05]
Multimedia Mode (maximize throughput)	[0.05, 0.15, 0.80]

VI. COGNITIVE RADIO ALGORITHM SIMULATION ENVIRONMENT

A. Simulation Framework

To implement the genetic algorithm, a cognitive simulation framework was developed. Using this framework, we can implement the GA in a software-defined radio architecture that provides an interactive environment and allows the cognitive controller to simulate controlling actual radio components. The framework used to create the cognitive radio architecture was based on the OSSIE cognitive radio architecture developed at Virginia Tech [30], [31]. The OSSIE architecture is a C++ implementation of the Software Communications Architecture (SCA) [1]. The SCA is an open architecture developed by the Joint Tactical Radio System (JTRS), which provides a common architecture for software radio developers to use, allowing them to build radios that are interoperable and modular across multiple radio domains. This modularity feature allows us to develop a cognitive component simply plug it into the existing OSSIE framework as needed. The SCA is currently being developed by a wide range of industry participants, and has a large academic research base. It is widely assumed that an SCA implementation would correctly simulate the architecture of a common cognitive radio.

B. Genetic Algorithm Module

The GA consists of multiple classes that define the algorithm and its components. It creates a randomly generated solution population consisting of 100 individuals. Each member of the population is a class instance, which contains a solution set of output parameter values represented as a chromosome. Evolution occurs by splitting and combining chromosomes to form new generations. The fitness functions described earlier are used to drive the selection of chromosomes for combining. During each generation cycle, every string is filtered to prevent non-possible solutions from entering the solution set. The genetic algorithm parameters used are from the DeJong settings [32], which are the defacto settings for common GAs. The probability for the crossover process to occur between two strings is 60%. Additionally, all strings are given the .1% chance to mutate, which randomly flips a bit in the string emulating a spontaneous mutation. The population size of each generation is 50. The newest generations of chromosomes are stored in the radio for future processing.

VII. Simulation Results

We simulated a multicarrier system with 64 subcarriers. Each subcarrier was assigned a random attenuation value, N, to simulate a dynamic channel. Hence, the SNR varied for each channel, inducing a need for the adaptation for each individual channel.

For this paper we only consider three different QAM constellations and BPSK as the modulation types of the system. If we were to consider more modulation types, only the BER equation used to determine the minimize BER fitness function would need to change to account for other modulations. These restrictions are in place to keep the implementation simple without taking away from the value of the simulations. This is because the addition of other modulation types would only slightly increase the parameter space, while complicating the GA program with conditional statements in the fitness function. The simulations used BPSK, and three modulation indexes corresponding to the three square QAM index values (e.g. 16-QAM, 128-QAM, 1024-QAM).

The transmit power ranged from 0.1 mW to 2.56 mW using increments of 0.0256 mW. This maximum power value was selected since it is close to the specified maximum transmit power level of 2.5 mW for a 1 MHz bandwidth, allowed in the lower UNII band (5.15 GHz - 5.25 GHz). The extra range was allowed to make the processing in the genetic algorithm simpler. With 100 possible values for the transmit power and 5 possible modulation indexes, this gives 500 possible values for each subcarrier. In the case of a 64 subcarrier system this gives a total search space of 32,000.

The first simulation was targeted to determine the convergence time of the GA using the fitness functions, along with the fitness converged to. The scenarios defined in Table V were used for the vector of weights to create three different search directions for the cognitive radio. Fig. 3 shows the convergence attributes of the GA when using the *Low Power Mode* scenario.

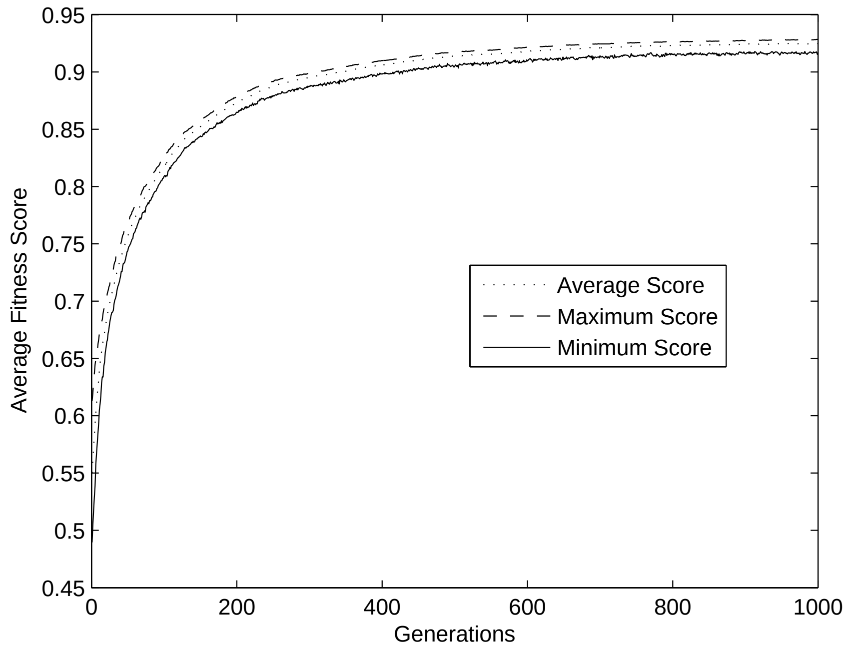

Fig. 3. *Low Power Mode* Convergence

Similarly, Fig. 4 shows the convergence attributes of the GA when using the *Emergency* scenario and Fig. 5 shows the convergence attributes of the GA when using the *Multimedia* scenario. For each simulation run, the average fitness is the average fitness of all 64 subcarriers which make up a chromosome. The figures shows these averaged fitness values over 10 simulation runs to ensure we get a time invariant average.

Each subcarrier has a random channel attenuation, N, using this value and the vector weights, the GA has optimized the transmission parameters so that the average chromosome, has a fitness value of 0.930 in the case of the *Low Power Mode*, after 1000 generations. Table VI shows the average fitness for each scenario after 1000 generations.

The convergence figures and tables validate the genetic algorithm implementation by demonstrating that the algorithm converges. However, a more important result is the transmission parameter values to which they converge. Fig. 6 shows a set of attributes corresponding to a snapshot of a final output at generation 1000 of a simulation run, for the *low power mode* scenario. The random channel attenuation is shown, along with the final values of throughput and power for each of the 64 subcarriers. The bottom window in Fig. 6 shows that all transmit

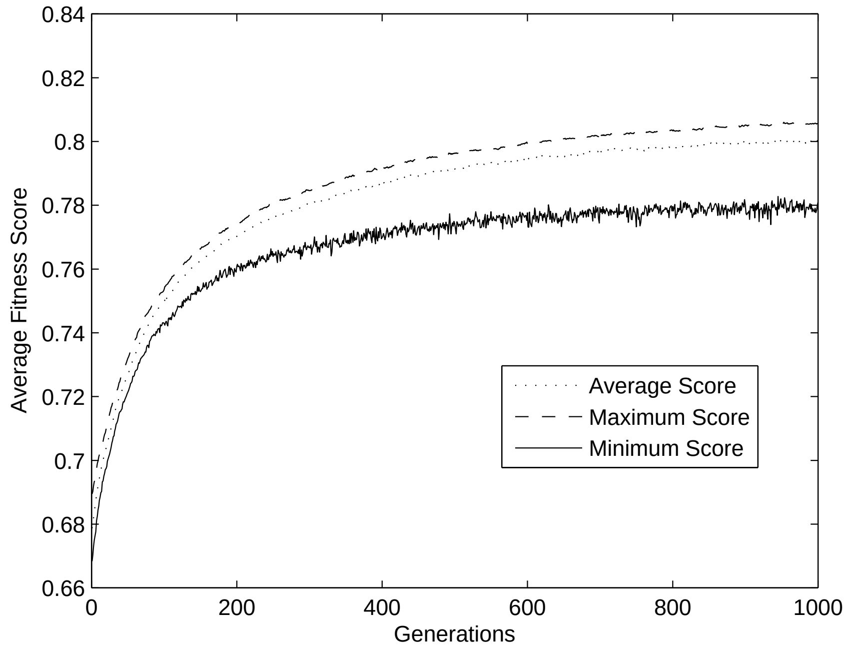

Fig. 4. *Emergency Mode* Convergence

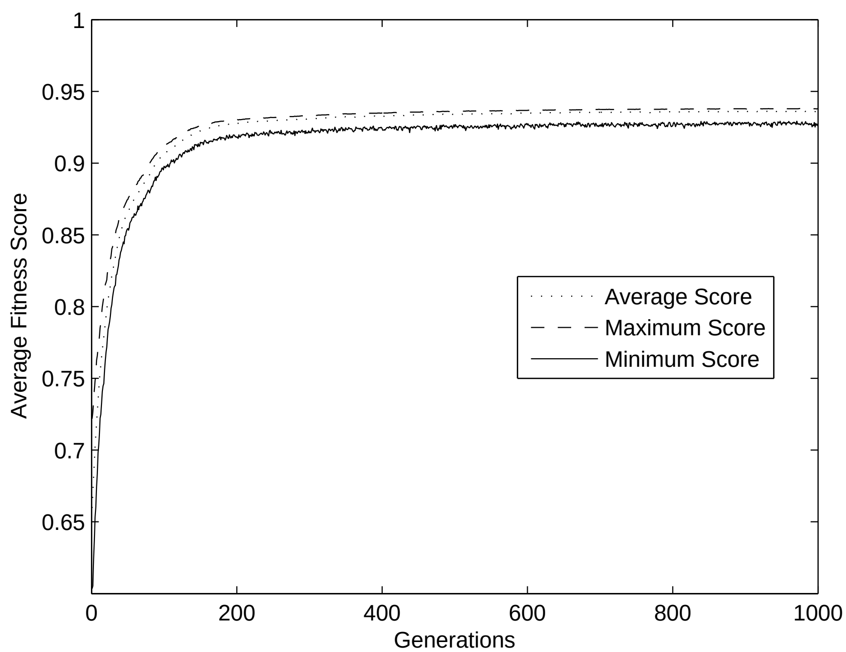

Fig. 5. *Multimedia Mode* Convergence

TABLE VI

CONVERGED FITNESS AFTER 1000 GENERATIONS

Scenario	**Converged Fitness**
Low Power Mode (minimize power)	0.930
Emergency Mode (minimize BER)	0.800
Multimedia Mode (maximize throughput)	0.938

powers on the subcarriers are below 0.1 mW. The average transmit power in this specific case is 0.0217 mW per subcarrier while the average modulation index is at 9.72. The low average power indicates the primary goal of the scenario, minimize power, was achieved. The other goals did not have quite an impact on the optimal parameter set, although because there is not much trade-off between power and throughput (e.g. modulation index), the small weight on the maximize throughput goal still allowed the system to provide for a high system throughput.

Fig. 7 and Fig. 8 also shows similar information for both the *emergency mode* and the *multimedia mode*. The *emergency mode* scenario figure shows that the final decision provided a low modulation index over all the subcarriers with an average of 2.5 per subcarrier. The transmit power was at approximately 40% of maximum power. This configuration yeilds a low BER due to the low modulation index, while keeping small balance on the minimize power objective with a weighting of 0.15. The middle window in the *multimedia mode* scenario validates that the maximum throughput is the primary objective for this scenario. All subcarriers are set to a maximum modulation index of 10 providing for the maximum possible throughput.

VIII. CONCLUSION

This paper introduced an implementation of a multicarrier cognitive radio that uses a genetic algorithm as the decision method. An important part of the genetic algorithm is the fitness function that directs the evolution of the GA parameter sets to the optimal set. We have introduced several fitness functions that are used to score how well a parameter set consisting of modulation index and transmit power match the given objectives. Fitness functions for multicarrier systems were presented and it was shown that the single carrier fitness functions could be easily derived using the multicarrier equations. Whereas the single carrier fitness functions were simple, the multicarrier systems present a much larger problem. Each subcarrier must be optimized to adapt

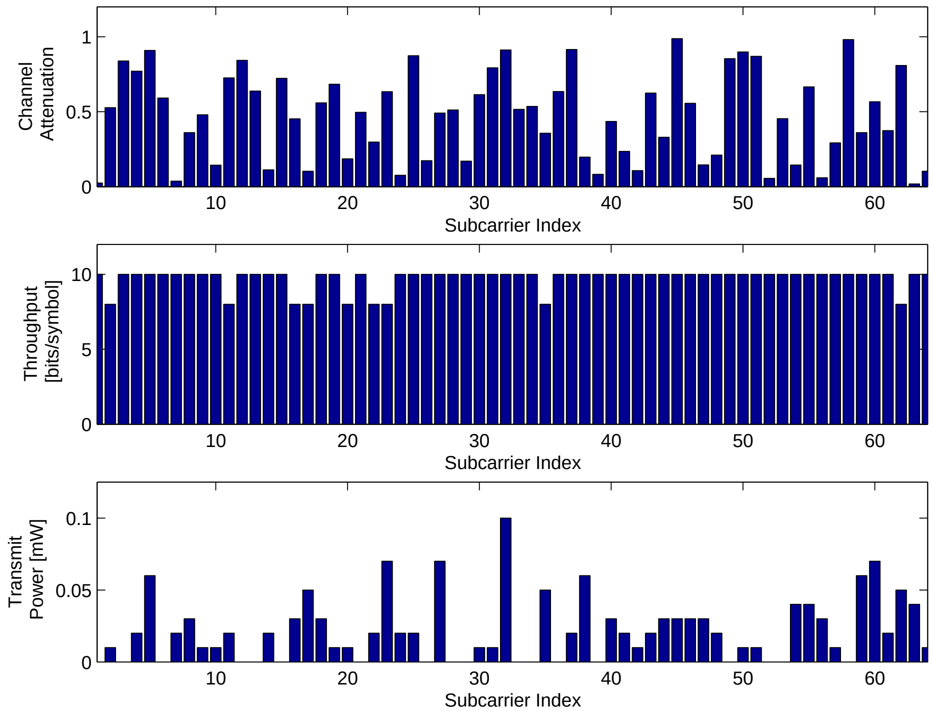

Fig. 6. Sample final decision for *low power mode* for channel attenuation (top), throughput (middle), and transmit power (bottom)

to the dynamic wireless environment. These functions provide a powerful and straightforward method for scoring sets of parameters given the goals and their weights. Using a weighted sum approach enables a higher level control component to easily modify the search direction of the GA by adjusting the weight vector values.

The simulation results illustrated the GA implementation by showing the convergence statistics of the GA when using the multicarrier fitness functions. A 64 subcarrier system was then simulated using three separate scenarios. The results of these simulations proved that the fitness functions steer the evolution of the GA in the correct direction to optimize the given objectives for each scenario. Each scenario consisted of a primary goal with an 80% weighting and two secondary goals with much smaller weighting. The parameter and objective trade-off were illustrated by the final decision values for the sample set. In all three cases the final decision provided a parameter set that put more emphasis on the primary objective while still balancing between the two secondary objectives.

The multicarrier fitness functions presented in this paper enable an interface for changing

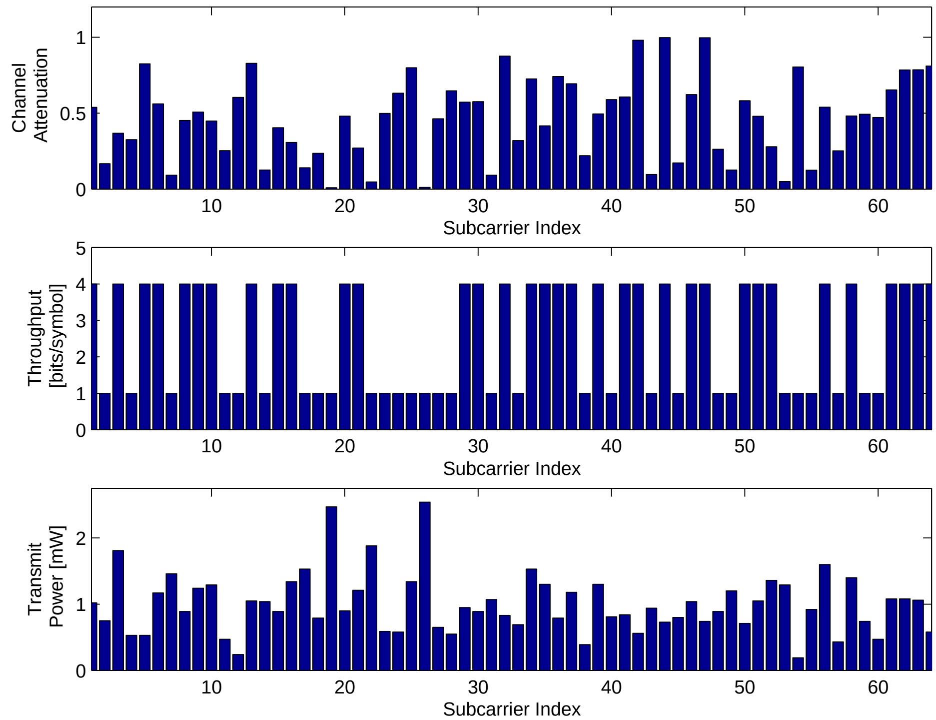

Fig. 7. Sample final decision for *emergency mode* for channel attenuation (top), throughput (middle), and transmit power (bottom)

the dynamic search direction of the GA. This, in turn, provides a simple way to control the intended operation of the cognitive controller. Extensive trade-off analysis needs to be done to relate the plethora of different cross-layer parameters that can be used by a cognitive component to determine the optimal transmission parameters.

ACKNOWLEDGMENT

The authors would like to thank Mr. Rakesh Rajbanshi and Mr. Qi Chen, both of The University of Kansas, for their assistance with the conceptualization of the genetic algorithm fitness function.

REFERENCES

[1] Joint Tactical Radio Systems, "Software communications architecture specification," November 2002.

[2] C. J. Rieser, "Biologically inspired cognitive radio engine model utilizing distributed genetic algorithms for secure and robust wireless communications and networking," Ph.D. dissertation, Virginia Polytechnic Institute and State University, April 2004.

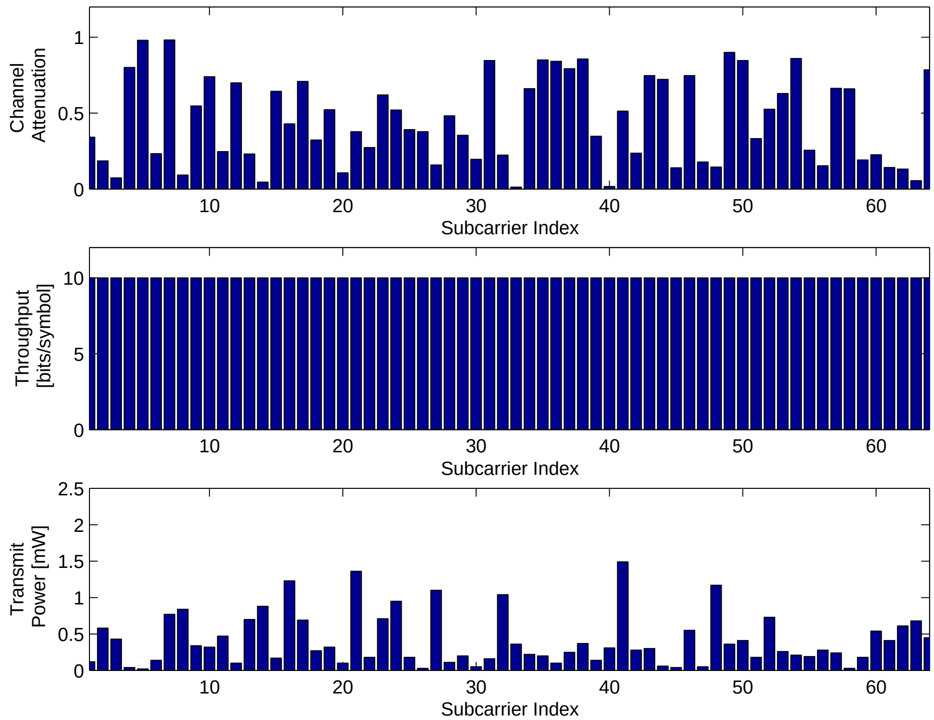

Fig. 8. Sample final decision for *multimedia mode* for channel attenuation (top), throughput (middle), and transmit tower (bottom)

[3] R. Etkin, A. Parekh, and D. Tse, "Spectrum sharing for unlicensed bands," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access*, 2005, pp. 251–258.

[4] Spectrum Policy Task Force, "Report of the spectrum policy workgroup," Novemeber 2002. [Online]. Available: http://www.fcc.gov/sptf/files/SEWGFinalReport_1.pdf

[5] S. M. Mishra, D. Cabric, and C. Chang, "A real time cognitive radio testbed for physical and link layer experiments," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access*, 2005, pp. 562–567.

[6] J. Chapin and V. Bose, "The vanu software radio system," in *Software Defined Radio Technical Conference*, November 2002.

[7] T. A. Weiss and F. K. Jondral, "Spectrum pooling: an innovative strategy foe the enhancement of spectrum efficiency," *IEEE Communications Magazine*, March 2004.

[8] T. Bck and H. Schwefel, "Evolutionary computation: An overview," *International Conference on Evolutionary Computation*, pp. 20–29, 1996.

[9] A. Fehske, J. Gaeddert, and J. Reed, "A new approach to signal classification using spectral correlation and neural networks," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access*, 2005, pp. 144–150.

[10] "DARPA XG Program web site." [Online]. Available: http://www.darpa.mil/ato/programs/XG/

[11] W. Horne, P. Weed, and D. Schaefer, "Adaptive spectrum radio: A feasibility platform on the path to dynamic spectrum access," in *International Symposium On Advanced Radio Technologies*, 2003.

[12] D. Maldonado, B. Le, A. Hugine, T. W. Rondeau, and C. W. Bostian, "Cognitive radio applications to dynamic spectrum

allocation," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access*, 2005, pp. 597–600.

[13] T. Rondeau, B. Le, C. Rieser, and C. Bostian, "Cognitive radios with genetic algorithms: Intelligent control of software defined radios," in *Software Defined Radio Forum Technical Conference*, 2004, pp. C3–C8.

[14] J. G. Proakis, "Adaptive equalization for TDMA digital mobile radio," *IEEE Transactions on Vehicular Technology*, vol. 40, no. 2, pp. 333–341, 1991.

[15] M. Gruteser, A. Jain, J. Deng, F. Zhao, and D. Grunwald, "Exploiting physical layer power control mechanisms in ieee 802.11b network interfaces," Department of Computer Science, University of Colorado at Boulder, Tech. Rep. CU-CS-924-01, 2001.

[16] T. Keller and L. Hanzo, "Adaptive multicarrier modulation: A convenient framewrok for time-frequency processing in wireless communications," in *Proceedings of the IEEE*, vol. 88, May 2000, pp. 611–640.

[17] C. M. Fonseca and P. J. Fleming, "An overview of evolutionary algorithms in multiobjective optimization," *Evolutionary Computation*, vol. 3, no. 1, pp. 1–16, 1995.

[18] S. Forrest, "Genetic algorithms," *ACM Computing*, vol. 28, no. 1, pp. 77–80, March 1996.

[19] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*. Addison Wesley, 1989.

[20] D. Bobrow, S. Mittal, and M. Stefik, "Expert systems: Perils and promise," *Comm ACM*, vol. 29, no. 9, pp. 880–894, September 1986.

[21] J. Williams, "When expert systems are wrong," in *Proceedings of the 1990 ACM SIGBDP Conference on Trends and Directions in Expert Systems, October 31 - November 2, 1990, Orlando, FL, USA*, E. M. Awad, Ed. ACM, 1990, pp. 661–669.

[22] R. Barletta, "An introduction to case-based reasoning," *AI Expert*, vol. 6, no. 8, pp. 42–49, 1991.

[23] J. Ammerlaan and D. Wright, "Adaptive cooperative fuzzy logic controller," in *Proceedings of the 27th Conference on Australasian Computer Science*, 2004, pp. 255–263.

[24] D. Dubois and H. Prade, "What does fuzzy logic bring to AI?" *ACM Computing Surveys*, vol. 27, no. 3, pp. 328–330, 1993.

[25] N. E. Sondak and V. K. Sondak, "Neural networks and artificial intelligence," in *Proceedings of the Twentieth SIGCSE Technical Symposium on Computer Science Education*, 1989, pp. 241–245.

[26] H. Ishibuchi and T. Murata, "A multi-objective genetic local search algorithm and its application to flowshop scheduling," *IEEE Transactions on Systems, Man, and Cybernetics—Part C: Applications and Reviews*, vol. 28, no. 3, pp. 392–403, 1998.

[27] A. E. Hans, "Multicriteria optimization for highly accurate systems," in *Multicriteria Optimization in Engineering and Sciences*, 1988, pp. 309–352.

[28] P. Wilson and M. Macleod, "Low Implementation cost IIE digital filter design using genetic algorithms," in *IEE/IEEE Workshop on Natural Algorithms in Signal Processing*, Chelmsford, U.K., pp. 4/1–4/8.

[29] J. G. Proakis, *Digital Communications*, 4th ed. McGraw-Hill, 2000.

[30] The Mobile and Portable Radio Research Group, "OSSIE Open SCA Implementation." [Online]. Available: http://ossie.mprg.org/

[31] T. R. Newman and G. Minden, "A software defined radio architecture model to develop radio modem component classifications," in *IEEE International Symposium on New Frontiers in Dynamic Spectrum Access*, 2005, pp. 585–588.

[32] K. A. D. Jong and W. M. Spears, "An analysis of the interacting roles of population size and crossover in genetic

algorithms," in *Parallel Problem Solving from Nature - Proceedings of 1st Workshop, PPSN 1*, vol. 496. Dortmund, Germany: Springer-Verlag, Berlin, Germany, 1-3 1991, pp. 38–47.