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A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks

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ABSTRACT

Due to exponential growth in demand for radio spectrum for wireless communication networking, the radio spectrum has become overcrowded. The fixed spectrum allocation policy of the radio spectrum leads to inefficient utilisation of the available spectrum, which diverted the attention of researchers towards different intelligent techniques to access the spectrum dynamically and efficiently. The concept of Cognitive Radio (CR) has been considered as a promising technology to solve the problem of spectrum scarcity through the utilisation of various unutilised spectrum bands. In a future network deployment, multiple radio access networks may coexist having different characteristics. Hence, it becomes a challenge for CR networks to select the optimal network out of available networks. For efficient realisation, CRs requires intelligent spectrum management techniques for Dynamic Spectrum Management (DSM). Till now, there does not exist a literature survey that addresses the spectrum management with machine learning techniques in an intelligent manner. Hence, this paper presents the detailed classification and comprehensive survey of various machine learning techniques for intelligent spectrum management with their paradigms of optimisation for cognitive radio networks. The paper also provides new directions and open issues for the research community to work further in CR networks.

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Cognitive Radio; dynamic spectrum management; heterogeneous networks; intelligent techniques; machine learning

Introduction

The exponential growth in the demand for extra spectrum resources become more prominent to support numerous wireless services leads to the advent of new technologies for high-speed data networks (X. Zheng et al., 2008). According to Cisco, global mobile data traffic will increase sevenfold between 2017 to 2022 (Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2017–2022, 2018).

But radio spectrum is an inherently limited resource in which frequency bands are exclusively assigned to the licenced users called Primary User's (PUs) for a long term basis which leads to spectrum scarcity in a particular spectrum band. In contrast, a survey of spectrum utilisation being conducted by the Federal Communication Commission (FCC) has indicated that many portions of the radio spectrum are not in use, called spectrum holes, for a significant amount of time which leads to under-utilisation of the assigned spectrum. To overcome this problem, FCC reforms the spectrum allocation policy and allows unlicensed users, also known as secondary users/Cognitive Radios (CRs) to borrow unused radio spectrum from licenced users through Dynamic Spectrum Access (DSA) (FCC, 2003).

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The CR as an intelligent radio that can be reprogrammed and reconfigured dynamically. Such intelligent radio automatically detects available channels in the wireless spectrum, changes accordingly its transmission and reception parameters to switch between available vacant spectrum bands dynamically. This process is known as Dynamic Spectrum Access which can be realised only with CR networks (Akyildiz et al., 2008).

Figure 1 presents a system model showing the available spectrum holes of various networks such as Television, GSM, Satellite, and Wi-Fi. CR requires a spectrum hole for its application which requires intelligent techniques to access the spectrum dynamically. The intelligent spectrum management includes spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.

Figure 2 shows the currently fixed spectrum allocation policy decided by governmental agencies. Due to this fixed spectrum allocation policy, some frequency bands are highly utilised and some are lightly utilised. It is observed from Figure 2 that networks 1 and 2 are lightly utilised whereas networks 3 and 4 are highly utilised. It is shown that there exist large numbers of spectrum holes of heterogeneous networks that can be utilised with dynamic spectrum allocation policy. Figure 3 shows a dynamic spectrum allocation policy where CR access the unused spectrum. Thus, the demand for extra spectrum bands for wireless applications can be solved with flexible usage of

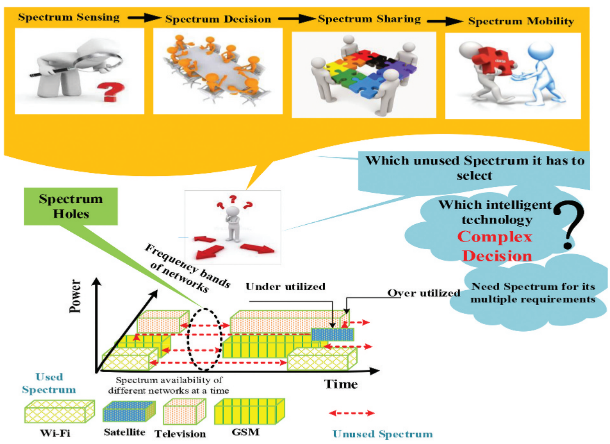

Figure 1. System model showing spectrum holes of various networks available for CRs having multiple requirements.

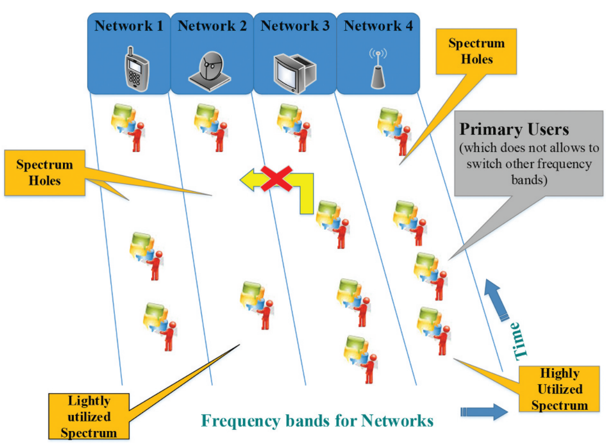

Figure 2. The fixed spectrum allocation policy.

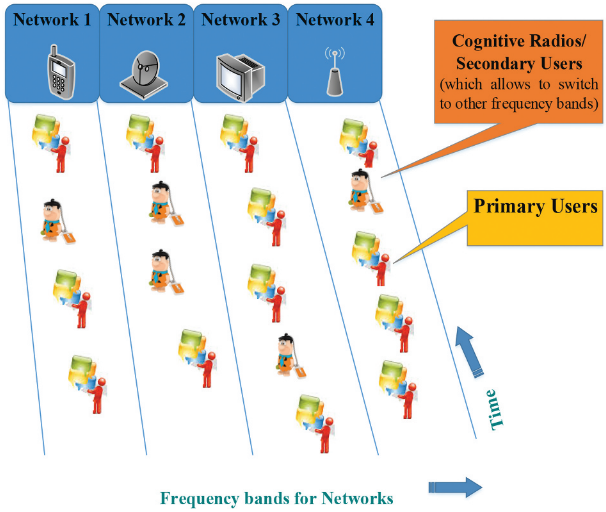

Figure 3. The dynamic spectrum allocation policy.

available spectrum holes. As an intelligent wireless network, CR shares the spectrum with PUs in an opportunistic manner to avoid interference among multiple spectrum users with its learning abilities to adapt and act in a dynamic environment (Xu et al., 2014).

To address the problem of spectrum scarcity, each CR:(Akyildiz et al., 2008).

- Determine the presence of spectrum holes called *spectrum sensing*.
- Determine available channels including spectrum selection, routing protocol, and reconfiguration called *spectrum decision*.
- Allocation of resources and serve its users without causing interference to PUs called *spectrum sharing*.
- Vacate the channel on the arrival of PUs called *spectrum mobility*.

The most important issue is how to access the spectrum dynamically without interference with PUs. This requires CR which is intelligent by nature and having learning capability to learn from past experiences, which is an essential part of intelligence. Haykin envisioned CR as an intelligent wireless communication system that is based on the methodology of *understanding by building* to achieve two goals: highly reliable communication and efficient utilisation of radio resources (Khozeimeh & Haykin, 2012). To perform these tasks, CRs must be equipped with intelligence like a human (Zafari et al., 2019). The implementation of such capabilities requires functional architecture like the brain to access the spectrum efficiently i.e. Cognitive Engine (CE) (Dong et al., 2012). The CE acts as a brain of CR to perform various cognitive functions intelligently and provides learning capabilities to implement the cognitive cycle by making use of machine learning algorithms. The CR technology is based on Software Defined Radio (SDR), which allows the radio to reconfigure through software, based on the interaction with the surrounding environment in which it operates. However, in recent years machine learning algorithms in CR networks gains a lot of attention from researchers (Kotsiantis, 2007) (Thilina et al., 2013). A look at a recent literature survey on CR networks reveals that various leaning techniques are proposed that have been applied to numerous CR applications (Yau et al., 2012)(A. He et al., 2010). Some authors presented machine learning techniques, particularly focused on spectrum sensing and decision making in CR networks (Abbas et al., 2015).

Further, CR has to work under unknown environments where complete Channel State Information (CSI) is not present or only partial CSI is available but it has to estimate the behaviour from other CRs present in network to coordinate its actions. Another author surveyed machine learning techniques for decision making and feature classification in different environmental conditions. In general, learning becomes an indispensable part of CR if the input-output relation of the system is not known, or as in the case of CR networks, due to channel uncertainty. Thus, learning becomes a necessary tool to estimate that channel characteristics to reduce error probability (Zafari et al., 2019). In CR's, several parameters need to be adjusted simultaneously such as availability of spectrum (Tripathi et al., 2011), transmit power (G. Yang et al., 2015), adaptive coding and modulation schemes (Zafari et al., 2019), antenna selection, rate control (Hanif et al., 2011), spectrum handoff (Thakur et al., 2017), etc., and it is not possible to identify and adjust all these parameters simultaneously. Thus, learning techniques can be applied to perform specific CR tasks with efficiency and accuracy.

An overview of an existing literature survey is presented in Table 1. The survey reveals that most of the authors have shown their interest in the specific issue of spectrum management. Most of the authors provide different types of solutions to address the spectrum scarcity problem. Some of the authors specifically discuss a problem related to spectrum management whereas no work has been presented with machine learning techniques for dynamic spectrum management which includes spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. In this survey, spectrum management with intelligent techniques, considering learning as an important parameter has been discussed. In particular, we provide an in-depth discussion on different types of intelligent techniques such as Artificial Neural Network, Metaheuristic Algorithms, Support Vector Machine, Bayesian Learning, Game Theory, and Hidden Markov Models. The pros and cons of each technique in the context of spectrum management have also been discussed. We firstly present a spectrum management framework. Then we introduced various intelligent techniques used in CR networks as well as a survey of state-of-the-art achievements of these techniques for dynamic spectrum management in CR networks. The major contributions of this paper are summarised as follows:

Table 1. Comparison with an existing literature survey.

Reference	Focused area	Description
Our paper	Spectrum management	This paper discussed complete spectrum management with intelligent techniques, its strengths, limitations, and evaluations based on the requirement of CR networks.
(Akyildiz et al., 2006)	Cross-layer design issues	The author briefly investigates next-generation CR wireless networks for DSM and addresses its cross-layer design issues.
(A. He et al., 2010)	AI in CR networks	This paper reviewed several artificial intelligence techniques that have been applied to numerous CR applications but not specifically to spectrum management.
(Bkassiny et al., 2013)	Feature classification & decision making	Machine learning techniques in CR networks for feature classification (spectrum sensing) and decision-making under the non-Markovian environment.
(Thilina et al., 2013)	Spectrum sensing	Unsupervised (K-means clustering, Gaussian mixture model) and Supervised (Support vector machine, weighted K-nearest neighbour) learning-based techniques implemented for cooperative spectrum sensing.
(Abbas et al., 2015)	Spectrum sensing & decision making	The paper provides a survey on artificial intelligence and machine learning techniques to address spectrum sensing and decision-making issues
(Qadir, 2016)	Routing	The authors targeted cognitive routing as an issue.
(Azhar et al., 2011)	AI in wireless networks	Here, the artificial intelligence framework of neural networks in wireless networks has been presented including CR networks.
(Ramzan et al., 2017)	Multiple objectives optimisation	This paper focused on the optimisation problem with multiple objectives.

- This paper presents a comprehensive survey of various intelligent techniques and presents their applications in CR networks. The target of this paper is to provide a focused survey of these techniques and evaluates its performance in spectrum management as major CR tasks which include spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility.
- This paper presented state-of-the-art achievements in applying intelligent techniques to CR networks along with their strength and limitations to provide an overview of active research in the area of CR networks.
- The paper discusses research issues and challenges that are still an open issue and need the attention of researchers.

The rest of the paper is organised as follows: Section 2 provides the spectrum management framework for CR networks. The taxonomy of various intelligent techniques is presented in Section 3. The evaluation of intelligent techniques along with their strengths and limitations are presented in Section 4. Section 5 presents research issues, challenges, and future directions in the area of spectrum management. Finally, the concluding remarks are given in Section 6.

Spectrum management framework

To address the critical challenges associated with the co-existence of PUs and CRs in CR networks, CRs are required with the following functions in spectrum management:

- **Interference Management**: The important role of CR is to resolve the interference issues with PUs which can be resolved in two manners:

(a) *Proactive*: In this, the CR switches its communication before the arrival of PUs.
(b) *Reactive*: CR switches its communication after the arrival of PUs.

- **Quality of service (QoS) Awareness**: In heterogeneous networks, the selection of an appropriate spectrum band is necessary to provide QoS aware communication

CR technologies provide intelligent spectrum management capabilities that could meet the ever-increasing demand of spectrum, thus empowers radio with etiquette to avoid interference. The complete spectrum management framework is presented in Figure 4. It shows that CR spectrum management framework has four main steps:

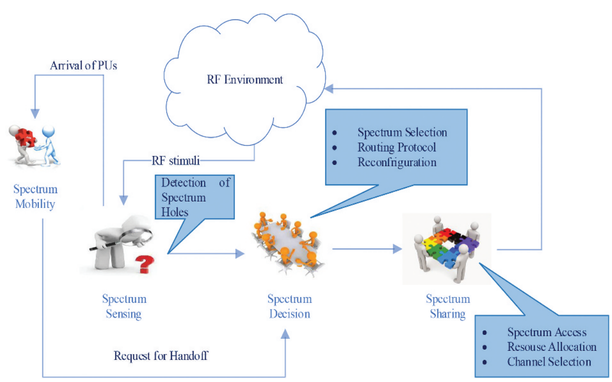

Figure 4. The complete spectrum management framework.

(a) ***Spectrum Sensing:*** The first step of spectrum management starts with spectrum sensing on the arrival of CR. Spectrum sensing provides the ability to detect the spectrum holes (in terms of the frequency band, location, duration of availability) and PU activity by periodically sensing the spectrum and use it without interference with PUs (Noorshams et al., 2010).
(b) ***Spectrum Decision:*** Spectrum decision includes spectrum analysis and decision making. It deals with the selection of appropriate spectrum bands according to the required QoS. The spectrum hole is characterised, with various parameters such as multipath environment, operating frequency, interference, link delay (Pourpeighambar et al., 2017) and number of PUs using the spectrum, being considered (X Liu et al., 2013). After spectrum analysis, the decision has been made to access the spectrum hole. Various optimisation techniques can be applied to obtain optimal decisions depending upon the radio environment whether it has to optimise single objective or multiple objectives (Ramzan et al., 2017).
(c) ***Spectrum Sharing:*** The main function of spectrum sharing is to avoid collision among the CRs as multiple users trying to access the spectrum while maintaining QoS. Spectrum sharing deals with coordination among CRs to access the shared channels, resource allocation, and spectrum access (Kour et al., 2018)(Akyildiz et al., 2008). The spectrum allocation includes the assignment of spectrum band in a cooperative (Bayrakdar, 2020). or non-cooperative manner using handshaking protocols of transmitter and receiver (X Liu et al., 2013). The spectrum access includes collision avoidance among CRs in the access phase
(d) ***Spectrum Mobility***: Spectrum mobility deals with spectrum handoff and connection management. CRs are usually regarded as visitors which often need to switch from one spectrum hole to another on the arrival of PUs in a dynamic environment (Christian et al., 2012). Spectrum mobility utilises a reactive and proactive approach for the detection of PUs whereas connection management ensures that CR continuously transmits its data in a new spectrum hole (Thakur et al., 2017).

Intelligent techniques in cognitive radio networks

A CR as an intelligent wireless device, which is aware of its environment, capable of learning and adapt from its surrounding environment and learning considered to be an indispensable component of an intelligent system which is considered to be a basic tool of CRs for dynamically access the available spectrum without interfering with PUs. CR must have the capability to learn from current observations and past experiences. However, CR has to work under different radio environments in which CR might have full or partial CSI or sometimes under a completely unknown environment. However, not being idealistic, due to fluctuations in the wireless channel, channel estimation errors, and quantisation errors, it is not possible to obtain perfect CSI. Thus, CR might apply an intelligent algorithm to estimate its actions concerning other CRs for spectrum management. Various techniques in CR networks are shown in Figure 5.

Intelligence with artificial neural networks

Artificial Neural Networks (ANN) provides Artificial intelligence (AI) which aims to incorporate intelligence in machines so that machines can perform like an expert. Also, machine learning, a subclass of AI, gained a lot of attention from the researchers in CR networks. Learning can be classified as supervised, unsupervised, and reinforcement learning (Jiang et al., 2017)(Duda et al., 2001). Supervised learning learns from the training set and requires prior information about the environment. On the other hand, unsupervised learning does not require any training set and it performs self-adapting actions without any prior knowledge about the environment.

Reinforcement learning or learning with critic, the learning agents learn by observing actions of other agents, and its performance is influenced by learning regime and operating environment (Duda et al., 2001)(Dandurand & Shultz, 2009). However, it is a particular point of interest here that

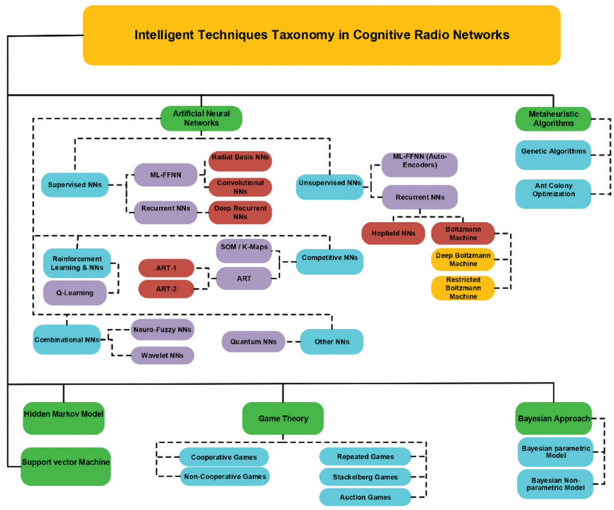

Figure 5. Intelligent techniques in CR networks.

how these intelligent algorithms have been applied to access the spectrum dynamically. In this section, we present various ANN techniques that can be applied to CR networks.

Artificial Neural Network (ANN)

Artificial Neural Network (ANN or simply NN) consists of several interconnected neurons, identical to the human brain, which is made up of real biological neurons. The first artificial neuron was introduced in 1943 by the neurophysiologist W. McCulloch and logician Walter Pits. ANN composed of a large number of artificial neurons which are interconnected to each other that mimics the behaviour and natural processing of biological neuron .i.e., learning and organisation (Tsagkaris et al., 2008). The human brain can perform fast due to its special ability of parallel data processing and NN tries to mimic the behaviour of solving narrowly defined problems. As stated earlier, NN consist of a pool of neurons, and these neurons are configured in the form of layers and connected to other nodes with links defined by the weight w_{jk}, which determines the effect of the signal of a neuron j on a neuron k. In NN, three types of layers are present, which are distinguished as the input layer, hidden layer, and output layer. The input layer consists of neurons, which receive data whereas output layers consist of neurons, which send data out from the NN layer and the hidden layer consists of neurons whose input, and output remain in NN. Each neuron within NN uses some activation function to process the input signals s_k it receives from (a) neighbours belonging to different layers (b) external sources. The type of activation function used depends on the problem to be addressed.

- *Types of NN and Machine Learning*

In this section, we describe different NN models.

Supervised NNs

In supervised NNs, the input and output are known and its objective is to discover the relationship between two. The two main NN models are as Feed Forward NNs (FFNNs) and Recurrent NNs (RNNs). FFNNs are further classified as: Single layer FFNNs (SL-FFNNs) and Multilayer FFNNs (ML-FFNNs).

(a) *Feed Forward NNs*

In FFNNs, neurons feed their values in the forward direction. It is of two types describes as:

(i) *Single-layer FFNN (SL-FFNNs)*: It consists of single-layer of neurons. Due to its single-layer network, learning and training mechanism is easy but it has limited utility, as it is not able to solve real-world complex problems.
(ii) *Multilayer FFNN (ML-FFNNs)*: It consists multiple layers (hidden layers) between input and output layer. These hidden layers solve complex problems using the activation function. As stated earlier, some activation function is required to process the information, and the selection of activation function depends on the problem to be solved. Table 2 shows various types of activation functions to address different problems.

Various type of ML-FFNNs using different activation functions leads to slight variation in the network. (Tumuluru et al., 2010), designed a multilayer spectrum predictor using a neural network, which does not require prior knowledge of traffic characteristics of PUs. CR may predict channel status based on sensing history which further saves sensing energy. (Liu et al., 2015) proposed ML-FFNN based dynamic Chinese restaurant game for spectrum sensing, which considered CR as customers to learn the table state (available spectrum hole) in the restaurant (network).

Some important examples of ML-FFNNs include Radial Basis Neural Networks and Convolutional Neural Networks which are described below:

- *Radial Basis Neural Networks (RBNN)*: RBNN composed of three layers: input layer, hidden layer, and output layer. The hidden layer consists of neurons using a Gaussian transfer function gives the output as

$$Y_j = \sum_j w_j \exp\left(\frac{-\left\| \overset{r}{x} - \overset{r}{\mu} \right\|^2}{\sigma_j^2}\right) \tag{1}$$

In Gaussian transfer function, $\vec{x}$ is input, $\vec{\mu}_j$ and σ_j represents centre vector and width of j^{th} neuron in hidden layer respectively, which need to be calculated for each neuron, $\|.\|$ denotes Euclidean distance. However, an initial value of the centre vector and width affects the prediction ability of the network. An unsupervised learning technique i.e. K-means clustering (K-RBF) algorithm can be used to obtain the values of centre vector and width of the hidden neurons associated to construct and train RBNN in a more accurate way. The output of the transfer function weighted and summed as shown in Equation (1).

Zhang (S. Zhang et al., 2013) proposed K-RBF for spectrum sensing based on previous information of the PU spectrum which reduced prediction error to one-third as compared to RBF. Researchers proposed a design of CE based on the RBF and Genetic Algorithm (GA) for multi-objective optimisation. RBF has strong learning capability while GA is good at multi-objective optimisation (Y. Yang et al., 2012).

Table 2. Types of the activation function.

Sr. No.	Activation Function	Equation	Application
1.	Log Sigmoid Function	$F_k(s_k) = \frac{1}{1+e^{-s_k}}$	Logistic regression problem
2.	Hyperbolic tangent	$F_k(s_k) = \frac{e^{s_k}-e^{-s_k}}{e^{s_k}+e^{-s_k}}$	Multi-layer NN
3.	Linear	$F_k(s_k) = s_k$	Linear regression problem

- *Convolutional Neural Networks (Conv-Nets or CNN)*: CNN is another variant of ML-FFNN that has been used effectively in the areas of image recognition and classification. CNN exploits spatially local correlation by enforcing local connectivity with adjacent layer neurons, which does not take entire data from preceding layers. LeNet was the very first CNN which become an important tool for machine learning. Key operations of CNN include convolution, non-linearity (ReLU), pooling (or sub-sampling), and classification (Fully connected layer). For example, when an image is passed to CNN, features are extracted from the image using convolution preserves the spatial relationship between pixels of an image by utilising a small square of input data. Another operation i.e. ReLU has been performed after convolution, which introduces non-linearity in CNN. ReLU stands for Rectifier Linear Unit, which is an element-wise non-linear operation (applied per pixel) and replaces negative pixels in feature map by zero. Pooling operation can be done after convolution+ReLU operation, which can be done in different ways such as sum, average, max, etc. This operation reduces the dimensionality of each feature map by only retaining important information. Finally, the classification process is done. The output extracted from previous operations extract high-level features that are used for feature classification of the input image. The term" Fully connected" means every neuron of the preceding stage is connected to every neuron of the succeeding stage that classifies and forms various classes based on the training dataset. Further, CNN can be trained using gradient descent and backpropagation (Lecun et al., 1998). Backpropagation calculates the gradients of error concerning all weights in the network and updates weights and parameter values using gradient descent to minimise an output error.

Lee (Lee et al., (2019) cooperatively implemented the CNN spectrum sensing technique, in which optimal strategy is used for combining sensing results of individual CRs obtained using CNN. Sensing based on deep neural networks is used to learn from a large set of data through a backpropagation algorithm. Deep sensing provides optimised combining strategy based on spectral and spatial correlations of channel i.e. based on the location of CRs and PUs characteristics. Selim et al. (2018) presented the CNN spectrum monitoring framework for radar bands in spectrum sharing scenarios. The main idea behind this framework is to detect the presence of radio signals in the radio spectrum even when this signal is overlapped by other signals due to simultaneous transmission.

(b) *Recurrent Neural Network (RNN)*

The idea behind RNN is to make use of sequential information, with the output being dependent on previous computations. Here, the neurons are connected in a cyclic manner, which allows exhibiting dynamic temporal behaviours shown in Figure 6. Unlike FFNNs, RNN does not propagate information directly to the next connected layer but use their internal memory to process the input.

RNN are called recurrent because they perform the same operations for every element in the input sequence.

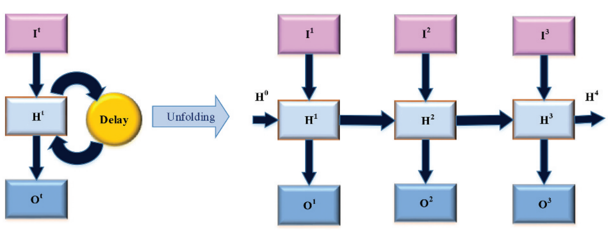

Figure 6. Recurrent neural network.

Let X^t,O^t andH^tbe the input, output, and state of the hidden layer(s) on time t. In simple mathematical form, RNN can be expressed as

$$O^t = F(H^t, \theta) \tag{2}$$

$$H^t = F(H^{t-1}, X^t; \theta) \tag{3}$$

where the parameter θ defines weight and bias for the network. Equation (2) states that outputO^tat a particular time t depends upon the state of the hidden layer H^t and θ. Further, H^t depends upon its previous statesH^{t-1} and inputX^tat a time t as stated in Equation (3). To train RNN, the backpropagation algorithm through time approach is used which 'unfold' RNN in time and converted into FFNNs consisting of identical copies of RNN. RNN consist of a large number of layers as compare to ML-FFNNs and also training process is based on the passage of information through these layers and propagation of unsuitable information through the network leads to the accumulation of large error which leads to inaccurate results. Usually, the gradient descent method is used for backpropagation training.

*Deep Recurrent Neural Network (*DRNN): DRNN (Tang & Li 2017) consists of multiple hidden layers that enable the prediction of the spectrum of multiple time slots in CR networks since existing methodology only predicts the spectrum of a single slot. Here, the channel state is divided into slots and forming time series of channel state. Due to multiple hidden layers in DRNN, it is difficult to train using a gradient descent method, which leads to slow convergence and gradient disappearance. To avoid these problems, Extended Kalman Filter (EKF) for estimation of weights is used which overcomes the problem of slow convergence and vanishes gradients in a gradient descent method.

Unsupervised NNs

As the name indicates unsupervised NNs only know the input and the main objective is to discover patterns in features of input data. The system learns using certain test dataset and allows a lower-dimensional representation of input data.

(a) *Unsupervised ML-FFNNs (Auto-encoders)*

Auto-encoders are the type of FFNNs specially designed for dimensionality reduction. In other words, auto-encoders provide the same output as the input. In auto-encoders, encoder function learns from input to representation and decoder function back from representation to input i.e. reconstruction. Denoising auto-encoders (Bengio et al., 2013) are the extension of basic auto-encoders, which attempts to address, identify function risk by introducing noise. Random noise is added to the input in the form of percentage and then this noisy data is fed in auto-encoder, which finds correlations within the input data to find correct data instead of noise added data. In Sparse auto-encoders, a sparsity constraint on the hidden layer is applied for extracting interesting features from unlabelled data even if numbers of hidden layers are large. Authors proposed a novel modulation classification method using denoising sparse auto-encoder as a classifier to improve spectrum sensing, i.e. to avoid interference with PUs (Zhu & Fujii, 2016). Moreover, the denoising process improves the performance of noise suppression by training the network with a corrupted database. Further, Variational Auto-Encoders (VAE) emerged as a powerful unsupervised learning framework for generating complicated data. They can learn a low dimensional representation of high dimensional data (Doersch, 2016). Contractive Auto-encoders (CAE) make use of explicit regulariser which learns a function even in slight variations of input values. CAE adding a well-chosen penalty term to cost function which enables an auto-encoder to perform better (Rifai & Muller, 2011).

(b) *Unsupervised Recurrent NNs (URNN)*

URNN is a complex type of NNs, which are inspired by ideas from statistical physics which model system as an *energy function*. RNNs are computationally powerful and learn from the temporal behaviour of given training data. Compared to the FFNN, RNN is more powerful in representing complex dynamics and having a compact size. Two main types of URNNs are Hopfield Network and Boltzmann Machine, which are described next.

- *Hopfield NNs*: Hopfield NNs is a dynamic auto-associative model, which can store information in a dynamically stable structure. Each Hopfield network has some energy function (Lyapunov function) associated with it, which always tries to converges to a local minimum of the function. Hopfield NNs is biologically plausible, as its working is similar to the human retina. Hasegawa (Hasegawa et al., 2014) proposed an optimisation algorithm for decision making on radio resources in centralised and decentralised CR networks. In a decentralised network, the energy minimisation dynamics of Hopfield NNs are considered.
- *Boltzmann Machine(BM)*: BM is a stochastic RNN, like the Hopfield network, in which the network unit finds a global minimum of the energy function. BM is designed for discrete variables having the disadvantage of being slow. Another problem with BM is it stops learning correctly when the machine statics grows exponentially with the size of the machine and with the magnitude of connection strength. Other variants of BM are Restricted Boltzmann Machine (RBM) and Deep Boltzmann Machine (DBM).

(i) *Restricted Boltzmann Machine (RBM)*: As the name indicates, a restriction is imposed with neurons that they have symmetric connection between different groups of nodes but no connections between the same group of nodes which allows more efficient training algorithms than BM. MohanaPriya and Shalinie (2017) presented a secure routing protocol for CR networks. The RBM algorithm self learns the routing procedure between source and destination node. Further, it provides energy-efficient routing to prevent flooding attacks.

(ii) *Deep Boltzmann Machine (DBM)*: DBM (Salakhutdinov & Hinton, 2009) have the potential to learn complex internal state representations, which is useful in speech recognition problem. It also develops high-level representations to tune its model for a specific task from unlabelled data as well as from limited labelled data.

Unsupervised competitive NNs

Unsupervised competitive learning is a form of unsupervised training where output neurons are said to compete for input patterns. It employs a winner-take-all strategy since only winning neuron is updated. Two major techniques of unsupervised competitive learning are

a. *Self-Organising Maps/Kohenon Maps*

Self-Organising Maps (SOM) are the special class of ANN, which is inspired by the cortex of the human brain. SOM makes use of competitive learning in which neurons compete with each other to win and then the winner neuron displaced to feature space to form clusters. The competition is induced by inserting negative feedback between neurons, which forces neurons to organise themselves. For obvious reason, such a network is called self-organising maps. SOM was introduced by Kohenon used to assist CRs to choose among various configurations to operate by considering bit rate predictions (Tsagkaris et al., 2012). Khozeimeh and Haykin (2012) proposed a self-organising dynamic spectrum management technique for CR networks in which CRs continuously senses the environment, extract PUs and neighbouring CRs activity patterns, and store to obtain knowledge that significantly reduces the probability of collision.

b. *Adaptive Resonance Theory*

Adaptive Resonance Theory (ART) is another class of unsupervised competitive NNs that is designed for object identification and recognition based on matching between observer expectations and sensory information. This ART matching criterion is set by vigilance parameter, p (threshold of recognition). High vigilance permits weight updation of winning recognition neuron while low vigilance inhibits weight updation of recognition neuron and search procedure is carried out (Carpenter et al. 2016). Another variant of ART is ART 1 and ART 2. ART 1 is the simplest type of ART which accepts an only arbitrary sequence of binary input patterns whereas ART 2 supports analog inputs patterns as well as binary input patterns (Carpenter & Grossberg, 1987).

In CR networks, a channel sensing algorithm based on ART-2 is proposed for cognitive wireless mesh networks in which the spectrum is divided into disjoint sub-bands and sensing is performed in each sub-band. This sensed information is further fused in a fusion centre, which is defined as a pattern classification problem. In this algorithm, only pattern phase information is considered which leads to wrong pattern classification (Zhu et al., 2008). Further modified ART-2 is described which considers amplitude as well as phase information.

Reinforcement learning and NNs

Reinforcement Learning (RL) is another AI approach that enables an agent (decision maker) to observe its state, choose an action in a particular state to obtain rewards. The transition from one state to another depends on several factors such as previous state, action taken, and next state. The main goal is to estimate the reward function for each state-action pair accumulates knowledge and maximise reward function. To apply the RL model (single-agent approach), identified by state, action, and reward. In the multi-agent approach, the set of agents is enabled to learn about each other information to maximise its reward function. Unlike supervised NNs, it does not have any prior knowledge about its input and output. It learns online from the environment and builds the knowledge to achieve its objectives.

RL in the context of CR networks which provides intelligence in terms of dynamic channel selection, spectrum sensing, routing, spectrum allocation (Y. Wang et al., 2019), power control mechanism (K.L.A. Yau et al., 2014). Further, enhanced RL techniques in CR networks have also been presented. The authors in (Saleem et al. 2015) addressed routing issues by clustering mechanisms using the RL approach. Further, routing based clustering improves network stability and scalability. Moreover, spectrum aware cluster-based routing is presented which overcomes the challenges of multihop routing.

In RL, an agent maps the situation (channel state) to maximise its reward function on a long term basis. The agent learns continuously and the environment responds to the state through its action by state transition after each epoch. The agent uses optimal policy to decide each time while taking the next step which maximises its rewards. To obtain an optimal policy, the Dynamic Programming approach can be used when perfect information about the system is available. The system is modelled using Markov property which makes the RL model equivalent to Markov decision Process (MDP). On the other hand, when perfect system information is not available, but the sequence of past state, action, and rewards are available then the Monte-Carlo method can be applied to obtain an optimal policy. Another approach named Temporal Difference (TD) learning approach does not form the system model and obtain its optimal policy based on prediction. Q-Learning (Q-L) and SARSA are the most widely used TD learning techniques (Sutton & Barto, 1998). These schemes are implemented for resource allocation in CR networks and it is observed that SARSA converges slower than Q-L as shown in Figure 7. This is due to the reason that Q-L follows a greedy approach for action selection according to off-policy whereas SARSA selects its action corresponding to the current policy obtained.

Lo et al., (2010) proposed RL based cooperative spectrum sensing model in which CR learns to find an optimal set of cooperative neighbours which reduces sensing delays. Further, RL based

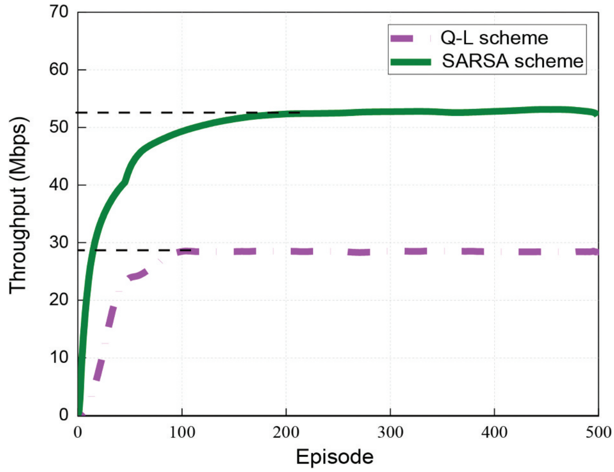

Figure 7. Comparison between the performance of Q-L and SARSA schemes.

optimum solution is provided which improves spectrum sensing under the shadowing effect. The reward function depends on reporting time delay i.e., the time duration between CRs request of cooperation to neighbouring node and arrival to sensing outcome. The authors in (Li, 2009) proposed Q-Learning to address resource allocation problems in a multi-agent environment. Koushik (Koushik et al. 2018) discussed RL based spectrum handoff and issues related to RL during handoff. In this paper, the authors presented hardware implementation of RL and Transfer Learning (TL) schemes to update its Q-value table greedily and shown that RL takes longer time to converge than TL which has expert node to transfer its knowledge in form of Q-table.

Combinational NNs

(a) *Neuro-Fuzzy NNs*

Fuzzy logic is an attractive technique, particularly where it is difficult to express the mathematical model of real-world problems. In fuzzy Sets, elements are assigned a certain degree of belongingness. The numbers in the range [0,1] are used to represent the degree of belongings. Fuzzy logic becomes a useful scheme to represent uncertain data. The fuzzy logic controller consists of three main components as shown in Figure 8.

(i) *Fuzzy Interface*: Converts real-world values to suitable fuzzy sets.
(ii) *Interference Engine*: Interference engine uses a knowledge base to decide output for a specific combination of input fuzzified variables and maps into output variables.
(iii) *Defuzzy Interface*: Converts output fuzzy sets to real-world values.

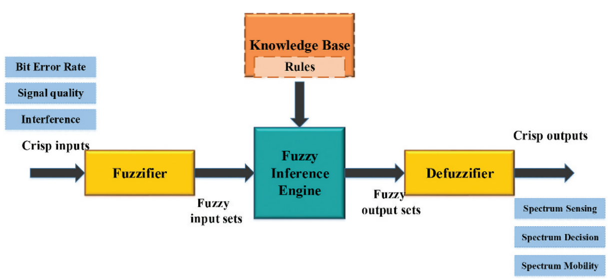

Figure 8. Illustration of fuzzy logic in CR networks.

The authors (Salgado et al., 2016) proposed a fuzzy algorithm is proposed for decision making and particularly for backup channels for spectrum mobility. This proposed algorithm based on multiple criteria decision-making techniques considers four parameters: availability probability of channel, estimated channel time availability, the signal to interference plus noise ratio of the channel, and bandwidth of the channel. Normalised weights (describes a relative degree of importance) are assigned according to the importance of each criterion for the selection of a backup channel. The pre-selection of back up channels decreases delay during spectrum mobility.

The authors (Matinmikko et al., 2009) proposed a fuzzy-based cooperative spectrum sensing technique. In this technique, spectrum sensing decision from the individual node is considered as input, fuses to form output based on combined sensing result. Spectrum sensing performance has been characterised based on the probability of false alarm and probability of detection in a fading environment.

However, fuzzy logic represents uncertain data, but it is difficult to design the degree of belongingness set. So Fuzzy logic combined with neural networks and forms the neuro-fuzzy combinational model. Neuro-fuzzy based spectrum mobility technique due to its capability to deal with uncertain environmental conditions as well as in the heterogeneous environment. This technique considers interference, bit error rate, and signal strength to find the quality of the channel in terms of fuzzy patterns. Based on generated fuzzy patterns, neural .networks trained to estimate channel gain, not only for spectrum mobility but also for spectrum assignment in a heterogeneous network (Maheshwari & Singh, 2015).

b. *Wavelets NNs*

Wavelet NNs replaces standard activation function (like a sigmoid function) by wavelet activation function. A wavelet is a small function that grows and decays in a finite amount of time. Unlike Fourier transform, wavelet NN can distinguish between stationary and non-stationary signals.

However, wavelet NNs uses wavelet function (called mother wavelet) to derive daughter wavelet function $\psi_{\lambda,t}(u)$through linear translation factor, t and scale/dilation factor, λ as shown in Figure 9. The daughter wavelet is expressed as

$$\psi_{\lambda,t}(u) = \psi\left(\frac{t-u}{\lambda}\right) \tag{4}$$

An author in (Eltholth, 2016) proposed a spectrum predictor model, which is based on a discrete wavelet transform nature that produces a time-frequency representation of the analysed signal. The

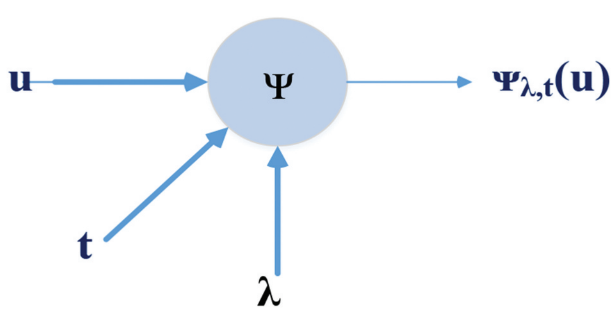

Figure 9. A daughter wavelet neuron.

analysed time series is broken into sub-series, which represents the previous occupancy status of a certain set of sub-channels. Thus, design an accurate wavelet NNs based spectrum predictor model with less complexity.

Wavelet approach for wideband spectrum sensing is sub-divided into small bands and characterised by frequency irregularities. Wavelet transform and multiscale wavelet approach have been used to detect local irregularities that carry information about power spectral density and structure irregularities of sub-bands that identify spectrum holes (Tian & Giannakis, 2006).

Other NNs

(a) *Quantum NNs*

Quantum NNs (QNNs) is based on quantum mechanics exploiting quantum information processing to improve classical ANN. In classical ANN, much of the power is required due to its massively parallel, distributed information processing and non-linear transformation operation performed by nodes. On the other hand, QNN makes use of powerful quantum parallelism, which provides quantum computing to process huge data sets. The author (Liu, 2016) presented QNN based spectrum sensing algorithm in which quantum neuron with multiple energy levels is considered as the excitation function of hidden layer neurons. Further, the improved version has been presented to increase convergence speed and stability. Table 3 summarises DSM with ANN in CR networks.

Intelligence with support vector machine

Support Vector Machine (SVM) is supervised machine learning algorithms used for classification and regression analysis. It is based on statistical learning theory with structural risk minimisation (Awe et al., 2013). It is initially preferred for the classification of complex problems. For a given training set, the input training vector belongs to one or another class of two groups. These two groups are separated by an optimal hyperplane that has the largest distance to the nearest training set of any class (maximal margin classifier) that achieves good separation. It is easier to train SVM when the classes are linearly separable. In non-separable classification, non-linear SVM is obtained by introducing a kernel function. The function is said to be valid kernel if it satisfies Mercer's Theorem (Hofmann, 2006), which provides necessary and sufficient characterisation of a function as a kernel function. A kernel represents a similarity measure in the form of a similarity matrix (Gram Matrix) between its input objects. The gram matrix fuses all the necessary information for learning algorithms merged in the form of the inner product. For more details, refer (Burges, 1998). SVM to develop a real-time approach to sense PU as shown in Figure 10. The input composite signal includes signal and noise, which is independent of each other in the time domain. The sampled data is classified as PU or not based on testing and training of the SVM classification model.

For linear classification, a kernel function is proposed to map input low dimensional vector into high dimensional features space (Zhang & Zhai, 2011). Y. Wang (Wang et al., 2014) proposed a spectrum mobility prediction scheme that considers time-varying and space varying characteristics of mobile CRs simultaneously. The joint feature extraction pattern is proposed which executes spectrum mobility prediction through the classification of SVM with fast convergence speed. The authors in Huang et al., (2009) presented an SVM based learning engine that is divided into three parts as environmental awareness, knowledge actuation, and decision making. The learning engine acquires knowledge about the environment through learning that puts intelligence in CRs. Table 4 summarises DSM with SVM in CR networks.

Table 3. Summarises DSM with ANN in CR networks.

Class	Type of NNs	Authors	Brief Description	Application Area	Other Related Applications
Supervised NNs	ML-FFNNs				
	Multilayer Layer NNs	Tumuluru et al. (2010) Liu (2016)	• Multilayer perceptron-based spectrum prediction scheme (1) Spectrum Sensing does not require priori knowledge of Traffic characteristics of PUs. (2) Predict channel status based on sensing history (3) Saves sensing energy and improves spectrum utilisation • ML-FFNNs learning based spectrum sensing technique (1) Dynamic Chinese restaurant game to learn table state based on ML-FFNN. (2) CR considered as customers to learn the table state (Available spectrum hole) in the restaurant (network). (3) CR also consider table state (spectrum hole) not for immediate as well as for future utility.	Spectrum Sensing	ML-FFNNs based learning and adaption in CR networks is discussed. (Baldo & Zorzi, 2008)(Katidiotis et al., 2010)
	Radial Basis NNs	Zhang, Hu et al. (2013)	• K-RBF for spectrum sensingK-Means clustering algorithms proposed • based on previous information on the PU spectrum. • More accurately trained as compared to RBF.	Spectrum Sensing	Multi-objective Optimisation in Cognitive Engine with RBF & GA(Y. Yang et al., 2012)
	Convolutional NNs	Lee et al. (2019)	• CNN based cooperative spectrum sensing technique (1) Deep neural network (DNN) having multiple hidden layers used for learning. (2) combining individual CRs sensing and optimised combining strategy through DNN.	Spectrum Sensing	CNN spectrum monitoring framework for radar bands in spectrum sharing scenarios(Selim et al., 2018)
	Recurrent NNs				
	Deep Recurrent Neural Network	Tang and Li (2017)	• DRNN based Spectrum Prediction model (1) Predict the spectrum of multiple time slots using the MIMO strategy. (2) Here, the continuous channel state is divided into slots and forming time series of channel state.	Spectrum Sensing	RNN and Matrix Methods for Cognitive Radio Spectrum Prediction and Security(Glandon, 2017).
Unsupervised NNs	ML-FFNNs (Auto-encoders)				

(*Continued*)

Table 3. (Continued).

Class	Type of NNs	Authors	Brief Description	Application Area	Other Related Applications
	Auto-Encoders	Zhu and Fujii (2016)	• Stacked Denoising Sparse Auto-encoder based modulation classification (1) Proposed modulation classification method to improve spectrum sensing. (2) Denoising process improves the performance of noise suppression by training the network with a corrupted database.	Spectrum Sensing	
	Recurrent NNs				
	Hopfield NNs	Hasegawa et al. (2014)	• Hopfield NNs based optimisation algorithm for decision makingTwo approaches are proposed to optimise centralised and decentralised networks. • In a centralised network, the selection of base stations is considered as a minimum cost flow problem that has to be optimised. • In a distributed network, energy minimisation dynamics of Hopfield NNs is considered as an objective function	Spectrum Decision	
	Boltzmann Machine				
	Restricted Boltzmann Machine	MohanaPriya and Shalinie (2017)	• RBM based secure routing protocol. (1) Provides a secure self-learn routing algorithm. (2) Energy-efficient routing to prevent flooding attacks in routing.	Spectrum Decision	
Competitive NNs C	SOM (CR Adhoc Networks)	Khozeimeh and Haykin (2012)	• SOM based dynamic spectrum management techniques (1) CRs continuously sense the environment, extract PUs and neighbouring CRs activity patterns, and stored to obtain knowledge, which significantly reduces the probability of collision. (2) Using the feedback channel, RSA information has been shared with neighbouring CRs. (3) After sharing RSA information, weights have been updated and sub-bands are allotted to CRs based on its cost function.	Spectrum Management	Advanced learning using SOM is presented (Tsagkaris et al., 2012).
		Salem et al. (2016)	• SOM based spectrum sensing and channel selection scheme (1) SOM improves network efficiency and spectrum utilisation by decreasing the probability of false alarm and miss detection (2) To select the best channel out of available channels segregates strategy has been applied.	Spectrum Sensing and Channel selection	

(Continued)

Table 3. (Continued).

Class	Type of NNs	Authors	Brief Description	Application Area	Other Related Applications
Reinforcement Learning	–	Saleem et al. (2015)	• RL based clustering and routing algorithm (1) RL provides artificial intelligence is applied as a tool to form clustering and routing. (2) A cluster-based routing algorithm is presented which improves network performance by decreasing flooding of routing overheads. (3) Further, Spectrum aware Cluster-based routing is presented to overcome the challenges of multihop routing.	Spectrum Decision	RL for dynamic channel selection in a single-agent and multi-agent environment is discussed (Yau et al., 2010).
	-	Lo and Akyildiz (2010)	• RL based cooperative spectrum sensing model (1) Cooperative spectrum sensing with Q-Learning is considered. (2) Scheme converges to Optimal solution under correlated shadowing and adaptable to environmental changes. (3) The reward function depends upon reporting delay time.	Spectrum Sensing	Q-Learning based Multi relay cooperative mechanism sensor network is presented (Peng et al., 2011).
	-	Li (2009)	• Q-Learning based channel selection in a multi-agent environment. (1) Q-Learning to address the resource allocation problem. (2) Multi-agent RL with a Q-Learning framework is considered for channel selection. (3) No coordination among CRs and each CR treated other CR as part of the environment.	Spectrum Sharing	Q-Learning based power allocation schemes are discussed (Wu & Fei, 2010).
	-	Koushik et al. (2018)	• Hardware testbed learning based spectrum handoff (1) RL (Q-Learning) and Transfer Learning scheme-based spectrum handoff is presented to update the Q-value of the table. (2) RL takes a longer time to provide an optimal solution (update Q-value) than the TL scheme. (3) RL each time restarts its learning process from scratch even if a similar kind of situation prevails before.	Spectrum Handoff	
Combinational NNs	Neuro-Fuzzy NNs	Maheshwari and Singh (2015)	• Neuro-fuzzy based Spectrum Handoff technique (1) This technique considers interference, Bit Error Rate (BER), and signal strength to find the quality of channel in terms of fuzzy patterns. (2) Based on generated fuzzy patterns, the neural network is trained to estimate channel gain and select the available spectrum in the heterogeneous network.	Spectrum Mobility	

(*Continued*)

Table 3. (Continued).

Class	Type of NNs	Authors	Brief Description	Application Area	Other Related Applications
	Fuzzy Logic	Matinmikko et al. (2009) Salgado et al. (2016)	• Fuzzy logic based cooperative spectrum sensing technique (1) Spectrum sensing decision from an individual node is considered as input cooperatively, fuses to form output based on combined sensing result. • Fuzzy based spectrum mobility algorithm (1) proposed algorithm for multiple criteria decision making and particularly for backup channels for spectrum mobility. (2) multiple criteria decision-making techniques consider four parameters: availability probability of channel (AP), estimated channel time availability (ETA), and the Signal to interference plus noise ratio of the channel (SINR) and bandwidth of the channel (BW). (3) Normalised weights are assigned according to the importance of each criterion for the selection of the backup channel.	Spectrum Sensing Spectrum Mobility	Fuzzy logic based cross-layer optimisation is presented (Baldo & Zorzi, 2008)
	Wavelet NNs	Eltholth (2016) Tian and Giannakis (2006)	• Wavelet NN based Spectrum prediction Model (1) Analysed signal has been represented in the time-frequency domain. (2) Spectrum predictor model is based on the discrete wavelet transform (DWT) nature (3) The analysed time series is broken into sub-series, which represents previous occupancy statutes of a certain set of sub-channels. (4) NN's performance has been enhanced by coupling it with Wavelet NNs. • Wideband spectrum sensing using wavelet approach (1) Wide frequency bands are decomposed into small frequency bands that are characterised by local irregularities in frequency. (2) Wavelet transform modulus and multiscale wavelet approaches are used for spectrum sensing.	Spectrum Sensing Spectrum Sensing	
Other NNs	Quantum NNs	Liu (2016)	• QNN based spectrum sensing algorithm (1) quantum neuron with multiple energy levels is considered as the excitation function of hidden layer neurons. (2) Energy is considered as input characteristics. (3) improves convergence speed and convergence stability.	Spectrum Sensing	

Intelligence with metaheuristic algorithms

a. Genetic algorithm (GA)

GAs are stochastic search algorithms, which effectively solve machine learning and image processing problems (Jedlicka & Ryba, 2016). The main advantage of using GA is parallelism, which speeds up its simulation results. The computation in GA starts with the collection of chromosomes, which has certain characteristics. The algorithm can be implemented using the following steps as shown in Figure 11 (Siddique & Azam, 2010).

(1) Initialise the population of chromosomes.
(2) Evaluate the fitness level of each chromosome to rank them.
(3) Construction of the new population until the production of next-generation completes using the following steps:
    (i) ***Selection***: The best chromosome is selected from the currently available population based on its fitness level.
    (ii) ***Crossover:*** With crossover probability, selected chromosome reproduces to generate a new individual.
    (iii) ***Mutation:*** Newly generated individuals will be mutated at a definite point in the chromosome.
(4) The above steps are repeated until the desired results are obtained.

In CR networks, the GA uses biological behaviour representing each channel by a chromosome. Each gene of the chromosome represents specific parameters. In the spectrum decision process, it is all about the fair distribution and utilisation of available resources, and for fair resource distribution, optimal distribution is required. According to L.Doyle, 'An optimization process can be defined as the process involved in selecting the best choice from the list of available choices to reach some kind of goal or at least as near as possible to goal' (Doyle, 2009). In CR networks, spectrum allocation also involves an optimisation task to assign spectrum holes to CR found during the spectrum sensing process.

The spectrum allocation scheme for CR networks using GA in which each gene of chromosome represents different parameters (data rate, frequency, bandwidth, error rate, and modulation/coding scheme) which is associated with specific weight (Siddique & Azam, 2010). The weight for each gene represented in binary form. Like the weight for each gene in the chromosome fitness point for each gene is assigned. Once the fitness of each gene in the chromosome is calculated, the next step is the construction of a new population, which involves selection, crossover, and mutation process. The whole process is repeated until the optimum solution among the available solution set is achieved. The authors in (Morabit et al., 2015) presented spectrum decisions based on GA to provide a new spectrum band as requested by CR in the network. GA defines radio in terms of genes and chromosomes and considers user quality of service (QoS) as an input to the GA procedure. Further, chromosome population size is defined by available spectrum resource size and chromosome genes define the efficiency of spectrum allocation.

b. Ant colony optimisation (ACO)

ACO considered as computational technique proposed by Dorigo which is based on the searching behaviour of Ants (Dorigo et al. 1997). Although real arts are blind, the search their food source via the shortest path by play on the information through a substance called pheromones. The ants on its transmission route release this liquid substance, which is accumulated on the shortest route and soon ants, start to follow the smallest route. The behaviour of real ant has inspired the ant system, which resolves many complex problems successfully. The characteristics of the ACO algorithm i.e. parallel computation, self-organisation, and positive feedback that can help CR to achieve self-adaption and learning capability to achieve global optimisation (Q. He et al., 2013) (Bayrakdar & Çalhan, 2018). Different steps in the ACO algorithm are as follows:

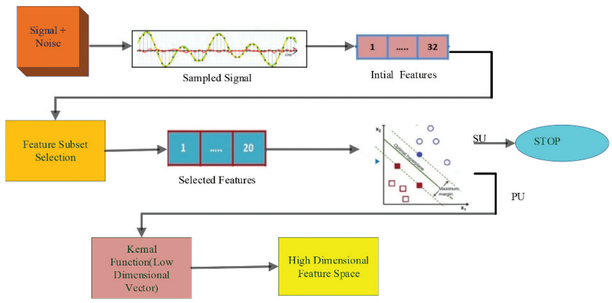

Figure 10. A diagram showing the basic idea of SVM for spectrum sensing.

(1) *Ant probability distribution rule*: In the ant system, artificial ants release the solution through moving among vertex follow the principle as:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}}{\sum\limits_{s \in C}[\tau_{ij}(t)]^{\alpha}[\eta_{ij}(t)]^{\beta}} if\, j \in C \end{cases} \tag{5}$$

where $p_{ij}^{k}(t)$ is state transition probability of ant moving from vertex i to j at the time t. C is a set of vertex and s is unselected vertex in the traversing process. $\tau_{ij}(t)$ and $\eta_{ij}(t)$ are pheromone intensity

Table 4. Summarises DSM with SVM in CR networks.

Type of SVM	Authors	Brief Description	Application Area	Other Related Applications
-	Dandan (2011) Awe and Lambotharan (2015)	• SVM based spectrum sensing technique (1) Presented SVM to develop real time approach to sense PU. (2) The sampled data is classified as PU or not based on testing and training of SVM classification model. (3) For linear classification, kernel function is proposed to map input low dimensional vector into high dimensional features space. . • Formulated multi-class SVM Algorithms for solving multi-class spectrum sensing problems. (1) The performance of the detector has been judged based on receiver operating characteristics curves and classification accuracy. (2) Robust to joint spatiotemporal detection of spectrum hole.	Spectrum Sensing	Eigen vector and support vector machine based learning approach for spectrum sensing in multi antenna CR networks is proposed (Awe et al., 2013)
-	Wang et al. (2014)	• SVM based spectrum mobility prediction scheme (1) Considers time-varying and space varying characteristics of mobile CRs simultaneously. (2) The joint feature vector extraction pattern is proposed which executes spectrum mobility prediction through the classification of SVM with fast convergence speed.	Spectrum Mobility	

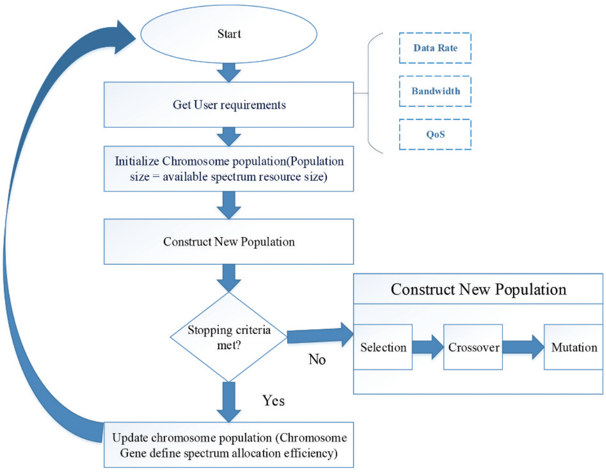

Figure 11. Illustration of genetic algorithm for CR networks.

and heuristic visibility (cost) of a direct route between the node *i* and *j*. The parameters α and β controls the importance of pheromone and heuristic information respectively.

2. *Local optimisation procedure*: To avoid residual pheromone submerging heuristic information, pheromone will keep updated after one ant finishes a path searching with follows the principle as:

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t) + \rho.\tau_0 \tag{6}$$

where τ_0 is the initial pheromone value and $\rho$is the evaporation coefficient of pheromone.

3. *Global optimisation procedure*: When all ants complete the cycle, the pheromones will be globally updated as:

$$\tau_{ij} \leftarrow (1-\alpha).\tau_{ij} + \alpha.\frac{1}{G_{\max}} \tag{7}$$

where α is constant and $G_{\max}$ is the maximum objective function.

4. Stopping procedure

The procedure is stopped after completing a predetermined number of cycles to achieve the globally best solution.

The author in (Jhajj, 2017) discussed the ACO technique to find the optimal sensing time of CR. As CR has a fixed time frame for its sensing the environment and transmission of data, an optimal sensing time is required that will maximise throughput with minimum interference with PUs. This optimal sensing time can be found by ACO which implements the above steps to find an optimised solution. The ACO has been proposed for reconfiguration decision making in CR networks (Q. He et al., 2013). Reconfiguration means configure terminals and network devices to intelligently adapt to environmental conditions, which is a challenging task. ACO deals with complex environmental conditions as well as target multi-objective optimisation through parallel computation. Moreover, ACO learns from the environment and reconfigure spectrum decision through self-organisation process. Three types of reconfiguration schemes have been considered i.e. parameter variation reconfiguration scheme, radio resource management reconfiguration scheme and network access reconfiguration scheme and showed the improved performance in the heterogeneous network.

A dynamic channel assignment as an optimisation problem to maximise the reward of CRs is formulated in (He & Zhang, 2012). The algorithm also considers interference with PUs and SINR constraints of CRs to maximise the spectrum utilisation. Table 5 summarises DSM with metaheuristic algorithms in CR networks.

Intelligence with Bayesian learning

Bayesian learning signifies the importance of prior distribution which represents knowledge of unknown parameters in uncertain environmental conditions. It is assumed that no prior information is available about the spectrum but some prior information is available about the status of the channel which should be explored through learning. Bayesian inference is an approach where Bayes' rule is used for driving posterior distribution from the prior distribution which further considered as prior for another posterior distribution and so on. In CR networks, CRs can compute the prior distribution of a system parameterθ, denoted by $P(\theta)$, which represents the spectrum occupancy status of PUs. Though spectrum sensing, data observed in n time slots $X = [x_1, x_2, \ldots\ldots x_n]$. The likelihood functions of the parameter θ,$P(X/\theta)$, for observed data, conditional on parameter θ. After acquiring prior probability distribution and the likelihood function, Bayesian inference can be used to derive posterior density function, $P(\theta/X)$which is conditioned on data X. Bayes' Theorem can be simply expressed as

$$P(\theta/X) = P(X/\theta).P(\theta)/P(X) \tag{8}$$

In CR networks, Likelihood function denotes the probability of busy/idle previous states for a busy/idle current state. In Baye's theorem, the posterior distribution combines the information in both the prior distribution function and the likelihood function, which represents stronger information and narrower possible values for θ. The Bayesian network has 2 types of models, Bayesian Parametric (BP) Model, and Bayesian Non-Parametric (BNP) Model. BP model has a finite set of parameters θ to compute prior distribution and In the BNP model, it does not mean a lack of parameters but an infinite-dimensional set of parameters is assumed to compute prior distribution. Recently BNP model applications in CR networks get a lot of attention of researchers because it provides flexibility to model to learn in an unknown environment.

A Bayesian approach based spectrum sensing in CR networks is presented in (Jacob et al., 2014). The authors presented Bayesian inferences over single and multiple sensing frames to calculate the posterior distributions of unknown parameters, which forms the basis of Bayesian learning (Manco-vásquez et al., 2014). In Bayesian inference over multiple frames, learning from past samples has been done using threshold-based approximation and Kullback Leibler based approximation. Further, A Bayesian approach based decision-making engine in CR networks is proposed in (Huang et al., 2010). CE learns from an environment and form rules to reconfigure transmission parameters (modulation, code rate) which ensures QoS of CRs. The reconfiguration can be achieved with parameter learning, structure learning, and inference algorithms that form rules to adapt to environmental conditions . Table 6 summarises DSM with a Bayesian approach in CR networks.

Intelligence with Hidden Markov Model

Hidden Markov Model (HMM) represented as a stochastic process that can be modelled as a Markov chain, whose actual states are hidden, to analyse the temporal or dynamic behaviour of PU activity pattern. In HMMs, several hidden states represent the probability of distribution over a sequence of observations. The HMM gets its name from two properties in which it assumes:

1) Observations at the time $t$generated by some process whose state S_t is hidden from the observer.

2) State of hidden process S_t satisfy Markov's property which states that for a given S_{t-1}, the current state S_t is independent of all states before $(t-1)$i.e. For a given S_t, the output Y_t is independent of all other time indices states and observations.

HMM has found remarkable applications in CR networks since many environmental parameters are partially observed or act as hidden states. Various authors proposed HMM-based spectrum sensing schemes (Saad et al.,2016), (Ghosh et al. ,2009). HMM-based spectrum prediction for industrial applications that accurately predict through multiple slots is proposed in (Saad et al.,2016). Large numbers of hidden layers are considered which interpret as different PUs activity levels and formulate the prediction problem as a maximum likelihood classification approach. Akbar et al., 2007 presented a Markov based channel prediction algorithm and considers channel state occupancy of PUs as Poisson distributed. Pham et al. (2014) presented the HMM based spectrum handoff model in CR networks. The proposed approach infers the efficiency of HMM in correcting the sensing sequence and prediction of channel status. Further, the proposed algorithm applied to the spectrum mobility function in CR networks. An HMM based channel selection framework that minimizes the delay incurred during channel selection is proposed in (Senthilkumar & Geetha Priya, 2016). The proposed approach achieves a significant reduction in data loss and an increase in transmission speed, by obtaining the best-matched channel for the users. Table 7 summarises DSM with HMM in CR networks.

Intelligence with game theory

Game theory technique accounts for multi-agent decision making, in which the decision of each player for action is based on the history of actions performed by other players. This involves the learning process by each player, which may ultimately lead to a stable state. Every game involves a set of players, actions, and payoff functions (or utility function). A player gets more rewards if it has a higher payoff function. Mathematically, a game can be represented as:

$$G = (N, A, P) \tag{9}$$

where N represents a set of players, A represents a set of actions, and P represents payoff functions. In CR networks, the players in the games are CRs, which take actions based on observations of its environment in which it operates. As time progresses, CR learns from past actions and from observing the action of other CRs and modify its actions accordingly. Several types of game theory approach in CR networks are shown in Figure 12.

- *Game-Theoretic Approaches:*

Two types of game-theoretic approaches are cooperative and non-cooperative games. In cooperative games, a group of players can make binding commitments and act jointly whereas, in non-cooperative games, the individual player acts selfishly. In cooperative games, cooperation among the players strengthens the position of the player in a game. Here the group of players forms a coalition act as a single entity.

In non-cooperative, each user takes care of its benefit and selects optimal actions to maximise its payoff function. The author in (Yu, 2013) presented cooperative games for spectrum sensing and sharing and found that the applicability of various games depends on several factors. A non-cooperative game can be classified based on information i.e. either complete information or an incomplete information game. In the complete information games, each player observes other players' information i.e. payoff and their action. On the other hand, with incomplete information, the game can be modelled as Bayesian game for decision making in which outcome can be estimated based on Bayesian analysis (Wang et al., 2010). Several types of games have been adapted to model various situations in CR networks. For example, in repeated games, each stage is usually repeated. Let us consider$N$ the set of CRs in the network and $a^{(k)}$denotes the action taken by a player

Table 5. Summarises DSM with a metaheuristic algorithm in CR networks.

Type of Metaheuristic Algorithms	Authors	Brief Summary	Application Area	Other Related Applications
Genetic Algorithm	El Morabit et al. (2015)	• The genetic algorithm-based spectrum allocation scheme (1) Defines the structure of chromosomes which is a set of genes. (2) Each gene represents frequency, modulation, power, and BER in particular. (3) Each gene will be considered in the decision-making process. (4) Provides a multi-objective optimisation technique to find fitness function using a weighted sum approach (rank associated with each objective) represents the importance of each objective.	Spectrum Decision	Importance of Genetic Algorithms in Machine learning (Shapiro, 2001)
	Siddique and Azam (2010)	• Genetic algorithm-based Spectrum optimisation techniques (1) Chromosome population size is defined by available spectrum resource size and genes define the efficiency of spectrum allocation. (2) Each gene of the chromosome represents a different parameter, which is associated with a specific weight. (3) The weight for each gene represented in binary form i.e., fitness point for each gene is assigned. (4) Once the fitness of each gene in the chromosome is calculated, the next step is the construction of a new population, which involves selection, crossover, and mutation process.	Spectrum Decision	
Ant Colony Optimisation	Jhajj (2017)	• ACO for Spectrum sensing (1) Optimal sensing time is calculated using ACO that will maximise throughput with minimum interference with PUs.	Spectrum Sensing	Self-Organisation paradigms and optimisation approaches for cognitive radio technologies: A survey is provided (Liu et al. 2013)
	He et al. (2013)	• ACO based reconfiguration Decision-making process. (1) ACO deals with complex environmental conditions as well as target multi-objective optimisation through parallel computation. (2) ACO learns from the environment and reconfigures spectrum decision through a self-organisation process (3) Three types of reconfiguration schemes have been considered i.e. parameter variation, radio resource management, and network access reconfiguration scheme.	Spectrum Decision	
	He and Zhang (2012)	• Dynamic channel assignment using ACO (1) Formulating a dynamic channel assignment problem as an optimisation problem and provide solution-based on ACO. (2) Manage and assign channel resources dynamically while considering interference and SINR constraints.	Spectrum Decision	
	P. Huang et al. (2013)	• ACO based on demand Routing Algorithm (1) M/G/1 queuing theory is introduced to characterise the spectrum usage behaviour of PUs and CRs. (2) It jointly considers path and spectrum scheduling to improve latency and packet loss rate.	Spectrum Decision	

Table 6. Presents DSM with Bayesian approach in CR networks.

Type of Bayesian Learning	Authors	Brief Summary	Application Area	Other Related Applications
-	Jacob et al. (2014)	• A bayesian approach-based Spectrum Prediction modelPredicts the spectrum occupancy status of PUs from its previous spectrum occupancy pattern using a Bayesian approach • Status of N previous time slots are considered to predict the next stage.	Spectrum Sensing	Service selection for CR based on the Bayesian approach has been presented (Homayounvala, 2015) Non -Stationary Hidden Markov Model with Bayesian inference for channel quality prediction presented (Xing et al., 2013). BNP model base Dirichlet process mixture model (DPMM) for unsupervised classification technique has been applied (Ranjan & Ahmad, 2016). Dynamic Bayesian games for decision making in Ad-Hoc networks are presented (Nurmi, 2004).
-	Manco-vásquez et al. (2014)	• Bayesian approach for multiantenna spectrum sensingBayesian detectors are proposed which learn from past decisions and to adapt to a continuously changing environment. • At each sensing period, Bayesian inference is applied and posterior for channel occupancy is calculated which act as priors for the next sensing frame • Perform Bayesian inference over single and multiple time frames to find the posterior distribution of unknown parameters.	Spectrum Sensing	
-	Huang et al. (2010)	• A Bayesian learning-based Decision engineBayesian network-based CR learning inference and decision-making engine • Form rule according to the variations in the environment (i.e. SNR) with learning which include structure and parameter learning. • Utilise these to reconfigure transmission parameters (modulation, code rate) according to environmental	Spectrum Decision	
-	S. Zheng et al. (2013)	• Bayesian approach-based spectrum sensing for digital signalsBayesian detector obtains prior distribution by considering PU activity and signalling information of PU (symbol rate, modulation) to improve CR throughput. • An optimal detector for digital primary signals(MPSK, $M > 2$) over the AWGN channel for low and high SNR regime has been presented.	Spectrum Sensing	

at $k^{\text{th}}$the stage of the game. In each stage k, players tend to maximise their payoff function, while considering the history of action collected in $h^{(k)} = (a^{(1)}, a^{(2)}, \ldots\ldots, a^{(k)})$. In other words, players map their actions from history $a_i^{(k)} = f_i(h^{(k-1)})$. In CR networks, their action is the selection of channel available and mapping of action depends on the history of PUs activity as well as activity pattern of other CRs. In dynamic/repeated games, players came across a similar game number of times. The cooperation among the players in repeated games can be introduced to get long term benefits. The repeated games are applied for spectrum sharing scenarios where multiple CRs exists in (Li et al., 2010). In this context, repeated games apply punishments to achieve a desirable outcome. When the PUs activity is considered as stationary with an unknown environment then Stochastic games, also known as Markov games, are introduced to model the network. The authors in (W. Wang et al., 2018) addressed the routing problem using stochastic games. Stochastic routing game is decomposed into several stages and at each stage stochastic learning is proposed to learn equilibrium strategy of channel selection.

The Stackelberg game can be modelled for implementing spectrum sharing where PUs can involve CRs as cooperative relays (H. Wang et al., 2010). In auction games, PUs act as auctioneer, selling idle spectrum bands to CRs which are allowed to select the appropriate bidding strategy for each channel to maximise their utility function. The concept of auction games has been applied to

Table 7. Presents DSM with HMM in CR networks.

Type of HMM	Authors	Brief Summary	Application Area	Other Related Applications
-	Saad et al. (2016)	• HMM-based Spectrum Prediction for industrial applications.Addressing the prediction problem as a sequence of the classification problem. • Large numbers of hidden layers which formulate the problem as maximum likelihood (ML) classification.	Spectrum Decision	Dynamic spectrum allocation using HMM is presented (Akbar & Tranter, 2007). Channel status predictor using HMM and/or Multilayer perceptron (MLP) (Tumuluru et al., 2012).
-	Ghosh et al. (2009)	• HMM in Spectrum SensingHMM predicts a busy or idle status of sub-band by its PU • Validate the existence of Markov chain by collecting real-time measurements in paging spectrum (928–948 MHz) • Likelihood method to determine true states, the complexity arises due to this method is then reduced using Viterbi coding	Spectrum Sensing	
-	Tran and Do (2014)	• The HMM-based Spectrum Mobility modelThe proposed approach infers the efficiency of HMM in correcting the sensing sequence and prediction of channel status. • Further, the proposed algorithm applied to the spectrum mobility function in CR Networks.	Spectrum Mobility	
-	Senthilkumar and Geetha Priya (2016)	• Channel selection framework based on HMM.Minimised channel selection delay • Further enhanced its performance with an optimum routing algorithm along with HMM. • The proposed approach achieves a significant reduction in data loss and an increase in transmission speed, by obtaining the best-matched channel for the users.	Spectrum Sensing, channel allocation	

spectrum sharing in CR networks (Khaledi & Abouzeid, 2013), as well as in spectrum sensing (Sendrei et al., 2015). Table 8 summarises DSM with game theory in CR networks.

Intelligent techniques evaluation: strength, limitations, and challenges

Intelligent techniques having many advantages but their implementation still facing some challenges. The intelligent techniques applications in CR networks, strengths, limitations, and implementation challenges are summarised in Table 9.

(a) Supervised NNs: Basically, supervised NNs accomplished its task under supervision which requires complete knowledge about the environment in which it has to operate. However, in the context of CR networks, CRs may not have complete knowledge about the radio environment in which it has to access the spectrum. NNs provides a high level of feature classification but also required data labelling. It requires training under different environmental conditions and outcome depends on the selection of initial parameters. Therefore, the selection of data for training must be task-oriented and free from noise. Also, with the increase of network size, the training process slows down which may lead to slower convergence. To improve its efficiency, multiple hidden layers are introduced which requires large training data which further slows down its training process.
(b) Unsupervised NNs: A major challenge CRs can face a lack of knowledge of the surrounding radio environment. Even in this situation, CRs are expected to adopt changes in the environment so that they may not collide with PUs. CRs must be able to extract knowledge about PU activities which makes unsupervised NNs an appealing approach in CR networks. In unsupervised NNs, learning is based on a correlation among input data, and no information about the correct output is available. So unsupervised NNs are used indirectly for spectrum

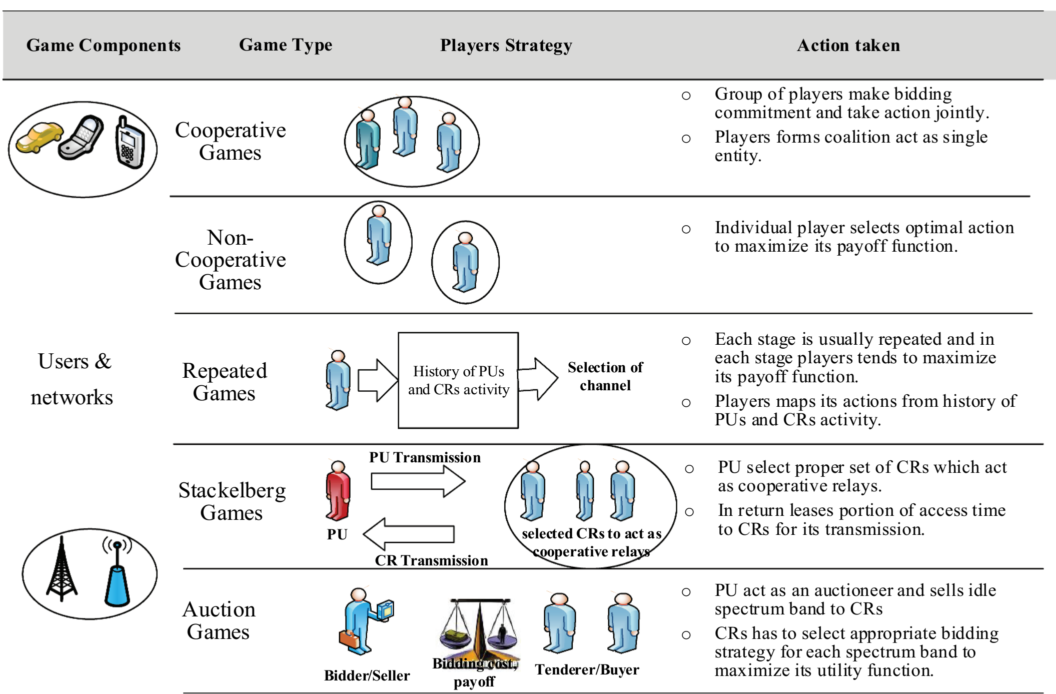

Figure 12. Various game theory approaches in CR networks.

management in CR networks like modulation classification, optimisation algorithm for spectrum decision, and routing algorithms.

(c) Unsupervised Competitive NNs: As the name indicates, it is a form of unsupervised learning where output and input neuron compete and employs winner take all strategy. SOM is one of the members of this class that make use of competitive learning in which neurons compete with each other to win and winner neuron displaced to feature space to form clusters. The authors in (Khozeimeh & Haykin, 2012) presented SOM based DSM for cognitive ad-hoc networks. In this proposed scheme, PU and CR activities patterns are extracted and stored in memory which significantly reduces the probability of collision. SOM seems to be more realistic as it does not require prior knowledge about the radio environment. Further, the application of SOM with a different type of input pattern does not require redesigning the existing learning mechanism. SOM can be easily interpreted and understood. Moreover, it requires sufficient data to form meaningful clusters. Another member of this category is ART which designed for object identification, recognition, and pattern classification problem. It has stable and self-regulating control structure but it does not always guarantee stability and it has to empirically fix its vigilance parameter. This technique is not suitable directly for DSM in CR networks.

(d) Reinforcement Learning: Reinforcement Learning is distinct from supervised and unsupervised learning as it focuses on online learning rather than offline learning. RL learns from positive and negative reinforcement (or rewards) to set its training examples. RL seems to be one of the promising intelligent techniques to solve the spectrum management problem in CR networks. RL is used in spectrum sensing, spectrum decision (in the multi-agent environment and with multiple objectives), spectrum sharing, and spectrum mobility. One of the major drawbacks of the RL technique is slow convergence. The authors presented hardware implementation of RL and Transfer learning for spectrum handoff in (Koushik et al., 2018) and found that RL takes a long time to adjust its learning parameters as compare to Transfer learning

(e) Combinational NNs: Combinational NNs have neuro-fuzzy NNs and wavelet NNs in this category. Fuzzy logic is an attractive technique that uses human-understandable fuzzy logic instead of using complicated mathematical modelling. The main advantage of fuzzy logic is that it is faster to train and also it requires less computational resources. With fuzzy logic, the solution can be obtained when the system has incomplete environmental knowledge. Some disadvantages of fuzzy logic are difficult to create its model as with increasing dimensions may lead to inefficient results. Further, it is difficult to estimate its membership function according to user requirement and it requires more tuning.

(f) Support Vector Machine: SVM comes under the supervised learning category which is used for object classification, pattern recognition, and regression analysis problem. SVM technique provides superior performance in many applications due to its generalisation ability and robustness against noise. SVM maps input vector from low dimensional feature to high dimensional features which make them linearly separable. For non-linear mapping, a kernel function is used. In CR networks, SVM is used as a classifier for signal classification. The sampled data is classified as PU or not based on the training of SVM. Unlike ANN, it is not suffered from overfitting problem and provides good performance in small problems. But in complex problems, it provides poor performance and may require a high training set which increases its computation complexity and storage requirements. Also, SVM requires large labelled data for training and complete knowledge of the radio environment which may divert the focus of researchers.

(g) Metaheuristic Algorithms: These algorithms solve multi-objective optimisation problems through parallel computation. GA provides multi-objective optimisation based on a fitness function but it may not always converge to the global optimum in case of large performance metrics. The performance of GA highly depends on fitness function which may be based on

Table 8. Presents DSM with game theory in CR networks.

Type of Game	Authors	Brief Summary	Application Area	Other Related Applications
Cooperative Games	Yu (2013)	• Cooperative games for spectrum sensing and sharingDifferent game models in a cooperative framework are presented. • Combinations of different approaches such as price-based, market-driven, agent driven, incentive-driven are also explored.	Spectrum Sensing & Spectrum Sharing	
Non-Cooperative games	Zhu et al. (2012)	• Non-cooperative game (Bayesian game) for spectrum decisionThe game can be modelled as a Bayesian game of incomplete information. • Statistical learning techniques and a radio environment map can be used to map uncertainties using Baye's rule.	Spectrum Decision	Spectrum sharing based on the non-cooperative game (Bing. et al., 2010)
Repeated Games	B. Wang et al. (2007)	• Self-learning Repeated game-based spectrum AccessSelfish behaviour due to non-cooperation among CRs are considered which are proved to be inefficient. • Modelling spectrum access as a self-learning process.	Spectrum Sharing	Stochastic game to address routing problem (W. Wang et al., 2018). Inspection based repeated spectrum sensing and sharing schemes (Kim, 2017)
Stackelberg Games	H. Wang et al. (2010)	• PU selects a proper set of CRs to serve as cooperative relays for its transmission and in return leases portion of channel access time to CRs for its transmission	Spectrum Sharing	Stackelberg games based relay selection for physical layer security (Fang et al., 2017)
Auction Games	Khaledi and Abouzeid (2013)	• Spectrum sharing mechanism, which considers channels with different qualities and CRs to express their preferences for each channel separately in the form of vector bids.	Spectrum Sharing	Spectrum allocation based on Auction framework with no regret learning (Kasbekar & Sarkar, 2010).
	Sendrei et al. (2015)	• Represents sealed bid multiple units sequential spectrum action to make a tradeoff between spectrum sensing time, risk, the revenue of PU, and payoffs of CRs.	Spectrum Sensing	

Presents the evaluation of various intelligent techniques along with their strengths and limitations.

Class	Intelligent Technique	Spectrum Sensing	Spectrum Decision	Spectrum Sharing	Spectrum Mobility	Strengths	Limitations and Challenges
Supervised NNs	ML-FFNNs Radial Basis NNs Convolutional NNs Recurrent NNs Deep Recurrent NNs					• High-level feature classification. • Adaption ability to minor changes.	• Multiple Hidden layers • Require different training Algorithms • Slow Convergence
Unsupervised NNs	ML-FFNNs (Auto- Encoders)	xxxx				• No prior knowledge required • Good performance in image classification problems	• Slow training • Lack of theoretical justification.
	Recurrent NNs Hopfield NNs Boltzmann Machine					• Used in optimisation problems. • Simple implementation. • Computationally efficient • Better in ignoring random data • Fast Algorithms	• Dimensionality reduction • Identify similarities in input data, which causes error. • Crude approximation
Competitive NNs	SOM/Kohenon Maps					• Easily interpreted and understood • Capable to handle several types of classification problems	• Requires sufficient data to form meaningful clusters.
	Adaptive Resonance Theory (ART) ART-1 ART-2					• Stable and fast learning • Self-regulating control structure • Requires no supervisory control • Suitable for online learning problems.	• Does not guarantee stability • Need to empirically fix vigilance parameter
	Reinforcement Learning & NNs					• Guaranteed to be optimal for data optimisation framework • Overall behaviour sensitive to changes in reward	• Slow convergence
Combinational NNs	Neuro-Fuzzy NNs Fuzzy Logic Wavelet NNs					• Faster to train • Robust to disturbances • Less computational resources required	• Difficult to create a model • Membership function estimation is hard. • Need more fine-tuning
Other NNs	Quantum NNs					• Easy to train due to quantum parallelism • Faster processing as compare to classical ANN	• Time and space complexity • Quantum associative memory has exponential gain in storage capacity as compared to classical ANN

(*Continued*)

(Continued).

Class	Intelligent Technique	Spectrum Sensing	Spectrum Decision	Spectrum Sharing	Spectrum Mobility	Strengths	Limitations and Challenges
	Support Vector Machine					• Overfitting is not common. • Not trapped in local minima due to convex optimisation • Fewer parameters and training samples need to be considered	• Long Learning period • Difficult to understand learned weights
Metaheuristic Algorithms	Genetic Algorithm					• Intrinsically parallel • Chances to get an optimal solution is more • Easy to understand • Better convergence with increasing genes	• Slow process • Not always provide an optimum solution • Require fitness function
	Ant Colony Optimisation					• Inherent parallelism • Adaptability	• Slower convergence
	Bayesian Approach					• More accurate decision • Probabilistic model	• Requires prior information of the system • High computational complexity • An incorrect assumption about prior skew to skew inferences
	Hidden Markov Model					• Efficient learning algorithm • Strong statistical model • The genetic Algorithm improves model training efficiency.	• Cannot express dependencies between hidden states • Difficult to decode. • Training computationally complex.
	Game Theory					• Provides a solution for multi-agent system • Reduces complexity of adaption	• An infinite number of strategies. • A finite number of players • Risk and uncertainty • Not always converges

prior knowledge. Wrong prior knowledge may lead to the generation of bad chromosomes. Thus, the selection of better genes (each gene represents bandwidth, modulation scheme, data rate, etc.) to generate the next genes are very critical. Further, GA is considered a very slow process since fitness function is calculated through selection, crossover, and mutation process. GA improves its convergence speed either by combining with RBNNs or by increasing the number of genes. In ACO, parallel computation, self-organisation, and positive feedback can help CR to achieve self-adaption and learning capability to achieve global optimisation. ACO algorithm involves local optimum value based on which global optimum value is obtained. ACO can easily adapt environmental changes but its performance is poor for local searches.

(h) Bayesian Approach: Bayesian approach relies on a probabilistic model which signifies the importance of prior distribution to derive posterior distribution using Baye's theorem. The Bayesian approach requires prior knowledge about the radio environment. Incorrect information may lead to skew inferences. It has high computational complexity due to high dimensional integrals. Bayesian learning can combine with other techniques such as HMM for channel quality prediction in CR networks. Dynamic Bayesian games are used for decision making. Further, the Non-Parametric Bayesian model-based Dirichlet process mixture model for unsupervised classification techniques can be used.

(i) Hidden Markov Model: HMM is a stochastic model based on the Markov model which is highly relevant to the CR network applications as environmental parameters that are partially observed and act as hidden states. The selection of appropriate models for training is a very important task in HMM. Due to the presence of multiple hidden layers, it is difficult to decode the sequence. HMMs have been extensively used in CR networks for spectrum sensing, channel selection, and spectrum mobility. One of the major drawbacks while using HMM is that it requires a training sequence. But its training process is quite complex. It can be combined with other techniques such as GA to improve its training efficiency.

(j) Game Theory: Game Theory is a mathematical model which provides a solution for self-centred multi-agent systems where the decision of individual agent affects other players decision. Particularly in CR networks, each CR act as a player and their action may include the selection of parameters according to user requirements. The goal of game theory is to provide the best outcome (optimal solution) while considering the interest of all players. Game-theory has been applied in several applications in CR networks such as spectrum sensing, decision making, spectrum access, etc. One of the major drawback while using game theory is to make a model which requires statistical information about the radio environment. As the environment is dynamic, which leads to the shift optimal solution before the convergence. It is difficult to structure a game that always provides an optimal solution. Another drawback is a limited number of players. As players increases, it may decrease its convergence speed which is another important factor need to be considered. Further, the game theory requires complete knowledge of the environment and also need labelled data for training. Incomplete or imperfect information can lead to uncertainty. Table 9 presents the evaluation of various intelligent techniques along with their strengths and limitations.

Research issues, challenges, and future directions

The intelligent techniques provide a promising solution towards the realisation of the DSM but there are certain research issues and challenges in DSM that need to be addressed carefully. New radio capabilities breed new demands for spectrum access, which presents an open challenge in CR networks. Some of these research issues, challenges, and future directions are summarised below:

- *Wideband and higher frequencies*: With the increasing demand for wireless traffic and applications, not only the higher spectrum efficiency but also more bandwidth resources are required which presents a major challenge in CR networks. As the number of users increases in current wireless systems, scalability becomes an extremely important issue. For such purpose, novel brain empowered/intelligent techniques need to be designed together with reconfiguration capability to achieve the best performance.

- *Interference management*: Due to coexistence among heterogeneous networks provide a new challenge in DSM. First and foremost, consideration is how well the devices are coexisting together. There is also a need to develop adaption in modulation schemes as well as other parameters, which enables devices to avoid interference. Moreover, cooperation between different networks and among CRs further mitigate the effect of interference. The amount of cooperation between heterogeneous networks and among CRs is also an additional challenge that needs to be addressed.
- *Privacy and security*: The deployment of new spectrum access technologies and their realisation raises new security challenges that have not been studied previously. Furthermore, regulators and policymakers have to consider what data from spectrum usage can be collected to access spectrum utilisation without trespassing on the user's privacy. There is a need to ensure the correct implementation of the deployed system and when they are not, enforcement procedures will be needed to solve the DSM problem.
- *Intelligent techniques based on green CR networks*: The recent exponential growth of wireless technologies used in daily life needs to consider issues related to health and the environment. Hence, the designing of the future CRs need to be energy efficient to cut carbon emission. There exist limited work for DSM with consideration of green communication. Thus, there is a need to design DSM techniques considering green communication.
- *Massive MIMO with intelligence*: Massive MIMO uses a large number of antennas to provide an extra degree of freedom and diversity to improve its performance. To use this extra degree of freedom efficiently, intelligence needs to be incorporated to improve the perception capability and reconfigurability of CRs.
- *Regulatory and policy reform challenges*: Beyond technical issues, there are also policy reform challenges in DSM. Future deployed systems may employ spectrum dynamically in which PUs can sell their spectrum to CRs temporarily. Thus, the service level agreements for spectrum sharing need to be reconsidered. Furthermore, strategies need to be designed for dynamic spectrum auctions and markets.
- *Multi-objective optimisation*: In CR networks, multi objectives are conflicting with each other such as minimisation of power consumption, maximisation of throughput, minimisation of BER, etc. The optimisation of multiple objectives is a challenging task that needs to be addressed carefully.

Other challenges include lack of incentives for spectrum sharing, authorisations constraints, and hardware, software, and protocols related issues need to be considered which require interdisciplinary collaboration among researchers of diverse backgrounds to address these challenges.

Conclusion

The paper has provided a comprehensive review and the classification of intelligent techniques for DSM in CR networks. For efficient realisation, CRs are combined with intelligent techniques so that dynamic and intelligent spectrum management can be done. The intelligent spectrum management schemes are surveyed in the context of spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. The main emphasis of the work is to elaborate on the role of intelligent techniques in CR to enhance its learning capability. We have presented state-of-art achievements in applying intelligent techniques for DSM along with their strength and limitations. It provides an overview of active research in the area of dynamic spectrum management in CR networks.

Unluckily, available techniques for spectrum management still lack the ample reflection of various network parameters in real-world scenarios which are quite complex to model, so some model-free schemes would become increasingly important. In future work, eliciting and encouraging cooperative behaviour through rewards and mechanism design will become important and looks promising to be an important area of further research.

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