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Energy Efficient Spectrum Sensing by Wireless Sensor Networks

By

SeyedehMarieh MirzaghaeianAmiri

A Thesis

Submitted to the Faculty of Graduate Studies

through the Department of Electrical and Computer Engineering

in Partial Fulfillment of the Requirements for

the Degree of Master of Applied Science

at the University of Windsor

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Energy Efficient Spectrum Sensing by Wireless Sensor Networks

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ABSTRACT

Today, due to the increase in the number of users and the need to provide high-rate multimedia services, cognitive radio techniques can be a promising practical solution. In cognitive networks, the unlicensed (secondary) users sense a spectrum utilized by the licensed (primary) users. Due to the interference of the primary users, fast and reliable spectrum sensing is an important challenge in cognitive radio networks. In this dissertation, the resource allocation problem is investigated under min-max optimization framework for establishing fair energy efficiency in wireless sensor networks (WSNs). In fact, we study the sensor selection and power allocation problem in a WSN to minimize maximum energy consumption among nodes. Since the formulated problem is a non-convex and discrete optimization problem, the exhaustive search algorithm can be applied to solve it. Because the exhaustive search is a high complexity algorithm, we propose algorithms with low complexity to solve the problem based on some relaxations and convex optimization methods. In fact, we convert the formulated problem to two sub problems: sensor selection (first sub problem) and power allocation (second sub problem). In the first sub problem, the discrete optimization problem is relaxed to a classical optimization with continuous optimization variables. Then the relaxed problem is solved by convex optimization methods, which derive a cost function for selecting sensors based on priority. On the other hand, solving the second sub problem with the help of convex optimization leads to the transformation of the optimization problem into a one-dimensional search problem. Finally, to find the joint solution, we propose an algorithm that has low computational complexity compared to the exhaustive search. In the following, we present the neural network approach to solve the formulated problem. In this approach, a feedforward neural network is designed to classify sensors into two classes (active mode and idle mode) in the joint problem. The simulation results show that the proposed methods and algorithms outperform the conventional benchmark methods in the energy efficiency literature.

Keywords: wireless sensor network- cognitive radio- spectrum sensing- sensor selection-power allocation- convex optimization- neural network.

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Chapter 1: INTRODUCTION AND PRELIMINARIES

With the development of sensing systems and network-related technology, the interest in providing measurement and control of the living environment using devices with low power consumption has increased. Sensors can monitor environmental and physical conditions such as heat, humidity, vibration, pressure, sound, movement, etc. with low energy consumption [1]. Sensors also can send and receive information to the base station. Wireless sensor networks are capable of remote sensing, which includes the collection of data sent from the sensor to the base station. With the development of wireless sensor networks, their applications in military, industrial, environmental, health and medical monitoring, smart homes were noticed. Wireless sensor networks can include hundreds or even thousands of sensor nodes. Each node can communicate with other nodes around it wirelessly. Sensor nodes are in very small dimensions, sometimes smaller than a coin. Their cost is very low and depends on the quality of the chips. Although wireless sensor networks are a network of sensors with self-configuration and distribution capability, they also have considerations such as energy consumption, low data transmission rate, etc. [2].

On the other hand, today, due to the exponential increase in the number of users and connected devices, as well as the need for high rates to support multimedia applications, the reason to use unlicensed and unoccupied spectrum is needed more than ever. The high cost of purchasing a frequency band and the non-continuous use of it by the primary communication system that purchased of this band prompted researchers to think of creating new methods for more efficient and optimal use of bandwidth, so that several systems be able to jointly use a certain frequency band. Due to the existence of limited spectrum bands, smart radio networks have been proposed as a solution for optimal use of the spectrum. The main trend of using the frequency bandwidth is that several users, called the network of primary users or the primary network for short, purchase a certain bandwidth, but in practice, they do not use all the purchased frequency bands all the time, and frequency holes are created. In other words, a frequency hole is a part of the frequency band that a primary user has purchased but is not used by that user in a specific time and place. The research conducted by FCC[1] shows that between 15 and 85% of the frequency band allocated to primary network users is used in various time and place situations [1].

In this way, the use of wireless sensor network technology in spectrum sensing and finding unoccupied spectrums has grown significantly in recent years. Compared to other common spectrum sensing methods, wireless sensor networks have more advantages and offer wider applications. The requirements that must be considered in the implementation of a wireless sensor network for spectrum sensing include determining the wireless sensor network node structure, topology (distribution configuration of sensors), spectrum sensing methods, various aspects of network security, as well as energy efficiency challenges related to the network. Failure to pay attention to the challenges of energy efficiency can lead to the collapse and reduction of the lifetime of wireless sensor networks. Therefore, these considerations will affect the proposed strategies and programs for wireless sensor network nodes [3].

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[1] Federal Communication Commission

1-1 Problem Definition

A sensor node can only communicate and perform limited calculations. Despite this, nodes in WSNs can coordinately perform signal processing tasks to obtain information about the occupation or non-occupancy of a certain spectrum. Optimizing energy consumption is the most important challenge in these networks. In general, the power of a sensor node is supplied by a battery, which means that the nodes have limited energy and it is very difficult to replace and recharge the batteries of the nodes. In this situation, the nodes that do not have the necessary energy should be discarded. Therefore, it is desirable to design protocols for these networks that are optimal in terms of energy consumption and extend the lifetime of the network. The lifetime of the network is the period in which a specified number of nodes are active, and the network continues to work without disruption. The purpose of this study is to provide a solution to minimize energy consumption in smart wireless sensor networks when detecting spectrum holes so that the spectrum sensing performance is still maintained at an acceptable level; This means that by reducing the energy consumption of the network, the quality of the network service, which is the probability of correct detection, the probability of false alarm, as well as the rate of information transmission, remains at a guaranteed and desirable level. To design such a solution, we use the clustering method (determination of active and inactive nodes) and assigning power (energy) to sensors. In this research, we intend to use probabilistic analysis as quality of service (QoS) of the network to analyze the quality of spectrum sensing. To provide an efficient energy algorithm in WSN networks with the application of spectrum sensing, we will use the combination of convex optimization (to allocate power to nodes) and learning based on neural network (to classify nodes into active or inactive mode). Therefore, in short, we can say that our goal of this research is to propose energy-efficient approaches in WSN networks to achieve acceptable quality spectrum sensing.

1-2 Necessity and motivation to research

Today, due to the exponential increase in the number of users and connected devices, as well as the need for wide bandwidth to access high-quality multimedia, video communications, and the use of social media platforms, more than ever, the lack of spectrum in access becomes the most important challenges in fifth generation communication networks. Therefore, various extensive researches have been conducted to improve the performance of communication networks in order to achieve higher spectrum efficiency. One of the promising solutions for that is the use of the cognitive radio approach. In a radio recognition system, it is possible for a secondary network to opportunistically benefit from the available spectrum of a primary network. In reality, spectrum of a communication network is not continuously occupied by all its users, so it is possible to use the available spectrum with full capacity when the spectrum is not occupied (underlay) and even when the spectrum is occupied, it can be used as controlled, took advantage of it (overlay).

One of the most important tools in identifying and revealing spectrum holes is the use of spectrum sensing techniques. Spectrum sensing techniques allow us to detect holes with high accuracy and speed. Spectrum sensing can usually be done by using a wide range of methods. One of the least expensive methods is the use of WSNs. In fact, with the help of small sensors, it is possible to reveal and identify the different spectrums available for the secondary network. Despite the advantages such as low setup cost, low maintenance cost, high accuracy, high comparability for WSNs, these spectrum sensing tools are extremely weak against energy consumption. In fact, one of the most important challenges facing this type of network is increasing the lifetime of these networks. In this thesis, we seek to propose solutions to provide energy efficiency algorithms in a WSN network that is responsible for spectrum sensing, so that this network survives for a long time. Another very important point is that in this type of networks, when several sensors are destroyed (battery becomes empty), the quality of the network performance drops drastically, so in this research, we consider the issue of establishing fairness between nodes to maintain the quality of the network for a long time. Proposing algorithms with low complexity to select the efficient energy of nodes and allocate optimal power in radio recognition systems is very important for the implementation of this technique in new generations of communications. In order to reduce the computational load and also increase the accuracy to achieve optimal solutions in the resource allocation problem, we will use convex optimization tools and neural network.

1-3 Our goal of this research and innovations

As mentioned in the previous section, one of the most important challenges facing WSNs networks that are used for spectrum sensing purposes is to provide approaches and methods to minimize the energy consumption among nodes. In general, the main goal that we pursue in this research is to provide energy efficient algorithms and approaches in WSN networks, whose goal is spectrum sensing in a radio recognition system. So far, various methods have been proposed to solve this challenge by various researches. But in this article, we will discuss this issue from two different perspectives:

1- Creating a fair optimization framework for clustering nodes and power allocation
2- Using neural network methods to cluster nodes

The meaning of the fair optimization framework is that, unlike the previous works, which tried to minimize the total energy consumption of all users, in this research, the goal is to make energy consumption among the nodes in a fair way, which itself causes that the average time of the number of dead nodes is reduced and the network service quality remains optimal for a long time. To establish a framework, the fair energy efficiency problem is treated as an optimization problem of minimizing energy consumption for the node that has the highest energy consumption. In fact, we will formulate the mentioned problem as a min-max optimization problem. On the other hand, for the formulated problem, we will follow two methods; first, with the help of convex optimization methods, we will try to find solutions for clustering nodes and assigning power to them. We will show that these solutions are noticeably less complicated than exhaustive search optimization methods. Then, in the second solution, we will design a feedforward neural network in which the network is trained with the help of the training data obtained from comprehensive search and the algorithms extracted by the first method. Then, in the second step, we will evaluate and analyze the efficiency of this neural network with test data.

In the following, we will see the most important contributions of this research:

1- Extracting detection probability and false alarm probability to detect spectrum hole.
2- Allocation of resources to minimize the maximum energy consumption between nodes while maintaining the quality of detection service and rate.
3- Deriving algorithms and methods for clustering nodes and assigning power to them based on classical methods of convex optimization.
4- Designing a feedforward neural network to cluster nodes.

Chapter 2: PROBLEM STATEMENT

The advances and widespread developments in wireless communications have led to the increasing need for spectrum sensing to use wireless services. But recent research shows that the static policy in the allocation of spectrum bands (the policy based on which only users can use the spectrum sensing that they have a license to use) has caused many of these bands to not be optimally used and applicants face a lack of spectrum sensing. According to studies conducted by the Federal Communications Commission, certain frequency bands are heavily used by licensed systems at certain times and locations, while many other frequency bands are rarely occupied. It shows that the use of the frequency spectrum is only focused on parts of it and a significant part of the spectrum remains unused. Considering the limitation of the frequency spectrum as a valuable resource and its inappropriate use, it is necessary to apply a new idea for the optimal use of the frequency spectrum.

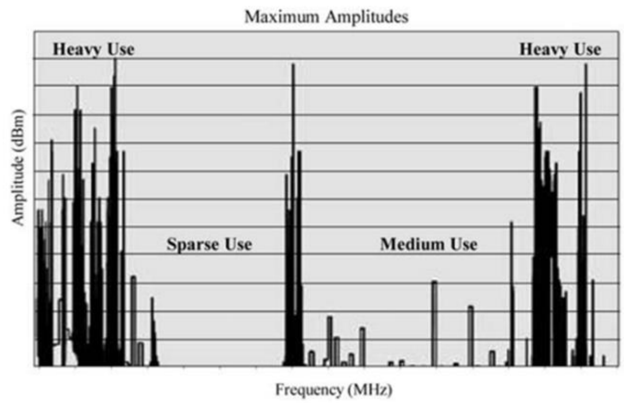

Figure 2-1 Improper use of licensed users of the frequency spectrum [4]

As mentioned earlier, the first task of a cognitive radio is spectrum sensing. Without the successful completion of this stage, it is not possible to carry out the next stages of the duties of the cognitive radio. In this chapter, an introduction including the introducing of the cognitive radio, its architecture and various tasks is provided. Then we will examine the objectives, methods, challenges and other issues related to spectrum sensing and at the end we will propose cooperative spectrum sensing along with its fundamental components and factors affecting it as a solution to overcome some of the obstacles of accurate and fast spectrum sensing [4].

2-1 Software-defined Radio (SDR)

SDR is a reconfigurable wireless communication system in which transmission parameters (such as working frequency, modulation type and protocols) are controlled by software-controlled signal-processing algorithms. SDR is a platform on which recognition radios are embedded [5]. The most important tasks of SDR are:

- Multi-band operation: SDR provides the possibility of wireless data transmission on a frequency spectrum different from the frequency spectrum used by various wireless access systems (such as cellular band and TV band).
- Multi-service Support: SDR can run various services such as telephone and internet.

- Multi-channel Support: SDR can receive and transmit on several frequency bands simultaneously.

The general structure of an SDR transceiver is shown in Figure 1-2. The components of SDR (data processing unit, analog to digital converter and baseband processing) are the same as a normal transceiver and it differs from a normal transceiver in that the components can be used by higher layer protocols. Or cognitive radio modules are implemented. In fact, the wireless receiver can reconfigure the transmission parameters to suit the communication specifications. In an SDR transceiver, a radio receiver receives the analog signal from the antenna and then filters the received signal by a low pass filter to achieve the desired frequency band. After amplification and processing, this signal is converted into digital data.

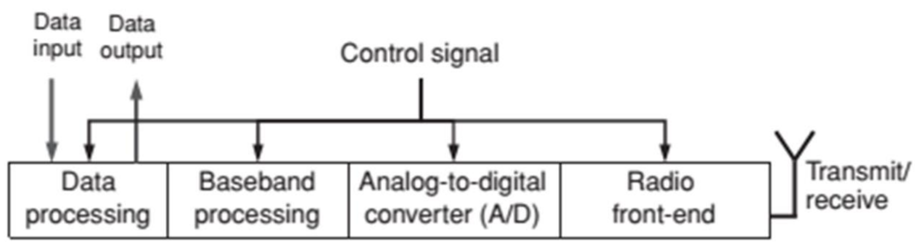

Figure 2-2 SDR receiver and transmitter [5]

2-2 Cognitive Radio

The cognitive radio identifier system, which is installed and operated on the SDR, provides the necessary mechanisms for the identifier users (secondary users in the radio identifier network) to measure the spectrum, manage the spectrum and access the spectrum. The idea of a cognitive radio was proposed for the first time by J. Mitola [6]. Various definitions have been provided for the cognitive radio, and we are satisfied with one of the relatively complete definitions. Radio recognition is an intelligent wireless communication system that is aware of its surroundings and learns from its surroundings and adapts its internal states by changing operational parameters (such as transmitted power, carrier frequency and modulation type) according to statistical changes in frequency stimuli. Communication parameters can be adjusted based on changes in the environment, topology, operating conditions, or user needs. Using this definition, two main characteristics of cognitive radio can be described [7].

- **Recognizability:** refers to the ability of the radio recognizer to obtain the required information from the surrounding radio environment. In order to monitor the temporal and spatial changes of the radio environment and prevent interference with the primary user, cognitive radio needs to use complex signal processing techniques. This capability provides the possibility of identifying spectrum holes at certain times and places, as well as the possibility of choosing the best frequency band and operating parameters.

- **Reconfiguration capability:** refers to the ability of the radio receiver to adapt its operating parameters based on information gathered from the surrounding radio environment. This feature provides the possibility of programming the radio identifier to send and receive in different frequency bands.

2-3 Architecture of Cognitive Radio

The architecture of the radio recognizer protocol is shown in Figure 2-2. In the physical layer, the input layers of the radio environment are embedded on the SDR transceiver. Environment-adaptive protocols must be aware of changes in the radio cognition's environment at the medium access control (MAC) layers of the network, transport, and request. Adaptive protocols must monitor the activity traffic of primary users, the forwarding requirements of secondary users, and changes in channel quality. To communicate with all modules, radio cognition control is used to interface between SDR transceivers, compatible protocols, and wireless requests and services. Using intelligent algorithms, the radio recognition module processes the measured signal from the physical layer and receives the necessary information about the transmission requirements through requests to control the protocol parameters in different layers.

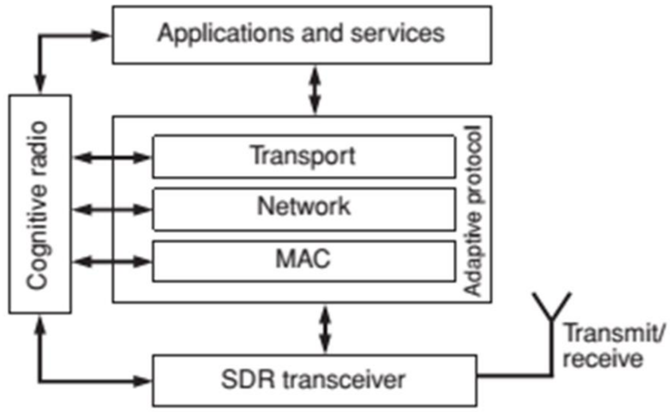

Figure 2-3 Architecture of Cognitive Radio [5]

2-4 Cognitive Radio Duties

The most important tasks of radio recognition systems to reach the available spectrums are [6]:

- **Spectrum sensing:** detection of primary network users and identification of existing frequency spectrum holes is called spectrum sensing. In the spectrum sensing process, the users of the secondary network must first identify the spectrum holes and use them optimally, and secondly, in case the primary users return, by switching to another frequency band or by completely stopping the transmission of information, they must prevent interference with the signal of the primary users. Therefore, the quality of detection performance in spectrum sensing plays a very important role in radio recognition systems.
- **Spectrum Analysis:** The obtained information from spectrum sensing is used for planning optimal spectrum to access of secondary network users. In each spectrum sensing analysis, specific information is extracted from the spectrum of the channels. Information such as interference estimation, duration of presence and the probability of encountering the primary user in case of wrong measurement. Then the decision about the amount of access to the spectrum such as frequency, bandwidth, modulation type, transmission power, position and time period after optimizing the system performance based on performance functions such as maximizing the information

transmission rate and limitations such as keeping the interference level lower with the primary user is determined by a certain desired threshold.

- **Spectrum Access:** Based on spectrum analysis, it is decided whether the desired spectrum will be available to secondary network users or not. If spectrum access is allowed, the access is based on MAC layer protocols, the purpose of which is to prevent collision between licensed users and other secondary users. The transmitter of the radio identifier is obliged to carry out the necessary negotiations with the receivers of the radio identifier to synchronize the transmission so that the sent data is received successfully.

2-5 Spectrum Sensing

As mentioned earlier, spectrum sensing is defined as detecting the presence of the primary user, identifying spectrum holes, and using it optimally without causing interference to the primary user. Spectrum sensing can be considered as gaining knowledge of how to use the spectrum and the presence of primary users in a geographical environment. Spectrum sensing in radio recognition can take on a wider meaning and understanding of the characteristics of the spectrum in various dimensions such as time, place, frequency, and code [6]. The success rate of spectrum sensing is determined by two criteria: detection probability and false alarm probability. The probability that the secondary user correctly reports the primary user as present (when the primary user occupies the spectrum) is called detection probability. The probability that the secondary user falsely declares the primary user present (while the frequency spectrum is empty) is called the false alarm probability. To optimize the detection, while the false alarm probability is limited to a certain value, the detection probability is maximized [4].

2-6 Spectrum Sensing Challenges

Before going into the details of spectrum sensing methods, a brief overview of the spectrum sensing challenges is presented in the following section:

- **Fading (Multi-path):** In a radio environment, there may be various obstacles such as trees, buildings, etc. between the transmitter and the receiver. (Fig 2-4) which causes the signal to reach the receiver from different paths with different amplitude, phase, and power after undergoing scattering, diffraction and reflection. The range and power in each of these paths can be considered a random variable. These variable fluctuations of the received signal power on the receiver side - which occur on a small scale - are called fading. Fading is divided into slow fading and fast fading in terms of time. The rate of fading is determined by the rate of change of size and phase of the signal by the channel. The period of time when the size and phase gain of the channel can be considered almost constant is called coherent time. Slow fading occurs when the channel time coherence is greater than the channel delay. In this situation, the size and phase changed by the channel (the size and phase of the channel) can be assumed to be constant in any time period. Fast fading occurs when the channel time coherence is less than the channel delay. In this condition, the temporal coherence of the channel is less than the symbol width. Therefore, in this case, in the time period of one symbol, the conditions of the channel will not remain constant and will change.

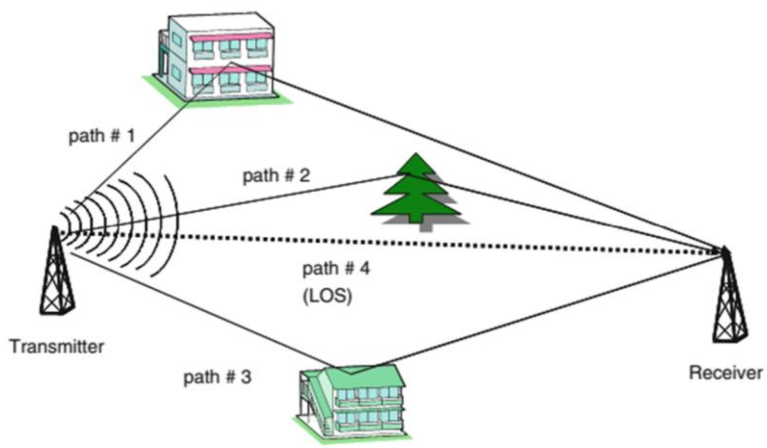

Figure 2-4 Multipath effect in wireless communication [9]

- **Hidden primary user problem:** If the secondary users are affected by strong fading or shadowing while observing the signal of the primary users, they may not be able to correctly detect the primary user's signal and mistakenly recognize the frequency band as empty, which causes unwanted interference to the primary users. and make spectrometry difficult [8]. (Figure 2-5) shows a clear picture of this problem. Collaborative spectrum sensing is a solution that has been proposed to solve this problem and we will talk about it in detail in the next section.

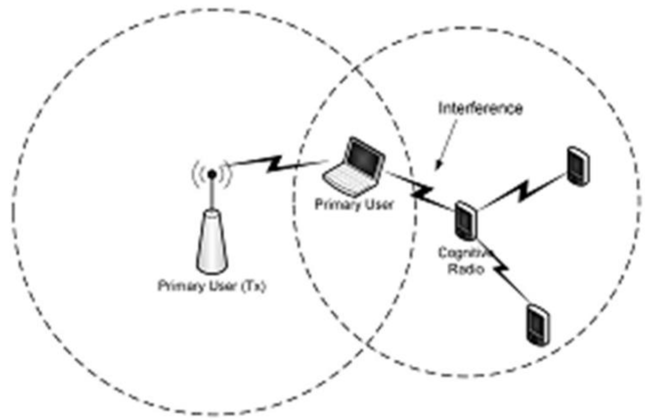

Figure 2-5 Hidden primary user problem [8]

- **Spectrum sensing in environments with low signal-to-noise (SNR):** In such environments, depending on the method adopted for Spectrum sensing, the signal power level received by the secondary users may be lower than the noise power level, and the secondary users consider the noise as the presence of the primary users' signal. Since the transmission power of early users who use wide spectrum signaling is spread over a wide frequency range, their detection is one of the challenges of Spectrum sensing.
- **Hardware requirements:** Spectrum sensing in the radio detector requires analog-to-digital (AD) converters with high sampling rate, high resolution, and high dynamic range, as well as high-speed processors. Noise variance estimation methods are used in optimal receiver designs, such as channel estimation, soft information generation, as well as channel allocation and power control methods. To take advantage of any opportunity in radio recognition, users must process data transmission on a wider frequency band. Therefore, the radio detector must be able to analyze a relatively large frequency band to identify spectrum holes. The large operational bandwidth imposes additional requirements on components such as antennas and power amplifiers. High-speed processing units must also perform the task of signal

processing with the least delay; A task that requires computational processing with high complexity.

2-7 Spectrum sensing models

Spectrum sensing is performed in three models: non-participatory measurement, cooperative measurement, and interference-based measurement as shown in Figure 2-6:

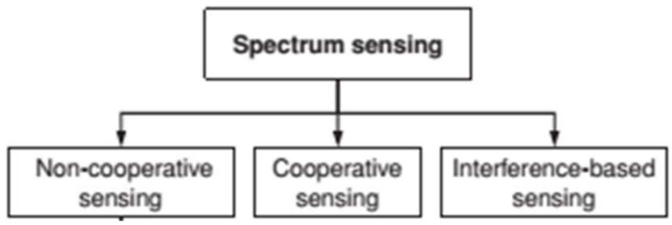

Figure 2-6 Spectrum sensing models in radio recognition systems [5]

2-7-1 Non-participatory sensing:

It is done by a recognized user and based on local measurements and observations to reveal the signal sent by the primary network user. The detection model at time t is described as follows:

$$x(t) = \begin{cases} H_0: n(t) \\ H_1: h(t)s(t) + n(t) \end{cases} \tag{2-1}$$

where x(t) is the signal received by the secondary user, s(t) is the signal sent by the primary network user, n(t) is the cumulative white noise and h(t) is the gain of the channel and is different depending on the model considered for the channel. Is. H_0 and H_1 are the hypothesis of absence and presence of primary user signal in the desired frequency band, respectively. Detection probability and false alarm probability are respectively defined as follows [10]:

$$P_d = Pr\{decision = \overline{H_1} \mid H_1\} \tag{2-2}$$

$$P_{fa} = Pr\{decision = \overline{H_0} \mid H_1\} \tag{2-3}$$

2-7-2 Cooperative sensing:

As mentioned, to solve or weaken some spectrum sensing challenges such as fading, shadowing, and hidden primary user problem, collaborative spectrum sensing method is used. In collaborative spectrum sensing, the spectrum measurement information of several cognitive users is used to detect the presence of the primary user. In collaborative sensing, two separate networks (sensor network and operational network) can be used to perform spectrum sensing and spectrum access. In this case, the sensor network collects information on how to use the spectrum, which can be processed by a central controller. Then, the primary users' usage map of the frequency spectrum is distributed among the secondary users in the operational network.

If we consider a radio recognition network with N recognition users (secondary users), each of which independently monitors the frequency spectrum to identify the primary user's signal, then the detection model in time is described as follows:

$$x_i(t) = \begin{cases} H_0: n_i(t) \\ H_1: h_i(t)\, s(t) + n_i(t) \end{cases} \tag{2-4}$$

where $x_i(t)$ is the signal received by the i-th user of the recognition, $s(t)$ is the signal sent by the primary network user, $n_i(t)$ is the Gaussian white noise accumulated on the receiver side of the i-th user, and $h_i(t)$ is the channel gain between the primary user and the i-th second user of the secondary network. The probability of detection and the probability of false alarm for the i-th recognizer user are shown by $P_{d,i}$ and $P_{fa,i}$ respectively, and similarly using relations (2-2) and (2-3) are defined Collaborative spectrum sensing can be done in two ways: centralized or distributed. In the centralized method, cognitive users send the information obtained from their local observations to the Fusion Center, and in that center, the final decision is made regarding the presence or absence of the primary user's signal, and the result is sent to the users. This combination center can be a separate receiver-transmitter (such as a base station) or one of the recognized users. In the distributed structure, users distribute the information obtained from their local observations to each other, and finally each of them independently decides on the presence of the primary user's signal. In environments with strong fading and shadowing, by using the cooperative exchange of spectrum sensing information, the probability of detecting the primary user's signal increases significantly, which is called cooperative gain. But the participation of cognitive users will lead to the creation of additional communication and computational overhead compared to the non-participatory model.

2-7-3 Measurement based on interference:

Based on the algorithm governing this model, the noise and interference levels of all signal sources are measured through the primary user's receiver. This information is used by the secondary user to control access to the frequency spectrum, without crossing the interference temperature limit (with the primary user's signal).

2-8 Spectrum sensing methods:

In terms of signal detection, spectrum sensing methods are divided into coherent and incoherent groups. In coherent, detection is done by comparing the characteristics of the received signal with the characteristics of the original user signal. As a result, knowledge of the primary user's signal characteristics is required in coherent methods. But in the asynchronous method, we do not need information from the initial user signal [4]. Cyclo-stationary feature detection, matched filters and radio identification based sensing from coherent methods and energy detection, Wavelet detection) and compressed sensing are inconsistent methods [4]. In this part, we will examine the methods of energy detection, detection based on the characteristics of the rotational constant, matched filter and measurement based on radio waves, as the most common methods.

- **Energy detection:** Due to its simplicity and lack of initial user signal information, it is considered the most common spectrum sensing method. In this method, by comparing the energy level of the received signal with a threshold, the signal is identified. To measure the energy, first the received signal is passed through a low-pass filter with a bandwidth of W, then its size reaches the power of two, and finally, an integral is taken from the resulting result in the observation interval T. This is the method that will be discussed in detail in the fourth chapter, and we will derive the related mathematical relations. Two basic problems of the energy detection method, one is its sensitivity to the uncertainty of noise power and the other is its inability to distinguish the signal of the main user from the signal of other users and noise. Despite these two problems, the energy detection method is still the most common spectrum sensing method [8].

- **Detection based on the properties of the circulation station:** It is a method to identify the signal of the primary user by using the characteristics of the received signals. These properties are derived from the periodic nature of the signal itself (embedded sinusoidal carriers, etc.) or its statistics such as mean and autocorrelation functions. In this method, the Cyclic Spectrum Density (CSD) function of the signal is used instead of its power spectrum density to reveal the signal in a frequency spectrum. The CSD function of a received signal is obtained from the following equation [8]:

$$S(f,\alpha) = \sum_{\tau=-\infty}^{\tau=\infty} R_y^\alpha(\tau)\, e^{-j2\pi f\tau} \qquad (2\text{-}5)$$

Where $R_y^\alpha(\tau)$ is defined as

$$R_y^\alpha = E\{y(n+\tau)y^*(n)\} \qquad (2\text{-}6)$$

- **Cyclic Autocorrelation Function (CAF) and α is the rotational frequency:** When the rotation frequency is equal to the fundamental frequencies of the received signal $x(t)$, the CSD function shows its values as peaks. If the cyclic frequency of the transmitted signal is known, if the cyclic frequency of the received signal matches the signal sent by the primary user, the presence of the primary user is announced. Since the noise is a wide sense stationary stochastic process (WSS) and has no periodicity, algorithms based on rotational stationary features can distinguish between the original user signal and noise even in environments with low SNR. On the other hand, the signals of different users have different periodic properties, and if you know the periodic characteristics of the main signal, you can distinguish it from other signals. These two characteristics show the strength of the detection method based on the characteristics of the signal circulation station compared to the energy detector. But due to the computational complexity and the very high measurement time required, it is less popular than the energy detection method [8].

- **Matched filter:** When we know the signal characteristics of the main users, matched filtering is known as the most optimal method. The characteristic feature of this method is the short time to reach a reliable and acceptable false alarm probability. But this method requires complete information about the transmitted signal such as bandwidth, working frequency, modulation type and so on. In addition, this method requires multiple receivers to receive various signals and suffers from the complexity of the spectrum sensing unit and high-power consumption [8].
- **Measurement based on the identification of radio waves [2]:** Full knowledge of the spectrum characteristics is possible by identifying the transmission technologies employed by early adopters. Such identification enables the radio detector to reach knowledge with greater dimensions and higher accuracy. Suppose the main user uses Bluetooth technology. The radio recognizer can use this information to extract useful information in the space dimension (considering that the Bluetooth signal range is about 10 meters). Additionally, the radio detector may wish to communicate with the detected system. To identify radio waves, methods of extracting and classifying signals are used. In the measurement based on the identification of radio waves, various properties are extracted from the received signal and by using different methods of classification of properties, the most probable technology for the main user is considered. These properties are obtained using other spectrum sensing methods. For example, the bandwidth of the channel and the center frequency of the received signal are among the properties that are obtained through energy detection. By using the hidden Markov model (Hidden Markov Model) it is also possible to identify and categorize the properties of the received signal.

Figure 2-7 shows a comparison between some methods mentioned in the previous section. The diagram of this figure compares various methods with each other in terms of accuracy and complexity of performing the method. As can be seen, the more the complexity of the method increases, the more accurate it becomes.

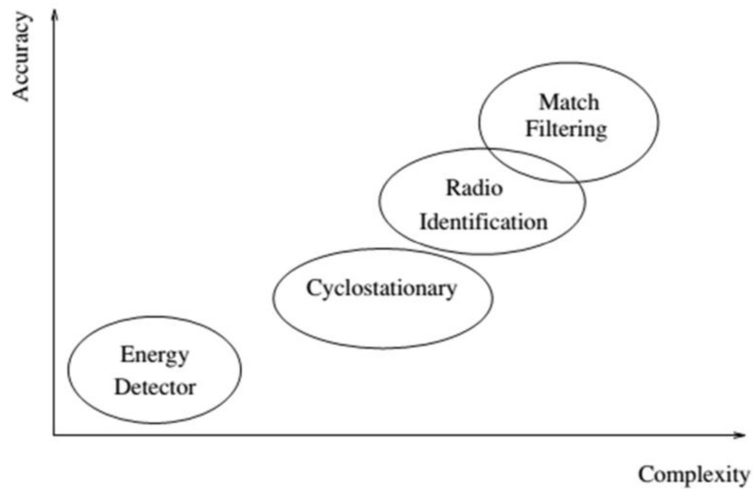

Figure 2-7 Comparison of different spectrum sensing methods
in terms of accuracy and complexity [8]

In environments with the presence of several adjacent channels that may interfere with each other, noise is a non-stationary process. Since determining the comparison threshold in the energy detector method depends on the noise variance, this method will practically lose its efficiency in such environments; While the algorithms based on the properties of the circulation station maintain their capabilities. On the other hand, the rotational stability method, in addition to the high computational complexity, is highly sensitive to sampling offsets [8].

In determining the spectrum sensing method, a trade off must be made between many parameters. The profile of primary users is the most important factor in choosing a method. Time/frequency characteristics, measurement duration requirements, computational complexity and network requirements are other determining factors. Considering that the energy detector is the easiest method and, unlike other methods, does not require information about the primary user signal, it is considered the best method in high SNR environments.

2-9 Collaborative Spectrum sensing

Spectrum sensing is one of the key tasks of a radio detector to identify the existing frequency spectrum and improve its use. But in practice, factors such as multi-path fading, shadowing and uncertainty on the receiver side cause a sharp drop in the spectrum sensing performance of the radio detector. As shown in Figure 2-8, user number 2 is unable to identify the original signal and user number 3 has fading and shadowing. But user number 1 receives the signal of the main user well and can send the results of spectrum sensing to other users through participation. It can be seen in Figure 2-8 that to reduce the effects of malicious factors and improve the detection performance, cooperative spectrum sensing can be used. used as an effective method [4].

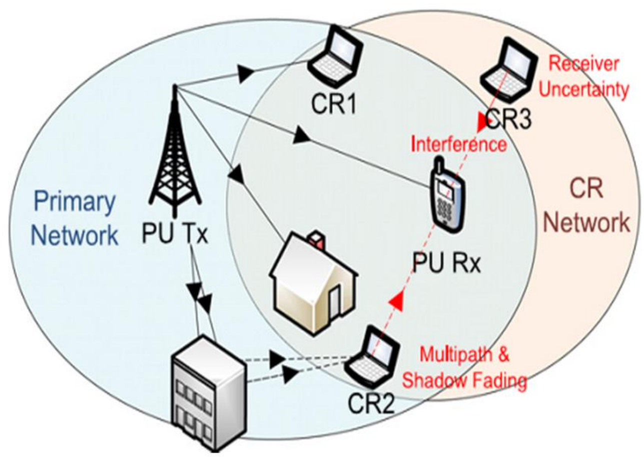

Figure 2-8 Fading, shadowing and receiver uncertainty [4]

Participatory interest, participation overhead and participation method are three important issues in participatory spectrum sensing. Collaborative benefit means the improvement of the detection performance by using the diversity of the position of the recognizer users. Participation overhead refers to any additional energy, delay, additional measurement time, and operations spent on user participation [6]. The factors affecting the participation interest and overhead due to participation are presented in this section. Also, the method of participation is examined in the part of fundamental components or elements of participatory spectrum sensing.

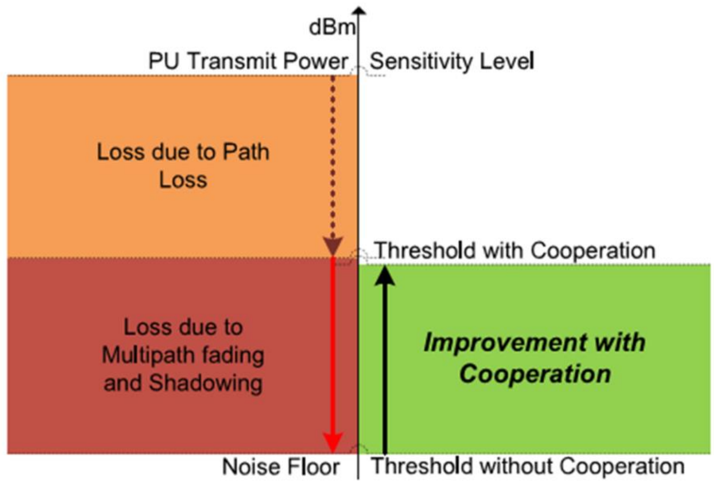

Figure 2-9 Spectrum sensing improvement with participation [4]

2-9-1 Elements of collaborative spectrum sensing

Collaborative spectrum sensing is generally considered a three-step process: local measurement, data reporting to the center, data synthesis and synthesis. In participatory spectrum sensing, there are fundamental components without which participation is not possible. We call these fundamental and important components the elements of collaborative spectrum sensing, and we will discuss them in this section [4]:

- **Cooperation Model:** It refers to the modeling of the participation of radio cognitive users during spectrum sensing. Parallel fusion models are the most common method in cooperation modeling, which originates from sparse detection and data fusion. In this model, the goal is to achieve optimal detection performance using sparse signal processing methods to determine how the observations are combined and tested. Among the models that have recently received attention are the models based on Game Theory. The focus of these models is on improving the Sensing-Parametric Utility Function by analyzing the cooperative and non-cooperative interactions and behaviors of radio cognitive users. It can be said that the parallel cooperation model emphasizes the "measurement" part, While the games model focuses on the "participation" part.

- **Spectrum sensing methods:** Regardless of the participation models, the process of collaborative spectrum sensing begins with the spectrum sensing of each of the recognized users. The purpose of local sensing is to detect the original signal. Since how to measure, sample and process the main signals is related to the participation of cognitive users, measurement methods in collaborative spectrum sensing are very important. These methods are reviewed in detail in section 3.1.
- **Hypothesis Testing:** Statistical hypothesis testing is usually done to test the results of measurements and make a binary decision about the presence of the main signal. This test can be done independently by each participating user (local decision making) or by the combination center (participatory decision making).

  The binary hypothesis test is one of the most common hypothesis tests in the energy detector. There are two general methods for binary hypothesis testing: Neyman-Pearson Test (NP) and Bayes Test. In the Nieman-Pearson test, the goal is to maximize P_d by limiting P_f to a certain value. This specific value is denoted by α, which is the maximum allowed value for P_f It has been shown that the NP test is equivalent to the following Likelihood Ratio Test (LRT):

$$\Lambda(\boldsymbol{y}) = \frac{f(\boldsymbol{y}|H_1)}{f(\boldsymbol{y}|H_0)} = \prod_{k=1}^{N} \frac{f(y_k|H_1)}{f(y_k|H_0)} \gtrless_{H_0}^{H_1} \lambda \tag{2-6}$$

  Where $\Lambda(\boldsymbol{y})$ is the likelihood ratio, $f(\boldsymbol{y}|H_j)$ is the governing distribution of the observations $\boldsymbol{y} = \{y_i\}_1^N$ under the hypothesesH_j ($j \in \{0,1\}$), λ is the detection threshold and N is the number of samples in detection. It should be noted that the second equality of the relationship (2-7) is established under the condition that the distributions are assumed to be independent and identically distributed under each hypothesis. In this case, if the likelihood ratio exceeds the detection threshold, H_1 is declared, and if it is less, H_0 is declared.

  In the Bayes test, the goal is to minimize the expected cost, which is called Bayes Risk and is obtained from the following relationship:

$$R = \sum_{i=0}^{1} \sum_{j=0}^{1} C_{ij} P(H_i|H_j) P(H_j) \tag{2-7}$$

Where C_{ij} and $P(H_i|H_j)$ are the amount of cost and the probability of announcing H_i under the condition of H_j, respectively, and $P(H_j)$ is the probability of the absence and presence of the initial user signal for j=0 and j=1, respectively. Bayes risk is the sum of the probability of all wrong detection states and the sum of the probabilities of all correct detection states. Under the condition of knowing$P(H_j)$, the likelihood ratio for the Bayes test is equal to:

$$\Lambda(\boldsymbol{y}) = \frac{f(\boldsymbol{y}|H_1)}{f(\boldsymbol{y}|H_0)} \gtrless_{H_0}^{H_1} \frac{P(H_0)|(C_{10} - C_{00})}{P(H_1)|(C_{01} - C_{11})} = \lambda \tag{2-8}$$

In this case, if the likelihood ratio exceeds the detection threshold, H_1 is declared, and if it is less, H_0 is declared. The composite hypothesis test and sequential test are other methods of testing measurement results.

- **Control Channel and data report:** In collaborative spectrum sensing, a common control channel is used to report local measurement results to the combination center or to share them with neighboring nodes. The control channel can be a dedicated channel in licensed or free bands. The physical point-to-point link between a radio-identifying user and the aggregation center is called a reporting channel. To report data from spectrum sensing, three requirements must be met: channel bandwidth, channel reliability, and channel security. Since the amount of data increases in proportion to the number of participating users, the bandwidth of the report channel has always been one of the problems of participatory spectrum sensing. Censoring part of the data that is less important to send is one of the solutions to the bandwidth problem of the report channel [11]. In addition to bandwidth, the reliability of the reporting channel has a significant impact on collaborative sensing performance. Like the data channel, the report channel can also be affected by fading and shadowing. While in many studies, the report channel is error-free and ideal, recently, studies have been conducted assuming the presence of the report channel in fading and shadowing, and it shows that these factors also affect the performance of collaborative disclosure.

- **Data combination:** The process of combining data from local measurements to test the hypothesis is called data combination. Depending on the limitations of the control channel, the reported results may be of various shapes, types, and sizes. In general, measurement results can be combined in three ways: hard combining, soft combining, and quantized soft combining. In hard combination, radio cognitive users make a local decision and send the result as a one-bit decision to the combination center. In soft synthesis, users send all the information obtained from spectrum sensing (local test data) to the synthesis center. In soft stepwise compositing, users categorize (quantize) the measured data and send the categorized data to the compositing center. Obviously, the soft combination method results in better performance, as opposed to using more bandwidth and causing more overhead; While the hard combination and soft step combination require less bandwidth for the control channel and have a weaker performance than the soft combination method due to the loss of part of the information. Equal Gain Combining and Maximum Ratio Combining are the most common soft combining rules, and AND, OR, and Majority are the most common hard combining rules.
- **User Selection:** The choice of radio cognitive users to participate in the measurement plays a key role in determining how collaborative spectrum sensing works. Because choosing the right users can lead to improving the participation benefit and dealing with the overhead issue caused by participation. As shown in shaded environments, choosing users who are independent from each other can make the measurement results more robust. Also, preventing the participation of malicious users can ensure the security and reliability of the network. User selection is done in two ways, centralized and cluster based. The user selection method is done centrally, in the composition center and to use the information collected from all participating users. In this method, the combination center is able to select independent users based on their approximate location to deal with shadowing effects. Centralized user selection may introduce high overhead in the form of bandwidth shortages, reduced energy efficiency, and reporting delays to the combination center; especially when the

number of users in the partnership is large. To overcome this problem, users can be grouped into clusters to reduce the amount of overhead caused by cooperation and the geographical range of participating users. This method is called user selection using clustering. Random clustering, statistical clustering, distance-based clustering is some of the clustering techniques chosen by users.

- **Knowledge Base:** The performance of collaborative spectrum sensing is highly dependent on the initial user's knowledge of the signal characteristics; Characteristics such as traffic pattern, location and signal transmission power. This information, if available in a database, facilitates the detection of the primary user signal. The database that stores information about the radio frequency environment is called a knowledge base. Knowledge base is an inevitable element of collaborative spectrum sensing and plays two basic roles in collaborative spectrum sensing:

  One is to improve detection performance by applying the collected information and experience gained, such as statistical models in the database; and the other is to lighten the burden of collaborative spectrum sensing by retrieving frequency spectrum information from the database. Radio environment map (Radio Frequency Map=REM) received signal strength profiles (Received Signal Strength=RSS), channel gain map and power spectrum density map can be information in the database [11].

Chapter 3: LITERATURE SURVEY

As stated in the second chapter, the use of a wireless sensor network is a suitable solution to increase the possibility of sensing and efficiency in limited environments such as emergency or military areas. But since wireless sensor networks have limitations such as limited sensor energy and battery as well as low processing ability, these limitations should be considered in the design and implementation of these types of networks. In case of unbalanced consumption of energy in the network and battery exhaustion, the sensors are not able to continue life in the network and this factor limits the lifetime of the sensor network. In this chapter, we will review the most important articles in the field of spectrum sensing sensor networks. We will explain its features, functions, and differentiation with our own work.

3-1 Overview of References

Networks of smart sensors capable of spectrum sensing and detecting the presence of a signal in the sensing channel have been interested in much research. In the following, we will mention the most important ones.

In [12], a review of non-cooperative spectrum sensing methods in cognitive radio networks, based on detection methods and a comprehensive comparison between these methods from the point of view of cost, implementation complexity, sensing time, power consumption and reliability is presented. In addition, the issue of the need for basic information as well as the usability in multi-channel spectrum sensing has been discussed in detail in [13].

Collaborative spectrum sensing has been considered in more research due to its higher efficiency and has been investigated from different perspectives, which sources [14-17] have suggested for further study on the types of cooperation and the rules of combination and spectrum sensing qualities resulting from different methods are introduced for collaborative spectrum sensing. The method of selecting spectrum sensing nodes, both in cooperative spectrum sensing and in non-cooperative spectrum sensing, has been done with different goals. For example, in [18], he addressed the challenge of a smart node's inability to perform spectrum sensing and send information at the same time and introduced the sensing Efficiency parameter to combine them and increase the opportunistic throughput. Then, by properly choosing the spectrum sensed and transmitter nodes, this parameter has been maximized in cooperative spectrum sensing with the assumption of interference.

In reference [19], assuming the Nakagami-m channel model, he presents a scheme to select sensing sensors for a channel, in which it is guaranteed that the probability of correct detection and the probability of false alarm remain optimal. Also, the effect of parameter m on the efficiency of cooperative spectrum sensing has been investigated. Multi-channel scenarios, both in cognitive radio networks and in non-cognitive radio sensor networks have many advantages in terms of throughput and interference reduction, but on the other hand, it requires that proper methods for channel allocation be carried out. Therefore, this challenge has been addressed in much research. For example, in [20], a scheme for channel allocation to sensors in a network based on tree analysis was presented to increase the throughput of the network and reduce the interference and delay of sending sensors to the data center. But the target network is not cognitive radio, and the discussion of spectrum sensing and cooperation has not been targeted, while the energy challenge has not been considered in the proposed plan.

In [21], a control solution for channel allocation to access points in the cognitive radio network is presented, the goal of the proposed solution is to increase the throughput of the network, and the discussion of the cooperation of smart nodes in spectrum sensing and the energy consumption of spectrum sensing is not considered. We will review some examples of research done on the problem of multi-channel spectrum sensing. A number of multi-channel spectrum sensing articles have only focused on determining the presence or absence of the spectrum generating source. In [22], a review of research in the field of multichannel spectrum sensing has been done. In [23], the use of continuous wavelet transform detector for spectrum sensing is investigated and its limitations are investigated, and the measurement method using compressive sensing is investigated and its challenges are presented.

In [24], a Phase-Field Segmentation method, which is a mathematical and generally applicable method in the field of image processing, is used to divide the frequency band into channels and reveal the power spectrum density of the signal in spectrum channels and cavities.

In [25], they investigated the problem of multi-channel spectrum sensing by considering the correlation of the channels and showed that the linear combination of the results of the energy detectors of each channel improves the performance characteristic in accordance with their correlation coefficient. In [26], considering non-Gaussian noise and using the Neyman-Pearson criterion, two detectors have been introduced to find frequency band holes.

In [27], detection for multi-channel spectrum sensing has been proposed based on the assumption of sending signals in contiguity bins. In [28], a scheme for multi-channel cooperative spectrum sensing is presented, in which each secondary user first uses the Bayesian Estimation algorithm, which is suitable for detection with the assumption of noise uncertainty, and then in the center of the combination of the likelihood ratio test. (Likelihood Ratio Test) is performed on the decisions of all secondary users. The authors in [29] and [30] have also extended the proposed method for the spectrum sensing of partners of a frequency channel in [31] to detect the combination of several channels with the aim of increasing throughput. In [29], the authors performed the maximization of the total throughput by considering the constraint on the total interference, by presenting a soft and linear combination scheme in FC. Also, in the reference [30], the maximization of the total throughput was done by considering the constraint on the total interference, by determining the optimal threshold level for the detection of each channel by two sequential and combined selection methods. In [32], a review of one frequency channel spectrum sensing methods based on the type of detector is done and then a review of multi-channel cooperative spectrum sensing methods is presented, most of the goals are on maximizing throughput and opportunities to use the spectrum. In [33], an algorithm is proposed to maximize the opportunistic capacity of all channels by considering the constraint on the interference of each channel. In [34], with the aim of maximizing the sensing capacity, the authors have presented an algorithm to select the best frequency band for measurement, in the case that several bands are available. In this article, the spectrum sensing capacity is modeled as a combination of the product of measurement efficiency, bandwidth, the probability of being empty and the efficiency of the selected frequency band. In [35], the problem of the time required for multi-channel spectrum sensing was addressed and for each radio detector sensor, the measurement time and the optimal allocated power were determined to maximize the throughput of the entire network. In [36], the problem of multi-channel spectrum sensing with the aim of maximizing the throughput of the entire network and taking into account the limited interference, has been investigated by jointly determining the detection thresholds of the channels. In [37], they presented an algorithm for maximizing Ergodic bandwidth by determining the time of spectrum sensing and the transmitted power on each channel, which actually optimized the two functions of sensing and spectrum acquisition at the same time. In [38], an algorithm for choosing the right channel for spectrum sensing in an ad hoc network is presented, which is aimed at both energy consumption and improving the network throughput, but the proposed design was non-cooperative.

Energy is one of the most important limitations of a wireless network. Due to the importance of green communications, energy efficiency is very important in the design of these networks [39], [40], [41]. If unbalanced energy consumption is used, the lifetime of the network and as a result the opportunistic use of the spectrum will decrease. Therefore, in addition to opportunistic capacity and permeability, it is necessary to pay attention to methods of minimizing energy consumption and increasing lifetime, which there has been some research in this field. Considering the importance of the lifetime parameter in wireless sensor networks and regardless of radio cognitive applications, the problem of energy consumption, efficient lifetime is of great importance. Studies have been conducted in this field and solutions have been presented to increase the lifetime of the network [42]. While many protocols and solutions have been presented to improve energy efficiency and increase the lifetime of these types of networks, it is very difficult to analyze the lifetime, because it depends on many parameters such as network structure, energy consumption model, channels, data collection type, reporting method to the center or other sensors, the model of the event being measured, etc. [43], [44] and [45]. Also, there is no specific definition for lifetime, but several definitions have been provided depending on the use of the network. For example, in [46], a specific definition of network lifetime is not provided, but according to its concept, increasing the network lifetime by reducing the sensing range of the sensors, while limiting the coverage of the network, has been implemented. In [47], they have defined a mathematical model for the lifetime of the wireless sensor network based on the energy of the sensors and considering the importance of the sensors and their location in the network, as well as their effect on connectivity, link quality, and network coverage. In [48], the lifetime of the network is defined as the time when the energy of the first sensor is exhausted. Based on the definition presented in [48], they defined schemes for routing between sensors with the aim of maximizing the lifetime of the network. Maybe this definition is suitable for sparse networks where connectivity or total coverage is lost by removing the first sensor, but in general, this definition is unfair. Another definition that is used for the lifetime of wireless sensor networks is the period of time that a certain percentage of the sensors of network have enough energy to continue to live and meet the network's goals. Since the participation of all sensors in spectrum sensing is not optimal [49], it is possible to save energy consumption by determining suitable sensors for spectrum sensing while meeting the desired goals. Therefore, once we know the model of the channels, choosing the right channel and sensors for spectrum sensing is a good option to optimize energy consumption and obtain the best spectrum sensing result with the possibility of optimal performance.

In [50] and [51], methods have been presented to improve the mechanism of energy consumption in radio detector wireless sensor networks, based on the sensor selection. In [52] and [53], the selection of cooperative sensors for cooperative spectrum sensing was done with restrictions on detection performance. In [54], the minimization of energy consumption in cooperative spectrum sensing has been investigated in the form of clustering sensors and with the optimal and simultaneous selection of cluster head and sensors. In [55], with the assumption of not having information about the location of the sources of spectrum generation and the distance of the convexity between the sensors and these sources, the minimum number of cooperating sensors has been determined to achieve the optimal detection probabilities. Also, the problem of choosing the right sensors in spectrum sensing, assuming that the location information of the sensors is known, has been investigated with the aim of minimizing the energy consumption and applying restrictions on the detection performance. In [56], the problem of maximizing throughput in radio detector wireless sensor networks, through the selection of suitable sensors for spectrum sensing and also the selection of suitable sensors for sending information in empty spectrums, is investigated and an algorithm is presented, which in addition to maximizing throughput, It leads to optimal energy consumption. In [57], the challenge of the measurement time of several channels in non-cooperative spectrum sensing is proposed and cooperation in spectrum sensing is proposed in order to minimize the sensing time and energy consumption, and an algorithm based on the division of secondary users into different groups and cooperation in each group to measure each channel and then determining the position of the entire band in a compound center is presented. In [58], lifetime maximization has been done by selecting cooperating sensors based on the Max-Min method of residual energy of sensors in radio cognitive networks. In [59], cooperative communication using relays has been proposed and the lifetime of each link has been maximized. In [60], the lifetime of cooperative spectrum sensing is maximized by choosing the sensors participating in spectrum sensing using the max-min method. Also, in [61], with the method of weighing each sensor based on its remaining energy, they maximized the lifetime, which finally showed that the max-min method has a better performance.

Other problems related to channel selection and sensor allocation to channels are reviewed below. In [62], the best channel for sensing is selected among N channels so that the throughput is maximized. In this method, the measured state of the channels in successive measurements is stored and considered in each step of channel selection. This method has not been investigated cooperatively and only one channel is selected in each step, so it is not suitable for cooperative multi-channel spectrum sensing. It is also assumed that during many measurement time intervals, the transmission status on the channels does not change, which is practically unknown.

In reference [63], first, for the case where we have only one channel, the optimal time interval between successive measurements has been determined so that the channel efficiency is maximized. Channel efficiency has been defined as the ratio of useful transmission time without secondary user interference to the total sensing and transmission time, so that the least interference with the primary system and maximum secondary transmission are possible. Then, in the case that there are several secondary users and several channels in the network, they have chosen the best channel to sense each secondary user. The objective function of the channel selection problem has also considered the efficiency of all channels and solved the problem by using the optimal transmission time for all secondary users in all possible channel selection modes. The disadvantage of this method is that with the increase in the number of secondary users and channels, the complexity increases because the problem is finally done with exhaustive search.

In [64], the issue of joint clustering and allocation with sensing time and information transmission with the aim of maximizing network energy efficiency in a single-band wireless sensor network is discussed. In this article, by presenting mathematical analysis and proposing a theorem and its proof, the authors propose an innovative algorithm based on one-dimensional bisection search algorithm, with far less complexity than exhaustive search numerical algorithms, which can achieve optimal solutions to the formulated problem. The authors of the article in [64,65, and 69] deal with the issue of the joint allocation of transmission power and sensing time to maximize the energy efficiency of the network.

According to the research we have done, so far, the issue of sensor allocation in fair scenarios with the aim of minimizing network lifetime and reducing energy consumption for the weakest node has not been studied. Fair spectrum sensing increases efficiency and fairly increases the lifetime of all nodes, while facing challenges such as the limitation of the selected nodes and the increase in energy consumption. It should be noted that in [65], the issue of selecting optimal nodes is not discussed.

3-2 Conclusion and summary

Previously, only the issue of selecting cooperating sensors for spectrometry of a frequency channel, with the aim of maximizing the lifetime of the network or minimizing the energy consumption, has been investigated. But this issue has not been resolved for fair spectrum sensing, considering the guarantees of detection quality and information transfer rate. Fair spectrum sensing requires the proper selection of nodes and the optimal allocation of transmission power, which greatly increases the complexity of the problem, and therefore it is important to provide a suitable method with an acceptable degree of complexity. In the next chapter, while stating the problem and its formulation, to solve the formulated problem, methods based on solving convex optimization problems (mathematical analysis) and using feedforward neural networks, suitable algorithms with a low degree of complexity are presented.

Chapter 4: PROPOSED TECHNIQUES

4-1 Introduction

In the previous chapters, the necessity of using radio recognition systems in new generations of communications was discussed in detail. The most important task of a radio recognition system is to detect vacant and unoccupied spectrums. Wireless sensor networks (WSN) can be one of the most effective techniques for spectrum sensing in this type of system. In this chapter, we intend to present algorithms to create fairness in the energy efficiency of sensors by considering various parameters such as the probability of correct detection and the rate of information transfer. For this purpose, at the beginning of the chapter, we will describe the system model that we will work with. In the next section, we will address the issue of resource allocation with the aim of creating fairness in energy efficiency between sensors in the context of an optimization problem. Then, in the rest of this chapter, we will present different methods and algorithms to solve the formulated problem.

4-2 System Model

Figure (4-1) shows in the proposed system model in which there are the N wireless sensors with spectrum sensing capability and a Fusion Center (FC) which make final decision about the channel has been occupied or not.

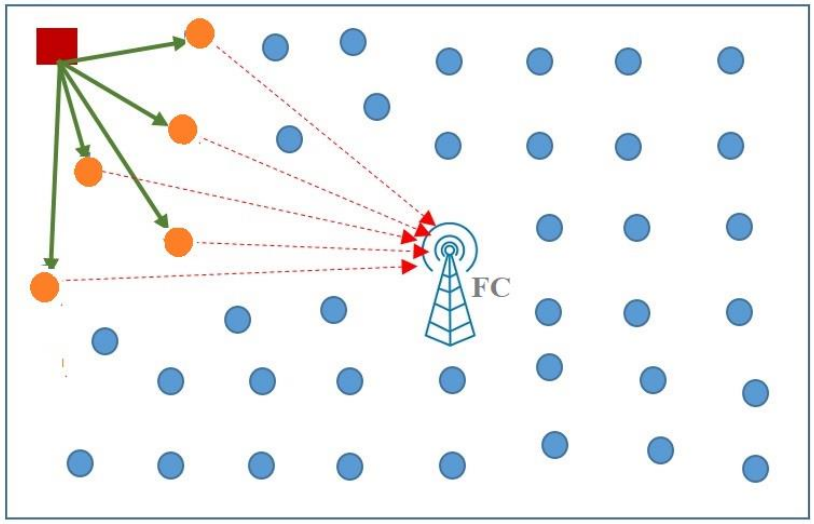

Figure 4-1 cooperative spectrum sensing system model in WSN

Here, it is assumed that the slot time is T and all smart sensors have the same sensing time, denoted by δ. Also, f_s represents the sampling frequency of the signal received from the primary user by the sensors. Therefore, the number of received samples will be equal to $N_s = \delta f_s$. Each spectrum sensing node decides about the state of the spectrum based on its observations. We introduce the received samples for the i-th sensor by $x_i[k], k \in \{1,2,\cdots,N_s\}$. There are two hypotheses for each observation sample. Hypothesis H_1 means that there is a primary user and hypothesis H_0 means that there is no primary user in the desired channel.

$$x_i[k] = \begin{cases} H_0: n_i[k] & k \in \{1,2,\ldots,N_s\} \\ H_1: h_i[k]s[k] + n_i[k] & i \in \{1,2,\ldots,N\} \end{cases} \qquad \text{(4-1)}$$

$s[k]$ is the signal related to the primary user and the channel gain is between the primary user and the j-th sensor and is defined as follows [56]:

$$h_i = 10^{-\frac{L_i}{20}} g_i \qquad i \in \{1,2,\ldots,N\} \qquad \text{(4-2)}$$

g_i is a Rayleigh random variable with a mean of zero and a dispersion of one. L_i represents large scale fading which has two main parts.

$$L_i = 20 \log\left(\frac{d_i 4\pi f_c}{C}\right) + u_i \tag{4-3}$$

The first part represents the path loss, where d_i is the distance of the i-th node to the primary network user, C represents the speed of light, and f_c is the frequency of the received signal carrier. The second part represents the shadowing effect, which is modeled as a random variable with log-normal distribution. Whereas additive white Gaussian noise (AWGN) is an i.i.d random process with zero mean and variance σ_n^2 and is assumed to be the same for all sensors. In channel spectrum sensing, the probability of correct detection P_d and the probability of false detection P_{fa} are defined respectively as the probability of detection of the primary user under the hypothesis H_1 and H_0. Therefore, with such probabilities, a smart sensor can detect whether the channel is busy or free. Therefore, the higher probability of correct detection prevents the interference of the signals of the primary network user with the signals of the secondary network user, and the lower probability of false detection provides the opportunity to use the free channel for the secondary users. Consequently, it is clear that higher P_d and lower P_{fa} are more favorable for the network.

In this thesis, an energy detector is used to detect the spectrum, so the i-th sensor is defined as follows [64]:

$$E_i = \frac{1}{N_s}\sum_{k=1}^{N_s} |x_i[k]|^2 \lessgtr_{H_0}^{H_1} Th : \begin{cases} D_i = 0 \ , if \ E_i < Th \\ D_i = 1 \ , if \ E_i > Th \end{cases} \tag{4-4}$$

In (4-4), Th is the decision threshold for all sensors. Based on the output of the energy detector, the node can make two decisions. The decision of the i-th sensor on the non-occupancy of the channel is indicated by D_i, and the decision on the occupancy of the channel is indicated by $D_i = 1$. That's mean:

$$\begin{cases} D_i = 0 \ , if \ E_i < Th \\ \\ D_i = 1 \ , if \ E_i > Th \end{cases} \tag{4-5}$$

Here it is assumed that each sensor decides one bit of information. It should be noted that in this research, it is assumed that the noise variance does not change during the observations and the i.i.d. condition is established between the sampled signals.

Under hypothes isH_0, E_i is a random variable whose probability density function (pdf) has a chi-square distribution with degrees of freedom $2N_s$ and with hypothesis H_0, it has a non-central chi-square distribution with degrees of freedom $2N_s$. Using the central limit theorem (CLT), for large N_s, the probability density function E_i can be approximated by a Gaussian distribution. Therefore, under hypothesis H_0, it is a random variable with mean

σ_n^2 and variance $\frac{\sigma_n^4}{N_s}$, while under hypothesis H_1, E_i is a random variable with mean $\sigma_{s_i'}^2 + \sigma_n^2$ and variance $\frac{1}{N_s}(2\gamma_i + 1)\sigma_n^4$. where $\sigma_{s_i'}^2$ and γ_i are defined as follows:

$$\sigma_{s_i'}^2 = E\{|h_i[k]s[k]|^2\} \ , \forall k \in \{1,2,\dots,N_s\} \tag{4-6}$$

$$\gamma_i = \frac{\sigma_{s_i'}^2}{\sigma_n^2} \tag{4-7}$$

γ_i can be interpreted as the signal-to-noise of the signal received from the primary network user at the i-th node. According to the proposed assumption, the probability of false detection for i-th smart sensor is equal to [66]:

$$P_{f,i} = Pr\left\{\frac{1}{N_s}\sum_{k=1}^{N_s}|x_i[k]|^2 > Th|H_0\right\} = Q\left(\left(\frac{Th}{\sigma_n^2} - 1\right)\sqrt{N_s}\right) \tag{4-8}$$

Similarly, for the probability of correct detection we have [66]:

$$P_{d,i} = Pr\left\{\frac{1}{N_s}\sum_{k=1}^{N_s}|x_i[k]|^2 > Th|H_1\right\} = Q\left(\left(\frac{Th}{\sigma_n^2} - 1 - \gamma_i\right)\sqrt{\frac{N_s}{2\gamma_i + 1}}\right) \tag{4-9}$$

4-3 Cooperative spectrum sensing

In this section, the topic of collaborative detection in a radio recognition system is discussed. In FC, various rules can be applied to combine the information (made decisions) obtained by the nodes. In this research, the "OR" criterion was used to combine information. In fact, this rule states that at least one of the sensors reports that there is a primary network user of the channel, which is using it, and thus the final decision, is that the channel is busy. Therefore, the overall correct detection probability $P_d^{(FC)}$ and the overall false detection probability $P_f^{(FC)}$ in FC are expressed as follows:

$$P_d^{(FC)} = 1 - \prod_{i=1}^{N}\left(1 - P_{d,i}\right) \tag{4-10}$$

$$P_f^{(FC)} = 1 - \prod_{i=1}^{N}\left(1 - P_{f,i}\right) \tag{4-11}$$

It has been shown in [60] and [61] that it is not necessary for all nodes to participate in spectrum sensing, which means that high energy efficiency in WSN can be achieved with fewer nodes. As a result, the number of sensing and selection nodes become a very important challenge in providing algorithms with high energy efficiency. Now, let us modify (4-10) and (4-11) as follows:

$$P_d^{(FC)} = 1 - \prod_{i=1}^{N} \left(1 - \rho_i \, P_{d,i}\right) \tag{4-12}$$

$$P_f^{(FC)} = 1 - \prod_{i=1}^{N} \left(1 - \rho_i \, P_{f,i}\right) \tag{4-13}$$

In the above, ρ_i introduces the assignment index and $\rho_i \in \{0,1\}$. The number one means that the desired node is selected for spectrum sensing, while the number zero means that the node is not selected for spectrum sensing. Another point is that $P_{f,i}$ obtained in (4-8) has nothing to do with γ_i or SNR, and as a result, it is the same for all sensors and can be represented by P_f, that is: $P_{f,1} = P_{f,2} = \cdots = P_{f,N} = P_f$.

4-4 The problem of establishing fairness in WSN network with spectrum sensing capability.

In this section, the issue of establishing fairness in WSN networks with spectrum sensing capability is discussed. In this research, we will follow the node selection problem (node clustering) and power allocation to nodes with the aim of ensuring fairness in energy consumption between nodes, considering the optimal detection probability, the optimal false alarm probability, and also the information transfer rate to FC. According to the system model considered in this research, energy consumption in the i-th sensor can be considered as follows [40]:

$$E_{c,i} = E_{s,i} + E_{t,i} \tag{4-14}$$

In the latter relationship, $E_{s,i}$ represents the energy consumed in spectrum sensing and its processing by the i-th sensor. On the other hand, $E_{t,i}$ represents the energy used to transmit information from the i-th sensor to the FC, which can be expressed as follows [41]:

$$E_{t,i} = E_{e,i} + P_{t,i} \, T_t \tag{4-15}$$

In the last relation, $E_{e,i}$ represents the electronic energy of the transmitter and $P_{t,i}$ represents the power allocated to the i-th sensor transmitter to transmit information in a single bit form to the FC. Also, T_t is the duration of information transfer of each sample (bit) sent. As mentioned earlier, the aim of this thesis is to provide a fair optimization framework with optimal selection of sensors and optimal allocation of power to minimize the maximum energy consumption between network sensors. In this proposed optimization problem, the constraints of the minimum desired detection probability, the maximum desired false alarm probability, and the minimum total desired transmission rate have been considered. According to the explanations given, the mentioned problem is defined as follows:

$$P0: \begin{cases} \min\limits_{\{\rho_i\},\{P_i\}} \left\{ \max\limits_{i} \rho_i \left(E_{s,i} + E_{t,i}\right) \right\} & \\ \quad s.t.\ P_d^{(FC)} \geq P_{d,th} & (4\text{-}16\text{-}1) \\ \qquad P_f^{(FC)} \leq P_{f,th} & (4\text{-}16\text{-}2) \\ \qquad \sum\limits_{i=1}^{N} \rho_i R_{t,i} \geq R_{t,th} & (4\text{-}16\text{-}3) \\ \qquad P_i \leq P_{max} & (4\text{-}16\text{-}4) \\ \qquad \rho_i \in \{0,1\} & (4\text{-}16\text{-}5) \end{cases} \tag{4-16}$$

In the above relationship, $P_{d,th}$, $P_{f,th}$ and $R_{t,th}$are the optimal threshold of correct detection probability, false alarm probability and total transmission rate, respectively. In addition, $R_{t,i}$represents the information transfer rate from the i-th sensor to the FC, which is expressed as follows:

$$R_{t,i} = log_2(1 + \alpha_i P_{t,i}) \tag{4-17}$$

Above, α_i is the power factor that depends on the two parameters of the accumulated noise power in the FC and the channel power gain between the i-th sensor and the FC. It should be noted that in the P0 problem, the constraint (4-16-4) is caused by the limitation of power amplifiers. In fact, it shows that the allocated power of each node in the phase of information transfer to FC will not exceed P_{max} power.

4-5 Solution of P0 problem

The P0 problem is a discrete non-convex optimization problem. In fact, in the formulated problem, according to the determination of the allocation indices ρ_i, it is a combinatorial optimization problem that is combined with a power allocation problem. Solving combinatorial optimization problems with methods based on exhaustive search increases exponentially with the number of sensors in the network. This means that to find an optimal set of suitable nodes, the power allocation problem must be solved for 2^N possible states. According to the explanations given, the important point in the P0 problem is that if the optimal sensors are selected, the power allocation problem can be solved as a convex optimization problem. For this purpose, we turn the P0 problem, which is a difficult optimization problem to solve, into two separate sub-problems. In the first problem, optimal sensors are selected. For this purpose, it is assumed that the powers allocated to all sensors are the same. The assumption of equal exponents is intended to deal with a fair optimization problem. In the second sub-problem, according to the selected nodes obtained in the first sub-problem, the power allocation problem is solved. We further show that the second subproblem is a convex optimization problem.

4-5-1 The first sub-problem: optimal sensor selection

In this section, we want to choose the optimal sensors. In this sub-section, we want to convert the optimization problem of P0 into an optimization problem of determiningρ_i. To solve the first sub-problem, we must use several relaxations. As mentioned before, the first sub-problem is a combinatorial optimization problem. Solving it with numerical methods will have many complications. For this purpose, we transform the discrete optimization problem into a continuous variable optimization problem by considering the assignment index continuously, i.e., $0 \leq \rho_i \leq 1$, so that classical optimization methods can be applied to them. In equation (4-16), condition (4-16-3) depends on both optimization variable ρ_i and $P_{t,i}$ variable. To reduce the complexity in the first sub-problem, we make this clause inactive. On the other hand, according to (4-8), the value of $P_{f,i}$ is independent of the index (number) of the sensors, so all $P_{f,i}$ will be equal, which we consider equal to P_f. That is: $P_{f,1} = \cdots = P_{f,N} = P_f$. Now it is easy to see that the constraint (4-16-2) can be rewritten as follows:

$$1 - \prod_{i=1}^{N} \left(1 - \rho_i \, P_{f,i}\right) \leq P_{f,th} \Rightarrow 1 - P_{f,th} \leq \prod_{i=1}^{N} \left(1 - \rho_i \, P_f\right) \tag{4-18}$$

Since $\rho_i = 1$ for the selected sensor and $\rho_i = 0$ for the unselected sensor, then if we represent the total number of selected sensors withN_{max}, according to (4-18), N_{max} can be expressed as follows:

$$1 - P_{f,th} = \left(1 - P_f\right)^{N_{max}} \Rightarrow ln\left(1 - P_{f,th}\right) = N_{max} \, ln\left(1 - P_f\right) \tag{4-19}$$

Considering that N_{max} is an integer, it will be:

$$N_{max} = \left\lceil \frac{ln\left(1 - P_{f,th}\right)}{ln\left(1 - P_f\right)} \right\rceil \tag{4-20}$$

In the last relation, $\lceil . \rceil$ is the ceiling function. Therefore, we can rewrite the constraint (4-16-2) as follows:

$$\sum_{i=1}^{N} \rho_i \leq N_{max} \tag{4-21}$$

According to the given explanations, the first sub-problem can be formulated as follows:

$$P1: \begin{cases} \min_{\{\rho_i\}} \left\{ \max_i \rho_i \left(E_{s,i} + E_{t,i}\right) \right\} & \\ \quad s.t.\ P_d^{(FC)} \geq P_{d,th} & \text{(4-22-1)} \\ \quad \sum_{i=1}^{N} \rho_i \leq N_{max} & \text{(4-22-2)} \\ \quad 0 \leq \rho_i \leq 1 & \text{(4-22-3)} \end{cases} \tag{4-22}$$

The P1 problem can be transformed into a standard minimization optimization problem with an additional constraint, namely:

$$P1': \begin{cases} \min_{\{\rho_i\},T} T & \\ s.t.\ P_d^{(FC)} \geq P_{d,th} & \text{(4-23-1)} \\ \sum_{i=1}^{N} \rho_i \leq N_{max} & \text{(4-23-2)} \\ 0 \leq \rho_i \leq 1 & \text{(4-23-3)} \\ \rho_i \left(E_{s,i} + E_{t,i}\right) \leq T & \text{(4-23-4)} \end{cases} \tag{4-23}$$

Although the objective function of the problem$P1'$, as well as the constraints (4-23-1), (4-23-2) and (4-23-3) are linear constraints, but $P_d^{(FC)}$ is a non-linear and non-convex function of ρ_i. Nevertheless, convex optimization methods can still be used to obtain solutions close to the global optimal solution. First, we write the Lagrange function corresponding to the problem $P1'$ [67]:

$$\begin{aligned} L(\{\rho_i\}, T, \nu, \lambda, \{\mu_i\}, \{\eta_i\}) \\ &= T + \nu\left(P_{d,th} - P_d^{(FC)}\right) + \lambda\left(\sum_{i=1}^{N} \rho_i - N_{max}\right) \\ &+ \sum_{i=1}^{N} \eta_i \left(\rho_i \left(E_{s,i} + E_{t,i}\right) - T\right) \end{aligned} \tag{4-24}$$

Now the optimality equations can be obtained as follows:

$$\frac{\partial L}{\partial T} = 1 - \sum_{i=1}^{N} \eta_i = 0 \tag{4-25}$$

$$\frac{\partial L}{\partial \rho_i} = -\nu \frac{\partial P_d^{(FC)}}{\partial \rho_i} + \lambda + \eta_i \left(E_{s,i} + E_{t,i}\right) = 0 \tag{4-26}$$

According to the relationship obtained for $P_d^{(FC)}$, (4-26) can be rewritten as follows:

$$\nu P_{d,i} \prod_{\substack{m=1 \\ m \neq i}}^{N} \left(1 - \rho_m \, P_{d,m}\right) = \lambda + \eta_i \left(E_{s,i} + E_{t,i}\right) \quad , \forall i \in S \tag{4-27}$$

Therefore, there are N equations and N unknowns ρ_i, which is difficult to solve these nonlinear equations due to the presence of unknown Lagrange coefficients, but since our goal is to determine the priority of the sensors for spectrum sensing, the value is not important, but it is enough to calculate the ratio for two sensors. $\frac{\rho_i}{\rho_j}$ is calculated and the sensor node with higher priority is selected, therefore, similarly for sensor j we have:

$$\nu P_{d,j} \prod_{\substack{m=1 \\ m \neq j}}^{N} \left(1 - \rho_m \, P_{d,m}\right) = \lambda + \eta_j \left(E_{s,j} + E_{t,j}\right) \quad , \forall j \in S \backslash \{i\} \tag{4-28}$$

To define the variable $Q = \prod_{\substack{m=1 \\ m \neq j,i}}^{N} \left(1 - \rho_m \, P_{d,m}\right)$, the two relations (4-27) and (4-28) can be rewritten as follows:

$$\rho_j \, \nu P_{d,i} P_{d,j} \, Q = \lambda + \eta_i \left(E_{s,i} + E_{t,i}\right) - \nu P_{d,i} \, Q \tag{4-29}$$

$$\rho_i \, \nu P_{d,j} P_{d,i} \, Q = \lambda + \eta_j \left(E_{s,j} + E_{t,j}\right) - \nu P_{d,j} \, Q \tag{4-30}$$

Now, according to the relations (4-29) and (4-30), we obtain the ratio $\frac{\rho_i}{\rho_j}$:

$$\frac{\rho_i}{\rho_j} = \frac{\lambda + \eta_j \left(E_{s,j} + E_{t,j}\right) - \nu P_{d,j} \, Q}{\lambda + \eta_i \left(E_{s,i} + E_{t,i}\right) - \nu P_{d,i} \, Q} \tag{4-31}$$

According to the goal of the problem, which is to establish fairness between sensors, η_i can be equal for all sensors, that is, $\eta_i = \eta$. Because initially only two sensors are selected and compared, then according to (4-31), the cost function for each sensor can be obtained as follows:

$$cost(i) = \frac{\lambda}{\eta} + \left(E_{s,i} + E_{t,i}\right) - \frac{\nu}{\eta} P_{d,i}\, Q \tag{4-32}$$

The derived cost function shows that a sensor node with a lower cost function has a higher priority to participate in spectrum sensing. Therefore, to recognize the priority of sensors, the cost function is calculated for all of them and sorted in increment order (from small to large) and sensors with higher priority are candidates for spectrum sensing. First, we compare the sensors two by two, under these conditions $Q = 1$ and since $\frac{\lambda}{\eta}$ are equal for all sensors, the cost function is obtained as follows:

$$cost(i) = E_{s,i} + E_{t,i} - \xi P_{d,i} \tag{4-33}$$

where $\xi = \frac{\nu}{\eta}$ is defined. On the other hand, according to KKT conditions, we have:

$$\nu\left(P_{d,th} - P_d^{(FC)}\right) = 0 \;\Rightarrow \begin{cases} \nu = 0, P_d^{(FC)} > P_{d,th} \\ \nu > 0, P_d^{(FC)} = P_{d,th} \end{cases} \tag{4-34}$$

$$\lambda\left(\sum_{i=1}^{N} \rho_i - N_{max}\right) = 0 \;\Rightarrow \begin{cases} \lambda = 0, \sum_{i=1}^{N} \rho_i < N_{max} \\ \nu > 0, \sum_{i=1}^{N} \rho_i = N_{max} \end{cases} \tag{4-35}$$

The issue of sensor selection should be such that one of the above KKT conditions is established. That is, if the number of sensors selected for spectrum sensing is less thanN_{max}, the equality condition is established according to (4-35) and if the number of nodes sensing the spectrum is equal toN_{max}, then condition (4-35) will be true. If the optimal value of ξ is zero, that is, $\nu = 0$, then according to (4-34), $P_d^{(FC)} > P_{d,th}$ will hold. On the other hand, we know that the detection probability function $P_d^{(FC)}$‘ is an Increment function of ρ_i. Therefore, it can be reduced so that $P_d^{(FC)} = P_{d,th}$ is satisfied. As ρ_i decreases, the detection probability function $P_d^{(FC)}$ decreases, which are more favorable solutions for the problem$P1'$.

Therefore, it should be chosen in such a way that $P_d^{(FC)} = P_{d,th}$ is satisfied and this is the condition (4-34). To find the optimal value, the nonlinear equation $P_d^{(FC)} = P_{d,th}$ must be satisfied, but due to the difficulty of solving it, the iterative Bisection algorithm is used. So first, $0 < \xi < \xi_{max}$ is considered. At each step of the iteration, the cost function in (4-33) is calculated for all sensors and sorted in increment order (from small to large). Then the sensors with the highest priority are selected until the constraint is satisfied and the number of selected sensors is less than N_{max}. Then value of detection probability function $P_d^{(FC)}$ is calculated and updated. The search space is halved and goes to the next iteration. The iterative algorithm terminates when the accuracy becomes less than the desired value of ϵ. It shows the accuracy of our algorithm. Unlike the exhaustive search method, which is an algorithm with complexity of the order of $O(2^N)$, the proposed algorithm is of the order of $O(N)$.

Algorithm 1: Proposed Sensor Selection Algorithm (PSSA)

1. Initial Setup: $\xi_{min} = 0, \xi_{max} = a\ enough\ large\ number, P_{t,i} = \frac{P_{max}}{N}$ & $\epsilon = a\ small\ number.$

2. While $|\xi_{max} - \xi_{min}| > \epsilon$

3. $\xi = (\xi_{max} + \xi_{min})/2$

4. $n = 1$

5. Compute the cost function (i.e., $cost(i) = E_{s,i} + E_{t,i} - \xi P_{d,i}$)

6. While $n \leq N_{max}$

7. Select n sensor with higher priority

8. Compute detection probability ($P_d^{(FC)}$)

9. If $P_d^{(FC)} > P_{d,th}$

10. Terminate algorithm

11. End (If)

12. End (While)

13. If $P_d^{(FC)} > P_{d,th}$

14. $\xi_{max} = \xi$

15. Else (If)

16. $\xi_{min} = \xi$

17. End (If)

18. End (While)

Note that in the PSSA algorithm, it is assumed that the same powers are assigned to all sensors. Now that sensors with high priority in terms of energy efficiency have been obtained, we will continue to examine the second sub-problem.

4-5-2 The second sub-problem: optimal allocation of power to the sensors

Like the explanations given in 4-5-2, in this section we want to address the issue of transmission power allocation to sensors. For this purpose, the problem considered in P0 can be rewritten as the following problem for the problem of power allocation to sensors:

$$P2: \begin{cases} \min_{\{P_i\}} \left\{ \max_{i \in S_c} (E_{s,i} + E_{t,i}) \right\} & \text{(4-36-1)} \\ s.t. \ \sum_{i \in S_c} R_{t,i} \geq R_{t,th} & \text{(4-36-2)} \\ P_i \leq P_{max} \end{cases} \tag{4-36}$$

In (4-36), S_c represents the set of selected sensors according to PSSA. The optimization problem P2 can be a convex optimization problem. With a variable change, the above max-min optimization problem can be converted into a minimization optimization problem. So, we will have:

$$P2': \begin{cases} \min_{T,\{P_i\}} T \\ s.t. \ \sum_{i \in S_c} R_{t,i} \geq R_{t,th} & \text{(4-37-1)} \\ P_i \leq P_{max} & \text{(4-37-2)} \\ E_{s,i} + E_{t,i} \leq T & \text{(4-37-3)} \end{cases} \tag{4-37}$$

To obtain the optimal values of P_i with the help of convex optimization methods, we will write the Lagrange function corresponding to the $P2'$problem:

$$L(\{\rho_i\}, T, \beta, \{\chi_i\}, \{\eta_i\})$$

$$= T + \beta\left(R_{t,th} - \sum_{i\in S_c} R_{t,i}\right) + \sum_{i=1}^{N} \chi_i\left(P_{t,i} - P_{max}\right) + \sum_{i=1}^{N} \eta_i\left(E_{s,i} + E_{t,i} - T\right) \tag{4-38}$$

Now, according to the obtained duality function, the optimality equations can be obtained as follows:

$$\frac{\partial L}{\partial T} = 1 - \sum_{i=1}^{N} \eta_i = 0 \tag{4-39}$$

$$\frac{\partial L}{\partial \rho_i} = -\frac{\alpha_i\, \beta\, ln(2)}{1 + \alpha_i P_{t,i}} + \chi_i + \eta_i T_t = 0 \tag{4-40}$$

It can be seen from (4-39) that there is at least one η_i which is opposite to zero. On the other hand, it is easy to understand from (4-40) that$\beta > 0$. If the KKT conditions corresponding to this Lagrange coefficient are written:

$$\beta\left(R_{t,th} - \sum_{i\in S_c} R_{t,i}\right) = 0 \;\Rightarrow \begin{cases} \beta = 0, \sum_{i\in S_c} R_{t,i} > R_{t,th} \\ \beta > 0, \sum_{i\in S_c} R_{t,i} = R_{t,th} \end{cases} \tag{4-41}$$

Since$\beta > 0$, it can be concluded from (4-41) that: $\sum_{i\in S_c} R_{t,i} = R_{t,th}$. On the other hand, it can be seen carefully in (4-40) that for each i, χ_i or η_i must necessarily be opposite to zero. Now the KKT conditions corresponding to each of the Lagrange coefficients χ_i and η_i will be given below:

$$\chi_i\left(P_{t,i} - P_{max}\right) = 0 \;\Rightarrow \begin{cases} \chi_i = 0, P_{t,i} < P_{max} \\ \chi_i > 0, P_{t,i} = P_{max} \end{cases} \tag{4-42}$$

$$\eta_i\left(E_{s,i} + E_{t,i} - T\right) = 0 \;\Rightarrow \begin{cases} \eta_i = 0, E_{s,i} + E_{t,i} < T \\ \eta_i > 0, E_{s,i} + E_{t,i} = T \end{cases} \tag{4-43}$$

If $\chi_i > 0$, according to (4-42), this means that $P_{t,i} = P_{max}$. Considering that the goal of the problem is to minimize the maximum amount of energy consumption, sending the maximum power increases the amount of energy consumption in the sensor. Therefore, the priority for one of the Lagrange coefficients χ_i and η_i to be non-zero is with the Lagrange coefficient η_i being non-zero. According to (4-43), $\eta_i > 0$ means:

$$E_{s,i} + E_{t,i} = T \tag{4-44}$$

According to the last equation, the value of $P_{t,i}$ can be obtained as follows:

$$P_{t,i} = \frac{T - (E_{s,i} + E_{e,i})}{T_t} \tag{4-45}$$

On the other hand, considering that $P_{t,i} > 0$ and according to the expression (4-37-2), $P_{t,i} \leq P_{max}$, the value of $P_{t,i}$ can be rewritten as below:

$$P_{t,i} = min\left\{max\left\{\frac{T - (E_{s,i} + E_{e,i})}{T_t}, 0\right\}, P_{max}\right\} \tag{4-46}$$

On the other hand, $P_{t,i}$ obtained from (4-46) should fulfill the equation $\sum_{i \in S_c} R_{t,i} = R_{t,th}$. It is very important that as it is inferred from (4-46), all the values of $P_{t,i}$ are dependent on the unknown parameter$T$. Therefore, the equation $\sum_{i \in S_c} R_{t,i} = R_{t,th}$ can be calculated in terms of the only parameter$T$. Since $R_{t,i}$s is incrementing functions of the T parameter, it is possible to obtain the optimal T value only with a one-dimensional search algorithm based on Newton's method such as bisection. In short, the pseudo code of the proposed algorithm can be expressed as follows:

Algorithm 2: Proposed Power Allocation Algorithm (PPAA)
1. Initial Setup: $T_{min} = 0, T_{max} = a\ enough\ large\ number,\ \epsilon = a\ small\ number.$
2. While $\lvert T_{max} - T_{min} \rvert > \epsilon$
3. $T = (T_{max} + T_{min})/2$
4. Compute $min\left\{max\left\{\frac{T-(E_{s,i}+E_{e,i})}{T_t}, 0\right\}, P_{max}\right\}$, $\forall i \in S_c$
5. Compute $R_{t,i} = log_2(1 + \alpha_i P_{t,i})$, $\forall i \in S_c$ and $R_t = \sum_{i \in S_c} R_{t,i}$
6. If $R_t > R_{t,th}$
7. $T_{max} = T$

8. Else (If)

9. $T_{min} = T$

10. End (If)

11. End (While)

4-6 The first proposed method to solve the joint problem.

In section 4-5, it is said that the formulated problem P0 is a combinatorial optimization problem and solving the sensor selection problem and power allocation is complex, the problem P0 was converted into two separate sub-problems. According to classical optimization methods, two initiative algorithms were extracted to obtain the solution of each of the sub-problems. Therefore, to solve the combined problem, it is suggested that with the help of the PSSA algorithm, the appropriate nodes are selected first, then the PPAA power allocation algorithm is used for the selected nodes.

4-7 The second proposed method to solve the joint problem.

The second proposed method to solve the joint allocation problem is to use a multi-layer feedforward neural network. In fact, in this section, an attempt will be made to design a multi-layer feedforward neural network that can be used to find a near-optimal solution for the P0 problem. The reason for using the neural network is to find the optimal answer for the problem of balancing fairness between sensors that with the help of a trained network, it can quickly classify different sensors in two sensing modes and idle mode and optimal allocation of power to them. In the rest of this section, brief explanations about feedforward networks will be provided.

4-7-1 Feedforward Neural Networks

Feedforward neural network (FFN) is a type of neural network that is also called Multi-Layer Perceptron (MLP); In fact, several perceptron layers that are fully connected form a feedforward neural network. A feedforward neural network has an input layer, hidden layers, and an output layer that are connected to each other. These layers are composed of several perceptron or neurons; Figure (4-2), shows a view of this type of network and how the neurons are fully connected.

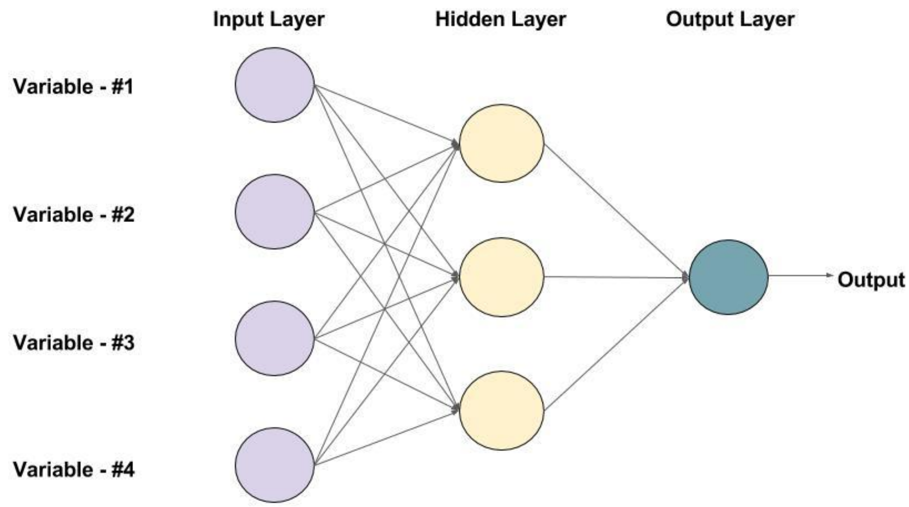

Figure 4-2: An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons) [68]

In a neural network, an artificial neuron is the basic unit of a neural network. As seen in the figure above, the neuron works in two phases: in the first phase, it calculates the weighted sum of the inputs, and then in the second phase, it applies an activation function to normalize this sum. Activation functions can be linear or non-linear. The activation function is used as the center of the decision maker in the output of a neuron. A neuron learns linear or non-linear decision boundaries based on the activation functions. This function also normalizes the output of the neurons to prevent the output of the neuron from becoming too large after multiple layers. The three most used activation functions are: sigmoid, Tanh and ReLU.

The three main layers of the network can be briefly defined as follows:

Input layer: The first layer of a neural network is the input layer. It is used to prepare and enter data or features into the network.

Output layer: The output layer is the layer that provides the results and predictions. The activation function used in this layer is different for different problems. For example, for a binary classification problem, the output should be either 0 or 1. Therefore, a sigmoid activation function is used, and for a multi-class classification problem, a SoftMax activation function (which is a generalized sigmoid for multiple classes) is used.

Hidden layer: A feedforward network applies a series of functions to the input. By having multiple hidden layers, we can compute complex functions with simpler functions one after the other. The selection of hidden units is a very active research field in the field of machine learning. Choosing the type of hidden layer differentiates different types of neural networks such as CNN, RNN, etc. The number of hidden layers is called the depth of the neural network.

In this type of networks, training examples are passed through the network and the output of the network is compared with the real output. The error of this system is used to change the weight of neurons so that the error is gradually reduced. This is done using the Backpropagation algorithm, which is also called Backprop for short. Passing a batch of data through the network and updating the weights, in order to reduce the error, is done with different optimization methods, one of the most famous of which is stochastic gradient descent (SGD).

4-7-2 Designing an FFN to establish fairness in the energy efficiency of sensors.

According to the explanations mentioned above, in this section, an FNN network is proposed so that it can be used to efficiently solve the optimization problem of selecting optimal sensors and allocating P0 power. According to Figure (4-3) in the proposed neural network, 3N neurons are considered in the input layer. whose vectorial vector is represented by $\boldsymbol{v} = [v_1, \dots, v_{3N}]^{\boldsymbol{T}}$. This input vector consists of three vectors of the distance between the sensors and the FC, namely $\boldsymbol{D_m}$, the signal-to-noise ratio of the signal received from the primary network user in each sensor ($\boldsymbol{\Gamma_m}$) and the energy used to sense the spectrum by the sensors ($\boldsymbol{E_{s,m}}$). where m represents the m-th data from the training (or test) data set $\mathcal{M}$={1, 2,...,M}. According to figure (4-3), the output of each neuron can be expressed by the following relationship:

$$y_l^{n_l}(m) = ReLU\left(\sum_{n_l-1} w_{n_{l-1}\to n_l}(m) y_{l-1}^{n_{l-1}}(m) + \theta_l^{n_l}(m)\right)\Bigg) \tag{4-47}$$

where $w_{n_{l-1}\to n_l}(.)$ is the corresponding weight between the n_{l-1}th neuron belonging to the $l-1$ layer to the n_lth neuron belonging to the l layer. Also, $\theta_l^{n_l}(.)$ represents the bias in the output of the n_lth neuron belonging to layer l.

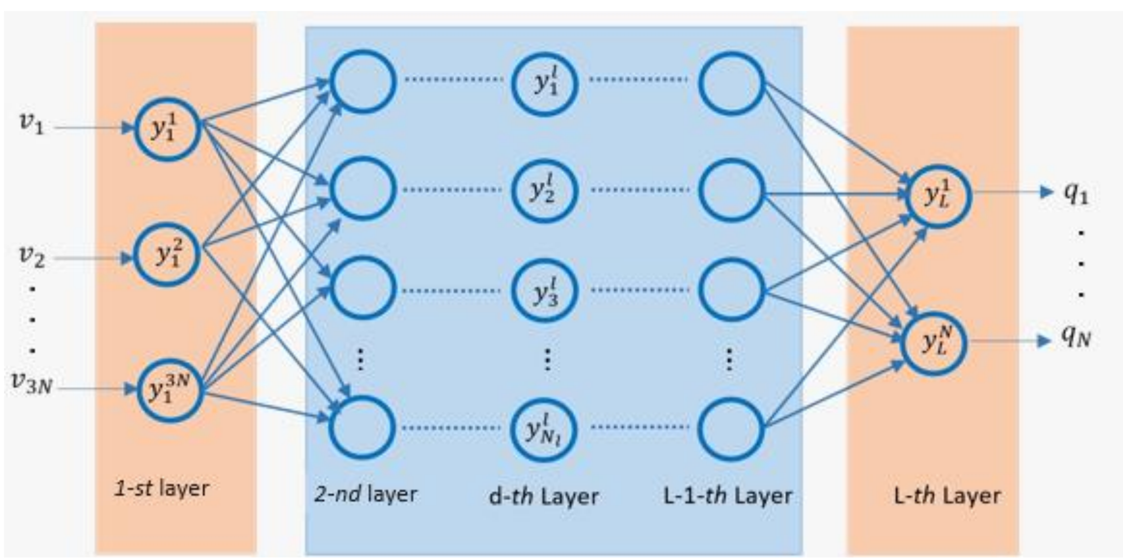

Figure 4-3 Proposed CNN neural network to create fairness
in energy efficiency in spectrum sensing WSN

4-7-3 Method of creating training and test data

In this section, how to create training (or test) data for network training will be discussed. As explained in Section 4.4, the problem of balancing fairness in energy efficiency between sensors is a combinatorial optimization problem. In Combinatorial optimization problems, global optimal solutions for the P0 combinatorial optimization problem can be obtained by exhaustive search methods. For the realization of communication channels, signal-to-noise ratios, and configuration of sensors in the network, for all possible modes of sensor selection, the power allocation problem is solved according to Algorithm 2. In this way, the optimal allocated power is calculated for all possible states. Then, finally, among all the possible states, the state in which the energy consumption of the lowest sensor is minimum is considered as the output of the proposed FNN network in the network. The pseudo-code of the training (or test) data generation algorithm is summarized as follows:

Algorithm 3: Training/Test Data Generation Algorithm
1- For $m \in \mathcal{M} = \{1,2,\dots,M\}$
2- Select set $\{\boldsymbol{D_m}, \boldsymbol{E_{s,m}}, \boldsymbol{\Gamma_m}\}$
3- For $n \in \mathcal{H} = \{1,2,\dots,2^N\}$
4- Select set S_n such that $num(S_n) \leq N_{max}$ where $S_n \subseteq S_{\mathcal{H}}$
5- Calculate optimal $\{P_{t,i}\}$ based on Algorithm 1 under the set S_n.
6- Compute $E_{tot}^{(n)} = \max_{i \in S_n}\{E_{s,i} + E_{t,i}\}$
7- End (For)
8- $n_{opt}^{(m)} = \underset{n \in \mathcal{H}}{argmin}\left\{E_{tot}^{(n)}\right\}$
9- Convert $S_{n_{opt}^{(m)}} \rightarrow \boldsymbol{q}^{(\boldsymbol{m})} = [q_1\ q_2\ \cdots\ q_N]^T$
10- End (For)

In the proposed algorithm above, the set $S_{\mathcal{H}}$ is all the possible modes of selecting sensors in a realization. Also, $num(.)$ is a function that specifies the number of members of each set.

What is proposed in Algorithm 3 is the generation of training and testing data based on exhaustive search, which is definitely very close to the global optimal solution of the P0 problem. But it is possible to generate training and test data based on the proposed method proposed in 4-6. In the fifth chapter, each of these types of data sets will be discussed in detail.

Chapter 5: RESULTS AND DISCUSSION

5-1 Introduction

Today, despite the huge progress in the field of the increasing network capacity (the number of users under the service) and improving the service rate in the new generation communication systems, the lack of spectrum remains a very big challenge in this type of networks. Different methods and approaches have been proposed to solve this challenge, but one of the most important methods to deal with this challenge is the use of radio recognition systems. The most important function of these systems is to identify and reveal spectrum holes. Therefore, the problem of spectrum sensing is one of the most important problems in the field of radio recognition systems. Spectrum sensing with the help of wireless sensor network has been a topic of interest for many researchers since the past. In the last chapter, a wireless sensor network with spectrum sensing capability was investigated, which is used in a radio recognition communication system. In the system model presented in chapter 4, the relationships of the probability of correct detection and the probability of false alarm during spectrum sensing were extracted and analyzed, and then a simple model for the energy consumption of each sensor was presented. In the fourth chapter, the methods and algorithms for allocating resources in a network to create fairness between sensors in terms of energy consumption were discussed. Now, in this chapter, with the help of numerical optimization methods, the proposed algorithms and approaches presented in the fourth chapter are reviewed and evaluated. For a fair comparison, in the first step, the proposed approaches will be compared with conventional approaches in the field of minimizing energy consumption between sensors. In the second step, the proposed algorithms will be compared with numerical methods in terms of complexity and efficiency. Also, to evaluate the FNN network proposed in the fourth chapter, 6 structures with different number of middle layers and number of neurons will be evaluated and analyzed under different optimizers (SGC and Adam) and finally the best structure and the best optimizer for FNN neural networks corresponding to the problem raised in the fourth chapter will be extracted.

5-2 Network specifications

In this section, the characteristics of the network modeled in the numerical simulation will be reviewed. The sensors are distributed in a space of $8m \times 8m$ with uniform distribution throughout this area, and the FC is in the center of this enclosed space. Communication channels have large-scale fading (path loss and shadowing effect) according to the model described in section 4-2, also small-scale fading is modeled as a Rayleigh distribution and assuming a flat channel and slow fading. An optimal detection probability of 0.9 and an optimal false alarm probability of 0.1 are assumed throughout this simulation, unless explicitly stated otherwise. Also, considering that the circuit power consumption in ZigBee is approximately $40\,mW$ [18], the energy consumption for sensing is approximately $190\,nJ$ on average with a tolerance of $\pm 30\,nJ$ for each sensor. The meaning of tolerance is that the energy used to sense the sensors is uniformly randomly distributed in the range $[160\ \ 220]\,nJ$. The processing energy consumption in the electrical circuits related to the signal processing section in the information transmission mode is approximately equal to $80\,nJ$ with a tolerance of $\pm 15\,nJ$ for each sensor. In this simulation, the maximum power sent by each sensor is equal to $10\,mW$ and the power spectrum density of noise is considered the same for all nodes and equal to $-174\,dBm/Hz$. The specifications of the network configuration considered in the simulation are listed in Table 1-5. Finally, it should be mentioned that the number of realizations considered in this research is $N_{iter} = 5000$.

Table 5-1 specifications of the network modeled in the simulation.

Value	Parameter
$190\,nJ \pm 30\,nJ$	$E_{s,i}$
$80\,nJ \pm 15\,nJ$	$E_{e,i}$
$10\,dBmW$	P_{max}

0.9	$P_{d,th}$
0.1	$P_{f,th}$
500 kb/s	$R_{t,th}$
10 μs	T_t
2.4 GHz	f_c
1 MHz	f_s
5000	N_{iter}

5-3 Evaluation of the proposed algorithms

In this section, the proposed algorithms in the fourth chapter will be reviewed and evaluated. In the fourth chapter, two approaches were extracted to obtain optimal solutions. In this chapter, each of these approaches is examined and analyzed, and they are compared with the benchmark methods that are common in this type of networks. According to the two proposed algorithms, PSSA and PPAA, the first approach is called the scheme of sensor selection and joint power allocation (JSSPA). Here, the consideration is that the JSSPA plan is in scheme with the approach followed in [64], which is modified according to the system model presented in this research. For a fair comparison between common benchmark schemes and the proposed JSSPA scheme, Equal Power Allocation (EPA) and Maximum SNR-Sensor Selection (MSNR-SS) are followed. In the following, two benchmark designs, MSNR and EPA, will be explained.

MSNR scheme: MSNR benchmark scheme is a sensor selection scheme to solve the first sub-problem, i.e., problem P1. In this scheme, sensors with the highest signal-to-noise value received from the sensing band are selected as active sensors. According to the limit on the possibility of false alarm, in this plan maximum N_{max} nodes can be selected. It should be noted that in this proposed scheme, since sensors with high SNRs are selected as active nodes, it necessarily satisfies the condition of minimum detection probability. If condition (4-16-1) is not fulfilled in the MSNR-SS scheme, the P0 problem will not be answered for the desired realization.

EPA scheme: The EPA benchmark scheme is a fair power allocation scheme to solve the second sub-problem, i.e., P2 problem. In this plan, assuming that the sensors are active, the same power is allocated to all the sensors. The value of the same power is determined in such a way that the condition (4-16-4) is satisfied.

According to the given explanations, MSNR-EPA, MSNR-PPAA, and PSSA-EPA schemes are compared as benchmark allocation plans to evaluate the proposed JSSPA scheme. As can be seen in Figure 5-1, the proposed JSSPA scheme has better performance compared to other schemes. The reason for this event is that in the MSNR algorithm, sensors are selected based on the priority of detecting better (more) spectrum. Meanwhile, in the PSSA scheme, a cost function is used to select sensors. In this cost function, in addition to considering better detection considerations, energy consumption considerations are also considered. On the other hand, in the EPA algorithm, to balance fairness between all sensors, all sensors are given the same power. It is very important that the same power allocation will not necessarily improve the performance of the weakest sensor in terms of energy consumption. Meanwhile, with the help of the PPAA algorithm, the power allocation to the sensors is done in such a way that the total energy consumption of each sensor, i.e., $E_{s,i} + E_{t,i}$, is equal for all sensors. Considering the significant superiority of both PPAA and PSSA methods over MSNR and EPA benchmark algorithms, it can be expected that the JSSPA scheme will perform better than other schemes in terms of energy consumption of the weakest node. Another very important point that can be seen from Figure 1-5 is that the number of small nodes ($N \leq 20$), the performance of the MNSR-PPAA scheme shows a better performance compared to the PSSA-EPA scheme. The reason for this issue can be found in the fact that when the number of sensors in the network is small, the optimal selection of sensors (using the PSSA algorithm) will face a lower diversity benefit. As a result of this lower diversity gain, the objective function of the P0 problem is improved with a lower gain. Meanwhile, with the optimal power allocation (PPAA), it is possible to overcome the gain obtained from the PSSA algorithm in the number of small sensors. On the contrary, the number of sensors (N≥20), as seen in Figure (5-1), with the increase diversity gain it leads to improve the total energy consumption of each sensor. It should be noted that in Figure (1-5), due to the randomness of the channels and the randomness of the values related to the energy consumed in the sensing process of the sensors, the performance of MNSR-PPAA and MSNR-EPA will be independent of the number of sensors or the size of the network.

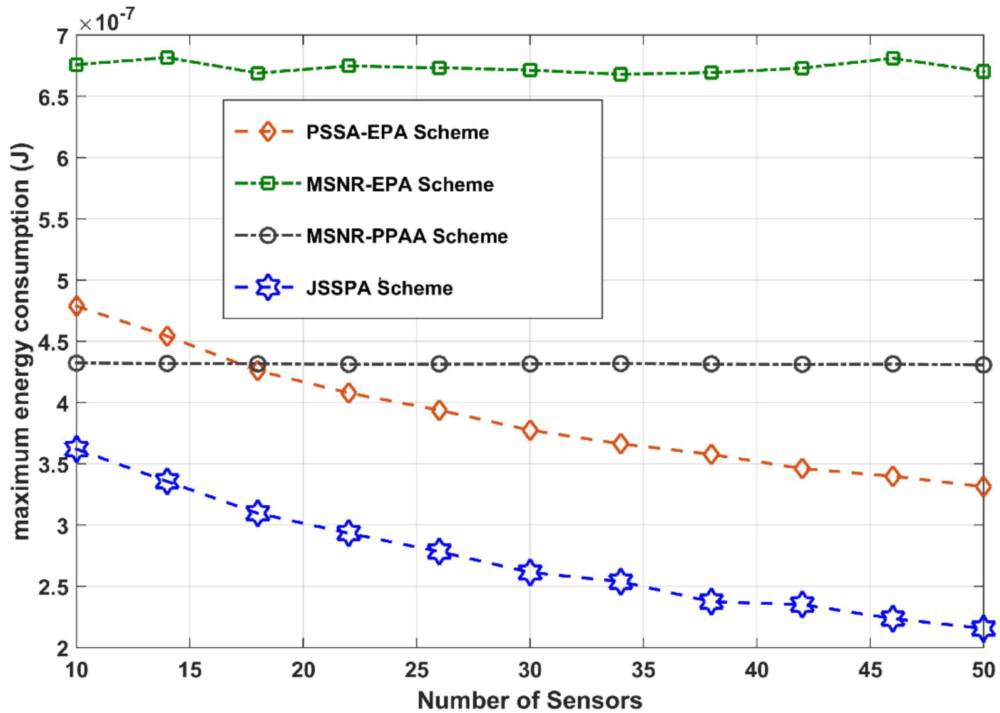

Figure 5-1 Changes in energy consumption according to changes in the number of sensors in different designs

The proposed JSSPA scheme has been evaluated in terms of efficiency with the benchmark algorithms mentioned above. In the following, this algorithm is also compared with the exhaustive search algorithm in terms of efficiency. Figure 5-2 shows the average energy consumption of the weakest sensor for two different network sizes N=10 and N=15 in terms of rate threshold changes for the two algorithms JSSPA and exhaustive search. It should be noted that exhaustive search means an algorithm in which for all the possible modes of sensor selection are solved, the power allocation problem is solved, then the (combined) mode in which the weakest sensor has the minimum energy consumption is extracted as the optimal solution. In Figure 5-2, it can be clearly seen that with the increase of the minimum total optimal rate in the WSN network, the energy consumption increases significantly. The reason for this is that by increasing the threshold rate, more power must be allocated when sending information to users. Another point that can be clearly seen in Figure (2-4), the slope of the graph is high at the beginning and starts to decrease with the increase of the threshold rate, or it seems to approach a saturation value. In fact, the reason for this event is that, as explained, as the rate increases, more power must be allocated to the sensors. But since in (4-25), according to the limitations of the power amplifier, there is a maximum power for power allocation, this power will not be greater than P_{max}. So, for very high rates, practically all sensors are allocated maximum power, so the amount of power consumption does not change much. It should be noted that there is practically no answer in the simulation, for $R_{th} > 2Mbit/s$. In fact, despite allocating the maximum possible power to the sensors, the condition (3-25) is not satisfied.

On the other hand, according to Figure 2-5, for both different network sizes, the JSSPA algorithm is very close to the exhaustive search algorithm, which shows that the algorithms proposed in the fourth chapter can effectively be close to the global optimal solution. Another remarkable thing that is clear in this figure is that for the larger network size, i.e., N=15, the proximity of these two algorithms is more than the situation where the network size is smaller. The reason for this issue should be found in the fact that with the increase in the number of nodes in the network, the diversity of the characteristics of the sensors (state of channels, energy consumption of sensing, energy of electrical circuits) increases, this diversity will have two very important effects: firstly, Increasing diversity allows better sensors to be selected from a larger set than a smaller set (small size network), which reduces the amount of energy consumed in the network. Second, with the increase in the number of sensors, the number of sensors with optimal status increases, as a result, the selection of sensors in the JSSPA method will face less error in choosing the optimal sensor. So, these two methods will be very close. At the end of the explanations related to Figure 2-5, it should be said that in the numerical simulation, the realizations in which the problem is not solved in general have been left out. Also, the brokenness of the graphs is specifically for the graphs related to the exhaustive search, where the number of repetitions was not enough for the purpose of averaging. The reason for this inadequacy is that in the exhaustive search method, all possible modes of sensor selection must be checked, with a large number of iterations, the computational load (runtime) increases significantly, so a smaller number is enough.

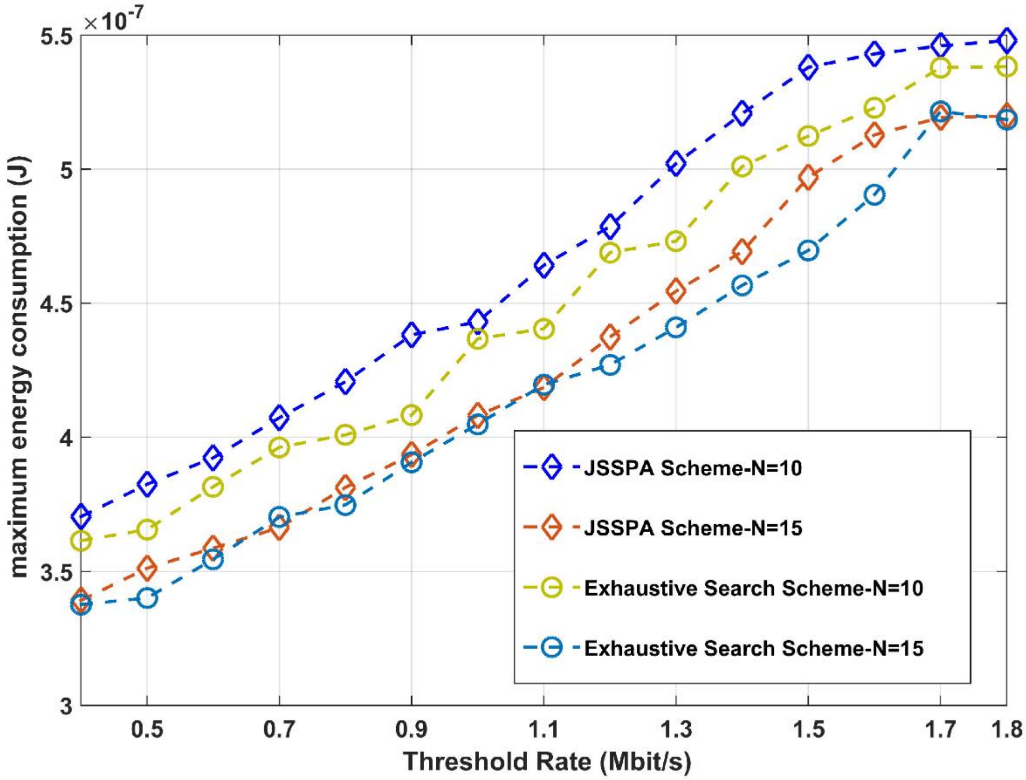

Figure 5-2 Changes in energy consumption according to changes in the threshold of the total network rate in different designs.

In the following, the performance of the neural network designed in section 4-7-2 will be discussed. As mentioned in the section 4-7-1, with the help of proper design of an FNN neural network, it is possible to significantly reduce the energy consumption of the worst sensor by properly classifying the sensors by converting them into two classes of active sensors and passive sensors (Idle). In section 4-7-1, the structure of FNN neural networks was discussed in detail. Each FNN neural network consists of three types of intermediate input and output layers. According to the structure of FNN neural network, different architectures can be made for it. In this research, 6 different types of structure will be made from FNN neural network. 6 types of structures are defined as follows:

Structure 1: $I, H\_1 \ , O$

Structure 2: $I \ H_1 \ H_2 \ H_1 \ O$

Structure 3: $I \ H_1 \ H_2 \ H_4 \ H_2 \ H_1 \ O$

Structure 4: $I \ H_1 \ H_2 \ H_4 \ H_8 \ H_4 \ H_2 \ H_1 \ O$

Structure 5: $I \ H_1 \ H_2 \ H_4 \ H_8 \ H_{16} \ H_8 \ H_4 \ H_2 \ H_1 \ O$

Structure 6: $I \ H_1 \ H_2 \ H_4 \ H_8 \ H_{16} \ H_{32} \ H_{16} \ H_8 \ H_4 \ H_2 \ H_1 \ O$

In the above structure, we represent the input layer, H is the hidden layer, and O is the output layer. The specification table of each layer is given in Table 5-2.

Structure	**Layer ID**	**Layer Type**	**Layer Connection**	**Neuron Number**	**Activation Function**
1	I	Input	FC	$3N$	ReLU
2	H_1	Hidden	FC	$3N$	ReLU
3	H_2	Hidden	FC	$6N$	ReLU
4	H_4	Hidden	FC	$12N$	ReLU
5	H_8	Hidden	FC	$24N$	ReLU
6	H_{16}	Hidden	FC	$48N$	ReLU
7	H_{32}	Hidden	FC	$96N$	ReLU
8	O	Output	FC	N	Binary Step

To evaluate the performance of the designed FNN neural networks, the obtained output vector q (according to Figure 3-4) can be compared with the optimal solution vector obtained from the exhaustive search or the PSSA algorithm. In this research, the $MSE = E\{\|\boldsymbol{q}_\boldsymbol{q}_{opt}\|^2\}$function will be used. In this regard, the expression E{.} is the same as the statistical average and $\|.\|^2$ represents the second vector norm or Euclidean norm. Also, we display the accuracy of the network with the relation $ACC(\%) = \frac{100}{MN}\ \mathbb{I}\{\boldsymbol{q} = \boldsymbol{q}_{opt}\}$.

In Figure 5-3, the average MSE for different proposed structures is plotted in terms of epoch number changes for a WSN network with size N=10 under Adam optimization (adaptive moment). As can be seen in this figure, as expected, as the number of epochs increases, the MSE or the output error rate starts to decrease rapidly with a large slope to reach a saturation value for each of the proposed structures. On the other hand, as can be seen in Figure 5-3, for each of the proposed structures, the error rate has been reduced acceptably. But it is very important that in this simulation structure 1 is the weakest because of its great simplicity. Also, structure 2 performs poorly compared to other structures for the regime of small epochs, i.e., epoch<6. But on the other hand, structure 3 to structure 6 are very close to each other in all epochs. Therefore, to reduce the computational load during neural network training, structure 3 under Adam optimization can be used.

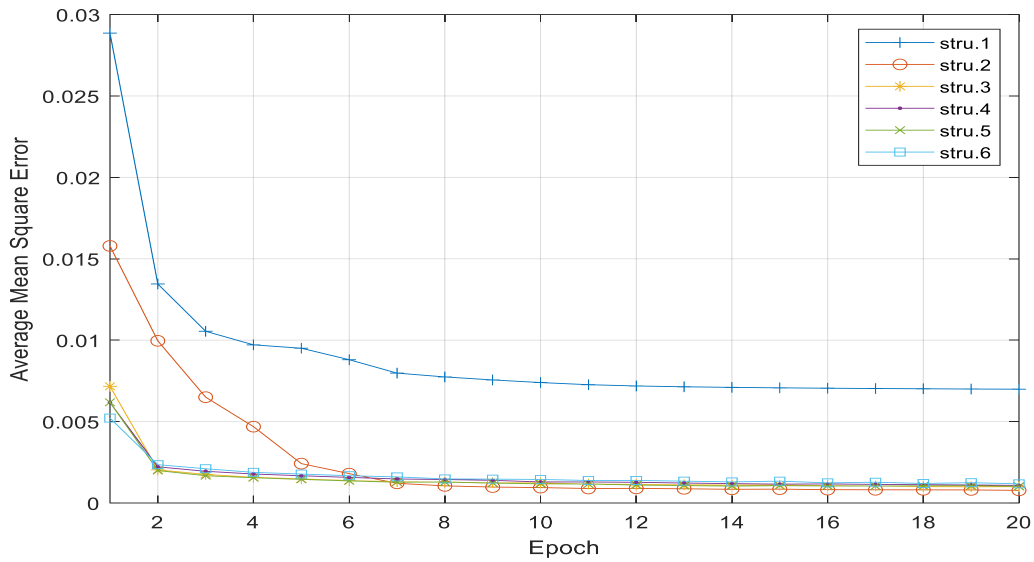

Figure 5-3 Average MSE changes according to changes in the number of epochs with the help of Adam optimization method (adaptive moment)

Similarly, in Figure 4-5, the average MSE for different proposed structures in terms of epoch number changes is simulated for a WSN network with size N=10 under stochastic gradient descent (SGD) optimization. As can be seen, unlike Adam's optimization method, the MSE of different proposed structures under training in SGD optimization method are very different from each other. As can be seen in Figure 4-5, with the increased number of hidden layers and the corresponding number of neurons, the MSE decreases significantly. A very important point that was also mentioned in Figure 3-5 is that structure 1 performs the weakest due to its great simplicity. On the other hand, it can be easily seen that the performance of structure 2 and structure 3 as well as the performance of structure 4 and structure 5 are very close to each other. By comparing structure 4 and structure 5, it is easy to realize that despite the closeness of the efficiency of these two structures, the presence of more complexity in structure 5 does not lead to better performance in all epochs. Therefore, due to the high complexity of structure 6, it is possible to use the neural network with structure 4 under SGD optimization to find optimal sensors.

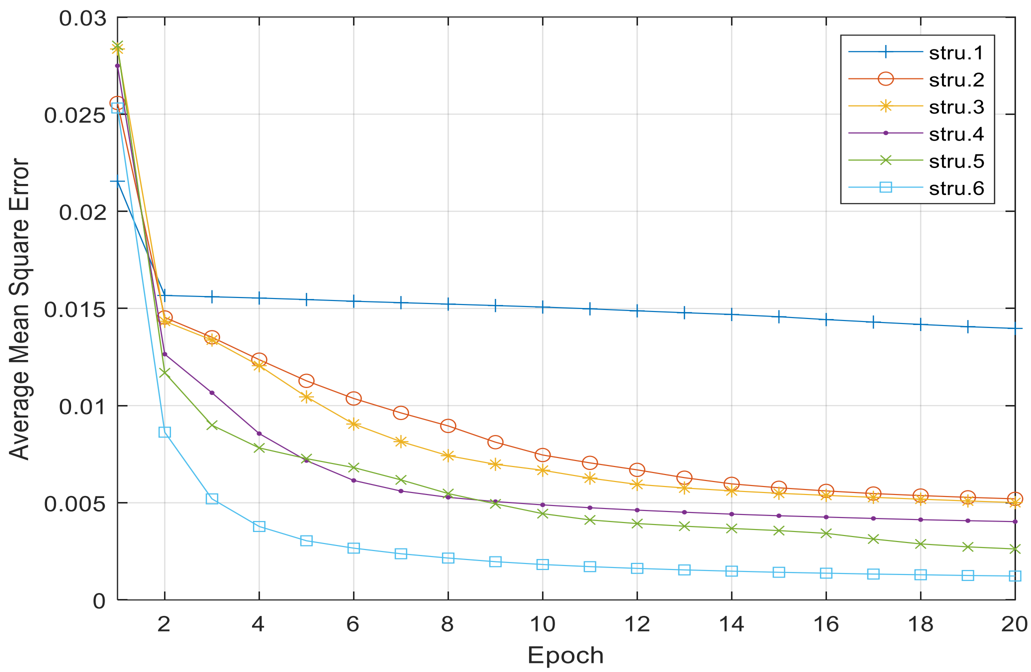

Figure 5-4 Average MSE changes in terms of changes in the number of epochs with the help of the stochastic gradient descent (SGD) optimization method.

According to Figures 5-3 and 5-4, we can conclude that to achieve an FNN network with low complexity and high efficiency, structure 2 under Adam optimizer can be used to classify wireless sensors into active and inactive classes. Idle), benefit. Next, to get a broader view of the obtained results, the MSE diagram for the training and test datasets in terms of epoch changes, for the FNN network with structure 2 and under the Adam optimizer, is examined. As can be seen in Figure 5-5, it is expected that the performance for both training and testing datasets improves significantly as the number of epochs increases. In fact, the MSE is also decreasing for both the training and testing datasets, which means that the overfitting event did not occur. Therefore, with epochs close to 30 in an FNN network with structure 2 and under the Adam optimizer, an error of close to 0.001 can be achieved for both data sets.

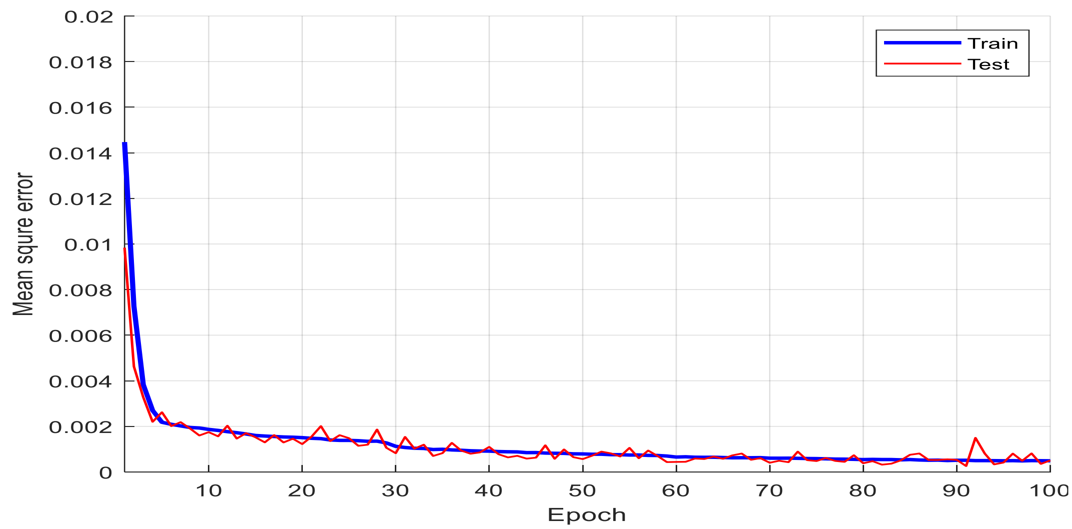

Figure 5-5 MSE for training, validation and testing datasets in each period.

In Figure 5-6, the FNN approach is compared with JSSPA approach. As it can be seen in this figure, as the detection probability threshold increases, the minimum of energy consumption among sensors increases as well. The slope of this increment is higher for small value of detection probability threshold, and for large value of detection probability threshold, the curve converges to a certain value for both schemes. This is because by increasing detection probability threshold, the number of sensors which can satisfy the detection probability constraint is low. Therefore, by reducing the diversity gain of the network, it can be expected that the performance of the network will decrease. On the other hand, we see that output of FNN scheme outperforms JSSPA approach. The reason for this is that during the training of FNN, the training data corresponding to exhaustive search was used. Therefore, we can expect that the output of FNN will be very close to the global optimal solution. Meanwhile, the JSSPA approach is obtained from a number of simplifications and relaxations.

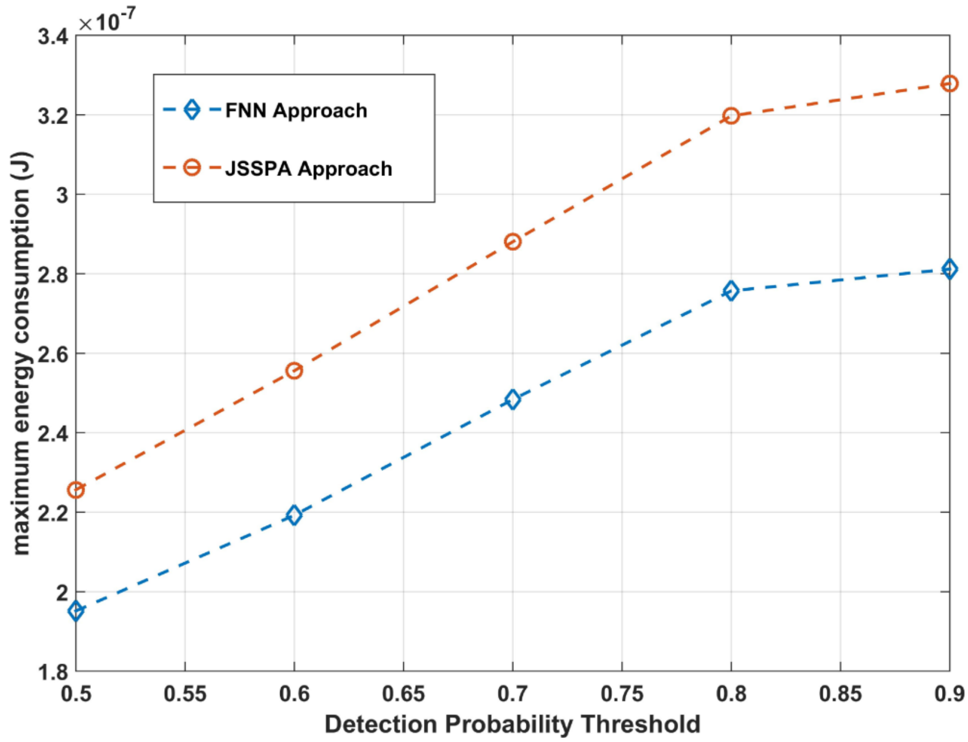

Figure 5-6 changes in energy consumption versus detection probability detection in the JSSPA and FNN approaches

In Figure 5-6, we will review and analyze the two proposed methods according to the first approach and the second approach. In Figure 5-6, the minimum energy consumption between sensors is simulated in terms of network size changes for the two approaches described in chapter 4. As it is clear in the figure, the proposed method corresponding to the first approach has a better performance compared to the second proposed method. The reason for this is that during the training of FNN, the training data corresponding to exhaustive search was used, the output of FNN will be very close to the global optimal solution. In fact, the minimum energy consumption among the sensors, as can be understood in Figure 5-2, is much closer to the global optimal solution compared to the JSSPA method. In addition, it can be seen here that with the increase in the number of sensors, which leads to an increase in diversity in the network, the difference between the first and second approaches decreases, and they approach each other. This is exactly the result discussed in detail below in Figure 5-2.

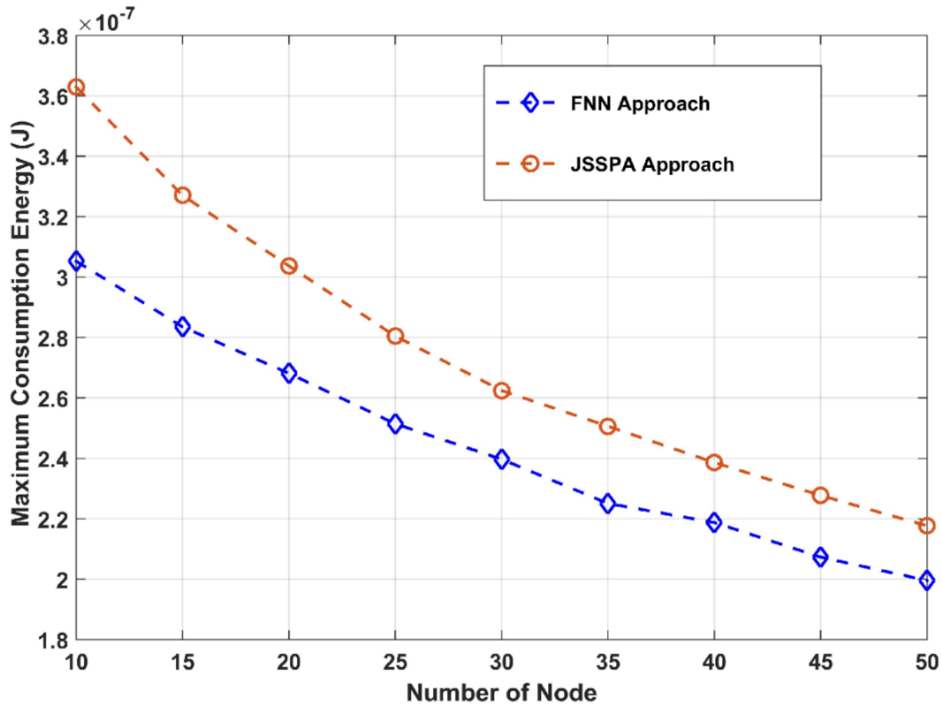

Figure 5-7 changes in energy consumption according to size changes in the first and second approaches

Chapter 6: CONCLUSION AND FUTURE WORK

6-1 Conclusion

In this dissertation, we studied the joint sensor selection and power allocation problem under min-max optimization framework for establishing fair energy efficiency in a cognitive radio system. Since the formulated problem was a non-convex and discrete optimization problem, we converted it to two sub problems: sensor selection (first sub problem) and power allocation (second sub problem). Since obtaining a solution to the first sub problem needs exhaustive search, the first sub problem was relaxed to a classical optimization with continuous optimization variables. Then the relaxed problem was solved by convex optimization methods, which derived a cost function for selecting sensors based on priority. This cost function included the consumption energy in spectrum sensing, consumption energy used to transmit information and local detection probability. Based on the bisection algorithm and the derived cost function, we proposed a heuristic algorithm which selected sensors with high priority. For the second sub problem under active sensors set, we derived the optimality equations based on the convex optimization methods and then we proposed an algorithm with low computational complexity. Now, due to the solutions obtained to sub problems, we presented an iterative algorithm (JSSPA) in order to find solution to the joint problem. In the following, we designed the feedforward neural network (FNN) to solve the formulated problem. The simulation results showed that JSSPA schemes outperform the MSNR-EPA, MSNR-

PPAA, and PSSA-EPA schemes. Although the FNN method has high computational complexity in the training step, FNN method has the performance better than JSSPA.

6-2 Future Work

As seen in the previous chapters, we investigated the resource allocation issue in cognitive radio networks with the aim of providing some fair energy efficient methods. The following can be suggested for the development of our done work and for future work:

1- In this dissertation, we only consider an accessible band, while we can generalize our work to multi band scenario.
2- In some pervious works, three slot time are considered for the system model (sensing duration, reporting duration and information transmission duration), while we have considered only two time slots in our work. Therefore, the information transmission duration in which FC transmits its information in the licensed band can be considered.
3- In this study, OR rule is the rule which is utilized in FC in order to combine information obtained by the active sensors. For future works, we can utilize rules such as AND or K-out-of-N.
4- Resource allocation problems are formulated in our work in order to minimize maximum energy consumption among sensors, while we can formulate resource allocation problems in order to minimize the sum of energy consumption of all sensors.

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