# Energy-Efficient, Learning-Inspired Channel Decision and Access Technique for Cognitive Radio-based Wireless Sensor Networks

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### Abstract

*Cognitive radio-based wireless sensor network is the next-generation sensor network paradigm. Important to this emerging sensor network is the need to reduce energy consumption, paving way for 'green' communication among sensor nodes. Therefore, in this paper, we have proposed an energy-efficient, learning-inspired, adaptive and dynamic channel decision and access technique for cognitive radio-based wireless sensor networks. Using intelligent learning technique based on the previous experience, the cognitive radio-based wireless sensor network agent decides which available channel to access based on the energy-efficiency achievable by transmitting using the channel. From simulation results, we found that as the channel packet availability increases, the energy-efficiency of the channel increase. This lends credence to the fact that the proposed learning-inspired algorithm is significantly energy-efficient for cognitive radio-based wireless sensor networks.*

*Keywords: Energy-Efficient, Packet, Cognitive-Radio, Channel, Learning*

## 1. Introduction

Cognitive radio (CR) technology provides a paradigm shift in the way scarce spectrum bands are being utilized. It is a relatively new area of research in wireless communication that provides efficient utilization of communication channels within the spectrum band. Wireless sensor network (WSN), which operates in the license-free industrial scientific and medical (ISM) band is faced with the problem of spectrum scarcity within this band due to over-crowding of different communication systems within this band. To solve this problem, CR is being proposed for WSN.

Cognitive radio-based wireless sensor network (CRWSN) is currently a hot research area. It is believed to be the next generation of sensor networks. There are lots of prospects of deploying CR functionalities in the traditional WSN. Among others, energy efficiency, efficient channel utilization, reliable packet delivery, latency reductions are some of the prospects of deploying CRWSN. Integrating the CR features into the traditional sensor networks in order to achieve these prospects is the main challenge confronting researchers due to event-driven nature of sensor networks.

There are few works in literatures which focused specifically on energy-efficiency in CRWSN. This is due to the fact that research effort in this area is still relatively new. However, some efforts have been made to look at energy-efficiency in relation to other network parameters in generic cognitive radio network (CRN).

In [1], the authors presented recent developments and open research issues in spectrum management based on CR technology. Specifically, their work focused on the

development of CRN that does not require modification of existing networks. However, this work failed to address issues like energy consumption, coexistence of multiple networks and interference.

As a result of energy constraint in CRWSN, it is imperative to develop a simple, energy-efficient channel decision strategy for CRWSN operating in the ISM band. The authors in [2] proposed a spectrum decision method that utilizes the information about the primary user (PU) as the input to the decision making process. However, the authors did not address the implementation of their methods in both the physical layer (PHY) and the media access control (MAC) layers of the protocol stack. Such implementation will be useful to enhance communication reliability and network continuity.

In a bid to increase communication reliability, authors in [3] proposed a multi-radio architecture for sensor nodes. This was done on the Incident Reporting Information System (IRIS) software platform using IEEE 802.15.4 standard in order to operate with two radios at 900MHz and 2.4MHz frequencies. Even though the results of the experiments showed improved link stability and delivery rate, the radios were used independently. Hence, CR functions were not considered. In other words, this cannot be adapted to CRWSN.

However, in a CRN where multiple channels exist, it is important to determine an order in which the different channels are sensed and accessed. Therefore, authors in [4] proposed a channel sensing order for CR secondary user (SU) in a multi-channel network without prior knowledge of the PU activities. The authors did not consider the inherent problem of energy depletion which is most critical to WSN.

In this paper, we propose an energy-efficient, learning-inspired technique for channel decision and access for SU sensor network. The SU decides and access any available channel by using the intelligent learning approach. Primarily, the CRWSN agent decides and access any available channel based on energy consumption rate, energy efficiency derived based on its previous experience in the channel access, and other network parameters which are discussed later in Sections 4 and 5.

The rest of the paper is organized as follows: in Section 2, we highlight related works. In Section 3, we describe the system model, while in Section 4 we explain the proposed learning-inspired technique. In Section 5, simulation and performance evaluation were discussed. Section 6 is the conclusion. The terms CR agent and CRWSN were used interchangeably and both terms refers to the SU according to our system model in Section 3.

## 2. Related Works

As mentioned above, there are few works in literature that examined dynamic channel access in CRWSN in relation to energy conservation. Different authors have focused on different research areas other than energy efficiency. For instance, in [5], the authors used reinforcement learning (RL) to search dynamically the optimal sensing order. However, their method is not adaptable to CRWSN. Computational complexities involved in this method make deployment in low power, battery-driven and less complex CRWSN impossible. The work in [6] proposed optimal sensing and access mechanisms, but not specifically adaptable to sensor networks for the same reason as observed with [5]. In [7], sensing time and PU activities were used to maximize the SU throughput and to keep the probability of collision below certain threshold. Nothing in terms of energy-efficiency was done and no decision strategy was applied in this work. The authors in [8] considered joint source and channel sensing as parameters on which energy-efficiency was based. However, there was no channel decision approach used for channel access. Therefore, energy consumption due to channel decision cannot be determined. Hence, the level of energy efficiency cannot be ascertained.

Furthermore, in [9], the authors tried to depict a typical CR scenario and proposed a new hardware structure of sensor nodes. They went further to analyze the critical issues involved in cognitive cycle in allusion to CRWSN, and suggested possible solutions as well. However, neither experimental work nor simulation was carried out to justify the suggested solutions. But, efforts in this work were considered heuristic to future research. Similarly, authors in [10] investigated the structure of traditional WSN, CR and dynamic spectrum access (DSA) technique. They presented a concept of CRWSN, and proposed new network topology and cross-layer architecture for CRWSN. They further discussed advantages and limitations of CR-based WSN. The efforts made in [10] were purely review without any preliminary results to prove the workability of their proposed idea, especially with specific focus on energy-efficiency of their proposed network architecture.

Opportunistic spectrum access (OSA) strategy for CRN under interference and energy consumption constraints was proposed by authors in [11]. The authors considered a single SU with a single PU. This is not practicable in real-life situation. However, the authors were able to show a relationship between the sensing time, channel utilization, interference and energy consumption due to transmission. The authors also did not consider energy consumption due to other CR functions such as channel switching and channel decision.

Optimal packet size for data communication in energy constrained WSN was considered by authors in [12]. Energy efficiency was chosen as the optimization metric in this work. The authors proposed the use of fixed packet size due to limited resources in WSN. The optimal fixed packet size was determined for a set of radio and channel parameters by maximizing the energy-efficiency metric. This work mainly considered traditional WSN. The roles of energy consumption due to CR functions were not considered in this work. Hence, the energy efficiency metric will have to be modified to cater for CR operation in CRWSN.

The authors in [13] presented the energy-efficient packet size optimization problem for CRWSN with consideration for interference level for PU and maximum allowed distortion between event signal and its estimation at sink. The authors also considered the effect of the PU behavior in the channel in relation to the energy-efficient optimal packet size. While the authors focused on optimal packet size using energy-efficiency metric, other network parameters such as throughput, data rates and link delay were not considered.

Using the PHY backbone parameters, the authors in [14] proposed various energy-efficient approaches to protocol and algorithm design for WSN. The authors showed how hooks and knobs in the PHY can be used to build energy-efficient protocols and algorithms. Though, the authors achieved excellent results under the traditional WSN, but their approaches is not directly adaptable to CRWSN. For the purpose of energy-efficiency in CRWSN, the PHY has to be modified to incorporate the CR functions. This is a key factor [14] did not consider. Cooperative sensing was the focus of the work in [15]. The authors attempted to jointly optimize sensing time and number of cooperating nodes in order to protect the PU's interest.

While attempts have been made in literatures to study energy-efficiency in CRN, little is being done in the area of energy-efficient decision strategy for channel access in CRWSN as mentioned earlier. Therefore, in our work, we focus on the use of RL strategy as a form of intelligent learning to achieve simple, energy-efficient decision for channel access in CRWSN. The justification for our approach-RL is that, RL affords the possibility of future action being determined based on the experience of the past action. In other words, the SU learn and decides its next action based on the previous experience during it last action in a channel. This experience is acquired based on the condition of the last channel visited.

## 3.  CRWSN Model and Operation

Channel access in a multichannel sensor network, better quality of service, throughput enhancement, energy efficiency and latency reduction are core operation requirements of CRWSN. However, due to the resource-constrained nature of the traditional sensor network, and the complexity of spectrum sensing in CR, integrating both CR and WSN pose great challenges. In this section, we will look at the conceptual model design and operation framework for our CRWSN. Possible network model, system architecture, hardware structure were also examined.

### 4.1 CRWSN Network Scenario

As illustrated in Figure 1, CRWSN scenario is made up of a licensed PU and unlicensed SU within the same spectrum band made up of different channels. CRWSN is a distributed network of sensor nodes, which sense an event signal and collaboratively communicate their readings dynamically over available channel in a multi-hop manner in order to satisfy the specific application requirements of the network. Most WSN applications use the IEEE 802.15.4 standard and operates in the unlicensed ISM band. This is due to flexibility and low cost of operating within this band. However, in recent time, the unlicensed band has become crowded with other wireless networks such as wireless local area networks (WLANs), wireless body area networks (WBANs) and worldwide interoperability for microwave access (WiMAX) operating within this band. This leads to the building of CRWSN in order to solve the problems associated with coexistence of multiple networks in the unlicensed spectrum band.
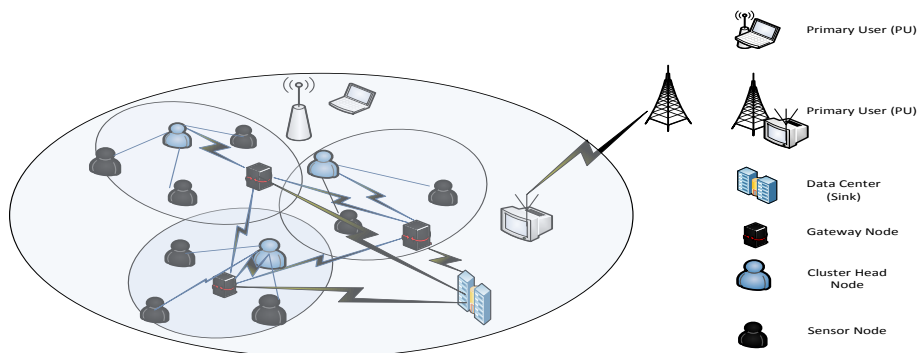


**Figure 1. CRWSN Network Scenario**

The low channel utilization among the licensed band users leaves a large amount of resources for WSN to serve traffic with strict quality of service requirements. Without having to access dedicated licensed spectrum, it is possible to build WSN with a low cost. There is little restriction on the air interfaces, coverage area and network topology.

### 4.2 CRWSN Architecture

The CRWSN hardware is typically composed of the power unit, sensing unit, processing unit, the CR platform and the radio frequency (RF) unit. This is shown in Figure 2. Location finding and mobilizer units are added based on the application specifics. CRWSN is different from the traditional WSN basically with the presence of the CR engine. The cognitive engine enables the CRWSN to dynamically adapt their communication parameters.

As promising as this hardware architecture is in terms of DSA for sensor nodes, there are noticeable challenges possed to a resource-constrained WSN. Constraint such as power, low complexity, communication and memory are faced by WSN. As a result of

these limitations, the CR capability is also affected. However, this architecture is adapted to energy-efficient channel access for CRWSN using our learning-inspired technique.
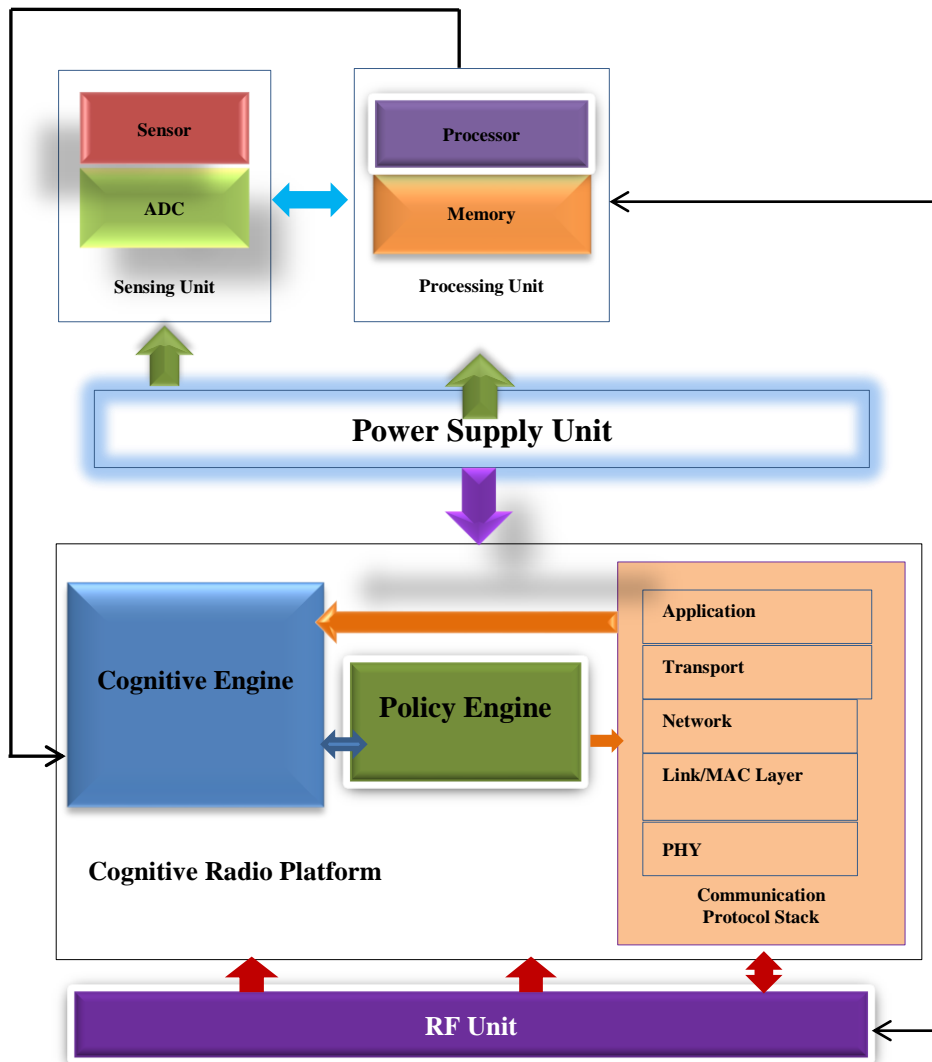


**Figure 2. CRWSN Architecture**

## 5. Energy-efficient Learning-inspired Channel Decision and Access Algorithm

This algorithm is aimed at finding optimal policy (state-action pair) which maximizes the long term expected reward. In this case, the state-action pair refers to the channel access with long term reward of energy efficiency. The policy, $\pi^i(s,a)$ is the decision making rule for selecting an action from a set of actions $a \in A$ when learning agent is in state $s \in S$ at a given time $t$. In this case, the actions are, channel sensing, transmission and channel switching. The state refers to the available channel and the time is the decision instance.

$Q_t^i(s,a)$ is the RL Q-value, which describes the probability of an action taken. It is calculated from reward earned for performing the action. It also specifies the benefits of selecting an action. $V_t^i(s)$ is the state value function (used to estimate future reward). That is, the channel condition metric. It shows how good the channel is. The channel

availability parameter $\left(Av^i(s)\right)$ is the measure of how reliable the state value $V_t^i(s)$ are (*i.e.*, a measure of the availability of a channel). This is updated when sensing action takes place.
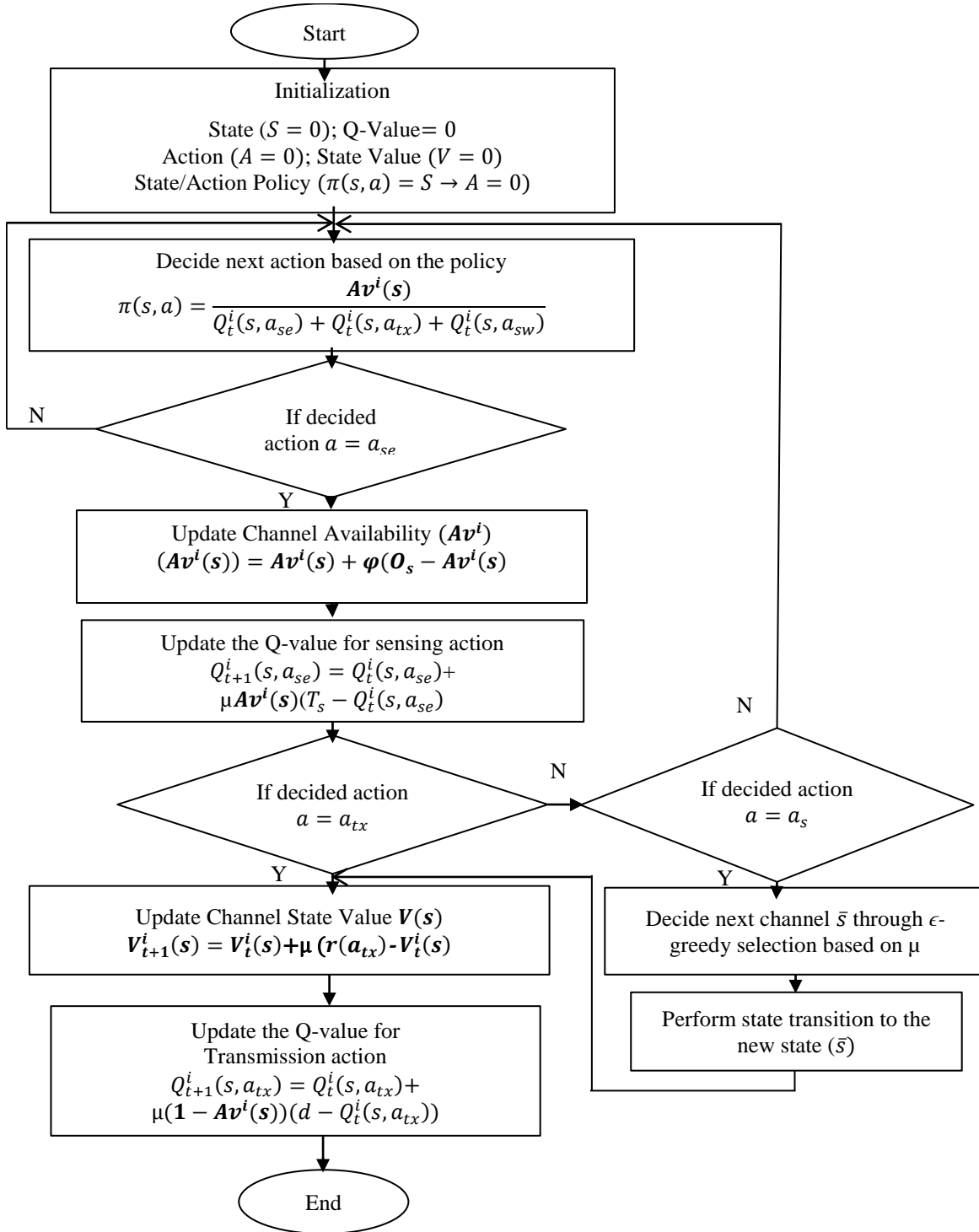


**Figure 3. Energy-efficient, Learning-inspired Channel Access Algorithm**

Given $C$ number of channels, the absolute number of possible states $|s| = C$. At a given decision time, a cluster head $CH_i$ performs one of the following actions; channel

sensing $a_{se}$, transmit packets $a_{tx}$, or switch channel $a_{sw}$ to a preferred available channel. The reward from each action is a function of time taken for the energy consumed to complete the action. The more the time and energy consumed, the lesser the reward.

In order to calculate the reward, each time there is packet transmission, the corresponding reward function for transmission action $(a_{tx})$ is given as;

$$r(a_{tx}) = \begin{cases} D_{max} - successful\ transmission \\ 0 \quad\quad loss\ of\ transmission \end{cases} \tag{1}$$

$D_{max}$ is the maximum allowable time for data transmission on the wireless link. That is, the maximum transmission time slot of the SU. This depends on the PU activity and maximum allowable interference $I_{max}$ of the PU network. $d$ is the time taken for successful packet transmission by the SU to be completed before the arrival of the PU.

The value of $V_t^i(s)$ gives the long term reward for $CH_i$ to use a channel $s$ at the transmission time. The value of $V_t^i(s)$ is updated after each $a_{tx}$ according to the following equation;

$$V_{t+1}^i(s) = V_t^i(s) + \mu\big(r(a_{tx}) - V_t^i(s)\big) \tag{2}$$

μ is RL parameter for controlling the learning rate and channel decision by scaling earned reward $r(a_{tx})$. From our previous work in [16], the value of μ is determined as,

$$\mu = \frac{k_a(L)}{k_a(L) + k_b R}(1 - BER)^L \tag{3}$$

In (3), the energy efficiency is described as a long term reward for transmitting packets in a given channel. This energy efficiency is a function of the bit error rate (BER) of the channel and packet size $L$, data rate R, and energy consumption during CR functions of the SU. $V_t^i(s)$ depend on the link delay to transmit packet successfully in the channel state $s$ also. From [16], the PU probability of ON $P_{ON}$ has been determined. Therefore, we obtain the maximum allowable interference between the PU and SU as determined by the PU as,

$$I_{max} \geq \frac{L}{R}P_{ON} \tag{4}$$

The policy $\pi^i(s, a)$ describes how the next action is chosen given an existing probability distribution over the three possible actions $(A)$. The higher the rate of PU activity on a channel, the more the variation of state value for $CH_i$. The channel availability parameter is updated as;

$$\big(Av^i(s)\big) = Av^i(s) + \varphi\big(O_s - Av^i(s)\big) \tag{5}$$

$O_s$ is the probability of sensing outcome action. This probability distribution is given as, $0 \leq O_s \leq 1$. When the channel is not available for transmission, $O_s = 1$. $\varphi$ is learning discount factor given each time the sensing outcome shows that PU is not present in the channel.

The Q-value is updated based on the $Av^i(s)$ and the $V_t^i(s)$. For each selected action there is an associated Q-value update method. For sensing action with $T_s$ as the sensing time, the Q-value is updated as,

$$Q_{t+1}^i(s, a_{se}) = Q_t^i(s, a_{se}) + \mu Av^i(s)\big(T_s - Q_t^i(s, a_{se})\big) \tag{6}$$

For Transmission, the Q-value is updated as,

$$Q_{t+1}^i(s, a_{tx}) = Q_t^i(s, a_{tx}) + \mu\big(1 - Av^i(s)(d - Q_t^i(s, a_{tx})\big) \tag{7}$$

We determine $d$ within the range $0 \leq d \leq D_{max}$.
For switching action, the Q-value is given as,

$$Q_{t+1}^i(s, a_{sw}) = max_{1 \leq \bar{s} \leq C}^i (V(\bar{s}) - V(s) - \theta) \tag{8}$$

$\theta$ is defined as the threshold value for channel access time. This accounts for the cost of switching from one channel to another. This parameter is also used to control the frequency of switching. The term $\bar{s}$ is another channel with lower access delay $t_h$, higher packet reliability, and availability, with efficient energy consumption. This is determined by the use of greedy probability, that is, a channel which maximizes (8). Greedy probability is a factor which decides the tradeoff between sensing (exploration) and access (exploitation) action. That is, how to decide on the new channel in the case of channel switching action.

The soft-max action selection rule is used for the action selection policy. This is determined based on (6), (7), and (8). The decision making process is therefore given as,

$$\pi(s, a) = \frac{Av^i(s)}{Q_t^i(s, a_{se}) + Q_t^i(s, a_{tx}) + Q_t^i(s, a_{sw})} \tag{9}$$

## 6. Simulation and Results Analysis

To demonstrate the effectiveness of the proposed algorithm, we carried out extensive simulation using MATLAB-based iterative tools based on the parameters introduced in the algorithm. We obtained some interesting results to prove the applicability of the proposed algorithm. Table 1 summarizes the simulation parameters. These parameters were set according to our previous work in [16] and other works in [8, 13, 14]. Few other parameters were introduced based on the network model and algorithm design as explained in subsections 3.1 and section 4.

**Table 1. Simulation Parameters**

| Parameter | Description | Value |
|-----------|-------------|-------|
| BW | Channel Bandwidth | 1MHz |
| ISM-Band | Operating frequency Band | 2.4GHz |
| λ | Energy Detection Threshold | 5 |
| $d_{SU-PU}$ | Distance between PU and SU | 50m |
| $d_{SU-SU}$ | Distance between SU and SU | 10, 15, 35, 55 (m) |
| R | Data rate | 40-100 (kbps) |
| δ | Path loss component | 2.5 |
| $P_{ON}$ | Probability of Channel busy | 0.8, 0.5, 0.25, 0.1 |
| $N_o$ | Noise Power | $1.38 \times 10^{-22}$ |
| $PU_p$ | PU Transmission Power | 10dB |
| $I_m$ | Maximum Interference Ratio | 0.1 |
| $\sigma_n^2$ | Noise Variance | 1 |
| $\sigma_s^2$ | PU signal variance | 1 |

From Figure 4, we can clearly see an almost linear relationship between the energy consumption rates during transmit and receive of packet and the packet size. This is expected because, as the packet size increases, the amount of energy consumption during packet transmission will also increase in a certain manner. It is also interesting to know that there is a similar trend in this variation for different data rates. However, at lower data rate, the rate of energy consumption for a unit packet transmission is higher than at higher data rates.

In Figure 5, our simulation showed that, as the packet availability increases, the energy efficiency of the transmitted packet increases. Packets available for transmission in a channel will improve the energy efficiency of packet transmission in that particular

channel. We noticed from the simulation also that the distance between SU transmitting nodes plays important role in the energy efficiency. This is shown in Figure 5 as well.

Figure 6 essentially shows how the energy efficiency of the CRWSN is affected by the BER. This effect was examined under different data rates. From our simulation, we noticed a sharp rise in the energy efficiency up to a peak of 0.8 (*i.e.,* 80%) when the BER is at all-time lowest value of $9 \times 10^{-4}$. As the BER increase, it was observed that the energy efficiency either remains constant or starts a downward decline in value. This, we found to be true and we conclude that, there is a maximum allowable BER of an available channel for transmission by the CRWSN above which the energy efficiency of the CRWSN will begin to decline. There is also a noticeable similar trend at different data rate.

In order to investigate the role of PU within the channel as it affects the energy efficiency of the SU packet transmission, Figure 7 shows how varying ON probability of a channel and ON duration affects the PU interference. It could be observed that as the ON duration of the PU in the channel increases under the circumstance that the CRWSN transmit in the same channel for the same duration, the interference noticed by the PU also increase. We noticed that when the probability of ON is high ($P_{ON}$=0.8), the interference becomes higher. But for a very low PU probability of ON in the channel, ($P_{ON}$=0.1), the interference to PU is significantly low. From a logical reasoning, this is so because, at a low ON probability, it suggests that the PU is not likely to be available within the channel. If the PU is absent, the SU occupying the channel exerts no interference because the PU is absent.
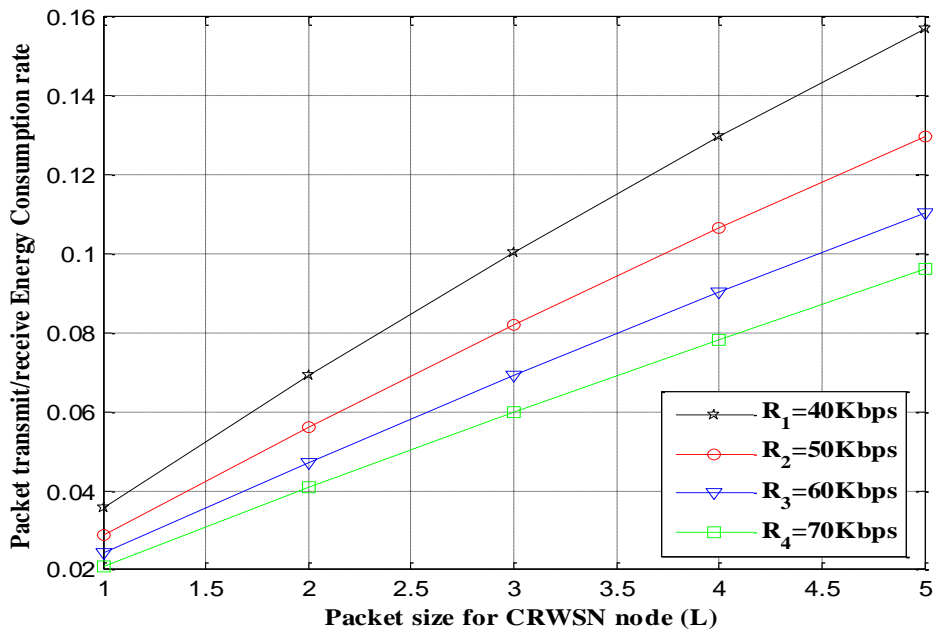


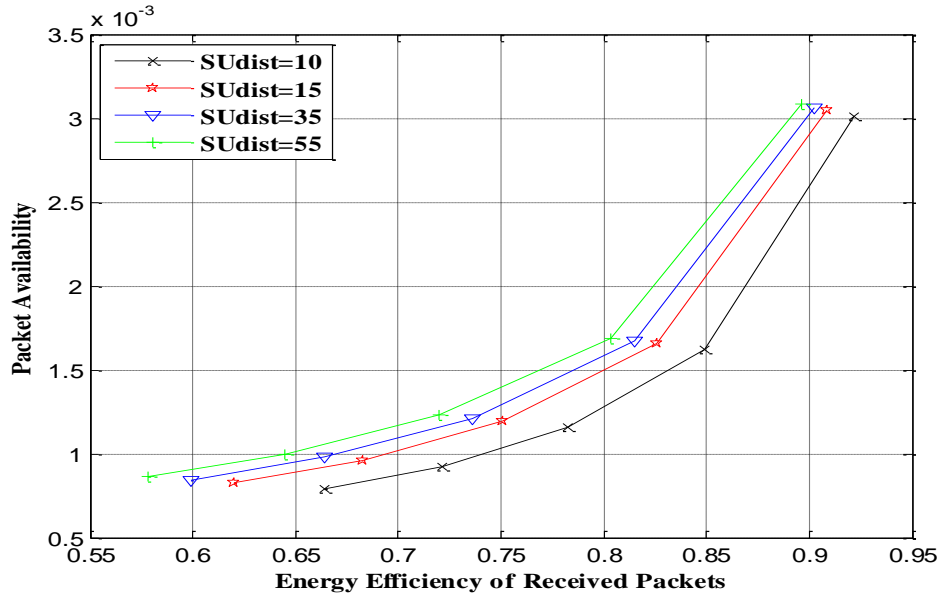**Figure 4. Energy Consumption Rate with Packet Size at Different Data Rates**

**Figure 5. Variation of Packet Availability and Received Packet Energy Efficiency with Varying Distance between Communicating SU Nodes**
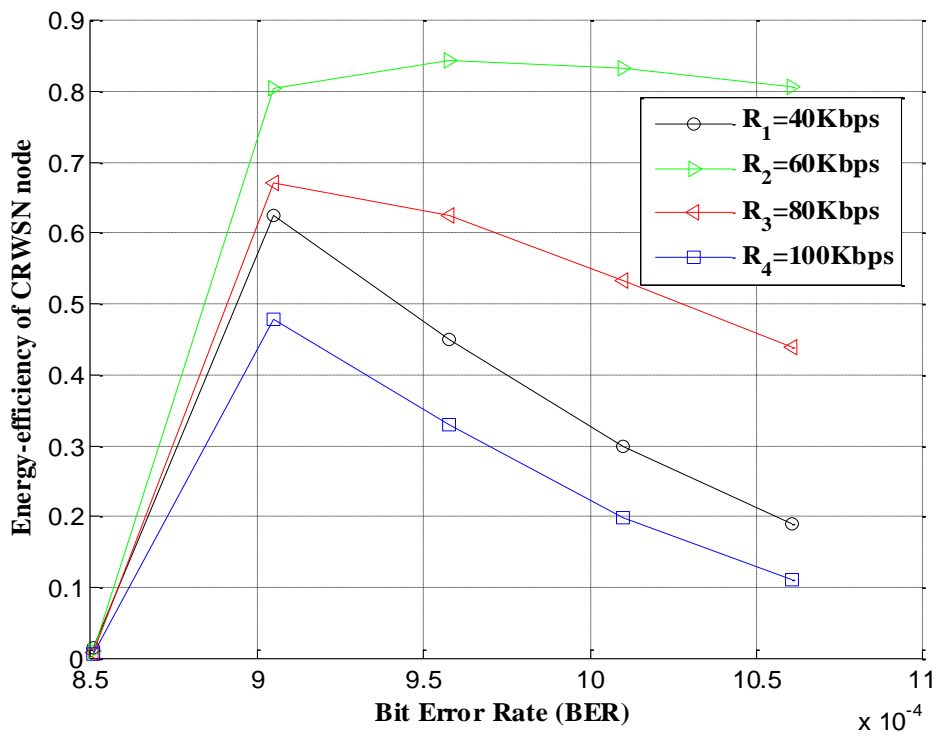


**Figure 6. Energy Efficiency of CRWSN Versus BER for Different Data Rates**
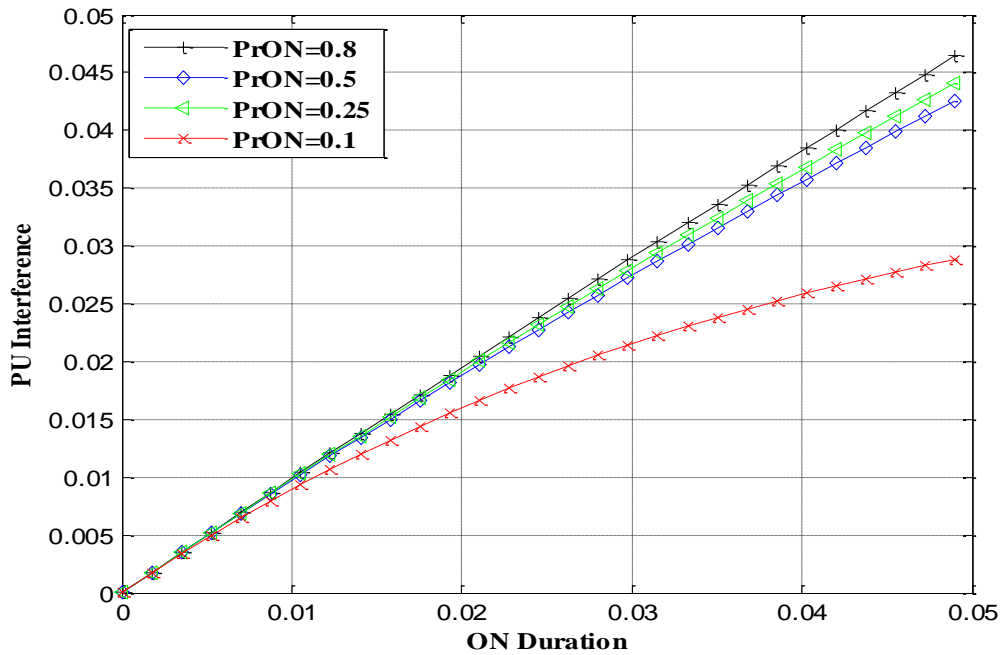
**Figure 7. PU Interference Variation with ON Duration for Varying Probability of ON**

## 7. Conclusion

In this paper, we propose an energy-efficient, learning-inspired technique for channel decision and access for CRWSN using intelligent learning approach based on the previous experience. We have used different parameters in our simulation based on our algorithm. Primarily, our CRWSN agent decides and access any available channel based on energy consumption rate and energy efficiency achievable by transmitting using the channel. From the results obtained, we can conclude that our learning inspired algorithm is significantly energy efficient for CRWSN.

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