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Survey of Artificial Intelligence Approaches in Cognitive Radio Networks

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Abstract

This paper presents a comprehensive survey of various artificial intelligence (AI) techniques implemented in cognitive radio engine to improve cognition capability in cognitive radio networks (CRNs). AI enables systems to solve problems by emulating human biological processes such as learning, reasoning, decision making, self-adaptation, self-organization, and self-stability. The use of AI techniques is studied in applications related to the major tasks of cognitive radio including spectrum sensing, spectrum sharing, spectrum mobility, and decision making regarding dynamic spectrum access, resource allocation, parameter adaptation, and optimization problem. The aim is to provide a single source as a survey paper to help researchers better understand the various implementations of AI approaches to different cognitive radio designs, as well as to refer interested readers to the recent AI research works done in CRNs.

Index Terms: Cognitive radio networks, Artificial intelligence techniques

I. INTRODUCTION

The radio spectrum is the unique natural resource totally assigned to different licensed holders according to the fixed spectrum assignment policy. It was then analyzed that a large portion of spectrum is not utilized under time and place [1]. Cognitive radio (CR) was proposed to solve this problem by opportunistically utilizing the spectrum during the absence of their owners. It was considered to play a major role for the under-utilization of spectrum resources to meet the continuous greatest demand of wireless systems.

Cognitive radio networks (CRNs) enable cognitive users (or secondary users) to sense the environment in order to identify spectrum holes, analyse the parameters, and make decisions for dynamic resource allocation management. These capabilities are realized through integrating artificial intelligence (AI) techniques in the heart of the CR. AI enables cognitive users to solve problems by emulating human biological processes such as learning, reasoning, decision making, self-adaptation, self-organization, and self-stability. Various surveys have been proposed in the literature for the applications of AI techniques in CRNs. In [2], a survey on different learning techniques such as fuzzy logic (FL), genetic algorithms (GAs), neural networks (NNs), game theory (GT), reinforcement learning (RL), support vector machine (SVM), case-based reasoning (CBR), decision tree (DT), entropy, Bayesian, Markov model (MM), multi-agent systems (MAS), and artificial bee colony (ABC) algorithm were presented. They discussed their strengths and limitation according to the spectrum sensing and decision-making. In [3], the state of the art in the use of AI in CR to ascertain available choices for implementing a practical CR and the relative merits of various proposed techniques in differing applications were surveyed. The survey's techniques include artificial neural networks (ANNs), metaheuristic algorithms (MEAs), hidden Markov models (HMMs), rule-

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based systems (RBSs), ontology-based systems (OBSs), and case-based systems (CBSs). In [4], a survey on different learning techniques such as RL, GT, NNs, SVM, and MM were presented. They also discussed their strengths, weaknesses, and the challenges. In [5], the authors considered GT, RL, and reasoning approaches such as Bayesian networks (BNs), FL, and CBR. In [6], a survey of the AI techniques, GA, ANN, HMMs, and MEAs were presented, and their strength and weakness, and open research issues were examined.

In this paper the use of AI techniques is studied in applications related to the main challenges of CRNs including spectrum sensing, spectrum sharing, spectrum mobility, and spectrum management regarding dynamic spectrum access, resource allocation, parameter adaptation, and optimization problem. The aim is to provide a single source as a survey paper to help researchers better understand the various and recent implementations of AI approaches to different cognitive radio designs. AI techniques mentioned in this paper includes ANNs, Markov chains (MCs), FL, GT, SVM, RBSs, OBSs, CBSs, MASs, simulated annealing, and tabu search. As well as, bio-inspired algorithms including GA, differential evolution (DE), particle swarm optimization (PSO), bacterial foraging optimization (BFO), ant colony optimization (ACO), cat swarm optimization (CSO), ABC, and artificial immune system (AIS) are considered.

A. Cognitive Radio Network: An Overview

CR was firstly defined by Joseph Mitola [7] as "a radio that is aware of its surroundings and adapts intelligently". It has been introduced to respond to the under-utilization of spectral resources by dynamically access the temporarily unused spectrum bands.

CRNs bring new cognitive radio users (CRUs) that should sense the licensed bands to identify the spectrum holes, and then exploit them as long as they don't interfere with the licensed users. To meet these capabilities, CRN executes the four main functions of the cognitive cycle [8]. These functions are: spectrum sensing, spectrum management, spectrum sharing, and spectrum mobility.

Spectrum sensing is an important function in CRNs using dynamic spectrum access. The CRU must identify available bands for its transmission and be able to detect the presence of the primary users (PUs) in order to avoid harmful interferences. Spectrum sensing can be done by one or multiple CRUs exchanging information in cooperative way or in competitive manner. Generally exist three spectrum sensing strategies includes transmitter-based sensing method, interference temperature-based sensing method or through the received Signal-to-Noise Ratio (SNR) [9].

Spectrum management decides and allocates the best available spectrum band among available bands to meet the user transmission requirements and improve his throughput.

Spectrum sharing coordinates access among SUs and share available spectrum bands between them in fair manner. Spectrum sharing techniques can be classified as interweave, underlay, and overlay [10].

Spectrum mobility: In CRNs, the CRUs are considered as visitors to the spectrum. Hence, if the PU returns to the channel, the CRU must vacate and switch to a new available channel, to avoid interfering with the PU as well as to avoid breaking the secondary communication.

B. Artificial Intelligence: An Overview

AI enables systems to solve problems by emulating human biological processes such as learning, reasoning, decision making, self-adaptation, self-stability, self-organization, etc. The intelligent equipment will learn from its environment to take advantage of its experience. However, programming equipment that is capable to adapt to all situations and possibly evolving according to new constraints is challenging.

Cognitive radios need to have the ability to learn and adapt their wireless transmission according to the ambient radio environment. Thus, the AI must be implemented and adopted in the heart of cognitive radio technology. Various of AI techniques are used and implemented in CRNs including ANNs, MMs, FL, GT, SVM, MEAs, RBSs, OBSs, CBSs, MASs, and evolutionary algorithms such as GA, DE, PSO, BFO, ACO, CSO, ABC, and AIS.

II. BRIEF OVERVIEW OF ARTIFICIAL INTELLIGENCE TECHNIQUES IMPLEMENTED IN COGNITIVE RADIO NETWORKS

In this section, the overview of several AI techniques that have been implemented in CRNs is presented. The taxonomy of these different techniques is illustrated in Fig. 1.

A. Artificial Neural Networks

Artificial Neural Networks (ANNs) are networks of connected elementary processors, operating in parallel distributed processing. Each elementary processor (artificial neuron) characterized by inputs $x_i (i = 0\ldots n)$, weights $w_{ij} (j = 0\ldots n)$, activation function $F(x,w)$, internal state of activation $a = F(x,w)$, transition function $f(a)$, and the output $s = f(a)$. Each artificial neuron computes a single output based on the received information. They are inspired from the biological brain behaviour.

Exist three types of ANNs used in CRNs, multilayer perceptron networks in two forms linear (MLPN), and nonlinear (MNPN). These networks consists of multiple layers of computational units, usually interconnected in a feed-forward

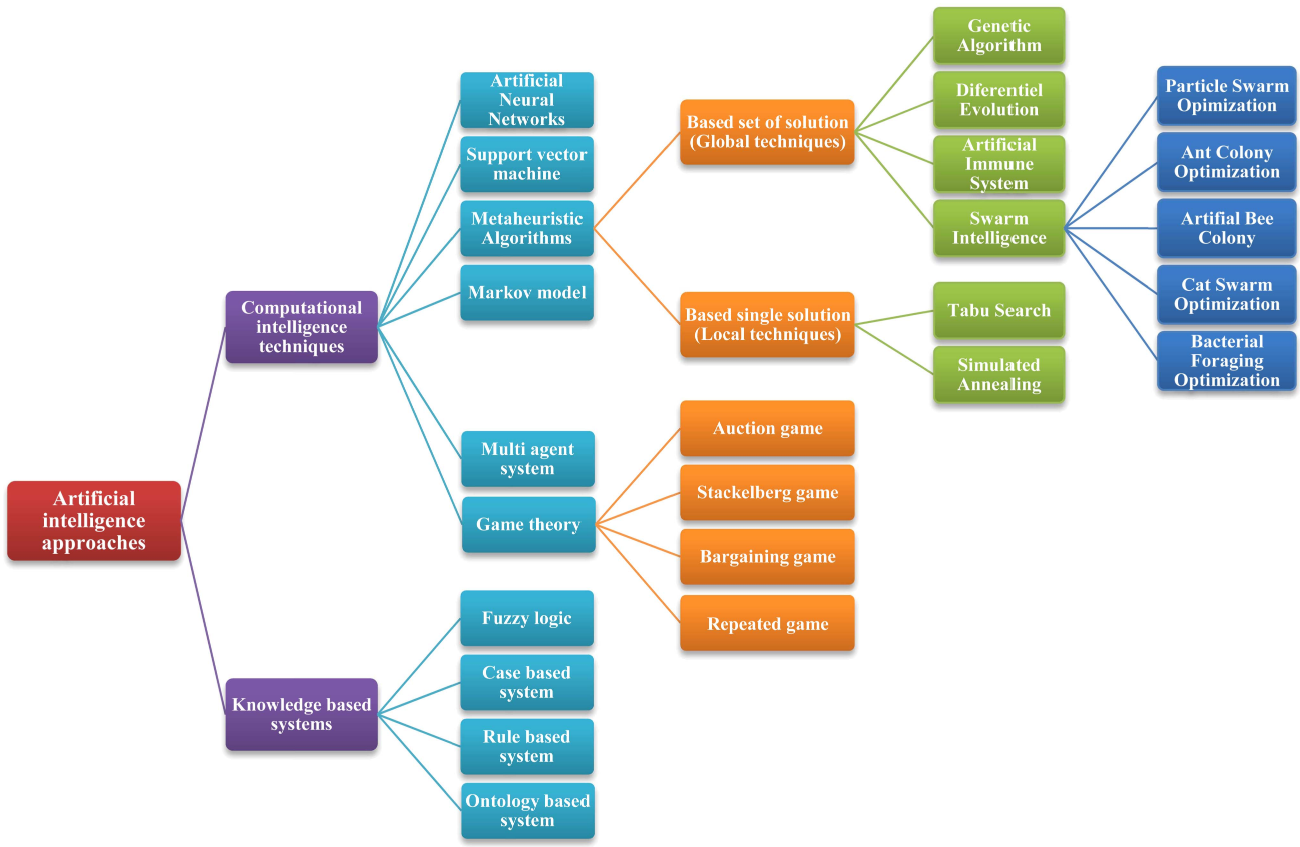


Fig. 1. Artificial intelligence approaches for cognitive radio networks.

way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In MLPN each layer is a linear combination of the previous layer's outputs. In MNPN, the units of these networks usually apply a sigmoid function as an activation function. The third one is radial basis function network (RBFN), which has two layers, and is a special class of multilayer feed-forward networks. Each unit in the hidden layers employs a radial basis function such as a Gaussian kernel, as the activation function. The radial function is centered at the point specified by the weight vector associated with the unit [11].

B. Markov Chains

Markov Models (MMs) are a mathematical formalism, which generalizes the short-path approaches in a stochastic environment. These models include state concepts that summarize the situation of the agent at each moment, the action that influences the dynamics of the state, and the reward that is associated to each state transition. They represent the temporal dependencies in a sequence of variables $S_0 \ldots S_t \ldots$, When each variable only depends on the previous one in the sequence, we say that we have a Markov chain: $P(S_t|S_0, \ldots, S_{t-1}) = P(S_t|S_{t-1})$.

C. Game Theory

Game theory (GT) is a mathematical decision technique that specifies the behaviours of multiple rational entities (players) into strategic situations to maximize their rewards. A game mathematically modelled by 3 variables $G = (N, S, U)$. N is the set of players, S is the set of strategies, and U is the set of utility functions. Each player acts according to its strategy to maximize its utility. Nash equilibrium of a game is defined as a point at which the utility function of each player does not increase if the player deviates from that point [12]. There are four categories of game theoretic approaches [13] which can used to model the behaviour of players in wireless environment: cooperative games, non-cooperative games, auction games, and stochastic games.

- In cooperative game, the players are grouped as coalitions and jointly improve their utility function.
- In non-cooperative game, each player aims to choose the optimal strategy to maximize his own reward. The famous concept of this category is the Nash equilibrium.
- In auction games the players are the buyers who must

select the appropriate bidding strategy in order to maximize their utility. They are conducted by an auctioneer.
- A stochastic game [13] is an extension of Markov decision process by considering the interactive competition among different agents. In a stochastic game, there is a set of states and a collection of action, one for each player in the game.

D. Fuzzy Logic

Fuzzy Logic (FL) is a suitable tool for handling inaccuracy, uncertainty, and ambiguity in intelligent systems. In a FL system, the values are represented by fuzzy sets rather than classical sets. The advantage of this representation is to simulate the human interpretations. The main components of a FL system are fuzzifier, fuzzy inference system, and defuzzifier. Fuzzification is the step that consists in the fuzzy quantification of the real values. The fuzzy inference system implements an inference engine of the type "if…then" that presents the relationship between the inputs and outputs. In the defuzzification, the output of the fuzzy system is mapped into non-fuzzy values as the output of the system.

E. Support Vector Machine

Support vector machine (SVM) is a binary classification method based on a linear classifier called hyperplane. This classifier is assumed to separate the data into two classes such that the distance between the closest points of each class to the hyperplane is maximized [14]. This method uses an efficient training dataset to learn the parameters of the model. It is based on the use of kernel functions that allow the optimal separation of data.

F. Rule Based Systems

Rule based system (RBS) is a classical method of knowledge representation. The rules are extracted from a specific area and used to make decisions. An RBS consists of rule base (RB) that contains the list of rules and the inference engine (IE) to take actions based on the RB.

G. Ontology Based Systems

Ontology based system (OBS) is the structured set of entities and concepts representing the meaning of a field of information and relationships among these concepts. Every field creates ontologies to limit complexity and organize information into data and knowledge. In OBS, the ontology is used to reason about the attributes of the domain of interest [3]. Ontology consists of:
- Classes: a set of objects of the area,
- Instances: individuals belonging to classes of the area,
- Attributes: properties of objects,
- Relations: links between entities,
- Ontology language: to facilitate machine processing, such as XML, Resource Description Framework (RDF), Web Ontology Language (OWL).

H. Case Based Systems

Case based system (CBS) is an analogical reasoning. The solution to new problems is selected from previous similar cases. The knowledge base is termed as the case base, where cases are representations of past experiences [5]. Upon new solutions obtained from case adaptation, the case database is updated with the new cases. Usually, CBS involves a 4-stages cycle [5]: retrieve, reuse, revise, and retain.

I. Genetic Algorithm

Genetic algorithm (GA) is considered as the earliest form of MEAs that is based on the natural selection and survival of the fittest. In the GA, the population is generated by randomly selecting a group of individuals called chromosomes. A chromosome is made up of a fixed number of genes. Each chromosome in the population is then evaluated using a fitness function. The individual with higher fitness has high probability to be selected for crossover operation. Two chromosomes are then selected to reproduce one or more new chromosomes. These later suffer mutation operation. Depending on the requirement of the user, this process continues for a certain number of generations or until an appropriate solution is obtained.

J. Differential Evolution

Differential evolution (DE) is a stochastic optimization metaheuristic that has been inspired by GAs and evolutionary strategies combined with a geometric research technique. In DE method, the initial population is generated by uniform random draw on all the possible values of each variable. The lower and upper bounds of the variables are specified by the user according to the nature of the problem. After initialization, the algorithm performs a series of transformations on the individuals, in a process called evolution. The DE standard uses three techniques (mutation, crossing, and selection) as GAs. At each generation, the algorithm successively applies these three operations to each vector to produce a test vector.

K. Particle Swarm Optimization

Particle swarm optimization (PSO) is an evolutionary computation inspired by the choreographed behaviour and dynamics motion of swarms of birds or fishes investigating the notion of "collective intelligence" in biological populations [15]. Unlike the GA, the basic PSO algorithm has no crossover and mutation operators. In PSO, a population of particles is created which are randomly distributed over the search space. The position of each particle is evaluated using the fitness function. Each particle stores the optimal solution, it has achieved so far, as personal best. The optimal solution, achieved so far by the population, is stored as global best. The position of each particle is updated towards its personal best and global best. The fitness of each particle's new position is evaluated using the fitness function. If the fitness of a particle's current position is better than that of its personal best position, then the personal best position is updated. The global best position is also updated which provides the final global solution to the optimization problem.

L. Bacterial Foraging Optimization

Bacterial foraging optimization (BFO) is an optimization algorithm based on the feeding behaviour of *Escherichia coli* bacteria (*E. coli*) present in the human gut [16]. The idea of the algorithm is the application of the foraging group strategy of swarm of *E. coli* bacteria in the multi-objective optimization problem. The search for nutrients by bacteria is done in order to optimize the energy obtained per unit of time. An individual bacterium can also communicate with others by sending signals. The process, in which a bacterium moves in small steps when searching for nutrients, is called chemotaxis. Thus, the main goal of BFO is to mimic the chemotactic movement of virtual bacteria in the multi-objective optimization problem.

M. Ant Colony Optimization

Ant colony optimization (ACO) is inspired by the performance of biological ants to produce optimized and shortest paths from their colonies to food sources. The ants randomly wander and upon finding food, they return to their colony while laying down pheromone trails. Upon finding a pheromone trail, other ants follow this trail and thus later continually reinforced. ACO mimics this ant behavior with "simulated ants" walking around a graph representing the problem to solve and finding locally productive areas [3]. ACO algorithms search in parallel over several constructive computational threads based on local problem data and a dynamic memory structure containing information on the quality of the previously obtained result.

N. Cat swarm Optimization

Cat swarm optimization (CSO) is a new evolutionary algorithm proposed by [17], which mimics the natural behaviour of cats when they trace and hunt their prey. Cats are always attentive and move very slowly. This behaviour is represented as a search mode. When the presence of prey is detected, the cats hunt it very quickly. This behaviour is represented as a tracing mode. These two modes have been modelled mathematically to solve optimization problems.

O. Artificial Bee Colony

Artificial bee colony (ABC) is a self-organization behavioral model presented by bee colonies [18]. This model was inspired by the feeding behaviour of bees. The bees leave their colony to look for promising food sources. By finding a good food source, a bee returns to the hive to inform others bees via an agitation dance which represent a communication tool. Through this agitation dance, the bee transmits three important information: the distance, the direction, and the quality of the source food to other bees. The bee uses this especially agitation dance to convince other bees to be the followers and go back the source food. Therefore, more the bees are attracted to the source food more this later is a promising source.

P. Artificial Immune System

Artificial immune system (AIS) is inspired by the human immune system functioning. It is a defensing mechanism that is able to learn. One of the immune response types is the secretion of antibodies. Antibodies are receptor molecules that recognize and block the antigen. This metaphor is used by AIS where an antibody will represent a potential solution to the problem.

Q. Simulated Annealing

Simulated annealing (SA) is a generalized Monte Carlo optimization technique in which a temperature parameter is introduced [19]. The historical analogy is inspired by the annealing of metals in metallurgy: a metal cooled too quickly has many microscopic defects. However, if it is cooled slowly, the atoms rearrange, the defects disappear and the metal then has a very ordered structure. The first phenomenon is equivalent to a local optimum in combinatorial optimization problem and the second one is equivalent to a global optimum.

The performance of this approach depends, among other, on the cooling rule that is used (i.e. the decrease of the temperature parameter T). The fast cooling leads to a local optimum that can be of poor quality. The slow cooling requires high computation time and the adjustment of the various parameters (initial temperature, number of iterations per temperature step, temperature decrease, etc.) can be long and difficult.

R. Tabu Search

Tabu search (TS) was introduced by Glover [20] and showed its performance on many optimization problems. The principle of the algorithm is to examine, at each iteration, the neighbourhood of the current solution and to select the best one. Applying this principle, the method allows going back to solutions that seem less interesting but may have a better neighbourhood. However, the risk is to cycle between two solutions. To avoid this phenomenon, the approach prohibits visiting a recently visited solution. For this, a tabu list of the attributes of the last visited solutions is maintained. Each new resulted solution removes from the list of the most formerly visited solution. As well as, the search for the next current solution is done on the neighbourhood of the current solution without considering the solutions of the tabu list.

S. Multi Agent Systems

Multi agent system (MAS) is a distributed system consisting of a set of reactive or cognitive entities interacting with each other and locating in a common environment. MAS are characterized by:

- Each agent has his own skills,
- No global control of the multi-agent system,
- Decentralized data,
- Adding new agents to MAS don’t affect the others, which explain the scalability and modularity,
- Learning and adaptation,
- Interaction capabilities.

III. APLLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES IN COGNITIVE RADIO NETWORKS

In this section, the state of the art of researches addressing AI techniques to CRNs is presented. They are grouped based on the major tasks of CRN as shown in Table 1.

A. Spectrum Sensing Task

Spectrum sensing is a binary hypothesis testing to determine the presence or absence of primary signal. The aim of spectrum sensing is to detect the spectrum hole, means a band of frequencies which are not being utilized by PU at a particular time and specific geographic location. The three known spectrum sensing methods in CRNs are matched filter detection (MFD), energy detection (ED), and cyclostationary detection (CSD). MFD require the prior knowledge about the PUs signal which will not be always possible. But no prior information is needed for CSD method and it can extract information about the primary signal waveform. But this method is complex to implement. ED is the most common spectrum sensing techniques because this method does not require any prior knowledge about the unknown signal. It is less complex and it takes less sensing time but at the same time it is susceptible to uncertainty in noise power and it cannot differentiate between PU and secondary user (SU) signal.

Considering the limitations of the previous sensing schemes, spectrum sensing for cognitive radio is investigated from binary classic aspect and combining it with various proposed AI tools. The aim of using AI techniques is to optimize the spectrum sensing time, the spectrum sensing error caused by false alarm rate and miss detection probability. As well as improve detection accuracy and enhance performance stability.

A neural network model is designed for spectrum sensing in [21]. The proposed ANN model is used to predict the status of channel for a fixed distance in the TV band. Depending on the channel capacity predicted, the channel status is decided. The parameters used for training are the distance, SNR, channel capacity, spectral efficiency over a TV band. In [22], authors suggested a novel hybrid spectrum sensing

Table 1. Main application of artificial intelligence techniques to cognitive radio networks

AI technique	Spectrum sensing	Spectrum sharing	Spectrum handoff	Spectrum management			
				Resource allocation	Optimization problem	Parameter adaptation	DSA
ANN	✓			✓			✓
MM	✓		✓	✓			✓
FL	✓		✓	✓			✓
GT		✓		✓			✓
MHA				✓	✓	✓	✓
SVM	✓				✓		
RBS							✓
OBS							✓
CBS					✓	✓	
MAS		✓					✓

scheme. The proposed scheme is a combination of classical energy detection, Likelihood Ratio Test statistic (LRS-G2) and ANN. The authors evaluated the performance of proposed scheme on several real-world primary signals of various radio technologies and it has been found out that for all those radio technologies the proposed scheme outperforms the classical ED and the improved ED.

The disadvantages of cyclostationary feature detection technique and Matched filter technique are overcome by the ANN model developed in [23]. The authors proposed double threshold method for spectrum sensing. They are combined the ANN with the cyclostationary and the ED techniques. ANN is selected to train the samples of signals and detects the existence of the primary user, specifically the back propagation algorithm.

Therefore, the ANN has been adopted in spectrum sensing for CRNs and it's usually combined with cyclostationary scheme to provide reliable signal classification and efficient PU signal prediction because of their ability to be trained at any time.

The Markov model is used to model random process changing from one state to another over time. In Markov models, the states are visible to the observer. However, in the HMM, some states are hidden or not explicitly visible. HMMs have been used for spectrum sensing in CR in [24, 25]. Ref [24] proposed to use the HMM to process signal cyclostationary features for primary signal detection in CR. In [25], the authors validated the existence of a Markov chain model for wireless channel utilization with real-time measured data in the paging band and formulate the spectrum-sensing problem using an HMM. The HMM-based prediction method has been widely used in CR networks. In [26] the authors investigated the use of Non-Stationary Hidden Markov (NSHMM) and Hidden Bivariate Markov (BHMM) Models through simulations and real-time application to predict RF channel occupancy in cognitive radio systems. The results exhibited good potential for enabling successful secondary use of a large fraction of the available spectrum. In [27], HMM-based channel state prediction was proposed. The predicted channel states are output together with corresponding probabilities that are helpful to subsequent decision. The results show that the proposed approach for prediction of channel state is effective and can be used together with traditional spectrum sensing techniques for spectrum sensing. Also it can be utilized to provide predictive information to upper-level modules of cognitive radio.

FLis another attractive technique particularly in cases where target problems are difficult to model with traditional mathematical methods, but are at the same time easier for human people to understand. In cooperative spectrum sensing the decisions on the presence of the PU are based on observation results from several cognitive radio nodes. The final decision making process is assumed by the fusion controller. A fuzzy based fusion rule is proposed in [28-30]. In [28], the considered parameters are energy and SNR received from the neighboring nodes. The Fuzzy rule has shown a better performance under probability of detection and probability false alarm compared to "AND" and "OR" rules. In [29] the authors proposed a novel distributed cooperative spectrum sensing approach by deploying a FLfor local decision-fusion, the environmental properties and SU-mobility are utilized in the decision-making process. The proposed approach is evaluated on a real-world measured power dataset. The results have been shown high robustness against instantaneous changes in SUs velocity levels, good probability of detection at very low SNRs at different mobility levels, and performance that surpasses the state-of-the-art research under different SNR and velocities levels. In [30], the technique takes into account the reliability of the sensing results at different cognitive radio nodes. The credibility of the sensing node is determined in a training stage with fuzzy evaluation. The FLis an efficient tool to CRN environment where there is limited or no information about certain environment factors. It is used in cooperative spectrum sensing to provide additional flexibility to existing combining methods.

SVMs have been also applied to CRNs. As mentioned in support vector machine theory, two groups of data easily separated with a line. However, it is difficult to linearly classify in practice. Thus, kernel function is proposed to map the input low dimensional vector into a high dimensional feature space for linear classification [12]. In [31], SVM is used for spectrum sensing and real-time detection. The sample data was classified as a primary user or not by training and testing on the proposed SVM classification model. In [32], SVM classification technique is considered for cooperative spectrum sensing. The SVM scheme is performed in three steps, gathering training samples, obtaining support vectors from the training samples, and putting a test sample into the SVM to classify the PU signals. In [33], authors apply SVM classification techniques to eigenvalue based spectrum sensing for cognitive radios. The applications of SVM to CRNs have been mostly limited to problems of signal classification [12]. SVMs produce very efficient classifiers with high prediction accuracy and less overfitting even if training examples contain errors. SVMs typically outperform ANNs for limit sample data, but require prior knowledge of the observed process' distribution and labeled data.

Other AI techniques like GT, MAS, and MEA are less investigated in spectrum sensing field, due to their development and evolution style. The GT is an interactive tool that requires interactivity between two or multiple agents, where the decision of one is influenced and having an effect on the other. Therefore, it can be useful in spectrum sharing task to model the interaction between SUs or between secondary and primary user. As well as the case of MAS, their applications found mainly in problem solving interactions and relations between different entities. The goal of MEAs is to succeed in finding a global optimum. For this, the idea is both to browse the search space, and explore areas that look promising. Thus, this kind of algorithms can be applied to computationally hard problems to search through the solution space while learning and establishing the requisite relationships [3]. Among the various MEAs, the GA has been widely adopted to solve multiobjective optimization problem. Ref. [34] has considered GA to optimize the scheduling of sensing periods. Ref. [35] uses hybrid approach in cooperative spectrum sensing framework. The evolutionary algorithm based approach for optimizing the global decision threshold and the weights assigned to different CRs in cooperative sensing and a FLbased decision making technique is proposed to find out a compromise solution on the Pareto front. A recent research [36] has investigated the multiband cooperative spectrum sensing optimization problem in CRN, with the purpose of achieving higher throughput through jointly optimizing decision thresholds and weight coefficients. ABC algorithm has been adopted to address the optimization problem. Table 2 present synthesis of some of researches addressing AI techniques in spectrum sensing for CRNs and Table 3 gives the advantages and disadvantages of these techniques.

B. Spectrum Management Task

After performing spectrum sensing, cognitive user (CU) has to decide the best available spectrum band to allocate, and to dynamically adjust its parameters to achieve the highest performance such as maximizing the exploitation of the spectrum, meeting users' quality of service (QoS) requirements like rate and delay [2]. This decision-making is affected by the environment information and is based on AI algotithms (ANN, MM, CBS, OBS, etc) adapted to the CR learning and reasoning capabilities. The self-adaptation capability is mainly based on optimization algorithms such as GA, DE, swarm intelligence algorithms.

The aim of the integration of these intelligent techniques to CR engine is to reduce the complexity and improve the

Table 2. Applications in cognitive radio spectrum sensing based artificial intelligence techniques

Application	AI approach	Reference
Channel occupancy prediction	ANN	[21]: determine the occupancy status of the TV channel using SNR, channel capacity, bandwidth efficiency and the distance of the scanning system from the primary TV base station.
	HMM	[25]: use HMM to predict the true states of the sub-band, the Viterbi algorithm is used to reduce complexity of obtaining likelihood solution.
		[26]: use the non-stationary hidden Markov and hidden bivariate Markov models to predict RF channel occupancy
		[27]: apply HMM to predict channel state. The result is combined with corresponding probabilities to help in decision making.
Primary user signal detection	ANN	[22]: incorporate classical ED and likelihood ratio statistics (LRS-G2) into the ANN. It uses the energy value from ED and the Zhang statistic from the likelihood ratio statistic scheme as inputs to the ANN. The ANN is used in three phases, ANN training, ANN model selection, and ANN testing.
		[23]: provide double threshold method for spectrum sensing. ANN, precisely back propagation algorithm is used to train the network for decision making.
Signal type classification	HMM	[24]: use cycle frequency domain profile (CDP) for signal detection. Signal features are extracted from CDP using a threshold-test method. For classification, a HMM has been used to process extracted signal features
	SVM	[31]: apply SVM to classify sample data as primary user or not by training and testing the SVM classification model in time domain
		[32]: investigate the MAC protocol identification, identifying the MAC protocol types and MAC layer parameters. SVM is used as the machine learning technique to perform the identification.
		[33]: provide eigenvalues of the sample matrix to constitute a training data point. SVM used to classify each new data point to decide the corresponding PU status
Fusion decision	FL	[28]: use FL based fusion rule to make decision by considering received energy and SNR of the neighboring nodes along with a two bit spectrum sensing result provided by energy detection.
		[29]: provide distributed cooperative spectrum sensing approach, where a FL is deployed for local decision-fusion, and such environmental properties and SU-mobility are utilized in the decision-making process.
		[30]: propose fuzzy collaborative spectrum sensing scheme. The final sensing decision is based on the combination procedure taking into account the credibility of each SU, which is evaluated using fuzzy comprehensive evaluation at the training stage.
Sensing | optimization	GA	[34]: apply GA to optimize the sensing periods.
	CSO + FL	[35]: use CSO to optimize global decision threshold and the weights assigned to different CRs, and FL is used in decision making to find out a compromise solution on the Pareto front.
	ABC	[36]: investigate the multiband cooperative spectrum sensing optimization problem, where ABC is addressed for non-convex optimization problem.

Table 3. Advantages and disadvantages of artificial intelligence techniques used in spectrum sensing issue

Algorithm	Advantages	Disadvantages
ANN	• Achieve better detection performance under low SNR • Reliable for signal classification • Efficient for PU signal prediction • Ability to be trained at any time	• Long training phase
HMM	• Achieve better classification performance under low SNR with only limited information on signal bandwidth • Efficient for PU signal prediction	• Require a huge memory space to store a large number of past observations with high computational complexity.
FL	• Efficient in case of limited or no information about certain environment factors. • Provide additional flexibility to combining methods	• High computation time to decide due to its wide range of possibilities • Highly depends on the fuzzy inference rules which may be tuned manually, and settings can be made by trial and errors.
SVM	• Efficient classification with high prediction accuracy for limit sample data	• Require prior knowledge of the observed process' distribution and labeled data • Overfitting

convergence in a limited time. As well as achieve efficient real-time resource allocation. However, the approaches that we will mention in this section are the main techniques used and applied in spectrum management in CRNs.

Managing the spectrum means making decision either in terms of spectrum allocation, or in dynamic spectrum access or in optimization problem or in parameter adaptation. Various AI approaches proposed to solve the later challenges in CRNs including, but not limited to, ANNs, MMs, FL, GT, MEA, SVM, RBS, OBS, CBS and MAS.

The ANN has been proposed for radio parameter adaptation in CRN in [37, 38]. In [37], the ANN determines radio parameters for given channel states to optimize three given metrics, adjust the BER, maximize the throughput, and minimize the transmit power. In [38], the authors proposed an ANN-based distributed optimization algorithm for cognitive wireless clouds, which consists of many heterogeneous terminals and networks. In [39], authors used ANNs to replace the current frequency allocation system to address the spectrum inefficiency problem. They introduced two scenarios: the single-user case scenario and the multi-user scenario with weighted allocation. In [40], hybrid approach based on GA and radial basis function (RBF) to design the cognitive engine in order to adjust the parameters of the system and to effectively adapt to the environment changes were proposed. Decision-making table is used to train the RBF learning model. The GA is used to adjust the operating parameters of the RBF neural network such as transmitting power, data rate, and Medium access control window. The ANN is also used in dynamic channel selection [41].

The beneficial capabilities of adopting the ANNs in CRNs are their ability to adapt to minor changes in the surrounding environment, as well their capability to provide information about the confidence in the decision making. In this field, the ANN is usually combined with another AI method such as GA in the training model. But the ANN still less investigated side spectrum management and as an excellent candidate side spectrum sensing for prediction and classification of PU signals. As the case for the SVM technique, where its application is restricted in this field, e.g. in [42], SVM was used to solve the optimization problem for the beam-forming weight vectors.

Several selected MEAs are presented here. They are classified into two categories: MEAs based set of solution (evolutionary algorithms) and MEAs based single solution as depicted in Fig. 1 (MEAs branch). Each algorithm has its own way of evolving as presented in Section II.

The GA has been widely adopted to solve multi-objective optimization problem, channel selection problem and dynamically configure the CR parameters in response to the environment dynamics in [43-48]. In [43], the authors are interested in finding the optimal spectrum to be allocated to users in CRN. The parameters used as genes for the decision making are frequency band, power transmission, bit error rate and modulation scheme. In [44], the authors combined GA and ON/OFF primary user activity models to address the spectrum allocation in CRN. The activity history patterns generated from four ON/OFF primary user activity models is combined with the GA as sensing vector to select the best available channel in terms of quality and least PU arrivals. In [45], multi-objective parameter adjustment in CR based on GA is proposed, where the GA is improved by introducing linear scale transformation and adaptive crossover probability and mutation probability. In [46] the authors presented the adaptation mechanism of a cognitive engine which used GAs to evolve a radio's parameters to a set of parameters that optimize the radio for the user's current needs. In [47], the authors addressed spectrum optimization in CRs using elitism in GAs. The parameters used for the chromosome structure are frequency, power, bit error rate, and modulation scheme. In [48], the authors used GA to solve the channel assignment problem in cognitive radio systems. The objective of this problem concerns minimizing the channel interference to the PUs. The use of GA is quite appropriate in the context of cognitive radio to control and avoid interference in the channel assignment problem. In [49], authors presented a novel hybrid dynamic spectrum access approach, combining classical and stochastic flavors being augmented with new genetic operators, for multi- channel single-radio cognitive radio networks.

Swarm intelligence refers to a class of evolutionary algorithms in which it's imitate the intelligence from social cooperative animals such as ants, bees, cats, etc. Swarm intelligence techniques highlight in general distributed implementation and coordination through communication. Solutions based on swarm intelligence techniques have been proposed for CRNs. Swarm intelligence techniques has been used recently in the CR systems to reduce the computational cost of GA. In [50], the authors propose an adaptive discrete PSO algorithm for adaptation of transmission parameters and achievement of Quality of Service (QoS) requirements of a CR node using multi-objective optimization. ACO is proposed in [51] to response to spectrum allocation problem in CRN. The authors designed an improved ant colony optimization algorithm (IACO) from two aspects: first, they introduced differential evolution (DE) process to accelerate convergence speed by monitoring mechanism; then they designed a variable neighborhood search (VNS) process to avoid the algorithm falling into the local optimal. The dynamic spectrum allocation is also investigated in [52] using an improved combined approach of particle swarm optimization (PSO) method and SA to form the PSOSA algorithm. The SA is used to modify the PSO. Multi-objective evolutionary algorithm based CSO is applied in [53] to the parameter adaptation problem of an OFDM based cognitive radio engine. A FLbased decision making technique is introduced. A comparative analysis of six evolutionary algorithms is presented in [17] to adapt the parameters of CR in a time varying wireless environment. The mentioned EAs are genetic algorithm (GA), particle swarm optimization (PSO), differential evolution (DE), bacterial foraging optimization (BFO), artificial bee colony (ABC) optimization and cat swarm optimization (CSO) algorithm. The performance of each algorithm is tested in single and multicarrier communication system in order to acknowledge the advantage of multicarrier communication systems in wireless environment.

After analyzing the existing researches, we noticed that each metaheuristic algorithm has its own advantages and disadvantages. GA is powerful in terms of its ability to determine the performance of unknown system with least knowledge and it can initialize itself from possible solutions rather than a single solution. While it lacks in convergence to the global optima due to poor parameter settings, infinite research and also the random processes of crossover and mutation. While PSO algorithm is simple and has fast converging behavior, it is effective in global search, but it suffers from the partial optimism, which causes the inaccuracy at the regulation of its speed and the direction, as well it requires high computation time. ABC Algorithm is simple and efficient, easy to implement, robust and highly flexible. The limitation of ABC result in its requirement of new fitness tests for the new parameters to enhance performance, which leads to high computation and the need for a high rate of objective function evaluations. ACO has various strengths include fast solution finding due to its ability to offer positive feedback, as well it has distributed computation which avoids premature convergence. Also it takes advantage of the existing collective interaction of a population of agents. But it suffers from slower convergence compared to other MEAs and lacks a centralized processor to guide it towards good solutions. Although the time for convergence is uncertain, the convergence is guaranteed. As well as, it gives poor performance within large search spaces. DE is beneficial in terms of improving the ability of local search and guarding the multiplicity of the population. The disadvantages of DE are the slow convergence and being unstable. The advantages of BFO are the ability to gather information very quickly from its environment and neighbours which leads to fast search of the optimum and the capability to ensure the cell-to-cell communication capabilities. Its limitations including poor convergence behaviour over multi-modal and don't hold the fittest bacterium for the succeeding generation. The beneficial capabilities of CSO that is fast in discovering good solutions and adapting quickly to changes. But it suffers from the sequences of random decisions which are not independent and from the slow convergence. Finally, as strengths of AIS, we cite the ability of self-stabilizing, providing superior performances in multi-modal and suitable in cases when no such prior knowledge is available, but is limited to lack running stability and requirement of higher number of iterations to locate the global optima. Therefore, an algorithm can be selected depending in one hand on the accuracy and the computation speed, in other hand on the hardware capabilities such as processor speed, memory, etc. In Table 4, we summarize the strengths and limitations of the several evolutionary algorithms considered in this work.

The key advantage of using MEA in CRN is their ability to dynamically reconfigure the CR over the changes and dynamics of the surrounding environment. They are considered as excellent candidate algorithms to solve multi-objective optimization problem in which the objectives are contradictory in nature such as maximizing data rate and minimizing bit error rate. Particularly, swarm intelligence provides a new structure for the design and implementation of MASs that are able to cooperate to solve a complex problem. As well, the majority of research in this field has so far focused on intelligent swarm-based cognitive radio systems for solving problems that require cooperation, self-configuration, self-organization, self-adaptability, self-stability, etc. On the other hand, the recent trend of research in meta-heuristic computing is mov-

Table 4. Advantages and disadvantages of different evolutionary algorithms used in spectrum management

Method	Strength	Limitation
GA	• Ability to define the performance of unknown system with few knowledge • Ability to initialize itself from possible solutions rather than a single solution	• Slow convergence to the optimal values since the crossover and mutation process are random • High computation time
DE	• Enhance the capacity of local search • Keep the multiplicity of population • Good convergence properties	• Slow convergence and unstable
PSO	• Simple to implement • Fast convergence behavior • Less computation time • Has only a few parameters to be set • Effective in global search	• Suffer from the partial optimism, which causes the inaccuracy at the regulation of its speed and the direction • Tendency to result in a fast and premature convergence in mid optimum points
BFO	• Have the cell-to-cell communication capabilities • Ability to gather information from their environment and neighbors very quickly which leads to fast search of the optimum	• Poor convergence behavior over multi-modal • Do not hold the fittest bacterium for the succeeding generation
ACO	• Offer positive feedback resulting in rapid solution finding • Have distributed computation which avoids premature convergence • Assume collective interaction of a population of agents	• Lack a centralized processor to guide it towards good solutions • Time for convergence is uncertain, but the convergence is guaranteed • Poor performance within problemswith large search spaces
CSO	• Fast discovery of good solutions • Adapts to changes	• Sequences of random decisions (not independent) • Time to convergence uncertain, but it is guaranteed
ABC	• Simple and efficient • Easy to implement, robust, and highly flexible	• Require more and correct information about the problem model • Require new fitness tests resulting slow computation • Need for a high amount of objective function evaluations
AIS	• Ability of Self-Stabilizing • Provide superior performances in multi-modal • Suitable in cases when no such prior knowledge is available	• Lack running stability • Require a higher number of iterations to locate the global optimum

ing towards the hybridization of these methods to take advantage of two or more methods and to mitigate the limitations.

FL is also adopted in the decision making for CR reconfiguration for adapting to user requirements and system resources in [55]. Recent attempts of using FL to channel selection in CRN are made in [56] and [57]. In [56], authors used FL for prioritizing channels in the backup and candidate channel. The result help to rank channels i.e. to help for selecting the operating channel from the backup channel list, and selecting better channel to promote to backup channel from candidate channels. In [57], an improved channel allocation mechanism was proposed. They considered the received signal strength to define the channel access priority of SUs applied by fuzzy theory. The results have shown the performance of the approach and the effectiveness of the mechanism. Fuzzy inference rules for resource management in a distributed heterogeneous wireless environment are proposed in [58]. The fuzzy convergence is analyzed in two levels, the first based on local parameters such as interference power, bandwidth and path loss index. The second based on aggregated information collected from all nodes to generate a global control for each node.

In general, the benefit of exploiting FLis its low complexity and its suitability for real-time applications. In addition of its ability to obtain solutions with imprecise and incomplete input information. Although it suffers from the stability, accuracy, and optimality of the system are not guaranteed.

GT presents an efficient platform for modelling interactions behaviour among cognitive users in CRNs. In [59], the authors presented game theory for modelling resource allocation in ad hoc CRNs. In [60], the authors used GT as a utility function to model the payoffs between considered players (SUs and PUs). Repeated games were applied for dynamic spectrum access (DSA) in [61]. GT is advantageous in terms of reduces the complexity of adaptation algorithms in large CRNs and provides solutions for decentralized MASs [2], but it is limited to its requirement for prior knowledge of the utility function of each user.

Also MMs have been participate to the decision making in the spectrum management under various utilizations. They are used in [62] for modelling and analyzing the competitive spectrum access among CRNs. MM is applied to DSA in [63], [64] where HMM is used to model a wireless channel and predict the channel occupancy. Since MM based on generating sequences of observation of success transition states, it stills a useful tool for prediction and classification in spectrum sensing task.

Several works are addressed the issue of CR resource management by introducing MAS in [65, 66]. In [65], a Bayesian Network based multi-agent railway communication model for channel accessibility using a fusion of prior and validated information is proposed. This model consists of Bayesian inference to calculate the probability of successful transmission on a single station along with team collaboration to maximize network performance within a group of base stations. Instead of only performing the traditional sensing and assigning, the base stations have an ability to learn from the interactions among others and the environment to gain prior knowledge. The base station agents further analyze prior knowledge and perform optimal channel assignment for global network performance. In [66], the authors uses multi agent Q-learning algorithm to model the spectrum allocation scheme. MAS provide solutions using interactions between agents or users to improve the performance of the system. Therefore, this technique can be considered as very important tool in the spectrum sharing area.

OBR has shown as well its potential to satisfy the awareness and reasoning requirement of CR. Cognitive radio ontology (CRO) has been proposed in [67]. In this paper, the authors refined the OBR concept and test it on a link optimization use case. They are developed a CRO in OWL to represent the basic terms of wireless communications. Based on this ontology, authors developed a set of policies and rules to optimize the link performance. The results shown that the ontology and policy approach can infer implicit knowledge and this implicit knowledge can bring benefits to the communication efficiency. OBR is also used to apply spectrum policy to DSA in [68], [69]. In [68] the spectrum ontology defines the various DSA concepts, models the domain of DSA networks in a machine-understandable manner, and uses Semantic Web Rule Language (SWRL) rules to represent spectrum policies. Our policy reasoner implementation is able to handle all ontology operations, including ontology-consistency checking and ontology information editing. In [69], ontologies and rules are combined to achieve a knowledge driven differential-response capability, which, as defined by the authors, is the capability of reasoning about a failure in an attempt and identifying alternative actions to satisfy the goal using knowledge of radio technology, policy, goals, and other contextual information. The advantages of this AI technique is its ability to make a terminal understandable, i.e. a radio equipped with an OBS can understand the capability and characteristics of itself and other radios using logic deduction. This understanding, as well as the understanding of the environment, helps the radio to deduce optimal operating parameters [3]. Another advantage is that OBR can infer implicit knowledge. However it is limited to the high size of an ontology which requires high processing time to meet user's need.

CBR is based on solving new situations by finding the previous similar case and projecting the solution to current problem. CBS is used in [70] to present spectrum allocation scheme. In this paper the CBS is used to identify the type of channel required by a cognitive user. In [71], the authors used hybrid approach of CBS and GA to resolve the parameter adaptation problem. In [72], the authors introduced a CBR engine to exploit candidate channels for a tactical cognitive radio node by taking into account the PU's channel occupancy patterns. The results confirmed the reliability of the functional aspect, which includes the learning engine, as well as the case-based reasoning engine. In [73], the authors combined CBS and FL to determine the channel type. The attractive property of using CBR in CRNs that is allows learning without knowledge on how rules and cases are created [2]. As well, CBR is simple and easy to implement. But it suffers from many limitations. It is highly depend on pre-constructed database. It can take high processing time searching in the database to identify similar cases. The decision processes relies on previous situation which can provide error patterns. Therefore, CBR needs to be combined with another method such as ANN, GA, etc. to provide an efficient training before decision making.

RBR is also adopted in CR to implement a cognitive radio engine in [74, 75] as a helpful tool in the decision making. RBR is advantageous in terms of its facility to be understood and interpret because it is similar to human reasoning. Another advantage is its modularity, because, it is possible to add and remove rules according to the user requirements. However, RBR is disadvantageous in terms of the accuracy depends on the completeness and accuracy of the underlying rule base. If the domain is not perfectly understood, the RBS might return inappropriate responses [3]. In the Table 5, we present synthesis of several literature works addressing spectrum management based AI techniques and Table 6 gives the advantages and disadvantages of each approach in this field.

C. Spectrum Sharing Task

Spectrum sharing allow to share and manage the available underutilized radio resources between multiple candidate CRUs, in order to avoid the interference to the PUs as well as to avoid the interference between CRU's transmissions.

Coexistence techniques of CRUs with PUs can be assumed under interference limit approach (underlay), interference avoidance approach (interweaved), or both (overlay). Interference limit technique allows CRU to access a licensed band simultaneously with PUs as long as a predetermined temperature limit constraint is met at all time. In interference avoidance method, CRU can only access a band if the PU is not currently occupying its band. Other access strategies allow CRUs to use licensed spectrum both simultaneously with the PU and when a spectrum hole is determined by adjusting their maximum transmission power. In addition to coexisting with PUs in a spectrum band, CRUs must coexist with each other, i.e. self-coexistence [76]. In this section we review proposed paradigms introducing AI techniques to spectrum

Table 5. Applications in cognitive radio spectrum management based artificial intelligence techniques

Application	AI approach	Reference
Reconfiguration and parameter adaptation	ANN	[37]: use ANN to adapt radio parameters for given channel states. Adjust the BER, maximize the throughput, and minimize the transmit power.
		[38]: provide ANN as a distributed and autonomous optimization machine for heterogeneous wireless networks.
	GA	[45]: apply improved GA by introducing linear scale transformation and adaptive crossover probability and mutation probability to address multi-objective parameter adjustment
		[46]: use GA to find a set of parameters that optimize the radio for the user's current needs.
	PSO	[50]: use adaptive discrete PSO algorithm for adaptation of transmission parameters and achievement of quality of service requirements of a CR node.
	CSO + FL	[53]: apply CSO to the parameter adaptation problem of a OFDM based cognitive radio engine, and use FL in decision making to find out a compromised solution on the Pareto front.
	FL	[55]: address decision making mechanism to avoid the ping-pong effect of multiple reconfigurations and exploit FL reasoning approach for terminal reconfiguration decision, focusing on resource management and protocol configuration.
	CBR + GA	[71]: use CBR quantum genetic algorithm (CBR-QGA) in cognitive engine to adjust and optimize the radio parameters. EVF is used to avoid the blindness of initial population searching and speed up the optimization of quantum genetic algorithm.
Resource allocation	ANN	[39]: use ANN to replace a complicated frequency allocation system in the CR. The solution makes sure that the frequency allocation working well in an easier system and with less waste of resource.
	GA	[44]: combine GA with primary user ON/OFF models to select the best available channel in terms of quality and least PU arrivals.
		[48]: present GA to solve the channel assignment problem in CRNs.
	ACO + DE	[51]: adopt ACO for spectrum allocation, which introduces DE to accelerate convergence speed by the monitoring mechanism, and employ a variable neighborhood search (VNS) to avoid falling into the local optimum.
	PSO + SA	[52]: solve the nonconvex optimization problem using PSO. Combine SA with PSO to form the PSOSA algorithm, to overcome the inherent defects and disadvantages of these two individual components.
	FL	[56]: utilize FL for prioritizing channels in the backup and candidate channels list.
		[57]: apply fuzzy inference system to define the channel access priority of SUs.
		[58]: develop Fuzzy Convergence approach to aggregate wireless node control with affordable message overload.
	GT	[59]: introduce the concepts of modeling resource allocation with game theory.
	MAS	[66]: use MA reinforcement learning (MARL), Q-learning algorithm, on channels selection decision by SUs in 2×2 and 3×3 CR system.
	CBR	[70]: introduce CBR to identify channel preferred by SU. Then automatic collaborative filtering for preference between two users which assigns the particular channel to the highest prioritized user.
Optimization	SVM	[42]: present SVM to solve the optimization problem for the beamforming weight vectors.
	GA	[47]: provide GA for optimization to accommodate the SUs in best possible space in the spectrum
	GA+PSO+DE+BFO + ABC + CSO	[54]: provide comparative analysis of six evolutionary algorithms for optimizing the predefined fitness functions in the radio environment.
DSA	ANN	[41]: introduce ANN to learn how environmental measurements and the status of the network affect the performance experienced on different channels, and therefore dynamically select the channel.
	GA	[49]: devise an intelligent DSA algorithm by exploiting a synergy between GA based stochastic method and classical local search based novel genetic operators.
	GT	[61]: apply repeated games for DSA.
	MMs	[62]: use MMs for modelling and analyzing the competitive spectrum access among CRNs.
		[64]: use HMM to model a wireless channel for DSA and predict the channel occupancy
	OBS	[68]: provide ontology-based policies to construct the policy reasoner that can understand and process any spectrum policies authored by any organization by relying on the spectrum ontologies.
		[69]: apply spectrum policy to DSA using OBS.

sharing task.

GT is found to be the most candidate mathematical tool to deal with interactions among users. It tries to find an optimal solution to maximize the reward of every agent without harming one another. In [77], the authors presented an overview of several categories of game theoretic approaches used in spectrum sharing for CRNs.

A spectrum sharing based cooperative game (CG) theory is proposed in [78-81]. In [78], A CG is formulated to quantify and share the benefits of cooperation by accessing identified idle channels in a fair manner. The characteristic function describing the CG is based on the worth of SUs, which is calculated according to amount of work done for coalition by increasing awareness about state of spectrum

Table 6. Advantages and disadvantages of artificial intelligence techniques used in spectrum management issue

Algorithm	Advantages	Disadvantages
ANN	• Ability to adapt parameters to minor changes in surrounding environment • Provide information about the confidence in the decision made	• Long training phase
MEAs	• Excellent for multi-objective optimization • Ability to dynamically reconfigure the CR over the environment dynamics • Ability of self-configuration, self-organization, self-adaptability, self-stability	• See Table 4
FL	• Low complexity • Suitable for real-time	• Suffer from the stability, accuracy, and optimality of the system
GT	• Reduce the complexity of adaptation algorithms in large CRNs	• Require prior knowledge of the utility function of each user.
OBS	• Ability to make a terminal understandable • Infer implicit knowledge	• High size • High processing time
CBS	• Simple and easy to implement • Similar to human reasoning	• Highly depend on pre-constructed database • High processing time searching • Decision processes relies on previous situation which can return inappropriate responses
RBS	• Facility to be understood and interpret • Similar to human reasoning • Modularity	• Can return inappropriate responses • Accuracy depends on the completeness and the underlying rule base

that may also be seen as reduction in uncertainty about PU activity. In [79], authors used gale shapely algorithm to achieve cooperation among the cognitive radios for spectrum detection and sharing. This algorithm results in formation of stable coalition of cognitive radio. In order to form cooperative group each cognitive radio prepares a preference list of other radio in the vicinity with which the cognitive radio wants to cooperate and hence form coalition. Each cognitive radio makes an offer to cognitive radio in its preference list. In [80], authors described a framework for modelling the spectrum sensing and sharing problem in cognitive radios as a cooperative coalition game. The worth of individual players and also of each coalition in the game is calculated with respect to the work done by the players for its coalitions. In [81], a Cooperative Bargaining game in cognitive small cell networks is proposed. This approach is used for Interference-aware resource allocation. In the bargaining process, each player follows its individual bargaining strategy that maximizes its utility.

A spectrum sharing scheme based Stackelberg game is introduced in [82-84]. In a Stackelberg game, one player acts as a leader and the rest as followers, and the main goal is to find an optimal strategy for the leader, assuming that the followers react in such a rational way that followers optimize their objective functions given the leader's actions [83]. In [82], authors formulated a Stackelberg game where licensed network is the leader followed by a number of non-cooperative cognitive radio sensor network (CRSN) as actor nodes. In the proposed game, the licensed user imposes a price on the shared frequency band and the CRSN nodes have to buy the band to serve their own networks. In [83], based on the multiple-leader multiple-follower Stackelberg game model, the authors increased opportunistic use of the licensed radio spectrum. To adaptively use the spectrum resource, control decisions are coupled with one another; the result of the each user's decisions is the input back to the other user's decision process. In [84], authors focus on spectrum sharing in heterogeneous wireless sensor networks (HWSNs) and consider Stackelberg game exploiting the CR technology. In the game, the licensed network controls and prices the available spectrum resource which the WSN relay: actor nodes can purchase and use to serve the attached sensor nodes as well as offload some nodes in licensed network. The authors evaluated the impact on throughput performance and they proved that the proposed approach significantly improve the throughput of victim licensed nodes with slightly decreasing network total throughput.

A spectrum sharing based auction game in presented in [85, 86]. In a simple spectrum auction scenario, the primary owners act as auctioneers and sell their idle spectrum bands to SUs to make a profit, and the SUs act as bidders who want to buy spectrum bands. In [85], authors considered a CRN consisting of a primary spectrum owner (PO), multiple PUs and multiple SUs. They designed an auction-based spectrum sharing mechanism where the SUs bid to buy spectrum bands from the PO who acts as the auctioneer, selling idle spectrum bands to make a profit. In [86], the authors investigated a spectrum trading problem under relatively realistic settings, where heterogeneous channels under buyers' budget constraints are considered, while maintaining incentive compatibility and individual rationality. The proposed auction game consists of a price-setting PO aiming on maximizing its total revenue and SUs bidding channels for reasonable values. The results have shown performance improvements in PO revenue and SU utility over reference approaches.

Generally, MAS has also been exploited for spectrum sharing in CRNs, in [87, 88]. Where authors considered cooperative MAS in which the agents are deployed on PU and SU devices. The PU agents exchange a tuple of messages and help neighboring SU agents to enhance their spectrum utilization. The individual SU agent should send messages to the appropriate neighboring PU agents whenever needed and, subsequently, the related PU agents should reply to these agents in order to make spectrum sharing agreements. The SU agents take their decisions based on the amount of spectrum, time and price proposed by the PU agents and start spectrum sharing whenever they find an appropriate offer. SU agents pay the agreed price to the respected PU agents after completely utilizing the desired spectrum.

The spectrum sharing challenge is also addressed using bio-inspired paradigms, such as GA, ACO and PSO. In [89], authors proposed a spectrum sharing technique based on the improved quantum genetic algorithm (QGA) in a non-cooperative game for CR system. They considered a CR environment where PUs are allocated with a licensed radio spectrum and the utilization of which could be improved by sharing it with the SUs. They formulated the spectrum sharing problem as a game SUs compete for the spectrum offered by the PU and the cost of the spectrum is determined by using a pricing function. The QGA used as a competitive strategy. In [90] spectrum sharing is addressed using adaptive task allocation model of an ant colony. In [91] the socio-cognitive particle swarm optimization algorithm is used to address spectrum sharing in an underlay system.

In Table 7 we present synthesis of several papers addressing spectrum sharing based AI approaches and Table 8 show the strengths and limitations of these approaches.

D. Spectrum Mobility Task

The major goal of spectrum mobility in CRNs is to provide seamless channel switchover without interruption of ongoing SU's transmission. Thus spectrum mobility is carried out according to two procedures, i.e. spectrum handoff and connection management [92]. The first one is the process of switching ongoing transmission data from the current channel to another available channel. For channel handoff, it takes significant time called as spectrum handoff delay, which is the time spent to search for another available channel and radio frequency reconfiguration process by SUs. To cover the inevitable handoff delay, connection management process occurs to manage protocol parameters depending on current situation.

Spectrum handoff occurs in three cases: PU arrival, SU mobility and link quality degradation. This three situations force SU to perform spectrum handoff. Generally, spectrum handoff in CRNs is categorized into two main strategies: proactive and reactive. In the primary, the channel selection is done based on sensing PU traffic before the switching event. In latter, the channel is selected by instant sensing after the occurrence of switching event. The SUs affected by the handoff event resume their transmission on a new searched free channel. Thus, in both types, the channel selection is done by continuously observing the signals of PUs [93]. Therefore,

Table 7. Applications in cognitive radio spectrum sharing based artificial intelligence techniques

Application	AI approach	Reference
Cooperative sharing	GT	[78]: apply cooperative GT to quantify and share the benefits of cooperation among SUs.
		[79]: use gale shapely algorithm to achieve cooperation among CRs for spectrum detection and sharing.
		[80]: present cooperative coalition GT.
		[81]: use cooperative bargaining game for Interference-aware resource allocation.
	MAS	[87, 88]: provide spectrum sharing based cooperative MAS.
	ACO	[90]: provide spectrum sharing based adaptive task allocation model of an ant colony.
	PSO	[91]: design spectrum sharing based socio-cognitive PSO algorithm.
Non cooperative sharing	GT	[82-84]: introduce spectrum sharing scheme based Stackelberg game
		[85, 86]: present spectrum sharing based auction game
	GA	[89]: present spectrum sharing based improved quantum GA.

Table 8. Advantages and disadvantages of artificial intelligence techniques used in spectrum sharing issue

Algorithm	Advantages	Disadvantages
GT	• Provide good analyzed behaviours and actions for users under formalized game structure • Provides well-defined equilibrium criteria	• Require prior knowledge
MAS	• Easy to implement since MAS provide similarities between an agent and CR (awareness, autonomy, working together…) • Ability to give information exchanges by working with their neighbours • Provide an infrastructure to enable the cooperation and negotiation between the participating agents. • Flexible	• Can provide spectrum loss in case of disagreements between users • Can give failure proof due to the redundancy of agents and the self-managed features

Table 9. Applications in cognitive radio spectrum handoff based artificial intelligence techniques

Application	AI approach	Reference
Proactive handoff	FL	[94]: present fuzzy analytic hierarchy process for the handoff decision. This strategy reserves a number of backup channels characterized on the basis of QoS required by SUs. [95]: propose two FL controllers. The first measures the distance between PUs and SUs and estimates he transmission power of the SU for not affecting the transmission of neighbouring PUs. The second designs to check whether an SU should stay or leave the current channel. [96]: combine analytical hierarchical process algorithm with FL for the selection of backup channel alternatives. [97]: use FL controller to help SU adjust the transmitting power of the radio signal.
Reactive handoff	MMs	[98]: hidden Markov model (HMM) has proposed to optimize handoff decision. [99]: propose two state continuous time Markov chain to model the channel availability for SUs by considering SU's mobility. [100]: present a handoff strategy for cognitive ultra-wide band industrial networks. The busy and idle states of a channel are modelled using MMs. [101]: use a discrete time Markov chain to model channel access and handoff scheme.

Table 10. Advantages and disadvantages of artificial intelligence techniques used in spectrum handoff issue

Algorithm	Advantages	Disadvantages
FL	• Provide high channel utilization • Assume high throughput achieved by cognitive users	• High design complexity • Lack stability and robustness • Wastage of backup channels
MM	• Define channel usage efficiently • Provide high accuracy	• In some cases, SUs can still affect PU's transmission

spectrum handoff decision is an important issue in CRNs. Different AI techniques have been used in the learning design of CRN to improve spectrum handoff decision made.

A proactive handoff scheme based FL is proposed in [94-96]. In [94], authors presented fuzzy analytic hierarchy process for the handoff decision. This strategy reserves a number of backup channels characterized on the basis of QoS required by SUs. In [95], the proposed algorithm is based on two FL controllers. The first is to measure the distance between PUs and SUs. It estimates as well the transmission power of the SU for not affecting the transmission of neighbouring PUs. The second is designed to check whether an SU should stay or leave the current channel. In [96], the proposed fuzzy algorithm is a multiple criteria decision making technique that has proven to be an effective method for the selection of backup channel alternatives. This algorithm is a hybrid between Analytical Hierarchical Process Algorithm complemented with FL, it improves the management of subjectivity and reduces uncertainty in the information. In [97], FL based spectrum handoff algorithm in multihop underlay cognitive radio Adhoc networks is presented. Authors used FL controller to help SU adjust the transmitting power of the radio signal. If power adjustment is unlikely to lower the aggregate interference, then SU should do spectrum handoff.

The random appearance of PUs on a specific channel can significantly degrade the secondary ongoing transmissions due to the various interruptions. For this effect, several authors have proposed MMs to manage spectrum handoff. In [98], a HMM has proposed to optimize handoff decision. The model is used to check the channel state and correct spectrum sensing decisions. In [99], the authors proposed a two state continuous time MC to model the channel availability for SUs by considering SU's mobility. In [100], the authors presented a handoff strategy for cognitive ultra-wide band industrial networks, by the coexistence of primary and secondary users on a channel. The busy and idle states of a channel are modelled using MMs. In [101], the authors used a discrete time MC to model channel access and handoff scheme. The scheme allows an SU to identify the channel state and to decide even to stay idle on the current channel or to perform handoff.

The main advantages and limitations of the intelligent techniques applied in spectrum handoff issue are summarized in table 10. Most of the existing spectrum handoff researches lack the intelligent learning features in their design. Despite the importance of spectrum handoff process in CRNs, still this issue requires further in depth investigation. Table 9 syntheses the various researches addressing spectrum handoff based AI techniques. Table 10 gives their strengths and weakness.

IV. CONCLUSIONS

This paper addressed a survey of several AI techniques that have been implemented in cognitive radio designs. The application of these intelligence approaches have been studied related to the decision making in the major issues of cognitive radio networks considering spectrum sensing, spectrum management, spectrum sharing and spectrum mobility. A discussion of the algorithms was provided related to each major task with their advantages and disadvantages.

We have seen that the relevance of AI techniques varied by application and implementation. The decision in choosing one or some AI techniques over other techniques to cognitive radio design can be done depending in one hand on the application requirement, the available prior knowledge, the accuracy, the robustness and the computation complexity, in other hand on the hardware capabilities such as processor speed, memory, etc.

REFERENCES

[1] I. F. Akyildiz, W.-Y. Lee, and K. R. Chowdhury, "CRAHNs: Cognitive radio ad hoc networks," *Ad Hoc Networks*, vol. 7, no. 5, pp. 810-836, 2009. DOI: 10.1016/j.adhoc.2009.01.001.

[2] N. Abbas, Y. Nasser, and K. Ahmad, "Recent advances on artificial intelligence and learning techniques in cognitive radio networks," *EURASIP Journal on Wireless Communications and Networking*, 2015. DOI: 10.1186/s13638-015-0381-7.

[3] A. He, J. Gaeddert, L. M. Tirado, and J. H. Reed, "A survey of artificial intelligence for cognitive radios," *IEEE transactions on vehicular technology*, vol. 59, no. 4, pp. 1578-1593, 2010. DOI: 10.1109/TVT.2010.2043968.

[4] M. Bkassiny, Y Li, and S. K. Jayaweera, "A survey on machine-learning techniques in cognitive radios," *IEEE Communications Surveys & Tutorials*, vol. 15, pp. 1136-1159, 2013. DOI: 10.1109/SURV.2012.100412.00017.

[5] L. Gavrilovska, V. Atanasovski, I. Macaluso, and L. DaSilva, "Learning and reasoning in cognitive radio networks," *IEEE Communications Surveys & Tutorials*, vol. 15, pp. 1761-1777, 2013. DOI: 10.1109/SURV.2013.030713.00113.

[6] H. B. Salau, A. M. Aibinu, E. N. Onwuka, A. J. Onumanyi, and M. E. Bima, "Applications of artificialiIntelligence techniques in cognitive radios: a survey," August 2015, [online] available: https://www.researchgate.net/publication/307935017.

[7] J. Mitola, and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, 1999. DOI: 10.1109/98.788210.

[8] Ž. Tabaković, "A survey of cognitive radio systems," Semantic Scholar, 2011, [online] available: https://pdfs.semanticscholar.org/19c8/471e97301e408c3e3fe08eb8f5027ef9eed6.pdf.

[9] Z. Ning, Y. Yu, Q. Song, Y. Peng, and B. Zhang, "Interference-aware spectrum sensing mechanisms in cognitive radio networks," *Computers and Electrical Engineering*, vol. 42, pp. 193-206, 2015. DOI: 10.1016/j.compeleceng.2014.10.011.

[10] S. M. Baby, and M. James, "A Comparative Study on Various Spectrum Sharing Techniques," *Procedia Technology,* vol. 25, pp. 613- 620, 2016. DOI: 10.1016/j.protcy.2016.08.152.

[11] A. K. Jain, J. C. Mao, and K. M. Mohiuddin, "artificial neural networks: A tutorial," *IEEE Computer*, vol. 29, pp. 31-44, Mar 1996. DOI: 10.1109/2.485891.

[12] M. Bkassiny, and S. K. Jayaweera, "AsSurvey on machine-learning techniques in cognitive radios," *IEEE Communications Surveys & Tutorials*, vol. 15, pp. 1136-1159, 2013. DOI: 10.1109/SURV.2012.100412.00017.

[13] B. Wang, Y. Wu, and K. J. Liu, "Game theory for cognitive radio networks An overview," *Computer Networks*, vol. 54, pp. 2537-2561, 2010. DOI: 10.1016/j.comnet.2010.04.004.

[14] J. Qadir, "Artificial intelligence based cognitive radio networksve routing for cognitive radio networks", *IEEE Communications Surveys & Tutorials*, 2013. DOI: 10.1007/s10462-015-9438-6.

[15] J. Kennedy, and R. Eberhart, "Particle swarm optimization," in *Proceeding of the IEEE International Conference on Neural Networks*, pp. 1942-1948, 1995. DOI: 10.1109/ICNN.1995.488968.

[16] S. S. Pattnaik, K. M. Bakwad, S. Devi, B. K. Panigrahi, and S. Das, "Parallel bacterial foraging optimization" *Handbook of Swarm Intelligence*, vol. 8, pp. 487-502, 2O11. DOI: 10.1007/978-3-642-17390-5_21.

[17] S.-C. Chu, and P.-W. Tsai, "Computational intelligence based on the behavior of cats," *International Journal of Innovative Computing, Information and Control*, vol. 3, pp. 163-173, 2007.

[18] A. Baykasoğlu, L. Özbakır, and P. Tapkan, "Artificial bee colony algorithm and its application to generalized assignment problems," *Swarm intelligence: focus on ant and particle swarm optimization*, pp. 129-156, 2007. DOI: 10.5772/5101.

[19] S. Kirkpatrick, D. C. Gelatt, and M. P. Vechhi, "Optimization by simulated annealing," *Science*, vol. 220, pp. 671-680, 1983. DOI: 10.1126/science.220.4598.671.

[20] F. Glover, "Future paths for integer programming and links to artificial intelligence," *Computers and Operations Research*, vol. 13, pp. 533-549, 1986. DOI: 10.1016/0305-0548(86)90048-1.

[21] S. Pattanayak, P. Venkateswaran, and R. Nandi, "Artificial intelligence based model for channel status prediction: a new spectrum sensing technique for cognitive radio," *International Journal of Communications, Network and System Sciences*, vol. 6 no. 3, pp. 139-148, 2013. DOI: 10.4236/ijcns.2013.63017.

[22] M. R. Vyas, D. K. Patel, and M. L. Benitez, "Artificial neural network based hybrid spectrum sensing scheme for cognitive radio," in *Proceeding of IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, pp. 8-13, 2017. DOI: 10.1109/PIMRC.2017.8292449.

[23] B. Varatharajana, E. Praveen, and E. Vinoth. "Neural network aided enhanced spectrum sensing in cognitive radio," *Procedia Engeneering*, vol. 38, pp. 82-88, 2012. DOI: 10.1016/j.proeng.2012.06.012.

[24] K. Kim, I. A. Akbar, K. K. Bae, J. S. Urn, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," *in Proceeding of the 2nd IEEE nternational Symposium on New Frontiers in Dynamic Spectrum Access Networks*, pp. 212-215, 2007. DOI: 10.1109/DYSPAN.2007.35.

[25] C. Ghosh, C. Cordeiro, D. P. Agrawal, and M. B. Rao, "Markov chain existence and hidden Markov models in spectrum sensing," in *Proceeding of IEEE International Conference on Pervasive Computing and Communications*, pp. 1-6, 2009. DOI: 10.1109/PERCOM.2009.4912868.

[26] L. Renault, L. Rodrigues, and E. L. Pinto, "HMM models and estimation algorithms for real-time predictive spectrum sensing and cognitive usage," in *Proceeding of xxxv simposio brasileiro de telecomunicacoes e processamento de sinais (sbrt2017)*, 2017. available: http://www.sbrt.org.br/sbrt2017/anais/1570361504.pdf.

[27] P. P. Roy, and D. M. Muralidhar, "Hidden Markov Model based channel state prediction in cognitive radio networks," *International Journal of Engineering Research & Technology,* vol. 4, no. 02, pp. 391-394, 2015.

[28] J. Jacob, B. R. Jose, and J. Mathew, "A fuzzy approach to decision fusion in cognitive radio," *Procedia Computer Science*, vol. 46, pp. 425-431, 2015. DOI: 10.1016/j.procs.2015.02.040.

[29] R. Elgadi, A. R. Hilal, and O. Basir, "A fuzzy logic approach for

cooperative spectrum sensing in cognitive radio networks," in *Proceeding of IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE)*, 2017. DOI: 10.1109/CCECE. 2017.7946841.

[30] A. Yang, Y. Cai, and Y. Xu, "A fuzzy collaborative spectrum sensing scheme in cognitive radio," in *Proceeding of International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, pp. 566-569, 2007. DOI: 10.1109/ISPACS.2007.4445950.

[31] D. Zhang, and X. Zhai, "SVM-based spectrum sensing in cognitive radio," in *Proceeding of the 7th International Conference on Wireless Communications, Networking and Mobile Computing*, 2011. DOI: 10.1109/wicom.2011.6040028.

[32] S. Hu, Y.-D. Yao, and Z. Yang, "MAC protocol identification using support vector machines for cognitive radio networks," *IEEE Wireless Communications*, vol. 21, pp. 52-60, 2014. DOI: 10.1109/ MWC.2014.6757897.

[33] O. P. Awe, Z. Zhu, and S. Lambotharan, "Eigenvalue and support vector machine techniques for spectrum sensing in cognitive radio networks," in *Proceeding of the Conference on Technologies and Applications of Artificial Intelligence*, 2013. DOI: 10.1109/TAAI. 2013.52.

[34] A. Balieiro, P. Yoshioka, K. Dias, D. Cavalcanti, and C. Cordeiro, "Adaptive spectrum sensing for cognitive radio based on multi-objective genetic optimisation," *Eletronics Letters*, vol. 49, pp. 1099-1101, 2013. DOI: 10.1049/el.2013.1173.

[35] P. M. Pradhan and G. Panda, "Cooperative spectrum sensing in cognitive radio network using multiobjective evolutionary algorithms and fuzzy decision making," *Ad Hoc Networks*, vol. 11, pp. 1022-1036, 2013. DOI: 10.1016/j.adhoc.2012.11.007.

[36] M. Li, Y. Hei, and Z. Qiu, "Optimization of multiband cooperative spectrum sensing with modified artificial bee colony algorithm," *Applied Soft Computing*, vol. 57, pp. 751-759, 2017. DOI:10.1016/ j.asoc.2017.03.027.

[37] N. Baldo, M. Zorzi, "Learning and adaptation in cognitive radios using neural networks," in *Proceeding of Conference Record - IAS Annual Meeting (IEEE Industry Applications Society)*, 2008. DOI: 10.1109/ccnc08.2007.229.

[38] M. Hasegawa, T. Ha Nguyen, G. Miyamoto, Y. Murata, and S. Kato, "Distributed optimization based on neurodynamics for cognitive wireless clouds," in *Proceeding of IEEE 18th International Symposium on Personal, Indoor and Mobile Radio Communications*, Athens, Greece, pp. 1-5, 2007. DOI: 10.1109/PIMRC.2007.4394658.

[39] X. Tan, H. Huang, and L. Ma, "Frequency allocation with artificial neural networks in cognitive radio system," in *Proceeding of the IEEE TENCON Spring Conference*, 2013. DOI: 10.1109/TENCON Spring.2013.6584473.

[40] Y. Yang, H. Jiang, C. Liu, and Z. Lan, "Research on cognitive radio engine based on genetic algorithm and radial basis function neural network," in *Proceeding of the Spring Congress on Engineering and Technology*, Xian, China, 2012. DOI: 10.1109/SCET.2012. 6342027.

[41] N. Baldo, B. R. Tamma, B. Manojt, R. Rao, and M. Zorzi, "A neural network based cognitive controller for dynamic channel selection," in *Proceeding of IEEE International Conference in Communications*, Dresden, Germany, pp. 1-5, 2009. DOI: 10.1109/ ICC.2009.5198636.

[42] M. Lin, J. Ouyang, and W. P. Zhu, "BF design in cognitive relay networks via support vector machines," in *Proceeding of the IEEE Global Communications Conference*, 2013. DOI: 10.1109/GLOCOM. 2013.6831572.

[43] Y. El Morabit, F. Mrabti, H. Abarkan, "Spectrum allocation using genetic algorithm in cognitive radio networks," in *Proceeding of IEEE 3rd International Workshop on RFID and Adaptive Wireless Sensor Network*, pp. 90-93, 2015. DOI: 10.1109/RAWSN.2015. 7173287.

[44] Y. Morabit, F. Mrabti, and H. Abarkan, "The allocation in cognitive radio network: Combined genetic algorithm and ON/OFF primary user activity models," *Advances in Ubiquitous Networking 2. Lecture Notes in Electrical Engineering*, vol. 397, pp. 3-14, 2017. DOI: 10.1007/978-981-10-1627-1_1.

[45] Z.-J. hui, F. Li, and X.-X. Zhang, "Parameter adjustment based on improved genetic algorithm for cognitive radio networks," *The Journal of China Universities of Posts and Telecommunications*, vol. 19, pp. 22-26, June 2012. DOI: 10.1016/S1005-8885(11)60260-4.

[46] T. W. Rondeau, B. Le, C. J. Rieser, and C. W. Bostian, "Cognitive radios with genetic algorithms: intelligent control of software defined radios," in *Proceeding Software Defined Radio Forum Technical Conference*, pp. 3-8, 2004.

[47] M. R. Moghal, M. A. Khan, and H. A. Bhatti, "Spectrum optimization in cognitive radios using elitism in genetic algorithms," in *Proceeding of the 6th International Conference on Emerging Technologies*, Islamabad, Pakistan, 2010. DOI: 10.1109/ICET. 2010.5638381.

[48] J. Elhachmi, and Z. Guennoun, "Cognitive radio spectrum allocation using genetic algorithm," *EURASIP Journal on Wireless Communications and Networking* vol. 2016, no. 1, 2016. DOI: 10.1186/ s13638-016-0620-6.

[49] M. J. Islam, M. M. Islam, and A. B. M. A. Islam, "Intelligent dynamic spectrum access using hybrid genetic operators," *Swarm and Evolutionary Computation*, vol. 36, pp. 1-17, 2017. DOI: 10.1016/j.swevo.2017.03.004.

[50] A. H. Mahdi, J. Mohanan, M. A. Kalil, and A. M. Thiel, "Adaptive discrete particle swarm optimization for cognitive radios," in *Proceeding of the 2nd IEEE International Workshop on Smart Communication Protocols and Algorithms*, 2012. DOI: 10.1109/ ICC.2012.6364817.

[51] L. Liu, N. Wang, Z. Chen, and L. Guo, "A novel spectrum scheduling scheme with ant colony optimization algorithm," *Algorithms*, vol. 11, 2018. DOI: 10.3390/a11020016.

[52] M. Tang, C. Long, X. Guan, and X. Wei, "Nonconvex dynamic spectrum allocation for cognitive radio networks via particle swarm optimization and simulated annealing," *Computer Networks*, vol. 56, pp. 2690-2699, 2012. DOI: 10.1016/j.comnet.2012.04.012.

[53] P. M. Pradhan, and G. Panda, "Pareto optimization of cognitive radio parameters using multiobjective evolutionary algorithms and fuzzy decision making," *Swarm and Evolutionary Computation*, vol. 7, pp. 7-20, 2012. DOI: 10.1016/j.swevo.2012.07.001.

[54] P. M. Pradhan and G. Panda, "Comparative performance analysis of evolutionary algorithm based parameter optimization in cognitive radio engine: A Survey," *Ad Hoc Networks*, vol. 17, pp. 129-146, 2014. DOI: 10.1016/j.adhoc.2014.01.010.

[55] A. Merentitis, E. Patouni, N. Alonistioti, and M. Doubrava, "To reconfigure or not to reconfigure: cognitive mechanisms for mobile devices decision making," in *Proceeding of IEEE 68th Vehicular Technology Conference (VTC 2008-Fall)*, pp.1-5, Calgary, Canada, Sept. 2008. DOI: 10.1109/VETECF.2008.267.

[56] G. P. Joshi, S. Acharya, and S. W. Kim, "Fuzzy-logic-based channel selection in IEEE 802.22 WRAN," *Information Systems*, vol. 48, pp. 327-332, 2015. DOI: 10.1016/j.is.2014.05.009.

[57] Y.-H. Wang, and S.-L. Liao, "Applying a fuzzy-based dynamic channel allocation mechanism to cognitive radio networks," in *Proceeding of the 31st International Conference on Advanced Information Networking and Applications Workshops*, 2017. DOI: 10.1109/WAINA.2017.130.

[58] H. Qin, L. Zhu, and D. Li, "Artificial mapping for dynamic resource management of cognitive radio networks," in *Proceeding of the 8th International Conference on Wireless Communications, Networking andMobile Computing*, Shanghai, 2012. DOI: 10.1109/WiCOM. 2012.6478437.

[59] O. B. Abdulghfoor, M. Ismail, and R. Nordin, "Application of game theory to underlay ad-hoc cognitive radio networks: an overview," in *Proceeding of the IEEE International Conference on Space Science and Communication*, 2013. DOI: 10.1109/IconSpace.2013. 6599484.

[60] S. Pandit, and G. Singh, "Spectrum sharing in cognitive radio using game theory," in *Proceeding of the IEEE 3rd International Advance Computing Conference*, Ghaziabad, 2013. DOI: 10.1109/IAdCC. 2013.6514449.

[61] H. Li, Y. Liu, and D. Zhang, "Dynamic spectrum access for cognitive radio systems with repeated games," in *Proceeding of IEEE International Conference on Wireless Communications, Networking and Information Security (WCNIS '10)*, Beijing, China, pp. 59-62, June 2010. DOI: 10.1109/WCINS.2010.5541766.

[62] X. Li, and C. Xiong, "Markov model bank for heterogenous cognitive radio networks with multiple dissimilar users and channels," in *Proceeding of the International Conference on Computing, Networking and Communications*, 2014. DOI: 10.1109/ICCNC.2014.6785312.

[63] W. Yifei, T. Yinglei, W. Li, S. Mei, and W. Xiaojun, "QoS Provisioning energy saving dynamic access policy for overlay cognitive radio networks with hidden Markov channels," *China Communications*, vol. 10, pp. 92-101, 2013. DOI: 10.1109/CC.2013.6723882.

[64] J. W. Wang and R. Adriman, "Analysis of opportunistic spectrum access in cognitive radio networks using hidden Markov model with state prediction," *EURASIP Journal on Wireless Communications and Networking*, vol. 2015, no. 1, Jan. 2015. DOI: 10.1186/s13638-014-0238-5.

[65] Z. Yin, Y. Wang, and C. Wu, "A multi-agent collaborative model for Bayesian opportunistic channel accessibility in railway cognitive radio," *International Journal of Performability Engeneering*, vol. 13, no. 4, pp. 479-489, 2017. DOI: 10.23940/ijpe.17.04.p15.479489.

[66] A. Azzouna, A. Guezmil, A. Sakly, and A. Mtibaa, "Resource allocation for multi-user cognitive radio systems using multi-agent Q-Learning," in *Proceeding of the 3rd International Conference on Ambient Systems, Networks and Technologies*, vol. 10, pp. 46-53, 2012. DOI: 10.1016/j.procs.2012.06.010.

[67] S. Li, M. M. Kokar, D. Brady, and J. Moskal, "Collaborative adaptation of cognitive radio parameters using ontology and policy approach," in *Proceeding of the SDR '10 Technical Conference and Product Exposition*, 2010 [online] available: https://pdfs.semantic scholar.org/6136/6383ee1985da34f3de057954ae2aa770a3de.pdf.

[68] B. Bahrak, J. M. Park, and H. Wu, "Ontology-based spectrum access policies for policy-based cognitive radios," in *Proceeding of IEEE International Symposium On Dynamic Spectrum Access Networks*, 2012. DOI: 10.1109/DYSPAN.2012.6478173.

[69] J. D. Poston, W. D. Horne, M. G. Taylor, and F. Z. Zhu, "Ontology-based reasoning for context-aware radios: insights and findings from prototype development," in *Proceeding of the 1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, MD, pp. 634-637, 2005. DOI: 10.1109/ DYSPAN.2005.1542685.

[70] Y. B. Reddy, "Efficient spectrum allocation using case-based reasoning and collaborative filtering approaches," in *Proceeding of the Fourth International Conference on Sensor Technologies and Applications*, 2010. DOI: 10.1109/SENSORCOMM.2010.62.

[71] Z.-J. Zhao, and H.-C. Lai, "A cognitive engine based on case-based reasoning quantum genetic algorithm," in *Proceeding of the 14th International Conference on Communication Technology*, 2012. DOI: 10.1109/ICCT.2012.6511219.

[72] J. H. Park, W. C. Lee, J. P. Choi, J. W. Choi, and S. B. Um, "Applying case-based reasoning to tactical cognitive sensor networks for dynamic frequency allocation," *Sensors*, vol. 18, 2018, DOI: 10. 20944/preprints201810.0294.v1.

[73] M. Khedr and H. Shatila, "Cogmax—A cognitive radio approach for WiMAX systems," in *Proceeding of IEEE/ACS International Conference on Computer Systems and Applications*, pp. 550-554, 2009. DOI: 10.1109/AICCSA.2009.5069379.

[74] J. H. Reed, "Development of a cognitive engine and analysis of WRAN cognitive radio algorithms—Phase II," *Wireless@Virginia Tech*, december, 2006.

[75] Y. Zhao, J. Gaeddert, L. Morales, K. Bae, J.-S. Um, and J. H. Reed, "Development of radio environment map enabled case- and knowledge- based learning algorithms for IEEE 802.22 WRAN cognitive engines," in *Proceeding of the 2nd International Conference on Cognitive Radio Oriented Wireless Networks and Communications*, Orlando, pp. 44-49, 2007. DOI: 10.1109/CROWNCOM. 2007.4549770.

[76] R. Kaur, A. S. Buttar, and J. Anand, "Spectrum sharing schemes in cognitive radio networks: a survey," in *Proceeding of the 2nd International conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2018. DOI: 10.1109/ICECA.2018.8474662.

[77] B. Wang, Y. Wu, and K. J. R. Liu, "Game theory for cognitive radio networks: An overview", *Computer Networks*, vol. 54, pp. 2537-2561, 2010. DOI: 10.1016/j.comnet.2010.04.004.

[78] J. Rajasekharan, and V. Koivunen, "Cooperative game-theoretic approach to spectrum sharing in cognitive radios", *Signal Processing*, vol. 106, pp. 15-29, 2015. DOI: 10.1016/j.sigpro.2014.06.013.

[79] M. Tahir, M.H. Habaebi, and M. R. Islam, "Coalition formation for cooperative spectrum sharing in cognitive radio wireless networks using Gale Shapley algorithm," in *Proceeding of the 6th Control and System Graduate Research Colloquium*, Shah Alam, Malaysia, 2015. DOI: 10.1109/ICSGRC.2015.7412462.

[80] S. K. Shah and K. R. Parmar, "A game theory based model for cooperative spectrum sharing in cognitive radio," *International Journal of Current Engineering and Technology*, vol. 4, no. 3 2014, [online] Available: http://inpressco.com/category/ijcet.

[81] H. Zhang, C. Jiang, N. C. Beaulieu, X. Chu, X. Wang, and T. Q. S. Quek, "Resource allocation for cognitive small cell networks: a cooperative bargaining game theoretic approach," *IEEE Transactions on Wireless Communications*, vol. 14, no. 6, pp. 3481-3493, 2015. DOI: 10.1109/TWC.2015.2407355.

[82] S. Sun, N. Chen, T. Ran, J. Xiao, and T. Tian, "A Stackelberg game spectrum sharing scheme in cognitive radio-based heterogeneous wireless sensor networks," *Signal Processing*, vol. 126, pp. 18-26, 2015. DOI: 10.1016/j.sigpro.2015.12.019.

[83] S. Kim, "Multi-leader multi-follower Stackelberg model for cognitive radio spectrum sharing scheme," *Computer Networks*, vol. 56, pp. 3682-3692, 2012. DOI: 10.1016/j.comnet.2012.08.004.

[84] S. Sun, N. Chen, T. Ran, J. Xiao, and T. Tian, "A Stackelberg game spectrum sharing scheme in cognitive radio-based heterogeneous wireless sensor networks," *Signal Processing*, vol. 126, 2016. DOI: 10.1016/j.sigpro.2015.12.019i.

[85] M. Khaledi, and A. A. Abouzeid, "Auction-based spectrum sharing in cognitive radio networks with heterogeneous channels," in *Proceeding of Information Theory and Applications Workshop (ITA)*, 2013. DOI: 10.1109/ITA.2013.6502923.

[86] W. H. Lai, P. Polacek, and C. W. Huang, "A posted-price auction for heterogeneous spectrum sharing under budget constraints," in *Proceeding of the 9th EAI International Conference on Bio-*

inspired Information and Communications Technologies (*formerly BIONETICS*), 2016. DOI: 10.4108/eai.3-12-2015.2262496.

[87] U. Mir, L. M. Boulahia, M. Esseghir, and D. Gaiti, "Dynamic spectrum sharing in cognitive radio networks: a solution based on multiagent systems," *International Journal on Advances in Telecommunications*, vol 3, no 3 & 4, pp. 203-214, 2010.

[88] U. Mir, L. M. Boulahia, M. Esseghir, and D. Gaiti, "A cooperative multiagent based spectrum sharing," in *Proceeding of the 6th Advanced International Conference on Telecommunications*, 2010. DOI: 10.1109/AICT.2010.31.

[89] F. Li, D. Zhu, F. Tian, and H. Li, "Cognitive radio spectrum sharing using improved quantum genetic algorithm," in *Proceeding of International Conference on Wireless Communications and Signal Processing,* 2011. DOI: 10.1109/WCSP.2011.6096690.

[90] B. Atakan and O. B. Akan, "Biologically-inspired spectrum sharing in cognitive radio networks," *in Proceeding of IEEE Wireless Communications and Networking Conference*, pp. 43-48, 2007. DOI: 10.1109/WCNC.2007.14.

[91] A. M. Vargas and A. G. Andrade, "Particle swarm optimization applied to a spectrum sharing problem," *AEU - International Journal of Electronics and Communications*, vol. 66, no. 12, pp. 969-978, Dec. 2012. DOI: 10.1016/j.aeue.2012.04.006.

[92] I. Christian, S. Moh, I. Chung, and J. Lee, "Spectrum mobility in cognitive radio networks," *IEEE Communications Magazine*, vol. 50, pp. 114-121, 2012. DOI: 10.1109/MCOM.2012.6211495.

[93] U. Mir and Z. A. Bhatti, "Time triggered handoff schemes in cognitive radio networks: a survey," *Journal of Network and Computer Applications*, vol. 102, pp. 71-85, 2017. DOI: 10.1016/j.jnca.2017.11.008.

[94] P. Yi, "A novel spectrum handoff method based on spectrum reservation," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 12, no. 1, pp. 653-660, 2014. DOI: 10.11591/telkomnika.v12i1.3573.

[95] L. Giupponi, "Fuzzy-based spectrum handoff in cognitive radio networks," in *Proceeding of International Conference on Cognitive Radio Oriented Wireless Networks and Communications (CrownCom)*, pp. 1-6, 2008. DOI: 10.1109/CROWNCOM.2008.4562535.

[96] C. Salgado, C. Hernandez, V. Molina, and F. A. B. Molina, "Intelligent algorithm for spectrum mobility in cognitive wireless networks," in *Proceeding of the 7th International Conference on Ambient Systems*, 2016. DOI: 10.1016/j.procs.2016.04.126.

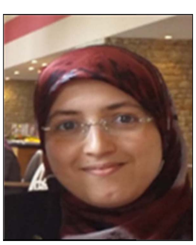
[97] L. Giupponi and A. I. Perez-Neira, "Fuzzy-based spectrum handoff in Cognitive Radio Networks," in *Proceeding of the International Conference on Cognitive Radio Oriented Wireless Networks and Communications* (*CrownCom 2008*), 2008. DOI: 10.1109/CROWNCOM.2008.4562535.

[98] C. Pham, "Spectrum handoff model based on Hidden Markov model in Cognitive Radio Networks," in *Proceeding of IEEE International Conference on Information Networking (ICOIN)*, pp. 406-411, 2014. DOI: 10.1109/ICOIN.2014.6799714.

[99] A. W. Min, K.-H. Kim, J. P. Singh, and K. G. Shin, "Opportunistic spectrum access for mobile cognitive radios," in *Proceeding of IEEE INFOCOM*, pp. 2993-3001, 2011. DOI: 10.1109/INFCOM.2011.5935141.

[100] M.-P. Tran, T. P. T. Minh, H.-M. Lee, and D.-S. Kim, "Effective spectrum handoff for cognitive UWB industrial networks," in *Proceeding of IEEE Conference on Emerging Technologies & Factory Automation (ETFA)*, pp. 1-4, 2015. DOI: 10.1109/ETFA.2015.7301616.

[101] Y. Wu, "Delay-constrained optimal transmission with proactive spectrum handoff in cognitive radio networks," *IEEE Transaction on Communications*, vol. 64, pp. 2767-2779, 2016b. DOI: 10.1109/TCOMM.2016.2561936.



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