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Original Article

A Polynomial Series-Based Data Aggregation and Spectrum Aware Clustering Technique for a Combined Model of WSN and Cognitive Radios in IoT Applications

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Abstract *- The demand for wireless communication has surged due to the rise of IoT applications. Wireless Sensor Networks (WSNs) are crucial in this field but often operate in license-free spectrums, causing interference and impacting Quality of Service (QoS). Cognitive Radio (CR) technology offers a solution by enabling opportunistic access to licensed bands, thus reducing interference and enhancing system performance. However, integrating CR with IoT and WSNs poses challenges due to the high energy consumption of CR tasks and limited power and computation resources in sensor networks. Continuous data collection also leads to redundancy. To address these issues, data aggregation techniques can eliminate redundant data, and energy-aware routing can reduce energy consumption during data exchange. This study proposes a combined model of WSN and CR for IoT applications, utilizing a polynomial series-based data aggregation and spectrum-aware clustering technique. The proposed approach achieves a packet delivery rate of 95.47%, energy consumption of 5.216J, and a delay of 0.554 seconds, outperforming existing schemes in CRSNs.*

Keywords *- Clustering, Cognitive Radios, Data aggregation, Spectrum management, Wireless Sensor Network.*

1. Introduction

Nowadays, a large range of applications use the Internet of Things (IoT). The IoT communication technology has emerged as a robust networking framework that permits communication among physical things. Due to developments in these technologies, it is also projected that soon, most offices, industries, and household gadgets will adopt these paradigms where IoT devices perceive the information and connect with other devices [1]. A study published by Fizza et al. [2] anticipated that roughly 29 billion IoT devices would be linked by 2022. Similarly, a study released by Bauer et al. in 2019 has forecast a rise in IoT devices of roughly 75 billion by 2025 [3].

This significant growth shows that IoT is destined to be one of the most essential communication paradigms. Moreover, its vast range of applications has intrigued the research community to increase the quality of communication to accomplish seamless connectivity. Nowadays, a large range of applications use the Internet of Things (IoT). The IoT communication technology has emerged as a robust networking framework that permits communication among physical things. Due to developments in these technologies, it is also projected that soon, most offices, industries, and household gadgets will adopt these paradigms where IoT devices perceive the information and connect with other devices [1]. A study published by Fizza et al. [2] anticipated that roughly 29 billion IoT devices would be linked by 2022. Similarly, a study released by Bauer et al. in 2019 has forecast a rise in IoT devices of roughly 75 billion by 2025 [3]. This significant growth shows that IoT is destined to be one of the most essential communication paradigms. Moreover, its vast range of applications has intrigued the research community to increase the quality of communication to accomplish seamless connectivity.

In this domain of IoT, Wireless Sensor Networks (WSN) are recognized as the main pillar of the IoT because it act as the source of the event. The WSNs are constructed by grouping a number of sensor nodes, which connect in a multi-hop way to deliver the event information to the base station. However, these networks have limited battery capacity and memory resources, making them resource-constrained networks. Thus, excessive use of these networks might lead to failure of the network, resulting in harming the user experience because these WSNs are massively utilized in various real-time systems such as monitoring, tracking, error detection, etc. Nonetheless, the current WSN standards operate in the ISM (Industrial, Scientific and Medical) frequency range, and this ISM band is also used by other communication technologies such as Wi-Fi, Bluetooth and IEEE 802.15 [4]. The enormous number of sensor nodes that are planned to be placed will have a significant bandwidth requirement that cannot be fulfilled by ISM or unlicensed spectrum. However, the Federal Communication Commission conducted studies where even in heavily populated locations, the FCC has reported that 70% of the authorized spectrum is underutilised [5]. Moreover, WSNs also suffer from many restrictions, like as delay, energy, localization, security, etc. As the number of devices increases, these networks demand spectral and energy-efficient approaches.

The number of IoT devices will expand, which would access the unlicensed bands, increasing the co-existence difficulty. Thus, these IoT enabled WSNs require an additional capability to alleviate these issues. Cognitive Radio (CR) technology can help IoT devices work more successfully using Opportunistic Spectrum Availability (OSA), which enhances spectrum resource provision and band management. Additionally, a Cognitive Radio Sensor Network (CRSN) has emerged to broaden the capabilities of WSN-enabled IoT by using the unique qualities afforded by the CR paradigm.

A CRSN is based on distributed networking where sensor nodes receive the event occurrence signal. Later, these nodes communicate in a hop-by-hop fashion to convey the message to the far situated base station based on the application requirement. Throughout this entire connection, these nodes arbitrarily employ the accessible spectrum frequencies. On the other hand, various applications of IoT have been presented which have reported the advantages and disadvantages of IoT networks, such as channel utilization to an individual IoT system becoming costly. In these settings, cognitive radio systems have emerged as a promising way to improve the effective use of the available licensed spectrum.

This combined paradigm of WSN and cognitive radio suffers from various constraints, such as limited energy and restricted computation resources. Generally, the channels available in CRSNs are dynamic, and their availability depends on the principal user’s actions and the location of secondary users. This unpredictability in channel availability might lead to network partition. This scenario arises when the principal user reclaims allotted channels and no channel is accessible for other users or nodes in the network [6-8]. Thus, channel allocation becomes one of the key objectives for these networks to maintain robust channel connectivity. On the other hand, the sensor networks cooperatively connect with other nodes by transmitting their sensed data. This cooperative nature of sensor nodes helps to increase the network performance by boosting spectrum sensing, spectrum allocation and routing, etc. Data aggregation plays a significant part in evaluating energy consumption since constant monitoring leads to an increase in the redundancy of data, which requires additional power to transfer to other nodes. Moreover, duplicate information exchange may influence the QoS of the system along with hurting the lifetime by diminishing its computational resources. Similarly, data transmission in these networks is the major reason for energy usage. Thus, competent data sharing is also viewed as a crucial component in reducing energy consumption and increasing the network lifetime.

In this subject, routing and clustering are the major strategies which have been employed in WSNs to prolong the network lifetime. However, typical clustering and routing methods do not address spectrum-related difficulties so these algorithms cannot be applied directly in cognitive radio-capable sensor nodes. Thus, it becomes a crucial purpose to build a strategy which can preserve the channel connectivity and improve the network lifetime. Recent research approaches have been published which are based on the clustering mechanism. The clustering methods are recognized as an important scheme to optimize the energy usage in the network. Much work has been done to improve the overall performance of cognitive radio-equipped sensor networks. The CRSN follows opportunistic communication techniques for spectrum sensing.

However, cluster head selection becomes critical in these networks; hence, Mortada et al. [9] introduced a new strategy by leveraging ad-hoc communication. This strategy utilized the importance of CH (Cluster Head) selection in CR-WSN. However, these networks are resource-constrained; consequently, resources need optimization for efficient utilization.

To overcome these challenges, Verma et al. [10] suggested applying meta-heuristic optimization strategies and introduced the Sooty Tern Optimization Algorithm (STOA) for efficient cluster head selection because of its faster convergence to optimal solutions. In [11], Shivaraj et al. have provided the Tylor-SHO method to pick the CH efficiently along with the trustworthy link selection using the M-kVDPR algorithm, which has proven the substantial energy efficiency of the network with reduced latency with varying number of sensor nodes.

According to the standards, WSN operates in ISM bands, which are becoming overcrowded; therefore, Prajapat et al. [12] introduced dynamic spectrum access along with the neighbour discovering approach and greedy k-hop routing method for spectrum management and energy efficient communication, respectively. Carie et al. [13] proposed the cognitive radio-assisted WSN with interference-aware AODV routing protocol.

In [14], Salameh et al. addressed the security considerations and suggested implementing an ensemble machine learning concept where historical patterns may be studied to create the correct conclusion to combine security aspects along with energy consumption optimization. In [15], Joon et al. introduced the Q-learning strategy, which learns from the environment and follows a reward mechanism to increase the system's performance.

Based on these studies, we have identified that energy consumption and spectrum sensing are the two main important aspects of CR-WSN. In this work, we have adopted the concept of data aggregation and clustering to maximize the network lifetime. Moreover, the proposed clustering scheme also considers the spectrum availability which makes it suitable to implement for cognitive radio WSNs. Despite these advancements, WSNs face several limitations:

- Energy Consumption: Continuous data collection and transmission consume significant energy, reducing network lifetime.
- Data Redundancy: Unattended environments lead to redundant data, increasing processing and transmission loads.
- Routing Efficiency: Effective data routing is crucial for minimizing energy consumption and ensuring reliable communication.
- Dynamic Channel Availability: The availability of channels in CRSNs depends on the activity of PUs, leading to potential network partitioning.

Several existing methods have been proposed to mitigate these challenges:

- Spectrum Sharing: Techniques like opportunistic spectrum access allow SUs to use idle licensed bands, enhancing spectrum utilization.
- Data Aggregation: Aggregating data at sensor nodes reduces redundancy and conserves energy.
- Routing and Clustering: Efficient routing algorithms and Cluster Head (CH) selection mechanisms help optimize energy use and improve data transmission.

However, these approaches have their restrictions. Traditional clustering and routing algorithms generally miss spectrum-related difficulties, rendering them unsuitable for CRSNs. Additionally, the dynamic nature of channel availability in CRSNs needs adaptive and robust channel allocation algorithms.

WSN is an information gathering technology which is evolving very swiftly. It is a necessary aspect of various applications, including urban transport systems, industry control, monitoring of the environment and military. The challenges experienced by the existing WSN applications are energy efficiency, dependability, and data redundancy. The constraints experienced by existing Cluster Head Selection methods, together with data routing ways, are taken as the inspiration for designing a novel model which can address numerous concerns in WSN run IoT applications. The main contributions of the research are elaborated as follows:

- Data aggregation to reduce the data redundancy in WSN.
- Here, the sensor nodes represent their sensed data as polynomial functions to aggregate the data.
- The Cluster Head selection process to route the data efficiently.

The remainder of the paper is structured as follows: The literature review and issues with current Cluster Head Selection and methods in CRSN are explained in Section 2. The data aggregation, Cluster Head Selection, and Spectrum sensing model are all shown in Section 3. Results and the comparative analysis are done in Section 4. In Section 5, the conclusion is discussed.

2. Literature Review

This section presents a brief discussion about existing data aggregation, routing and clustering methods for cognitive WSN IOT enabled networks. As discussed, traditional IoT-WSN networks do not consider the spectrum availability scenario. Moreover, combined with IoT, the WSN consumes more energy due to its high usage, and IoT enabled networks work in an unlicensed spectrum environment where interference becomes the prime issue.

Mortada et al. [9] presented the operation of CRSN, where sensor nodes operate as secondary users and can access the channel when the primary user is not present. However, this process is opportunistic and is completed without PUs. This shows that the sensor nodes are equipped with the spectrum sensing capability which monitors the PUs activity. The authors provided a CH selection technique for spectrum sensing, data gathering and transmitting it in the direction of the BS by employing ad-hoc communication topology.

The expanded clusters minimize the energy consumption during data transmission; however, spectrum sensing increases energy consumption since more CHs do spectrum sensing before transmitting the data. This approach considers data aggregation, spectrum sensing and transmission into the network. This highlights the advantage of adding data aggregation in these networks. However, it increases the complexity of the CH as it has to conduct the spectrum detection and data transmission processes simultaneously.

Verma et al. [10] discussed the challenge of managing the enormous volume of data in WSN combined with the transmission in resource restricted networks. To tackle this issue, the authors presented energy-efficient routing, which considers the elements of cognitive radio, IoT, and WSN. The authors defined this challenge as an optimization problem and provided a Sooty Tern Optimization Algorithm (STOA) way to tackle this. The faster convergence and increased exploration capabilities of STOA make this algorithm suited for energy-efficient clustering. This helps to obtain efficient clustering as the output of the optimization technique to increase the network performance. The proposed work is directed towards the static nodes, thereby limiting its use cases.

Shivaraj et al. [11] present cases of numerous meta heuristic techniques utilized for CH selection in WSN. The suggested Taylor-SHO algorithm considers the behaviour of Spotted Hyenas and the Taylor series to develop the optimal solution for the CH selection. Further, the Modified k-VDPR approach is employed to execute the data routing. Route maintenance is also undertaken to mitigate the network faults. This technique has shown considerable benefits in terms of energy usage, delay and distance. However, the calculation time is dependent on the number of coefficients considered while executing the CH selection procedure. This limits the number of sensor nodes active in the CH selection process at a given time.

Prajapat et al. [12] addressed the spectrum-related issues in WSN and used the notion of dynamic spectrum access with cognitive radio networks. The dynamic spectrum access capabilities of these networks help to tackle the spectrum shortage issue. However, DSA overcomes the spectrum problem, but the energy consumption associated difficulties still need to be resolved. Thus, the authors chose a clustering mechanism and created a neighbour discovering strategy and greedy k-hop routing process for intra and inter-cluster data transmission. The clustering approach includes numerous criteria such as remnant power, quality of the communication link and channel, PU's arrival, Euclidean distance, spectrum awareness, etc. With the aid of these principles, it tries to obtain stable clustering. Due to the inclusion of extra parameters, the suggested method demonstrates increased computational complexity.

According to Carie et al. [13], the WSNs operate in the ISM bands, which are very crowded and communication in these bands can deteriorate the communication performance due to channel saturation and an increase in collision rate. To tackle this, the authors suggested an opportunistic spectrum sensing routing with dynamic spectrum access capability. In order to formulate the clusters, nodes broadcast the advertisement message, and other nodes join these nodes according to their distance from the node. This operation is undertaken to form the cluster. Later, cluster update, channel routing, and channel route discovery are conducted. The routing strategy considers RREP and RREQ message exchange. Finally, a power control technique is also described to lessen energy depletion and extend the network lifetime.

Salameh et al. [14] cited various advantages of cognitive radio sensor networks but reported that maintaining security owing to resource hungry operations becomes a laborious issue for these networks. Thus, the authors presented a security aware routing strategy which mainly considers the jammer threats and formulated the optimization issue. To deal with this issue, the authors presented an ensemble-based jamming behaviour detection method. This ensemble model uses Random Forest, Bayesian learning, and k-NN based techniques to construct the ensemble classification mode, and lastly, majority voting is performed to get the final result. The complexity of the proposed method is relatively greater compared to the present work.

Joon et al. [15] focused on energy consumption, network lifetime and throughput of cognitive radio sensor networks. To tackle these issues, the authors presented a Q-learning based solution as Energy Aware Q-learning AODV (EAQ-AODV). This methodology is based on AODV routing together with a Q-learning algorithm. The Q-learning technique uses a reward-based mechanism for CH selection, and AODV focuses on determining the routing path based on multiple limitations such as remaining energy, hop count, channel condition, communication range and trust factor.

Similarly, Vimal et al. [16] have claimed that coupled data aggregation and clustering could be a suitable option to ease the performance related difficulties in cognitive radio IOT sensor networks. To accomplish this, the authors developed an optimisation-based solution technique with a multi-objective ant colony optimization scheme and a greedy optimisation strategy. Further, the deep reinforcement learning method is also offered with double Q-learning to gain robust input as a reward. This approach helps increase the inter-cluster data aggregation, boosting the overall performance of the network.

Raj Kumar et al. [17] suggested an optimization-based solution for energy-efficient clustering, which uses the centroid based ant colony optimization method to increase the network performance. During the early phase, it uses centroid based clustering for information collecting, and afterwards, ant colony optimization is used to transfer the acquired data to the base station. For the centroid, the energy of the sensor nodes is considered as the key parameter. Further, the clustering strategy incorporates energy cost and channel uniformity of cognitive sensors for super cluster head selection. Furthermore, the path optimization is also performed between super cluster heads with the help of an ant routing model.

Thareja et al. [21] suggested a combined technique for spectrum sensing and enhancing the network lifetime execution by limiting the network energy consumption. To alleviate the energy consumption issue, scientists presented the inter and intra cluster model and later posterior transition probability-based model to improve the spectrum sensing. Yadav et al. [18] proposed the event driven cluster-based routing approach. The routing protocol for CRSN is used to relay the samples from event detecting nodes to the sink via intra and inter-cluster communication. The intra-cluster communication is aimed at reducing the distance and power consumption. CHs of each spectrum aware cluster are selected based on the residual energy, available channels, and distance to the sink node. More importance on intra and inter-cluster has increased the computation time and hence the delay.

The optimum distance formulation has been proposed by Tripathi et al. [19], considering the energy consumption in inter and intra cluster data-forwarding. The number of packets will decide the size of the cluster. The routing takes place through energy-efficient paths. The clusters are adaptable and the nodes are given the cognitive capability to calculate the residual time of the unused licensed channels. This is a complex process where sensor nodes have to perform multiple operations of calculating the residual time along with the data processing and forwarding. Siddesha et al. [20] proposed a machine learning based technique and adopted a deep reinforcement learning approach. In this approach, a novel policy to maximize the reward for task scheduling actions is performed.

A temporal event driven clustering technique has been proposed by Ozger et al. [22]. The cluster is formed upon detecting the event. The nodes in the vicinity of the event are detected and are made part of the cluster. The two-hop communication to the sink reduces energy consumption. However, the even driven temporal clusters formation and deformation, selection of CHs among these clusters and rotuing the data with the efficient paths is the costly operation.

Ozdemir et al. [23] presented a polynomial regression based secured data aggregation protocol. Sensor node represents their sensed data as polynomial functions. Data aggregation is performed on these functions and the sink node will have the ability to approximate the data from this aggregation. This method successfully catered for the purpose of reducing data redundancy along with securing confidential data in sensitive WSN applications. In [24], Kim et al. reported the issues associated with MAC layer sensing in CRSNs as the frequency of sensing the available licensed channels and the order of sensing. The authors have adapted the sensing period to maximize the discovery of the spectrum while reducing the delay. The proposed method has shown significant improvement when compared with the nonoptimal schemes.

Wang et al. [25] emphasized the necessity of multi-hop clustering and routing technique to assist the efficient data transmission in CRSNs. In prior approaches, the false alarm and missed detection rate parameters are ignored because of the assumption of flawless spectrum sensing but it leads to transmission failure in real-time settings. To tackle this, the authors develop an Incomplete Spectrum Sensing-based Multi-hop Clustering Routing Protocol (ISSMCRP) CH and relay selection is performed based on the detection level function and relay with high spectrum sensing capabilities. Similarly, inter and intra cluster data transfer criteria are derived based on idle detection accuracy. Additionally, a control overhead is also introduced for CH selection and cluster formation which helps to minimize the energy usage and regulate the network overhead.

Satyavathi et al. [26] presented an efficient QoS conscious approach for intra and inter-cluster data aggregation by employing hybrid optimization schemes. The optimization approaches include modified bowerbird optimization to increase the clustering performance, and later, multi-objective seagull optimization based decision-making methodology is introduced to estimate the CH of a cluster. Finally, a teacher-inspired cappuccino search method is introduced to improve the data transfer.

Srividhya et al. [27] created Energy-efficient Distance-based Spectrum Aware Optimization (EDSO). This approach uses Honey Bee Mating Optimization (HBMO) for clustering, and Donkey and Smuggler Optimization (DSO) is used to perform the routing to the base station. The HBMO technique helps in identifying the optimum cluster and minimizes energy consumption. Nasirian et al. [28] created a cluster-based hierarchal routing system dubbed as Pizzza. The suggested protocol improves network longevity by establishing minimum spanning trees across nodes in each sector-shaped cluster, enabling only first-level nodes to become cluster chiefs. This eliminates energy waste by reducing reverse data flow from the base station, enabling efficient data transfer to neighboring nodes, and balancing energy usage throughout the network.

3. Proposed Data Aggregation and Clustering Model for CRSN

This section describes the proposed solution for data aggregation, spectrum and energy aware cluster head selection for cognitive radio sensor networks for IoT based applications. According to the proposed approach, data aggregation is the first stage, and the energy and spectrum aware cluster head selection are the next stages of this work.

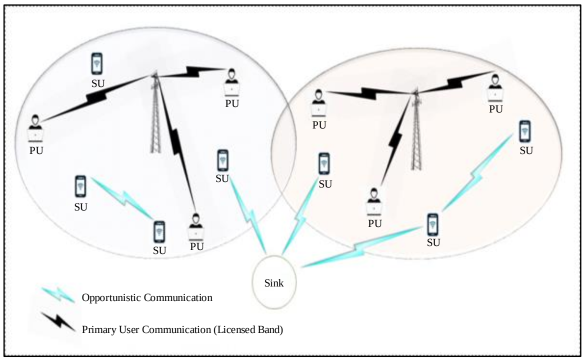

Fig. 1 Illustration of a general architecture of CRSN

3.1. Network Model and Parameters

According to the proposed approach, we have considered a Cognitive Radio Sensor Network (CRSN) model. This network model consists of N number of Secondary Users (SUs), which are positioned in the $m \times m$ network area $\mathcal{A}$. The deployment density is denoted by ρ, which can be computed by taking the ratio of total nodes and network region as $\frac{N}{\mathcal{A}}$. These IoT sensors have a component which is used to switch the communication between the Control Channel (CC) and traffic channel (C). These two channels are accessed opportunistically.

Similarly, this network also consists of $\mathcal{M}$ number of primary users who can access the channels at any point in time. The utilization period is denoted as τ_{on} and the silent period when these nodes are not using the channel is denoted as τ_{off}. Furthermore, the energy detection method is applied to identify the inactive channels, and the proposed clustering mechanism is enforced to distribute the network into K number of clusters. Figure 1 depicts the general architecture of the deployment of CRSN.

Here, we assume that the wireless transceivers either work in transmitting mode or reception mode. According to this process, once the SU has initiated the transmission, it finishes the existing communication before releasing the communication channel. This scenario may lead to interference or cause a delay in transmission. The secondary user detects the transmission instance S_t of primary users. The received signal $S_r(t)$for this step can be articulated as:

$$S_r^s(t) = \begin{cases} n(t), \ if \ H_0 \\ n(t) + S_t(t), if \ H_1 \end{cases} \tag{1}$$

Where H_0 represents the hypothesis for the inactive state of PU and H_1 denotes the hypothesis characterizing the data exchange stage of PU, $n(t)$ is used to represent the additive white Gaussian noise. According to this model, the probability of false alarm (P_f) and probability of detection is expressed as:

$$\begin{aligned} P_f &= \Pr\{Y > \epsilon | H_0\} \\ P_f &= \Pr\{Y > \epsilon | H_1\} \end{aligned} \tag{2}$$

Where Y is the output of the energy detection algorithm used as a decision for energy detection, and ϵ is the detection threshold. The lower value of the probability of detection P_d represents the absence of a primary user, resulting in increased interference, whereas a high value of P_f represents the low spectrum utilization. Thus, in this work, we introduce a binary variable x_c to signify the channel accessibility. Based on this expression, for i^{th} node and c^{th} channel, the channel availability is represented by x_c^i and if the probability of detection is $P_d < 0.1$, then it represents the absence of the primary user.

3.2. Data Aggregation

Data aggregation plays an important role in these networks because redundant data processing and transmission consumes extra energy, which affects the network performance. In this phase, the data is periodically collected and aggregated within the data aggregation session.

Each data aggregator sends the notification to the sensor nodes in its cluster at the beginning and the end of each data aggregation session. Each sensor node performs n sensor readings, resulting in a data set of size n. Upon completing the data aggregation, the data aggregator requests the sensor nodes for these data sets to send it further to the Base Station.

Sensor nodes decide to store the last n reading as m-order polynomial curve where m<n. To mitigate the transmission of the entire data, the sender node transmits only the coefficients. Figure 2 demonstrates the process of data aggregation. According to this illustration, the cluster is formed by grouping numerous sensor nodes (SN_1, SN_2, SN_3, SN_4, SN_5) in this work where sensor nodes 1, 3 and 5 are collecting the data D_1, D_2, and D_3 and transmit to the data aggregator node, where the aggregator node performs the assigned operation and generates the final aggregated data vector, which is transmitted to the Base Station (BS) via the multihop communication link.

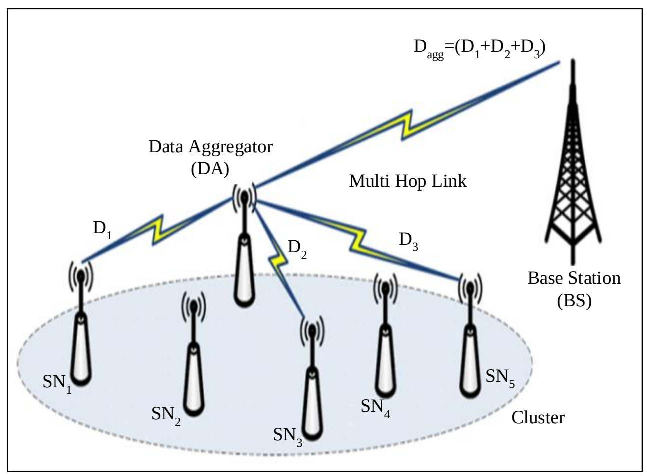

Fig. 2 Data aggregation illustration

Here, we assume that the data generated from sensor nodes is correlated, and to reduce the data size, each node i fits the data in m degree polynomial. This can be expressed as:

$$f_i(x) = a_{i0} + a_{i1}x + a_{i2}x^2 + a_{i3}x^3 + \cdots + a_{im}x^m \tag{3}$$

Where $n > m$ and $i = 1, \ldots n$, this polynomial form can be re-written as:

$$f_i(x) = \sum_{j=}^{m} a_{ij}x^j, n > m \ and \ i = 1, \ldots n \tag{4}$$

Thus, the final data aggregation function using the polynomial function can be articulated as [23]: Where s denotes the sensor readings.

$$D_{agg}(x) = \sum_s f_s(x) = \sum_j \left[\left(\sum_s a_{sj}\right) x^j\right] \quad (5)$$

3.3. Cluster Realization and CH Selection

This section describes the proposed method for cluster establishment and selection of cluster heads. The clustering mechanism helps to regulate the data transmission in such a way that it reduces energy consumption. In these communication cases, inappropriate traffic management may lead to exceeding the capacity of links and routes which can reduce the overall performance of the network. The cluster-based communication methods formulate the cluster, and the cluster becomes the important entity to control the data transmitted by nodes to prevent excessive energy consumption. Moreover, maintaining fair QoS with spectrum cognition is a challenging task.

In this stage, we focus on finding the vacant condition of the channel and the availability of the channel as important parameters to obtain the information for cluster head selection. Once the spectrum sensing task is finished, the information-sharing process takes place to exchange the information with neighbouring nodes. This is done by broadcasting $Info$ message, which contains several parameters such as channel availability, residual energy, and distance, which are further used for cluster head selection.

Let us consider that $v_i(t)$ denotes the channel emptiness matrix of the node i at a time stamp t in $\mathbb{C}$ channels. This is obtained based on the decision of binary element $x_c^i(t)$ which is obtained as (1), which shows the vacant channel condition. Thus, the vacant channel matrix $v_i(t)$ is represented as $v_i = \left[x_1^i(t)\, x_2^i(t) \ldots x_C^i(t)\right]^T$. Similarly, we focus on identifying the channel availability $a_i(t)$ for node i. This channel availability matrix is formulated as follows:

$$a_i(t) = \left[a_1^i(t)\, a_2^i(t) \ldots a_C^i(t)\right] \quad (6)$$

The channel availability is obtained based on past channel statistics, which include channel usage patterns. In order to determine the pattern, the channel is represented as ON-OFF. A channel can be represented as an ON-OFF source, switching between two states, ON (busy) and OFF (idle), depending on the usage pattern of its PUs. This model effectively captures the time intervals during which SUs can utilize the channel without causing any detrimental interference to PUs [24].

The channel availability is obtained based on past channel statistics. With the help of these channel vacancy and mean availability, the channel availability between node i and j can be computed as:

$$\mathbb{A}^{ij}(t) = \left(v_i v_j\right) \times \min\{a_i, a_j\} \quad (7)$$

Where v_i and v_j denotes the channel vacancy matrix for node i and j, respectively, which are element wise multiplied with the minimum of expected channel availability for node i and j, denoted as a_i and a_j, respectively. At this stage, the communicating node computes the spectrum availability based on the ranks, which is denoted as:

$$\varphi^{ij}(t) = \frac{1}{C} \times \mathbb{A}^{ij}(t) \quad (8)$$

With the help of these expressions, we obtained the spectrum related information and presented a model to rank the spectrum energy φ. Similarly, we extend this process for wireless sensor network scenarios for IoT applications. For the IoT-WSN scenario, we consider the spatial, temporal interdependency and residual energy parameters.

The combined spectrum energy rank and IoT based parameters are used to select the final cluster head. The channel availability is subjected to geographical locations; therefore, spatial interdependency is required to identify the relationship between channel availability and geographical location. This relation can be written as:

$$\mathcal{S}_{i,j,t} = \begin{cases} 1 - \frac{d_{i,j,t}}{\min\{r_i, r_j\}}, d_{i,j,t} < \min\{r_i, r_j\} \\ 0, d_{i,j,t} \geq \min\{r_i, r_j\} \end{cases} \quad (9)$$

Where $d_{i,j,t}$ denotes the Euclidean distance between communicating node i and j; if the distance $d_{i,j,t} < \min\{r_i, r_j\}$ then, the two communicating nodes are in the communication range where r_i, r_j denotes the communication radii of two nodes. The average spatial interdependency among the communicating node i and the next hop is determined as:

$$E(\mathcal{S}_{i,t}) = \frac{1}{n_{i,t}} \sum_{j=1}^{n_{i,t}} \mathcal{S}_{i,j,t} \quad (10)$$

Further, we need to describe the time-based interdependence between communicating nodes i and j because at some specific time stamp nodes may have high interdependency. Thus, to obtain the final decision, we apply temporal interdependency given as:

$$\mathcal{T}_{i,j,t} = \frac{|c_{i,t} \cap c_{j,t}|}{n_c} \quad (11)$$

Where $c_{i,t}$ and $c_{j,t}$ denotes the sensed sequence of idle channels for node i and j, we try to obtain the interdependency between these channels by identifying the common idle channel as $|c_{i,t} \cap c_{j,t}|$. High energy consumption is one of the key issues with spectrum-aware clustering, particularly when exchanging sensing data and making local spectrum decisions. For energy-limited CRSNs, this problem becomes more difficult; hence, energy-efficient clustering is required to increase network lifespan. A node with more remainder energy has a higher probability of being elected as a CH since CHs require extra computational resources to make spatial decisions and distribute the perceived inactive channels for cluster members. Thus, we measure the remainder energy level of the node, which is characterized as:

$$\mathbb{E} = \frac{e_{res}}{e_{max}} \tag{12}$$

Where e_{res} signifies the remainder energy levels of the node and e_{max} signifies the maximum assigned energy of that node. Based on these parameters, we formulate an index for CH selection which considers spatial, temporal interdependency, and spectrum ranking. This index is expressed as:

$$CH_{idx} = \mathbb{E}(\mathcal{S}).\mathbb{E}(\mathcal{T}) + \varphi_{i,t} + \mathbb{E}_{i,t} \tag{13}$$

The higher value of CH_{idx} represents more possibility of the node becoming the cluster head. In the next phase, packet routing is performed. The proposed approach considers the cluster head communication, which is used to set the path to the base station. The major steps followed in the proposed approach are described in Table 1.

Table 1. Packet routing tasks to establish the path to the base station

Step	Message	Tasks Performed
1	$CH - RREQ$	This message is initialized by the cluster head, where it broadcasts the route request message on the common channel. The member node receives the packet and waits for the backoff timer.
2	$CH - RREP$	The neighbouring cluster head or member receives the RREQ packet and waits for the backoff timer. During this backoff timer, the node waits for the response from the other neighbouring nodes present in the cluster and assigns the path which is present in its cache. If no path is found, then the member node directs the RREQ data packet to the cluster head. At this stage, the cluster head sends the RREP message in response to the RREQ.
3	$TempPath$	Once the next cluster head sends the RREP to the RREQ of the previous cluster, then the first cluster head stores this as a temporary path for the next hop
4	$CH - DREQ$	If the initial path is obtained, then the cluster head announces the data request $DREQ$. Therefore, member nodes start transmission of the information gathered from events. However, we have aggregation functionality at the cluster head.
5	$EmpPack$	This message is generated at the cluster head if there is no route is present. Then, the cluster head allocates TDMA slots to transmit the packets.
6	$PcktSchd$	This is the final stage of the routing process. When TDMA slots are assigned, the cluster head sends the scheduling message. Once the cluster members receive this message, then these nodes synchronize with CH and TDMA. In this way, each node transmits data in the assigned TDMA schedule.

Algorithm 1. Pseudo Code of Developed Method
1. Input: Primary and Secondary Users
2. Output: Cluster Heads for the clusters
3. Start
4. Initialize parameters
5. Perform spectrum sensing.
6. calculate P_f and P_d
7. Perform the data aggregation $D_{agg}(x) = \sum_s f_s(x) = \sum_j\left[\left(\sum_s a_{sj}\right)x^j\right]$
8. for every secondary user, do
9. estimate spatial, temporal interdependency $\mathbb{E}(\mathcal{S}).\mathbb{E}(\mathcal{T})$
10. end for
11. for every secondary user, do
12. estimate the residual energy $\mathbb{E}_{i,t}$
13. end for
14. for every secondary user, do
15. estimate the residual energy $\mathbb{E}_{i,t}$
16. end for
17. for every secondary user, do
18. estimate the spectrum ranking $\varphi_{i,t}$
19. end for
20. Calculate $CH_{idx} = \mathbb{E}(\mathcal{S}).\mathbb{E}(\mathcal{T}) + \varphi_{i,t} + \mathbb{E}_{i,t}$
21. Select the CH based on the higher value of CH_{idx}
22. Perform the message exchange to establish the communication path to the Base Station.
23. Stop

4. Results and Discussion

In this section, the analysis of the proposed methodology and evaluation of its performance against several cutting-edge methods are discussed in the context of cognitive radio sensor networks. The efficiency of the suggested technique with that of current schemes like energy aware clustering [18], event-driven (ESAC) [21], and adaptive clustering [19] is demonstrated with respect to the performance. We assume that sensor nodes are dispersed arbitrarily over a 2-dimensional geographic area to establish the simulation scenario. The simulation settings utilised in the experimentation are shown in Table 2 and the simulation is carried out with MATLAB tool with 4GB RAM, Intel i3 processor and Windows 10 OS.

Table 2. Experimental setup and parameters

Simulation Parameter	Value
Network Deployment Area	1500mX1500m
Primary Users	2-10
Bandwidth of Channel	2 Mbps
Secondary Users	50-100
Communication Range	500 m
Preliminary Node Energy	50J
Size of Data Packet	512 byte
e_{Elec}	50nJ/bit
e_{amp}	100 pJ/bit/m^2

Based on these simulation parameters, we analyze the performance of the proposed approach in terms of spectrum sensing probability for varied SNR levels. Figure 3 depicts the comparative analysis of the probability of false alarms and the probability of detection. The probability of detection P_D of the proposed approach is achieved similar to the theoretical value and similarly, the probability of false alarm P_f is also obtained similar to the theoretical values. According to this analysis, the match between empirical and theoretical values indicates that the statistical model used to derive the theoretical probabilities accurately represents the real-world system. Moreover, it shows that the detection algorithm is performing as expected under the given conditions. This suggests that the theoretical analysis and the implemented algorithm are correctly aligned. This experiment shows that the proposed approach is able to maintain coherence with the aforementioned hypothesises as mentioned in Equation (2), and demonstrates the robustness of the presented approach to identify the spectrum availability. Moreover, if spectrum availability is marked, then further processes such as aggregation and clustering can be carried out.

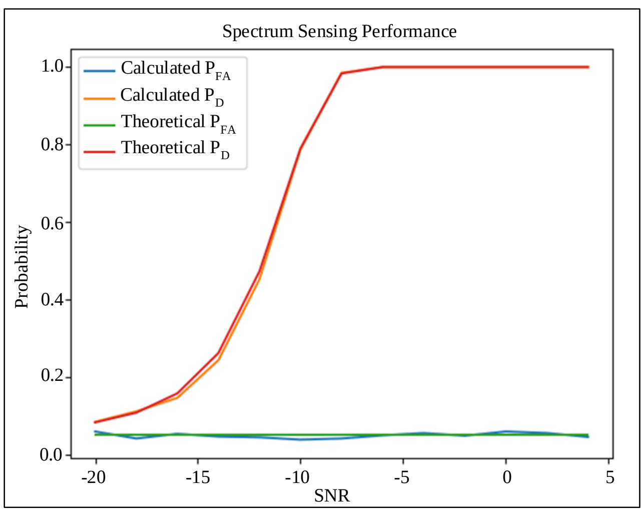

Fig. 3. Spectrum sensing performance

In the next phase, we quantify the overall delay outcome where we have a number of secondary users. Figure 4 shows the graphical representation of this relative analysis.

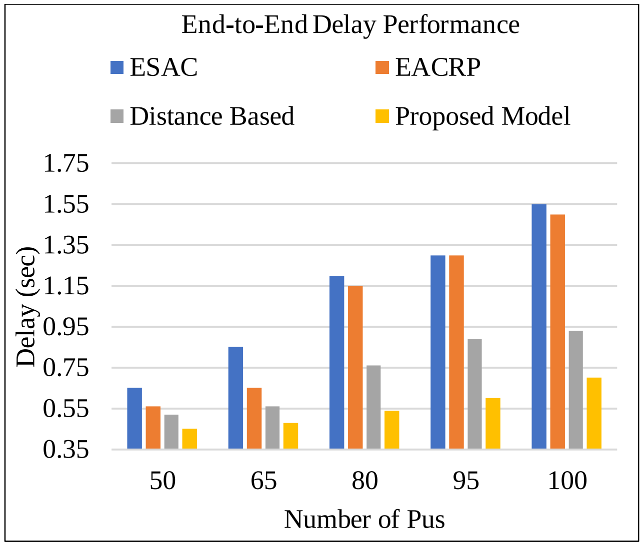

Fig. 4 Overall delay performance: varied SU (50:100)

This investigation shows the delay analysis for the diverse number of secondary users. As the amount of SUs is increased the overall delay also rises to deliver the packets. The average delay performance for this observation was 1.11 s, 1.032 s, 0.732 s, and 0.554 s, respectively, employing the event-driven [21], energy aware clustering, suggested method, and Adaptive clustering [19] approach. The values obtained are displayed in Table 3.

Table 3. Analysis of overall delay for different numbers of SUs

Number of PUs	Event Driven	Energy Aware Method	Adaptive Clustering	Proposed Model
50	0.65	0.56	0.52	0.45
65	0.85	0.65	0.56	0.48
80	1.2	1.15	0.76	0.54
95	1.3	1.3	0.89	0.6
100	1.55	1.5	0.93	0.7
Avg.	1.11	1.032	0.732	0.554

Further, we considered the same experimentation setup and extended the research to measure energy depletion. In this experiment, we have different numbers of PUs, ranging from 5 to 10. Figure 5 demonstrates the graphical representation of average energy consumption.

The overall energy utilization rate for varied numbers of primary users is obtained as 8.36J, 7.84J, 7.56J, and 6.8J by using event-driven [21], energy aware clustering [18], Adaptive clustering [19] and proposed model, respectively. An increasing number of primary users affects the energy consumption performance and leads to an increase in the energy consumption because of increased delay. Table 4 illustrates the obtained values for energy consumption for this test.

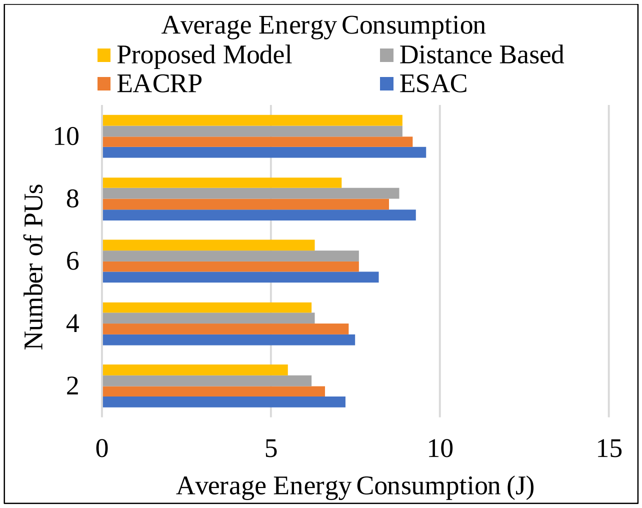

Fig. 5 Overall energy depletion analysis for varied PUs

Table 4. Average energy consumption analysis for varied PUs

Number of PUs	Event Driven	Energy Aware Method	Adaptive Clustering	Proposed Model
2	7.2	6.6	6.2	5.5
4	7.5	7.3	6.3	6.2
6	8.2	7.6	7.6	6.3
8	9.3	8.5	8.8	7.1
10	9.6	9.2	8.9	8.9
Avg	8.36	7.84	7.56	6.8

Figure 6 demonstrates the outcome in terms of average energy consumption for the varied number of secondary users. According to this evaluation, event driven [21], energy aware clustering [18], Adaptive clustering technique [19] and proposed model achieve the average amount of energy depletion obtained as 8.35J, 6.96 J, 6.191 J, and 5.216 J, respectively.

The average throughput performance by varying the number of PUs is represented in Figure 7. In this investigation, the average throughput performance is obtained as 8920kbps, 8982 kbps, 9060 kbps, and 9252 kbps by using EVENT DRIVEN, energy aware clustering [18], Adaptive clustering [19] approach and proposed approach, respectively. Figure 8 depicts the packet delivery performance for the varied number of SUs.

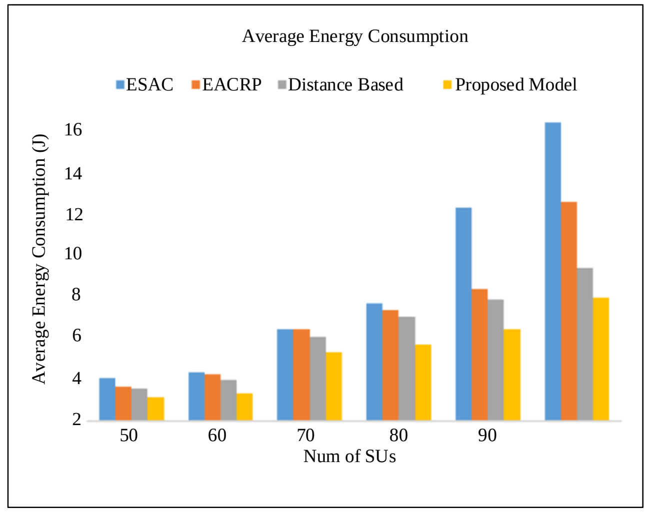

Fig. 6 Analysis of average energy depletion for different numbers of SUs

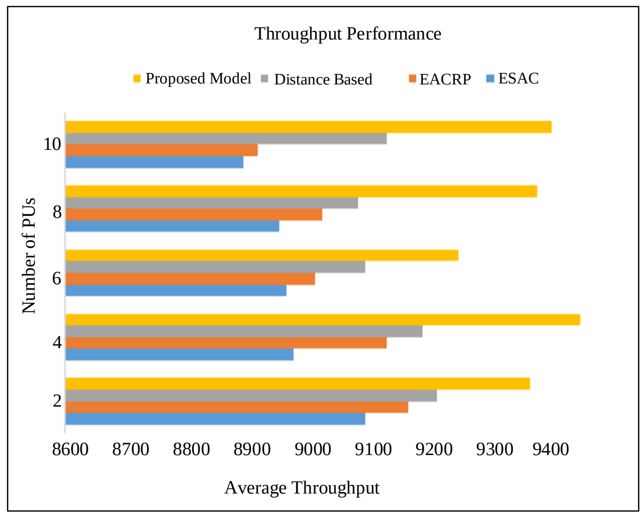

Fig. 7 Throughput analysis for varied primary users

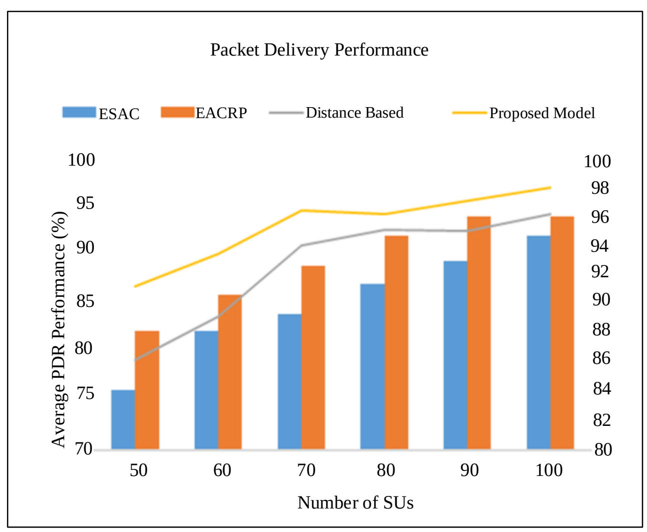

Fig 8. Average throughput analysis for varied SUs

Conferring to this experimentation, we have measured the average packet delivery performance for different numbers of SUs. The average packet delivery rate is obtained as 85.25%, 89.65%, 92.685%, and 95.475% by using EVENT DRIVEN, energy aware cluster clustering, Adaptive clustering technique [19] and the proposed model, respectively. Table 5 shows the corresponding value for each set of secondary users, and finally average packet delivery performance is also presented.

Table 5. Average packet delivery for varied SUs

Event	Event Driven	EACRP	Adaptive Clustering	Proposed Model
50	76.2	82.3	86.2	91.25
60	82.3	86.1	89.2	93.5
70	84.1	89.1	94.11	96.5
80	87.2	92.1	95.2	96.3
90	89.5	94.2	95.1	97.2
100	92.2	94.1	96.3	98.1
Avg.	85.25	89.65	92.685	95.475

The experiments for varied simulations demonstrate a significant improvement in the performance of the proposed approach when compared with other existing techniques. The initial outcome of this research demonstrates the close match between theoretical and simulated values. This alignment indicates that the statistical model used is accurate and that the detection algorithm performs as expected under the given conditions. This robust performance validates the hypothesis that the proposed methodology can reliably identify spectrum availability. Moreover, this alignment ensures that secondary users can accurately detect the presence or absence of primary users, thereby reducing interference and improving spectrum utilization.

In another experiment, the performance of the proposed model is compared with the existing schemes, such as Event Driven [21], Energy Aware Clustering [18], and Adaptive Clustering [19] approaches. As shown in Table 3 and Figure 4, the proposed method demonstrates significantly lower overall delay, with an average delay of 0.554 seconds compared to 1.11 seconds for Event Driven, 1.032 seconds for Energy Aware Clustering, and 0.732 seconds for Adaptive Clustering. This reduction in delay can be attributed to the efficient spectrum sensing and decision-making process implemented in the proposed approach.

The CH selection process in the existing methods has increased computational time and the complexity of the algorithm is more compared to the proposed method. The metaheuristic algorithms discussed in Section 2 show a significant increase in computational time and are mainly focused on the CH selection and data routing techniques. The proposed methodology incorporates data aggregation, CH selection, and data routing along with the utilization of the available resources effectively. The proposed method has attempted to incorporate CH selection, spectrum sensing and data aggregation in the CRSNs based IoT applications, which has shown significant improvement through its simulation with varied SU when compared with the existing methodologies.

Applications like agriculture, weather monitoring systems, forests, etc are the ideal applications for the proposed method. In these applications, the SU count increases with respect to time to cover a large area. However, this method proves to provide more stability considering the applications where the number of SUs is fixed.

5. Conclusion

In this work, we have presented a polynomial series-based data aggregation and spectrum and energy aware clustering technique to prolong the network lifetime by minimizing energy depletion and efficiently utilising resources. The proposed model has shown a significant improvement in terms of overall energy consumption of the network, throughput performance and average packet delivery ratio. Results have been compared with the event driven, EACRP and adaptive clustering models. The model has been tested for different numbers of PUs and SUs, and the results show an improvement when the number of PUs and SUs is increased. The spectrum sensing performance for the proposed model has shown similar results as per the theoretical values for detecting the spectrum and the false alarms. This facilitates the model to perform better in the co-existence of the devices utilizing the same frequency spectrum. The future work of the research will be to implement more efficient CH selection optimization techniques to enhance the data routing more efficiently. Future research will also incorporate the mobile sensor nodes as the present work is implemented considering the static nodes.

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