An Energy Aware Routing for Cognitive Radio Wireless Sensor Network using $Fuzzy_Q$

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Abstract: ***Currently, the wireless communication technology has noticed explosive expansion in its demand and it is increasing rapidly whereasdue to their wide range of applications and uses, Wireless Sensor Networks (WSNs) have attracted the attentions of the academic community in various offline and online applications. These networks are deployed in the unattended and harsh environment due to which maintaining the network lifetime becomes a challenging task. The energy consumption in these networks is a challenging task which needs to be addressed for increased network lifetime. Moreover, the conventional wireless communication standards are utilizing the radio spectrum. Currently, the spectrum is very limited and excessive exploitation creating overburdening on the network. Thus efficient spectrum allocation is also becoming a tedious task. Nowadays, Cognitive Radio (CR) has appeared to be a viable way out to efficiently utilize the available spectrum. According to this CR concept, cognitive radio technology helps to opportunistically and dynamically access the spectrum bands which improve the utilization of radio spectrum resources.Several techniques have been presented to deal with the issue but these techniques suffer from various issues such as uncertain energy harvesting and resource (channel) allocation which becomes a critical issue for these networks. To overcome these problems, the workproposes a novel approachcalled $Fuzzy_Q$-EACWSNR (an energy aware cognitive wireless sensor network routing) scheme which minimizes the energy consumption by using reinforcement based Q-learning scheme for packet forwarding in cognitive enabled wireless sensor nodes.This novel scheme considers the optimal cluster formulation, cluster head selection, spectrum sensing and allocation.The experimental study reported thenoteworthy improvement in the communication performance by evaluating and comparing the performance with EACRP, ESAC andOptimum distance based clustering in terms of network throughput, average packet delay, and energy consumption.***

Keywords: Cognitive Radio, Wireless Sensor Network, Energy Aware Routing, Spectrum Sensing

1. Introduction

A steep rise in the requirement for high speed communication in 4G and 5G wireless networks has been fuelled by the growth of wireless applications. Also, the wireless sensor networks have attracted the research community because of their miscellaneous usage in various real-time online and offlinecommunication systems [1]. Generally, these networks are positioned in harsh and unattended environment conditionswhere the sensor nodes perform the event based communication by accessing the channel. Currently, these networks are widely adopted to monitor sensitive and vital activities. Moreover, these networks are deployed in a region where replacing the power sources is a challenging task thus maintaining the network lifetime is a challenging task [2].

Contemporary wireless communication systems are using the radio spectrum for communication. The spectrum is a limited resource and its scarcity is increasing rapidly. An increased demand for wireless communication based application has led towards increased number of requests for sufficient spectrum allocation for seamless communication [3]. The frequency channel bands are occupied by the primary users (PUs) remains underutilized. Recently, the Federal Communication Commission (FCC) presented a report where it concluded that some of the frequency bands of PU remains unutilized or underutilized which creates the problem of spectrum hole or white spaces. Similarly, the conventional unlicensed spectrum considers the industrial–scientific–medical (ISM) for communication [4]. However, due to excessive use of this communication bands, the ISM bands have become overcrowded with several different types of applications such as WiMax, Bluetooth, Wi-Fi, etc. thus adding more number of wireless communication applications becomes an overburden for these bands. In order to deal with these issues and improving the spectrum utilization researchers have suggested to facilitate the opportunistic spectrum access to unlicensed users. Due to this facility, unlicensed users can access the available spectrum holes. These unlicensed users are known as secondary users, who usesan unoccupied frequency band of PUs.

Thus, addressing the scarcity problem of spectrum resources has become the challenging issue. Based on these assumptions of spectrum access, the CRis consideredasa best solution for efficient utilization of the wireless spectrum. The cognitive radio technology helps to opportunistically and dynamically access the spectrum bands which improves the utilization of radio spectrum resources [5]. Cognitive radio technology is considered as an advanced process used in communication where it performs continuous upgradation via learning, reasoning, insight, planning and its working. CR is able to detect a vacant spectrum in both licenced and unlicensed frequency bands and is able tohave an opportunistic accessibility in the vacant spectrum zones [6]. According to the concept of CR, the primary user is privileged to utilize the spectrum all the time, whereas the secondary user can only have the accessibility of the spectrum when the primary user isn't using the available spectrum. The notion of combining CR and WSN technology could be of help in solving a number of issues in existing WSNs. Spectrum inefficiency, a large number of sensor nodes, high transmit power, a wide coverage area, and widespread implementation of WSNs can all considerably reduce their efficiencywhile being operated in overlapping frequency bands. CR-WSN is a new communication paradigm where sensor nodes are enabled with the cognitive capacity. With the help of the cognitive capacity, these networks are able to perform the spectrum sensing operation along with the data exchange. The communication between these sensor nodes is performed in a multi-hop manner by considering the vacant spectrum bands. These sensor nodes are different from the conventional WSN nodes due to the presence of RF unit. Below given figure 1 depicts the illustration of CR-WSN.

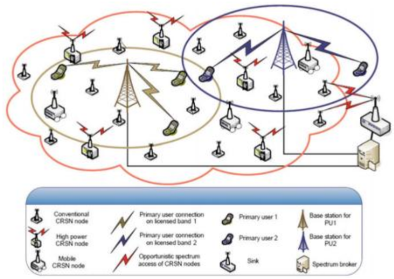

Figure 1: Cognitive wireless sensor network

Furthermore, coexistence interferences cause inefficient communication methods in WSNs [7]. Several techniques have been presented in this context of CR enabled WSN such as Wu et al. [7] discussed the spectrum allocation for cognitive WSN, Suguna et al. [8] presented a hybrid scheme by using an amalgamation of energy detection and cyclostationary approaches which are performed in time domain scenarios. Moreover, a Low Latency Column Bit Compressed (LLCBC) MAC algorithm is also presented to design the application oriented integrated circuit using VLSI. Mukherjee et al. [9] used a cognitive WSN scheme where authors considered the secondary users and evaluated its communication behaviour to obtain the dynamic correlation by using the cooperative communication scheme. It eliminates the repetitive and uneven communication between secondary users. Thus, this method analyses the time-varying spectrum sensing characteristics of numerous SUs using Gaussian copula theory and an enhanced particle swarm optimization scheme.Moreover, below given table 1 depicts the comparative analysis of CR enabled WSN and traditional WSNs.

Table 1: Comparison between Cognitive WSN and traditional WSN

Parameters	CWSN	WSN
Frequency Band	Licensed and ISM	Only ISM band
Energy consumption	Low	High
Accuracy	High	Low
Delay	Low	High
Spectrum hole utilization	Yes	No
Memory	High	Limited
Computational capability	Moderate	high

Currently, the necessity of these communication systems is increasing rapidly thus several challenging arise due to network overhead, power consumption, reliability and quality of service related issues. These issues need to be addressed for improvement the overall communication performance. Thus, in this article, we present a novel scheme for cognitive WSN called EACWSNR, which uses reinforcement learning based approach to mitigate the performance related shortcomings in the wireless network. The main contributions of this work can be listed as follows:

- Presenting the cluster formation and cluster head selection strategy for cognitive enabled WSN
- Incorporating fuzzing logic based approach to estimate the link quality by considering residual energy, vacant spectrum or spectrum availability and received signal strength
- Incorporating the Q-learning based approach to select the optimal path with minimum delay and best quality link between node.

The remaining sections of the manuscript is structuredas, section II presents the literature about present standard techniques, section III elaborates the proposed $\boldsymbol{Fuzzy_Q}$ scheme for cognitive wireless sensor networks, including clustering and routing scheme for CRNs, and section IV presents the comparative analysis to show the significance of $\boldsymbol{Fuzzy_Q}$approach, section V presents the concluding remarks.

2. Literature Survey

This section outlines the brief overview of conventional techniques which are based on the amalgamation of cognitive radio and wireless sensor networks. The previous section has elaborated the significance of a cognitive radio network in real-time online and offline applications such as MIMO cognitive radio systems [10], which has focused on dealing with the scarcity of an electromagnetic spectrum. To achieve the higher spectral efficiency and throughput, it uses underlay and interweave CR schemes. This hybrid scheme uses narrowband and wideband technology corresponding to interference threshold limit. During communication, if PU is present, then CR-SU exchanges the data by using a narrowband scheme of MC-DS–CDMA scheme based on the transmission selection algorithm. On the other hand, if PU is not present in the network then SUs use interweave communication technique.

Prajapat et al. [11] concentrated on combined energy and spectrum efficient solutions in the field of Internet of Things (IoT). However, a dynamic spectrum access technique based schemes have presented some promising solutions to overcome the spectrum scarcity issues, but these techniques do not provide the solution for energy-efficient communication system requirements. Thus, authors introduced a combination of neighbour discovery algorithm and two greedy k-hop clustering algorithm for IoT applications where intra-cluster and inter-cluster communication is required. This scheme considers several clustering parameters such as spectrum awareness, residual energy, appearance of primary users, channel quality, robustness of PUs and Euclidean distance between nodes which are considered for communication. Stephan et al. [12] used this concept of clustering scheme and presented artificial intelligence based energy and spectrum aware cluster based routing protocol. However, the existing clustering schemes do not consider the CR functionalities and challenges. To overcome these issues, authors developed spectrum and energy aware clustering routing protocol to improve the performance of CRSN. Clusters are formed based on the residual energy of secondary user and relative spectrum awareness. This scheme performs energy efficient channel sensing by deciding the channel states based on previous channels. Tripathi et al. [13] focused on adaptive transmission strategies to improve the performance of the cognitive radio sensor network. Authors developed a new scheme to find the optimum distance for data packet transmission in intracluster and inter-cluster communication. These communicating nodes are arranged in the form of adaptive clusters with respect to the total number of packets in the cluster. Moreover, it considers the primary and secondary user activity to evaluate the residual time of unused licensed channels. This scheme is based on finding the optimal distance identification and cognitive optimal data forwarding scheme through energy efficient communication paths. Jyothi et al. [14] focused on improving the network lifetime by incorporating energy saving mechanism. In order to achieve this, authors presented an enhancedspectrum-aware routing scheme where authors described the problem of packet drop due to unavailability of the spectrum and buffer overflow which affects the connectivity of nodes. In order to overcome these issues authors presented a new routing scheme named as, drop factor based energy efficient routing technique. This evaluates the drop ratio and energy consumption of spectrum links. Similarly, Carieet al. [15] also introduced a routing scheme for cognitive radio networks to deal with interference related issues and presented interference aware AODV routing protocol. This issue is addressed by presenting an opportunistic routing protocol. Srividhya et al. [16] reported that efficient utilization of spectrum, appropriate routing technique, and minimizing the data collision are considered as the primary tasks for any cognitive enabled WSN. To achieve this, authors presented an energy aware distance based clustering scheme which uses multi-hop communication model. This distance parameter is used to evaluate and divided the region and allocate the spectrum to the divided region. Liu et al. [17] discussed that problem of spectrum management in WSNand suggested that the use of CRN to improve communication performance. To achieve this, authors introduced a delay sensitive opportunistic pipeline routing protocolwhich considers nodes outside from the outside of man forwarding path which is used to transfer the data opportunistically whenever the transmission fails.

Zheng et al. [18] developed stability-aware cluster-based routing (SACR) routing approach for CRSNs. The main novelty of this approach is the combination of opportunistic routing with a stable clustering mechanism. The cluster formation considers spectrum dynamics and energy consumption in the clustering scheme. According to Deng et al. [19] energy harvesting also can be considered as a promising solution to minimize the energy consumption in the network. Moreover, cognitive radio scheme helps to alleviate the congestion problem in the unlicensed spectrum. Generally, primary users suffer from the issue of uncertain energy harvesting, and resource allocation which becomes a critical issue for these networks. In order to overcome from it, authors proposed a new Q-learning approach for channel selection. Further, resource management and allocation is handled by the Lyapunov optimization scheme.

3. Method-Proposed model

In previous section I and II we have discussed about the use of cognitive radio-WSN, and its challenges in various applications. Mainly, these nodes are placed in a harsh environment with a limited battery capacity where replacement of power sources becomes a tedious task, thus network lifetime becomes a challenging issue. The poor network lifetime also affects the network throughput and other performance related issues. To deal with these issues, we present a novel approach called $\boldsymbol{Fuzzy_Q}$by using reinforcement based Q-learning scheme for packet forwarding in cognitive enabled wireless sensor nodes. The proposed $\boldsymbol{Fuzzy_Q}$ approach is implemented by using modules mentioned below:

1) Presenting the energy consumption modules.
2) Presenting the optimal cluster formation, CH selection.
3) Presenting the routing scheme and packet forwarding scheme to minimize the energy consumption.

The appropriate cluster formation helps to maintain stability to the communication links in the network which ensures the continuous packet delivery. The spectrum sensing and allocation scheme helps to improve the spectrum utilization. Finally, the routing scheme helps to minimize the energy consumption to prolong the network lifetime.

3.1. Energy consumption modelling

Here, we create a network scenario where sensor nodes and cognitive nodes are deployed randomly in a 2D geographical region. We consider that n sensor nodes are deployed in a 2D geographical region and total m channels are present in the network. The sensor node which is located at far point from the sink uses multi-hop routing technique to forward the data. Some of these nodes are licensed nodes and other remaining nodes are considered to be the unlicensed nodes i.e. primary users (PU) and secondary users (SU), respectively. The energy consumption of this network depends on the packet transmission and receiving the incoming packets by various nodes. Below given figure 1 depicts the energy consumption in radios.

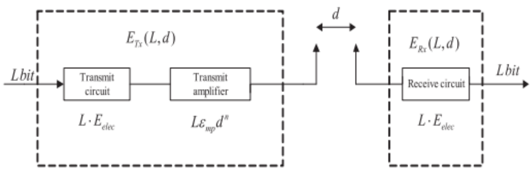

Figure 1: Energy consumption in radios

During data transmission, the transmitter mode requires some specific amount energy to operate the electronics and power amplifiers whereas receiving mode in the network require different amount of energy to run the radio

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electronics. The overall energy consumption is divided into "free propagation" and "multipath fading" modes of data transmission. The "free propagation" energy consumption mode is applied when the transmission distance is less than the d_0 where the transmitting power is attenuated by d^2, d is the distance between transmitter node and receiver node. Similarly, if the transmission distance is greater than the d_0 then "multi-path fading" model is applied. In free space, the signal is attenuated by d^2 whereas in multipath fading the signal is attenuated by d^4. Thus, in order to deliver the L bit data, the energy required by transmitter circuit or module can be expressed as:

$$E_{Tx}(L,d) = \begin{cases} L\,E_{elec} + L_{\varepsilon_{fs}} d^2 & d < d_0 \\ L\,E_{elec} + L_{\varepsilon_{mp}} d^4 & d \geq d_0 \end{cases} \quad (1)$$

Where E_{elec} represents the electronic energy parameters, ϵ_{fs} is the amplification factor of free-space model and ϵ_{mp} is the amplification factor for multipath fading model and d_0 denotes the threshold distance which is represented as $d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}}$. Similarly, the required amount ofpower to receive the L bit data is expressed as:

$$E_{Rx} = L.E_{elec} \quad (2)$$

Thus, the total energy consumption can be estimated by energy consumed by transmitter and receiver module. For simplicity, we do not consider the other energy consumption parameters such leakage power, idle power consumption etc.

3.2. Optimal number of cluster

In this section, we present the clustering scheme for primary and secondary users. In this type of multi-hop hierarchal approaches, we generally select a cluster head where sensed data is sent to their corresponding cluster head and then it forwarded to the sink node. During the communication initialization phase, nodes starts transmitting the "Hello" packet to its neighbouring nodes where it contains several information such as node ID, residual energy of node, spectrum availability information hop count and location of node. Below given figure 2 depicts the cluster model of two clusters where communication between cluster, PU and SU is depicted.

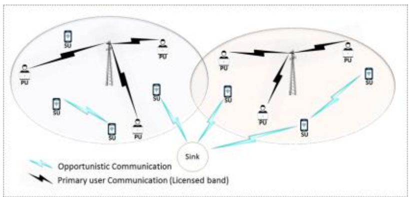

Figure 2: Illustration of clustering.

This model also uses multi-hop clustering and if the node is located at a far place and distance between transmitter and receiver is more than d_0 then it consumes extra energy. The energy consumption of CH in one communication round can be expressed as:

$$\begin{aligned} E_{CH} = ML_1.E_{elec} + NL_2.E_{elec} + ML_1.E_{DA} \\ + E_{sense} \\ + L_3.E_{elec} + L_3.\epsilon_{fs}.d_{toNEXT}^2 + L_4.E_{elec} \\ + L_2.E_{elec} + L_2.\epsilon_{fs}.d_{toNEXT}^2 \end{aligned} \quad (3)$$

Where M denotes the average count of sensor nodes in the cluster, L_1 is the size of data which is sensed by the sensor nodes, N denotes the average number of non-cluster head in the cluster, and L_2 denotes the size of detected results by cognitive nodes, E_{DA} shows the average energy consumption for data aggregation, d_{toNext} is the distance between cluster member and its corresponding cluster head, E_{sense}denotes the average energy consumption by cognitive nodes to detect the channels. L_3represents the average of data which is transmitted by CH in the considered specific time duration and L_4represents the average of data which is by the relay CHs while performing the multi-hop communication.

Other than these nodes, we also consider the sensor nodes and non-CH cognitive nodes. These nodes also participate in communication thus we consider the energy consumption by these nodes. The energy consumed by a sensor node in one round can be computed as follows:

$$E_{SN} = L_1.E_{elec} + L_1.d_{toCH}^2 + L_2.E_{elec} \quad (4)$$

Similarly, the energy consumption by non-CH cognitive node can be computed by consideringL_2 and sensing enegy consumption criteria. This can be represented as:

$$E_{non-CH} = 2.E_{elec} + L_2.\epsilon_{fs} + L_2.E_{elec} \quad (5)$$

Let us consider that n is the ratio of cognitive nodes in total number of nodes in the deployed region, p denotes the final optimal number of cluster head, thus, average number of sensor node in each cluster is determined by $\frac{K(1-n)}{p}$ and the total non-Cognitive nodes in the cluster can be represented as $\left(K.\frac{n}{p}\right) - 1$. Thus, the total energy in one round can be computed as follows:

$$E_{cluster} = \frac{K(1-n)}{p}.E_{SN} + \left(K.\frac{n}{p}\right) - 1 \times E_{non-CH\ CN} \quad (6)$$

In this scenario, we consider a sensor nodes follow the random and uniform distribution during deployment phase, thus the energy consumption can be rewritten as:

$$\begin{aligned} E[d_{toCH}^2] &= \iint (x^2+y^2)\rho(x,y)dxdy \\ &= \iint r^2\rho(r,\theta)rdrd\theta \\ &= \rho\int_{\theta=0}^{2\pi}\int_{r=0}^{\sqrt{S/\pi p}} r^3 drd\theta \\ &= \frac{\rho S^2}{2\pi p^2} = \frac{S}{2\pi p} = \frac{H^2}{2\pi p} \end{aligned} \quad (7)$$

Where $\rho(x,y) = \frac{1}{\frac{S}{q}}$ denotes the distribution of nodes, S is the deployment area and $S = H^2$ is considered due to the square region. The average distance for next hop can be computed as:

$$d_{toNext} = 2\sqrt{\frac{S}{\pi p}} = \frac{2H}{\sqrt{\pi p}} \quad (8)$$

Here, we assume H is the deployment width, thus the maximum number of nodes from the sink node which is located at a far position, can be computed as:

$$l_{tr}^{max} = \frac{H}{d_{toNext}} = \frac{\sqrt{\pi p}}{2} \quad (9)$$

Further, the average transmission time to transmit the data packet can be computed as follows:

$$l_{tr}^{avg} = \frac{l_{tr}^{max} + 1}{2} \quad (10)$$

Here, we assume that the redundant data is aggregated by cluster head and it is fused in the fixed-size packet. Thus, this data is considered as total data sensed by the sensor node, and presented as L_1. Based on this the average amount of data which is transmitted by CH is computed as follows:

$$L_3 = l_{tr}^{avg}.L_1 \quad (11)$$

Based on the count of maximum number of hops from the cluster head to sink node, the average and maximum number of relay time can be obtained as:

$$l_{relay}^{max} = l_{tx}^{max} - 1 \quad (12)$$

Similarly, the L_4 can be expressed as$L_4 = l_{relay}^{max}.L_1$. The total energy consumption in the network for one round can be denoted as

$$E_{round} = p.E_{cluster} \quad (13)$$

Finally, by applying the partial derivation on the concave function, we can obtain the optimal number of clusters in the considered network. This can be presented as:

$$p_{opt} = \left[\left(\frac{(2H^2K\epsilon_{fs}(L_1(1-m)+mL_2)}{3\pi^{\frac{3}{2}}L_1E_{elec}}\right)^{\frac{2}{5}}\right] \quad (1$$

In the case of decimal number, we perform rounding operations to obtain the appropriate values.

3.3. Cluster head selection and cluster formation

The CH selection is a process where we identify the best suitable node which can be selected as cluster head to prolong the network lifetime by considering multiple aspects. The conventional schemes only consider the residual energy which is not an efficient criterion for CH selection in the CRSN scenario. However, some techniques consider the number of vacant channel for CH selection without considering the energy criteria. To overcome these issues, we present a model which considers higher residual energy and vacant channels to present the energy efficient and a spectrum aware CH selection process.

In the initial phase, each node computes its probability to be the cluster head based on the initial energies. The existing schemes consider both residual and initial energy parameters which increases the computational load on the network which consumes extra energy. The probability of becoming CH is computed based on the channel availability in a reigon R. This probability can be expressed as:

$$P_i = K\left(\frac{c_i}{\sum_{k=1}^{N} c_k} * \frac{E_0(i)}{\bar{E}_0}\right) \quad (15)$$

The obtained probability value helps to obtain the final clusters. In the deployed network.

3.4. Energy aware routing using Q-learning scheme

In this approach, we formulate various clusters and select the cluster head based on the higher residual energy and vacant spectrum. However, we assume that the information of vacant spectrum is available at each node of cluster. In this type of scenarios where node energy and spectrum availability in the spectrum is varying according to the simulation time duration, the communication link between sensor nodes also varies thus maintaining the reliable link between sensor nodes is a challenging task. In order deal with this issue, we present the Q-learning algorithm which is a self-learning technique and applied to obtain the shortest path dynamically from source node to destination node. In order to achieve this, we present fuzzy logic based link quality estimation technique and later, Q-learning based approach for data transmission.

3.4.1. Fuzzy logic algorithm

The learning performance, slow updating, slow learning and adaptation of topology change has the significant impact on the network performance. The existing schemes suffer from these issues due to which the learning and routing algorithms are not able to adapt the frequent topology changes during the communication. To overcome this issue, we introduce the link reliability estimation module using fuzzy logic to improve the learning process of the network. The proposed fuzzy logic considers three Fuzzy membership functions which are: residual energy, vacant spectrum or spectrum availability and received signal strength. The fuzzy system is depicted in below given figure 4.

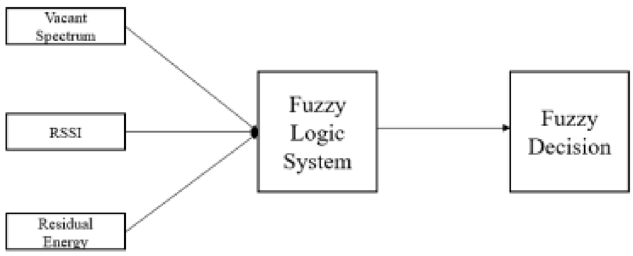

Figure 4: Fuzzy logic based link quality estimation

- Vacant spectrum: as mentioned before that each node has its own spectrum information which is dynamically updated during each round of communication. For simplicity, we do not apply spectrum sensing scheme at this stage.
- RSSI: it denotes the strength of signal which being transmitted from node x to node v, measured at receiver end node v. The higher value of RSSI denotes that the closeness of node and it has the high chances of node being selected as next hop. The RSSI helps to improve the packet delivery and mitigates the issues of retransmission.
- Residual energy: this shows the energy level of node while computing the link quality between node. Lower value of residual energy increases the cost of link estimation whereas the high residual energy helps to obtain the best suitable solution for selection of next hop.

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3.4.2. Reinforcement learning algorithm

Generally, the RL algorithm deals with the optimal control problems where it interacts with the environment and learns the conditions to control the system. The Q learning algorithm is considered as a type of model-free reinforcement learning which contains an agent, various of states S and their corresponding actions A. In this process, the sensor node performs the action as $a \in A$ thus it transitions from one state to another state. The agent node which is in state s interacts with the environment and performs the specific action a to obtain the information about environment. Based on this action, it achieves a reward value as $r(s,a)$. The main goal of any agent to maximize the reward value according to the considered scenario. A general process of reinforcement learning for state, action and reward is depicted in below given figure 3.

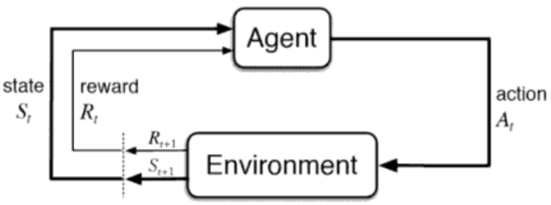

Figure 3: Q learning scheme

We consider some basic components of this scheme. The learning environment includes the entire network for the agent where each data packet is regarded as an interacting agent denoted by $P(o,d)$, all sensor nodes are denoted as in the network are considered as packet state spaces. The one hop neighbour nodes in the network are assigned as action sets. During the packet transmission phase when next hop receives the packet, it indicates the state change of packet. The immediate reward of any action is denoted by R. The initial reward value is expressed as:

$$R = \begin{cases} 1, if\ d \in N_d \\ 0, otherwise \end{cases} \quad (16)$$

Here, d denotes the distance between two nodes, if the next hop is the sink node then the packets are directly transmitted to the sink node and value of R is obtained as 1.

The Q-value is updated continuously by exchanging the data packets between the communicating nodes. In this algorithm the entire network is considered as learning space thus learning algorithm quickly converges to the obtain the optimal solution. The Q-learning algorithm maximizes the reward by continuously updating the Q-table [21] which is expressed as:

$$Q_s(d,x) \leftarrow (1-\alpha)Q_s(d,x) + \alpha\left\{R + \gamma \max_{y\in\tau(x)} Q_s(d,y)\right\} \quad (17)$$

Where $Q_s(d,x)$ denotes the Q-value of node which transmit the packet from x to destination node d, α denotes the learning rate , and γ represents the discount factor during learning process, R is the reward, τ is the group of neighbour node of x and $\max_{y\in\tau(x)} Q_s(d,y)$ is the maximum value of Q from node x to d

In order to transmit the data packet from any node to next hop with the maximum Q-value, the action set is defined as:

$$a = \begin{cases} \arg max_{y\in\tau}[Q_s(d,y) + \epsilon H_s(d,y) + \delta E_s(d,y)], if\ q \leq \\ a_{randomly}, \quad otherwise \end{cases}$$

Where $Q_s(d,x)$ characterize the Q-value, $H_s(d,x)$ denotes the Heuristic function which stimulates the current optimal action if it increases the Qvalue, $E_s(d,y)$ is the evaluation function which evaluates the success of the current action, $a_{randomly}$ denotes that if any action, or reward values are not obtained then it considers random data transmission from one node to another node and then it evaluates the reward for data transmission, ϵ denotes the weight factor which influence the heuristic function, δ is used to evaluate the impact of heuristic evaluation function, p denotes the selection of node probability for next hop based on the Q values, and q is considered as a threshold value for assigning the cluster probability.

In order to select the next hop, we consider the delay value to reach the packet from transmitter node to destination node, this delay is computed as:

$$\mathbb{D}(s,d,x) = \sum_{n=x}^{d-1} T(n,n+1) \quad (19)$$

This delay value is calculated from one hop to next hop until the destination node is reached. Based on this, the optimal action set is assigned to the path which requires less amount of time, thus, the action set can be expressed as:

$$a_{opt} = \min_{x\in\tau(x)} \mathbb{D}(s,d,x) \quad (20)$$

This minimized delay helps to minimize the energy consumption and reward mechanism along with link quality estimation improves the packet delivery.

4. Results and discussion

This section presents the experimental investigation by using $\boldsymbol{Fuzzy_Q}$scheme and compared the attained efficiency outcomes with existing schemes. The $\boldsymbol{Fuzzy_Q}$approach is implemented by using MATLAB 2020b simulation tool. The obtained outcome of the proposed $\boldsymbol{Fuzzy_Q}$approach is compared with existing techniques such as EACRP [20], ESAC [13], and optimum distance based clustering [13]. For this simulation scenario we consider that sensor nodes are deployed randomly in a 2 dimensional geographical region. Below given table 2 presents the simulation parameters used in the experiment.

Table 2: Simulation Parameters

Simulation Parameter	Value
Network dimension	1000mX1000m
Number of Primary Users in CWSN	2-10
Number of Secondary Users in CWSN	30-100
Data packet size	512 byte
Range of PUs	500 m
Initial energy of node	50J
Communication channel bandwidth	2 Mbps
e_{Elec}	50nJ/bit
e_{amp}	100 pJ/bit/m^2

Based on these parameters, we measure the end-to end delay performance where we have considered varied number of

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primary users. The obtained delay performance is depicted in below given figure 3.

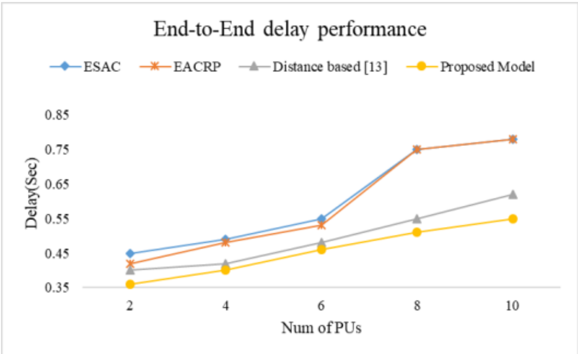

Figure 3: End-to-end delay for different number PUs

In this experiment, we illustrate that as the number of primary users are increasing the average end-to-end delay also surgesbecause of multiple steps performed before delivering the packet to the destination node. Thus, it shows that the low PU density has the less density. In this experiment, the average delay performance for this experiment is attained as 0.604s, 0.592s, 0.494s, and 0.456 by using ESAC, EACRP, Distance based [13] approach and $\boldsymbol{Fuzzy_Q}$technique, respectively. The obtained values are presented in below given table 2.

Table 2: End-to-End delay (in secs) for varied number of primary users(PU)

Number of PUs	ESAC	EACRP	Distance based [13]	$\boldsymbol{Fuzzy_Q}$
2	0.45	0.42	0.4	0.36
4	0.49	0.48	0.42	0.4
6	0.55	0.53	0.48	0.46
8	0.75	0.75	0.55	0.51
10	0.78	0.78	0.62	0.55
Avg	0.604	0.592	0.494	0.456

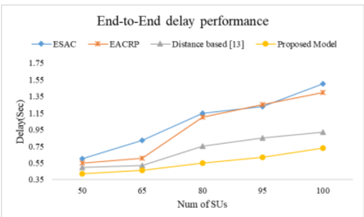

Figure 4: End-to-end delay performance for varied number of secondary users

Figure 4 illustrates the overall analysis of proposed and existing schemes based on end-to-end delay for varied no. of secondary users. Similar to previous experiment, in this experiment the secondary user density affects the communication delay performance i.e. increment in density increases the delay in the packet delivery. However, the proposed approach has significant packet delivery scheme thus it delivers packets efficiently. Below given table 3 shows the end-to-end delay performance for varied no. of SUs.

Table 3: Delay Performance for diverse number of SUs

Number of PUs	ESAC	EACRP	Distance based [13]	EACWSNR
50	0.6	0.55	0.5	0.42
65	0.82	0.61	0.52	0.46
80	1.15	1.1	0.75	0.55
95	1.23	1.25	0.85	0.62
100	1.5	1.4	0.92	0.73
Avg.	1.06	0.982	0.708	0.556

For similar experimental setup, we measure the average energy consumption performance. The achievedoutcome for this experiment is depicted in below given figure 5

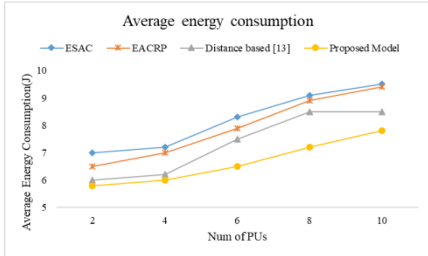

Figure 5: Average energy consumption for varied PUs

According to this experiment, we obtained the average energy consumption for varied no. of PUs as 8.22J, 7.94J, 7.34J and 6.66J by using ESAC, EACRP, distance based technique [13] and Proposed Model, respectively. Results depict that the average energy consumption is affected due to the delay. More delay in packet delivery leads to increase in energy consumption. The obtained values for energy consumption are presented in below given table 6.

Table 6: Average energy consumption

Number of PUs	ESAC	EACRP	Distance based [13]	EACWSNR
2	7	6.5	6	5.8
4	7.2	7	6.2	6
6	8.3	7.9	7.5	6.5
8	9.1	8.9	8.5	7.2
10	9.5	9.4	8.5	7.8
Avg	8.22	7.94	7.34	6.66

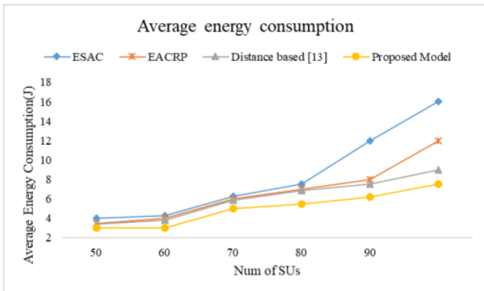

Figure 6: Average energy consumption for varied number of secondary users

In figure 7, we demonstrated the experimental setup for varied no. of secondary users and measured the energy consumption performance. According to this experiment, we obtained the average energy consumption as 8.35J, 6.75J, 6.08J and 5.03J by using ESAC, EACRP, Distance based technique [13] and Proposed Model, respectively. This is obtained due to the distribution of load and continuous packet delivery of proposed technique

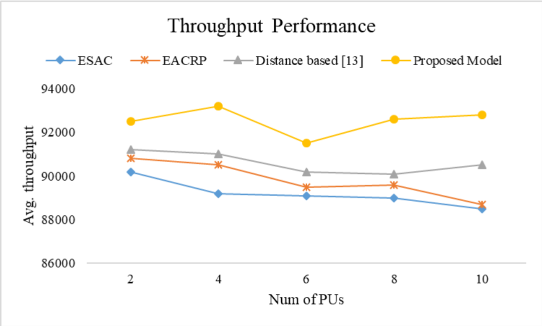

Figure 8: Throughput Performance for varied primary users

For these experiments, we measure the average throughput performance for varied primary users and secondary users. The above given figure 8 shows the average throughput performance for varied number of primary users. The throughput performance is not affected due to delay and energy consumption, however, the complete energy drain can lead to packet drop but proposed multi-hop routing scheme maintains the appropriate energy levels to deliver the packets.

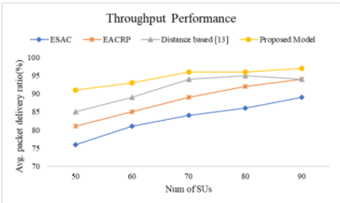

Figure 9: Average throughput performance for varied secondary users

Similar to previous experiment, in this experiment also we consider the varied secondary users and measured the overall throughput for this scenario. The average throughput of the existing schemes is obtained as84.5%, 89.16%, 92.16%, and 95.1% by using ESAC, EACRP, Distance based technique [13] and Proposed Model, respectively. The obtained values of average throughput are presented in below given table 7.

Table 7: Average throughput for varied SUs

Event	ESAC	EACRP	Distance based [13]	EACWSNR
50	76	81	85	91
60	81	85	89	93
70	84	89	94	96
80	86	92	95	96
90	89	94	94	97
100	91	94	96	97.6
Avg	84.5	89.16667	92.16666667	95.1

These experiments show the significance of proposed scheme in the parameters of throughput, energy consumption, and end-to-end delay for diverse number of primary and secondary users.

5. Conclusion

The increased demand of wireless communication systems has led toward the efficient allocation of available communication resources. Currently, the WSNs are widely adopted in various applications but these networks are deployed in unattended and complexatmosphere and comes with restricted battery capacitythus maintaining the efficient network lifetime and replacing the battery are challenging tasks. These days, cognitive radio has been considered as a promising technology which can deal with the spectrum related issues by using opportunistic spectrum access for secondary users. In this concept, the primary user is considered who has the licensed spectrum bands and the secondary user doesn't have the licensed spectrum band. Due to its advantageous nature of opportunistic spectrum access, we adopt the combination of cognitive wireless sensor network scheme and focused on improving the performance of the system. In order to achieve this, we present a novel scheme EACWSNR, which considers the optimal cluster formation, CH selection, spectrum sensing, spectrum allocation and routing scheme for packet forwarding. The extensive experimental study is performed which shows the significant enhancements in the communication performance of cognitive WSN using EACWSNR.

6. Future Scope

Our present work considers cluster formation, CH selection and routing scheme. The future work includes spectrum sensing, spectrum allocation and thereby showing how the spectrum can be efficiently utilized.

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