

## APPLICATIONS OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN COGNITIVE RADIOS: A SURVEY

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### Abstract

*Advances in radio technology have led to the proliferation of a smart software radio device called Cognitive Radio (CR). The radio integrates several techniques taken from information theory, statistical signal processing, game theory, artificial intelligence to wideband/multiple antenna techniques in providing marvellous dynamic behaviour by enriching the transceivers with desirable properties such as capability of learning, adaptability and self awareness thus enabling technology for Next Generation wireless systems. This paper presents a survey of various Artificial Intelligence (AI) techniques which are utilized in CR implementations with the goal of examining their strength, weakness and open research issues. AI techniques review in this paper includes the Genetic Algorithms (GA), Artificial Neural Networks (ANNs), Hidden Markov Models and the Metaheuristic Algorithms. In addition, the paper examined various areas of applications of ANNs and their performance based metrics.*

**Keywords:** Artificial Intelligence, Artificial Neural Networks, Cognitive Engine, Cognitive Radio and Genetic Algorithms

### Introduction

The increasing growth in wireless communications technologies and the emergence of new devices and services associated with wireless communications in offices, homes and public zones have led to a further demand of frequency spectrum (Mitola, 2000; NCC, 2014; Odufuwa, 2010). The current technique of allocating fixed portions of spectrum to each service provider i.e., the traditional spectrum licensing model, where a spectrum regulator (e.g. Nigerian Communications Commissions (NCC) in Nigeria), allocates spectrum by assigning exclusive licenses to service providers to operate their networks on different bands (NCC, 2014) is not cost-effective. This is because a licensee may not always put every part of his band to use. Moreover, some outdated wireless services no longer effectively use their allotted spectrum bands. Therefore, a band lies idle when not in use by the license holder, which gives the false impression of spectrum scarcity (Mitola, 1999) to other users.

Advances in radio technology have led to the proliferation of a smart software radio device called Cognitive Radio (CR) which is the key enabling technology for Next Generation wireless systems (Akyildiz, Lee, Vuran, & Mohanty, 2006). This type of radio integrates several techniques ranging from information theory, statistical signal processing, game theory, artificial intelligence to wideband/multiple antenna techniques in providing marvellously intelligent and dynamic behavior by enriching the transceivers with desirable properties such as capability of learning, adaptability and self awareness (Akyildiz, et al., 2006). This CR has been proposed as an enabling technology that can effectively combat the under utilization of frequency spectrum,

which might result in the imminent spectrum scarcity problem by enabling user's access to spectrum dynamically and fairly shares the spectrum with other users (Mitola, 1999, 2000). It promises intelligent radios that can learn from and adapt to their environment by using a smart technique based on cumulative learning to decide on which spectrum it can opportunistically utilize (Akyildiz, et al., 2006).

A CR can be taken as a paradigm for wireless communication in which either a network or a wireless node dynamically changes its transmission or reception parameters in order to communicate efficiently in a licensed band without interference with licensed users (Mitola, 2000). Therefore, a CR is fundamentally a type of software radio with additional capabilities and functionalities such as environment sensing, learning and decision-making which necessitate its attainment of the required dynamic performance. The extreme flexibility of CR, which includes adaptation to any channel condition, facilitates its easy coexistence with numerous other communication systems. It does this by changing its operating parameters such as modulation scheme and channel coding to achieve the highest possible level of quality of service (Akyildiz, et al., 2006; He, Bae, Newman, Gaeddert, Kim, Menon, Morales-Tirado, Neel, Zhao, & Reed, 2010). These CR emanated from the advancement of software radio technology with cognitive capabilities. Usually, these capabilities are provided by an intelligent instantiation of a software package called cognitive engine (CE) (He, et al., 2010).

CE is the intelligent agent of CR, hence can be regarded as the brain of CR. The CE uses the policy and goals to determine an appropriate utility function by putting the specific application or radio scenario into consideration (Katidiotis, Tsagkaris, & Demestichas, 2010). The most efficient reasoning and learning technique can be chosen by the CE by leveraging on past experience and knowledge. The CE can utilize this strength to make optimal and or cross layer adaptation subject to regulation, policy and radio equipment capability constraints. The feedback performance is collected by sensing the environment or from other radio nodes thus enabled the closure of the CE learning loop. The radio environment mapping, case library and knowledge base are updated based on the observed performance result (Katidiotis, et al., 2010; Rewagad & Soanawane, 1998).

There exist various forms of Artificial Intelligence (AI) techniques that can be applied to the design of CR systems. These include the Artificial Neural Networks (ANNs), Genetic Algorithms (GA), Metaheuristic Algorithms and the Hidden Markov Models. These AI techniques can be used to achieve the fundamental components of a CR viz awareness, learning and reasoning. This paper presents a survey of various AI techniques that are utilized in CR implementations with special emphasis on ANNs techniques. Furthermore, the paper examines various areas of applications of ANNs and their performance based metrics. The remainder of the paper is structured as follows: A review of various types of artificial intelligent techniques and their relative merits are presented in Section 2. Section 3 presents a specific survey of areas of application of ANNs in CR and their performance metrics based approach. Conclusion and recommendation are presented in section 4 which concludes the paper.

#### AI Techniques Used in CR Implementation

A general review of different types of AI applicable to CR implementation is presented in this section. Furthermore, the benefits and drawbacks of each approach are also highlighted.

**Genetic Algorithm (GA):** GA is a kind of evolutionary algorithm (EA) used in CR, which is founded on the bases of biological evolution process. It uses natural evolution process to mimic nature in the search of optimal solution for a specific problem (Chen & Yu, 2005; Ding, Xu, Su, & Zhu, 2010). Chromosome and fitness functions definitions are essential to the description of GA (Ding, et al., 2010). An abstract representation of candidate solutions is referred to as Chromosomes. The desirability of a solution is quantified by the fitness function, which is closely correlated with the objective of the algorithm or optimization process. Candidate solutions are evaluated on the basis of the fitness levels, that is, the values they generate for the fitness function, which characterize the performance of candidate solutions (He, et al., 2010).

The GA uses a probabilistic rule to guide its search thereby reducing the risk of convergence to local minima and exploring the most promising areas in search space. This is achieved by considering many points in the search space simultaneously and favouring the mating of the fitter individuals. GA is an effective and robust search algorithm that allows the quick location of high quality solution areas in a large and complex search space (Chen & Yu, 2005; Ding, et al., 2010; Ding, et al., 2011; He, et al., 2010). GA stands out among other search algorithms and distinguishes itself by working on a population of individuals, each representing a possible solution to the problem (Ding, et al., 2011). The fundamental principle of GA includes fitness function evaluation, population solution encoding and decoding, selection, reproduction and convergence (Ding, et al., 2010; He, et al., 2010).

**Areas of Practical Application to CR:** There are various areas of application of GA to CR. This includes its utilization in the intelligent control of software defined radios (Rondeau, Le, Rieser, & Bostian, 2004), its adoption to solve multi-objective optimization problems and to dynamically configure the CR in response to the changing wireless environment (Ding, et al., 2011; He, et al., 2010), and its utilization in optimizing CR for autonomous vehicle communication (Hauris, 2007).

**Artificial Neural Network (ANN):** Biological neurons constitute the basic component on which the biological neural network is made up. They are physically connected or functionally-related in the human nervous system specifically in the human brain. In contrast, ANNs are made up of artificial neurons interconnected with each other to form a programming structure that mimics the behavior and neural processing of biological neurons (Katidiotis, et al., 2010).

ANN is basically a set of nonlinear functions with adjustable parameters to give a desirable output (Aibinu, Salami, & Shafie, 2012; Aibinu, Shafie, & Salami, 2012; He, et al., 2010). Classification of ANNs can be done through their training methods and network configurations, which facilitate a multitude of applications. A concise detail of those peculiar to CR are highlighted:

- (i) *A multilayer nonlinear perceptron networks (NPNs):* The NPNs enable the incorporation of non-linearity in the network and provide a highly flexible and dynamic results. The use of back propagation for training results in increase in processing time needed to achieve a precise result. Consequently, it is slow to converge during training(He, et al., 2010).
- (ii) *A radial basis function networks (RBFNs):* The RBFN has a built-in distance criterion with respect to a center in its hidden layer. This prevents the network from settling into local minimal which is a challenge peculiar to perceptron networks (He, et al., 2010).

(iii) *A multi-layer linear perceptron networks (MLPNS):* This network is made up of layers of neurons where each neuron is a linear combination of the previous output (A. Aibinu, Salami, & Shafie, 2010; A. M. Aibinu, Salami, & Shafie, 2011; He, et al., 2010). The size of the network and application determine the performance of the training algorithms.

Types of Neurons used in ANN

ANN is made up of a collection of simple processing units called neurons. Basically they are three distinguishable types of neurons within the ANN namely, (1) the input neurons, which are the neurons that is responsible with receiving data from outside the neural network and is organized in a layer known as the input layer. (2) the output neurons, which are the neurons that shoulder the responsibility of sending data out of the neural network, and is generally made up of the output layer, and (3) the hidden neurons whose input and output signals remain within the neural network and form the so called hidden layer (Katidiotis, et al., 2010). Neuron communicates with each other by sending signals over a large number of weighted connections (Katidiotis, et al., 2010). These resulted to a network with high degree of interconnection. Generally, a *weight*  $w_{jk}$  is used to define each connection. This weight determines the effect that the signal of neuron  $j$  has on neuron  $k$ . Each neuron has an activation state  $Y_k$ , which could be the equivalent output of the neuron. Each neuron  $k$  receives input  $S_k$  from two possible sources viz (1) neighbors belonging to different layers and (2) external source referred to as bias offset  $b_k$ , and uses them to compute an updated level of activation  $Y_k$  as illustrated in Fig.1. This is achieved through the utilization of an activation function  $F_k$  as expressed in equation (1).

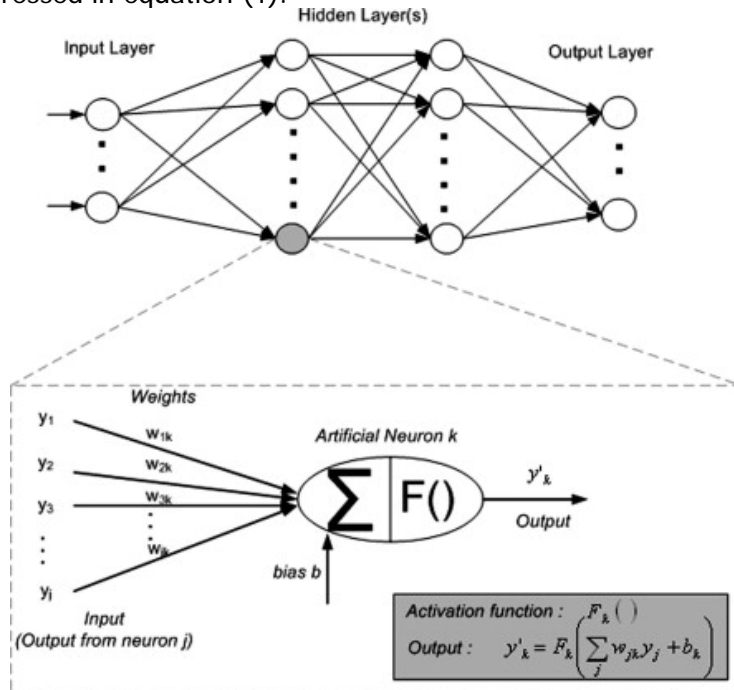


Figure 1: A Typical Neural Network

$$F_k = [\sum_j w_{jk} y_j + b_k] \quad (1)$$

There are several types of activation function used in ANN, this includes threshold, signum, ramp, step, unipolar sigmoid and bipolar sigmoid function (Ding, et al., 2010; Ding, et al., 2011; Katidiotis, et al., 2010).

### Training of ANN

There are so many algorithms that can be utilized in ANN training. However the most common and presumed effective algorithm is the backpropagation algorithm, which will be discuss in this paper.

#### (i) Backpropagation Algorithm (BP)

The BP is the most common type of algorithm utilized for the training of ANN. It is a supervised learning algorithm that uses a batch mode or sequential method to train a multilayered perceptrons or feedforward neural network (Ding, et al., 2011; Katidiotis, et al., 2010). In a multilayered structure, the backward propagation of an error signal through the network is achieved using gradient search technique. The changing of the synaptic weights connected to the neurons in the hidden and the output layer is achieved by the back propagation of errors through the network (Ding, et al., 2011; Katidiotis, et al., 2010). The BP is a generalization of the delta rule that is utilized for training multi-layer feed-forward neural networks with non-linear units. Basically, it is a gradient descent method designed to minimize the mean error or total error of the output computed by the network. The architecture of BP neural network is illustrated in Fig. 2.

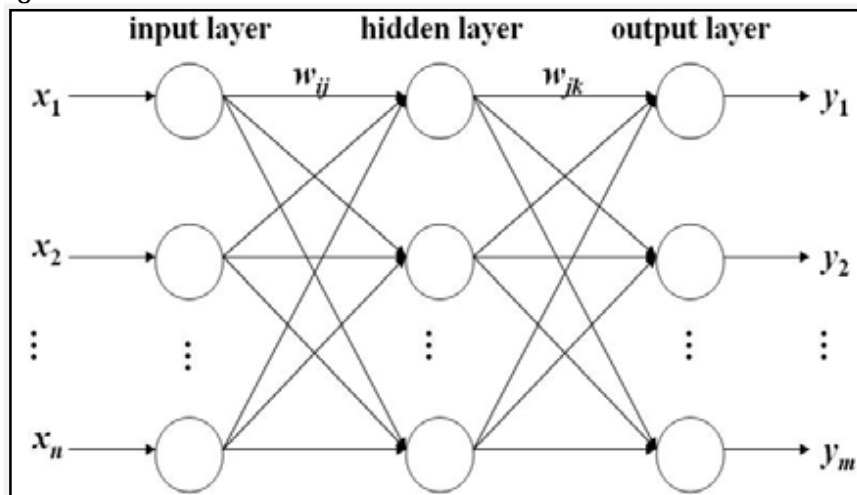


Fig. 2: Architecture of BP Neural Network (Ding, Xu, Zhu, Wang, & Jin, 2011)

Assuming, there are  $n$  inputs layers,  $m$  output layer and  $s$  neurons in the hidden layer of the network. The output of the hidden layer  $b_j$  and that of  $j$ th neuron in the hidden layer can be obtained using equation (2) and (3) below

$$b_j = f_1(\sum_{i=1}^n w_{ij} x_i + \theta_j) \quad (2)$$

Where,

(  $i = 1, 2, \dots, n; j = 1, 2, \dots, s$  ),  $\theta_j$  is the assumed hidden layer threshold,  $w_{ij}$  is the weight from input layer to the hidden layer and  $f_1$  is the hidden layer transfer function.

The output  $y_k$  is obtained as shown in equation (3)

$$y_k = f_2(\sum_{j=1}^s w_{jk} b_j + \theta_k) \quad (3)$$

Where,

( $j = 1, 2, \dots, s$ ;  $k = 1, 2, \dots, m$ ),  $\theta_k$  is the output layer threshold,  $w_{jk}$  is the weight from the hidden layer to the output layer and  $f_2$  is the output layer transfer function.

The error function ( $e$ ) is defined as the difference between desired output and network actual output and is expressed as

$$e = \sum_{k=1}^m (t_k - y_k)^2 \quad (4)$$

Where,

$t_k$  is the desired output and  $y_k$  is the output of the network

The continuous process of readjusting the weight and the threshold value is used for the network training. These readjustments is done in order to minimize the network error to a pre set minimum or stop at a pre set training step. The forecasting result is then obtained by inputting forecasting samples to the trained network.

### Areas of Application of ANN in CR

There are numerous areas of application of ANN in CR which includes its utilization in signal classification by utilizing the extracted cyclostationary signal features (Fehske, Gaeddert, & Reed, 2005), its application in spectrum sensing (Qi, Zhihui, & Keqin, 2012). The ANN is also used for radio parameter adaptation in CR with threetypes of optimization namely, (1) minimizing the transmit power, (2) meeting the BER and (3) maximizing the throughput [11]. Furthermore, the ANN is used for pattern classification in a pattern-based transmission for CR [5] and in characterizing real time achievable communication performance in CR as proposed by Baldo and Zorzi (Baldo & Zorzi, 2008). A detailed discussion of several areas of applications of ANN is presented in section 3.

### Hidden Markov Model (HMM)

The hidden markov model was developed to analyze and describe a complex random phenomenal behavior that can be modeled as a markov process with observable and unobservable states. This model is a convenient and mathematically tractable statistical model (He, et al., 2010). This technique has the capability of prediction based on experience. Also, it is easily scalable, excellent for classification and can be used to model complex statistical processes. However, it requires a good training sequence and it is computationally complex.

### Areas of Application in CR

The hidden markov model has several areas of application in CR. This includes its utilization in processing signal cyclostationary features for primary signal detection (Kim, Akbar, Bae, Um, Spooner, & Reed, 2007). It can also be used for spectrum sensing as demonstrated in (Akbar & Tranter, 2007). An HMM-based dynamic spectrum access algorithm was used in predicting the spectrum occupancy of the licensed radio bands for CR networks.

### Metaheuristic Algorithms

A metaheuristic algorithm is used in CR to search through a solution space while learning and establishing the requisite relationships in computationally hard problems (He, et al., 2010). The technique is good in optimizing parameters and other learning techniques can be used in the training phase. However, the formulation of rule space is difficult if optimization or learning is not restricted. There are various types of metaheuristic algorithms as highlighted below.

- (i) *Tabu search*: This technique can be easily implemented, the performance of the search method is enhanced by using a memory structure called tabu list, which ensures that a

recent move is not repeated or reversed (He, et al., 2010). Its efficiency is determined by an appropriate parameter selection.

- (ii) *Simulated Annealing*: The simulated annealing is a simple approach for global optimization in a large search space. It is easy to implement however, it has a slow convergence rate (He, et al., 2010).
- (iii) *Ant colony optimization (ACO)*: The ACO mimics ant behavior by walking around a graph representing the problem to be solved and finding locally productive areas (Dorigo & Blum, 2005). It is easy to adapt to real time change however, it is not efficient for local searches.

#### Areas of Applications in CR

There are various areas of application of metaheuristic algorithm to CR. These include its utilization in the dynamic configuration of the CR in response to the changing wireless environment (He, et al., 2010) and in the adaptation of the radio parameters of a software defined radio to the changing radio environment.

#### Areas of Application of ANN in CR

A survey of various areas of application of ANN in CR is presented in this section. Furthermore, a general performance metrics for different areas are also examined.

#### Survey of Areas of Application of ANN in CR

There are a considerable number of areas where ANN can be applied in the design of CR. For instance, in (Baldo & Zorzi, 2008), Baldo and Zorzi proposed multilayered feed forward neural networks as an effective technique for real-time characterization of communications performance. This provided a general-purpose black box modeling (it consists of analyzing input-output relations of the system under consideration, and trying to build a predictor with the purpose of estimating output values for unknown combinations of the inputs) of the performance as a function of the measurements collected by the CR device, thus providing good modeling accuracy. Also, it is flexible and as such can be used for runtime modeling in different applications and scenarios and no prior knowledge of the laws driving the real system is required. Furthermore, it avoids all assumptions which are not verifiable in practice and has the ability to account for non-idealities in parameters i.e. tolerance of components, device failures, etc. However, a great challenge is how to effectively determine the values of the weights and biases that will provide the desired approximation for arbitrary continuous functions defined over compact subsets during training. Also, an additional effort and time is needed in training the multilayered feed forward neural network (MFNN) when adding a new variable to an MFNN performance predictor.

A technique that can be used in adjusting radio parameter was presented in (Rondeau, et al., 2004). In this work, an adaptation mechanism that uses GA to optimize the radio parameters on the physical layer was proposed. The GA is used to realize cross layer optimization and a method of adaptive waveform control (He, et al., 2010; Rondeau, et al., 2004). It is referred to as the Wireless System Genetic Algorithm (WSGA) (Rondeau, et al., 2004). The adaptive component that uses the GAs leads to the development of a radio defined by a chromosome. The chromosome's genes represent the adjustable parameters in a given radio and by genetically manipulating the chromosome; the GA can find a set of parameters that optimize the radio for the user's current needs. In the WSGA, the radio behaviour is interpreted as a set of physical and MAC layer operation parameters defined by traits encapsulated in the genes of a

chromosome (Rondeau, et al., 2004). Power, frequency, pulse shape, symbol rate and modulation are used to represent chromosome for GA manipulation and are also identified as possible genes in the chromosome definition to allow for future growth through each layer of the radio communication's stack.

The advantage of this technique is that it has a dynamic fitness definition and evaluation where the weighting of each function is adaptive. Also, it has the capability of enabling any fitness function to be used as required by the current link conditions and user requirements. Furthermore, it has the capability of applying constraints to the optimization problem, which facilitated the incorporation of regulatory and physical restrictions during chromosome evolution, and the WSGA is capable of working with real hardware to accomplish real goals. However, the use of proximal radios, which has a limited number of adaptable parameters for experiment is a demerit. In addition to this, the convergence speed of the system is slow and there is no assurance that the winning member, after all the single comparisons in all dimensions is the best or non-dominated member of the population.

Tsagkaris *et al.* focused on the channel estimation and predictive modeling phases where a benchmarking work that aims at evaluating the applicability of multiple types of NNs in the learning module of the cognitive engine (CE) within a cognitive terminal is developed (Tsagkaris, Katidiotis, & Demestichas, 2008). The proposed ANN-based learning schemes relax the reasoning process and assist in the optimum decision regarding the radio-configuration settings (mainly PHY and MAC layers) that provide the best QoS for the given problem and user application needs. A potential solution is proposed that assists the CRs in the derivation and enforcement of decisions regarding the selection of desired radio configuration which will optimize its QoS. ANN was used as the proposed solution, which was motivated by the fact that the NNs have the ability to learn from given examples. Two NN-based learning schemes were set up and tested namely, the 'basic' and the 'extended' one. While the former one aims at building the framework for developing such learning schemes and applying them into future CR based systems, the latter one stresses that such a learning scheme should be extensible, i.e., flexible in incorporating further information data in the learning process (Tsagkaris, et al., 2008).

In the basic NN-based learning scheme, an Elman network is the NN that was selected for the basic scheme which, is a two-layer back-propagation, recurrent network, with the addition of a feedback connection from the output of the unique hidden layer to the input layer (Tsagkaris, et al., 2008). This recurrent connection allows the Elman network to both detect and generate time-varying patterns. The NN uses the Tansig function shown in equation (5) for the neurons in its hidden (recurrent) layer, and the Logsig function in equation (6) for the neuron in its output layer respectively.

$$F_k(x_k) = \frac{1}{1 + e^{-x_k}} \quad (5)$$

$$F_k(x_k) = \frac{e^{2x_k}}{1 + e^{2x_k}} - 1 \quad (6)$$

where  $S_k$  = input neurons from neighbors belonging to different layers and  $F_k$  = Activation function. A delay line of five slots was inserted in the input layer, which corresponds to the time window which are slots that was used to represent past experience and knowledge collected by the NN.

The proposed approach has the ability to learn from given example and hence perform better in cognitive tasks. Furthermore, it has a good data rate prediction capability. However, the assumption that the NN-based scheme should be tuned in an arbitrary radio configuration is a drawback of the technique. Also, there may be overtraining or over fitting of the training data as a result of the network not being properly trained, which may lead to the network not learning the basic structure of the data but instead learning irrelevant details of the individual cases. In addition to this, a realistic input time series and environment situations are not considered; this may affect the NN-based schemes validity and robustness.

Feng *et al.* proposed a statistical mean throughput as evaluation criteria for cognitive user with fixed rate service in spectrum sensing (Qi, et al., 2012). It was assumed that the state of vacancy and occupancy time of objective license channel are independent of each other with exponential distribution. Furthermore, it was also reported that N objective license channels is being predicted based on the result of machine learning at each time slot. The cognitive user with fixed rate service based on machine learning spectrum sensing has better performance compared to random spectrum sensing. Also, there is decrease in the packet loss rate as the channel time detection threshold increases. However, there is decrease in effective transmission time and difficulty is encountered in determining an appropriate method of increasing the sample size for the statistical mean throughput since it is impossible that the sample size tends to infinity.

In (Fehske, et al., 2005), ANN-based signal classifier was developed. It utilizes the extracted cyclostationary signal features, a new method for classification of communication signals based on cyclic spectral analysis and pattern recognition performed by a neural network was proposed (Fehske, et al., 2005). Two cases were studied: Classification with and without prior knowledge of carrier and bandwidth of the signal. Distinct features of each signal type were extracted using cyclic spectral analysis, and a neural network was designed to classify signals based on these features. The combination of the cyclostationary analysis and ANN provides an efficient and reliable signal classification. A multilayer linear perceptron network (MLPNs) with 4 neurons in the hidden layer was used for each signal class during training. Each MLPN was trained with a back propagation algorithm.

The strength of the approach was in the reduction of the online processing time. Also, it provides an efficient and reliable signal classification and is robust to stationary noise. However, difficulty is encountered in comparison due to the practical limitations of the number of modulation type analyzed. Furthermore, a scenario where there are two or more signals such as BPSK, QPSK, FSK etc being present at a time was not considered.

#### A Concise Details of CR Performance Metrics

The most essential and challenging steps in the successful CR design by researchers is usually in establishing and choosing the effective performance metrics (Zhao, Mao, Neel, & Reed, 2009). It is consensus that the formalization of CR benchmarking methods and performance metrics would assist in hastening the integration of CR paradigm into existing wireless networks (Zhao, et al., 2009).

A quite reasonable numbers of metrics can be defined and has been utilized to evaluate CR performance since CR can support numerous various applications. Despite the great number of choices that are available, there is still need for careful selection of performance metrics as the

selection will impact many aspects of CR design. The Cognitive Engine (CE) needs to adopt dynamic situation-aware utility functions, in order to be responsive to changing radio scenarios and the tradeoffs among various (possibly conflicting) objectives, rather than relying on a single static function.

Generally, CR node can be evaluated based on four areas namely, the cognitive functionality, the overall node performance, complexity, and technical maturity. Some performance metrics that can be used in the CE to drive the operation of CR are highlighted in Table 1 for easy and quick comparisons.

Table 1: Summary of Performance Metrics of ANN in CR

Paper	Input Parameters	Output Parameters	Usage	Environmental and other factors considered	Activation Function	Layers	Performance Metrics
(Qi, et al., 2012)	Alternate time of channel vacancy/ occupancy state	Throughput, Packet loss rate	Spectrum Sensing	Number of detected transmission	Threshold Function	Statistical mean throughput	Throughput, Packet Loss rate
(Fehske, et al., 2005)	Carrier Frequency, Symbol Rate, SNR	Spectral coherence function, Reliability	Signal Classification	The signal's carrier and bandwidth is known. It was assumed that there is no prior knowledge of the signal other than its presence	Linear Function	Multi-layer linear perceptron network	Spectral coherence function of each of the signal type i.e., BPSK, QPSK, FSK and MSK Probability of classification for varying SNR, Probability distribution for confidence levels
(Rondeau, et al., 2004)	BER, Frequency, Power	Spectral Occupancy, Throughput, Interference	Radio Parameter Adaptation	Incorporation of regulatory and physical restrictions during chromosome evolution	It utilizes the dynamic fitness definition and evaluation where the weight of each function is adjustable and any fitness function	Multi objective genetic algorithm	Interference avoidance, Throughput, Spectral Occupancy

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						may or may not be used depending on the current link condition and user requirement			
(Baldo & Zorzi, 2008)	SNR, Received Frames, Erroneous Frames, Idle Time	Throughput, Delay, Reliability	Performance characterization of the components of a cognitive radio system	Number of detected transmissions/ Number of users	of A	Sigmoid Function	Multi layer feed forward neural networks	Throughput	
(Tsagkari, et al., 2008)	Time series collected by the radio-scene analysis phase	Mean squared error	Channel estimation and predictive modeling phases	Estimation of time zone parameter		Sigmoid Function	Multilayer linear perception	Mean squared error	

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### Conclusion and Recommendation

This paper reviewed different types of AI techniques namely GA, ANN, Metaheuristic Algorithm and Hidden Markov Models that have been proposed in literature to provide the cognition capability in a CE. It was shown that the AI technique is the pivot for numerous CR applications such as its utilization in spectrum sensing, radio parameter adaptation and signal or pattern classification. The understanding of the tradeoffs in the selection and design of AI processes is crucial in the successful design in CR. The AI techniques have been utilized in many CR applications as expounded in the paper. However, numerous implementations are still rudimentary probably due to the interdisciplinary nature of the field. Furthermore, there is need to pay more attention to the CE training process, which is crucial to its performance. The use of cooperative sensing can fasten training. However, in order to limit potential security vulnerabilities, there is need for the authentication of the sources and the externally learned behavior should be evaluated against self generated field measurements. Also, in order to maximize the payoff of CR there is need to design a CR that will support self organizing network that can improve the continuous management of heterogeneous network elements and radio resources far beyond what the CR designers could conceive.

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