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Active Channel Selection by Sensors using Artificial Neural Networks

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ABSTRACT- Efficient channel selection is essential for optimizing resource utilization in wireless communication. Traditional static allocation often results in underutilization and wastage of channels. This research addresses these inefficiencies by using cognitive sensors, known as secondary users (SUs), to dynamically identify and utilize available channels, thereby minimizing channel wastage and deficits. The proposed strategy configures sensors cognitively to detect real-time channel availability. Secondary users (SUs) identify free channels initially allocated to primary users (PUs) and list these channels based on parameters such as capacity, transmission range, data load, and distance. An Active Channel Selection Network (ACSN) using artificial neural networks is employed to evaluate and allocate the optimal channel based on multiple parameters and sensor queue levels. This cognitive approach significantly reduces network channel deficits and wastage by dynamically detecting and utilizing free channels, ensuring more efficient channel usage. The ACSN improves the quality of channel selection, ensuring optimal allocation even when multiple channels are available. This method effectively addresses the challenges of channel underutilization and wastage in wireless communication networks, optimizing resource usage and enhancing overall network efficiency and performance.

Keywords: Cognitive, Secondary User, Primary User, Active Channel, Queue Level Allocation.

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1. INTRODUCTION

Cognitive technology is utilized to mitigate channel shortages in wireless networks, addressing the issue of underutilized channels that lead to resource wastage. As wireless communication continues to grow and data exchanges increase, there is a heightened demand for large-scale channel usage, necessitating the development of alternative technologies. In cognitive radio networks, users are classified into primary (licensed) and secondary (unlicensed) categories. Primary users have unrestricted access to channels, while secondary users can access these channels for limited periods. This technology enhances channel utilization and reduces network limitations.

Primary channels employ various methods to facilitate secondary user access, including channel perception, selection, and dynamics based on node movements, and sharing among sensors. When a channel is required, secondary users identify available channels and update their free channel list. If multiple free channels are available, they use a channel selection system to choose the most suitable one. This free channel list is shared with other sensors within the coverage area. If a primary user requests the same channel, the secondary user redirects to another suitable channel.

For efficient channel perception, secondary users must minimize the time spent locating channels and enable a swift decision-making process, thus reducing the channel selection period and network delay. Minimizing the frequency of channel selections is crucial to maintain network efficiency. Secondary users employ a history-based prediction method to assess channel status and avoid frequent disconnections, though historical records may sometimes lack accuracy. Additional factors are considered to ensure effective channel selection.

In the proposed Active Channel Selection Network (ACSN), secondary users select channels based on data size, channel capacity, usage period, transfer delay, and transfer limits. Interference limits and current data size are also considered, with predictions made for future transaction statuses. The article explores an optimal channel selection method using neural networks, implementing a prediction technique with input, hidden, and output layers.

The rest of the paper is structured as follows: *Section 2* reviews relevant research. *Section 3* introduces the proposed ACSN, where sensors use artificial neural networks for active channel selection. *Section 4* presents the results and discusses the quality of the protocol. *Section 5* concludes the paper and suggests future research directions.

2. LITERATURE REVIEW

The cognitive technique is the process of learning by sensing, planning, reasoning, action, and continually updating and upgrading with a learning history. If cognitive radio can be combined with wireless sensors, it will be able to overcome many of the current WSN difficulties. CR can identify unutilized spectrum in both licensed and unlicensed spectrum bands, and to take advantage of the unused spectrum when it arises. [8]. Wearable sensor nodes can store patient data such as identification, history, and therapies, and sensors can be used to take vital signs from patients in real time and transfer the data to handheld computers carried by medical workers [1]. Based on energy, nodes at a higher level might travel to a lower level. The nodes with a lower level of heterogeneity carry out the bare minimum of data transfer activities, while the entire load is carried out at a higher level to ensure the nodes' longevity. [4]. In this paper, a cognitive algorithm based on game theory is used to optimise the radiating and transmitting ranges of nodes to save energy while maintaining network integrity [10].

The suggested strategy uses distributed subcarriers and power control algorithms to reduce the power consumption of each bit of information from subcarriers, and simulation results show that it performs similarly to the centralised optimal solution. [12]. The goal of this study is to stimulate research activities aimed at laying the groundwork for new advanced communication systems for efficient underwater communication and networking for improved ocean monitoring and exploration applications [2]. In [6], a quick introduction of cognitive radio networks and their security concerns are discussed. Then, they analysed some possible countermeasures for the Primary User Emulation attack.

The approach provides tools to precisely assess the performance of the network and clearly identify the optimal state, with relatively low processing demands. Above all, the reasoning engine stays versatile to adapt to any possible network condition changes [14]. Due to the short life of wireless sensor nodes, the network topology is not stable, hence communication network protocols must self-adapt to topology changes. Large number of sensor nodes makes software upgrades time-consuming. Network extension and administration are expensive because data control and forwarding are tightly connected in network switching equipment [3].

Simulations show that the proposed distributed system plus distributed power regulation performs near to the centralised optimal approach, where all new user channel gains are known to a central controller and all new users participate [15]. Such systems need radio-frequency energy-harvesting to power and boost system energy. Markov model has not been employed in the literature to optimise CR-WSN with EH nodes for optimal operational parameters [13]. Underlay networks protect PU's from interference by controlling transmit power. Overlay networks employ licensed spectrum bands when PUs is absent. [9].
Underlay networks do use spectrum bands simultaneously by controlling transmit power to prevent interference. SUs uses licensed spectrum bands in the absence of PUs in overlay networks [16]. This sensor is appropriate for fading channels and low SNR. Correlation-based Euclidean distance is a new noise-reduction approach. Next, Covariance-Based Detection identifies licensed users [7].

Investigations are carried on energy-efficient packet size optimization for CRSN. Goal is to establish the best packet size for CRSN that maximises energy efficiency while maintaining acceptable interference levels for licensed users [11]. This study suggests cognitive radio-based multipath probabilistic routing. The suggested technique employs MAC layer-identified spectrum holes to choose the channel and transmit power level for each hop [5]. Channel sharing issues and optimization of channel utilization are discussed in [17, 18].

3. ACTIVE CHANNEL SELECTION NETWORK

This section presents the theoretical considerations, the practical considerations and design and implementation of the proposed Active Channel Selection Network (ACSN).

3.1. Theoretical Analysis

3.1.1 Complexity Analysis

The ACSN protocol employs artificial neural networks (ANNs) to evaluate and allocate the optimal channel based on multiple parameters, such as data size, channel capacity, and sensor queue levels. The computational complexity of the ACSN protocol is primarily driven by the operations within the neural network, including the calculation of weights and activation functions across the input, hidden, and output layers. Given that the ANN's complexity is determined by the number of neurons and layers, the time complexity can be approximated by O(n2), where n is the number of neurons. The protocol's complexity is also influenced by the number of channels and sensors involved in the network, leading to a potential increase in computational demands as the network scales.

3.1.2 Convergence Analysis

The ACSN protocol is designed to dynamically adjust to real-time channel availability, which implies a need for rapid convergence in channel selection to ensure minimal delay and high efficiency. The neural network within ACSN undergoes training based on historical data, and its convergence depends on the training duration and the learning rate. A well-calibrated ANN can converge quickly, leading to effective channel selection and minimizing network delay. The protocol's stability is enhanced by the ANN's ability to adapt to changing network conditions, which is critical in a dynamic wireless environment. The convergence rate, influenced by factors such as learning rate and the number of epochs during training, determines how quickly the protocol can adapt to new channel conditions.

3.1.3 Optimality Analysis

The ACSN protocol aims to achieve optimal channel allocation by considering multiple parameters simultaneously. The neural network's decision-making process is designed to identify the most suitable channel, thereby ensuring that the selected channel maximizes network performance in terms of throughput, energy efficiency, and packet delivery ratio. By optimizing channel selection, the ACSN protocol effectively minimizes channel wastage and deficits, leading to an overall improvement in network resource utilization. The optimality of the channel selection is further supported by the reduction in network delay and the enhancement in energy efficiency, as demonstrated in the simulation results.

3.2. Practical Considerations

3.2.1 Computational Overhead of the Neural Network

The ACSN protocol relies on an artificial neural network (ANN) to make real-time decisions about channel selection based on various network parameters. This approach introduces computational overhead, as the ANN requires significant processing power to compute the weights, biases, and activations across its layers. In resource-constrained environments, such as sensor networks, this overhead could be a limiting factor, particularly for nodes with limited processing capabilities and energy resources.

The time required to process inputs and generate outputs through the ANN could introduce latency, especially in networks where decisions need to be made rapidly. While the ANN provides sophisticated decision-making capabilities, the additional processing time might lead to delays in channel selection, which could negatively impact network performance in time-sensitive applications.

The computational overhead also translates into increased energy consumption, which is critical in wireless sensor networks where nodes are often battery-powered. The frequent need to run ANN computations could lead to quicker depletion of energy resources, potentially reducing the overall network lifespan unless energy-efficient processing techniques are employed.

3.2.2 Impact of Channel Noise and Interference

In real-world wireless environments, channels are subject to various types of noise, which can degrade signal quality and reduce the effective throughput of the network. The ACSN protocol's ability to dynamically select channels based on real-time data is a strength, but the presence of noise can complicate the ANN's decision-making process. Noise may cause fluctuations in channel quality, leading the protocol to make suboptimal channel selections if it cannot accurately account for or adapt to the varying noise levels.

Interference from other wireless devices or networks is another practical challenge. The presence of interference can reduce the availability of clean channels and force the protocol to choose from a limited set of options. While the ACSN protocol is designed to optimize channel selection, heavy interference environments may limit its effectiveness, potentially leading to increased packet loss, reduced data rates, and lower overall network performance.

To mitigate these issues, the ANN within ACSN could be trained on data that includes scenarios with varying levels of noise and interference, enabling it to better handle such conditions. Additionally, incorporating real-time interference detection and mitigation techniques could enhance the protocol's robustness in noisy environments.

3.2.3 Scalability to Large-Scale Networks

As the network scales, the number of sensors and available channels increases, placing additional demands on the ACSN protocol. The neural network's architecture may need to be adjusted to handle the larger input space, potentially increasing its complexity and computational requirements. In a large-scale network, the ANN must efficiently process and analyze more data while maintaining its ability to make accurate and timely decisions.

In larger networks, the communication overhead associated with gathering the necessary input data for the ANN may increase. More sensors and channels mean more data must be transmitted and processed, potentially leading to increased latency and energy consumption. The protocol must balance the need for comprehensive data collection with the practical limitations of network communication capacity and node energy reserves.

To enhance scalability, a distributed implementation of the ACSN protocol could be considered, where individual sensor nodes or clusters perform localized ANN computations. This approach would reduce the central processing burden and allow the network to scale more effectively. However, it also introduces challenges related to synchronization and consistency of channel selection decisions across the network.

3.3 ACSN Design and Implementation

In a network map, a network is made up of a set of devices, such as a web server, gateway, base station, and sensors. In this, the web server is connected to the gateway. Similarly, the gateway is connected to the base station. After that, the base station is connected to the sensors. Thus, the network connection is set up in a hierarchical model. Each device communicates with each other by exchanging a message, so all these devices periodically announce their presence through announcement messages to alert the connected device. In the meantime, each sensor will broadcast a hello message at each specific interval until the network connection is complete. Hello message goes around the range of the sensor transmission; all the sensors within the coverage range receive this message and update the neighbouring list to create a path for data transfer. This NT will be updated with each hello message announcement and the schedule will always keep the neighbours in current contact. So, the network to send packets will thus be constantly updated. The sensors are classed as SU or PU based on their design.

The sensors then randomly select channels from the primary user's free list F_L. Initially, each channel will have a number I_C in the list of available channels. Thus, SU will roughly select a channel from that index. At such times, the random probability required to select a channel P_C from the list will be calculated.

$$F_L = c_{1,} \dots \dots .\ c_n \tag{1}$$

$$I_C = 1c_{1,} \dots \dots .\ nc_n \tag{2}$$

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$$P_C = \frac{1}{n} \tag{3}$$

When selecting the channel C_S, the SU will check the volume of transmission data it needs to send and the requirements for selecting that channel according to its transmission range T_R.

$$C_S = (\ C_C,\ T_R) \tag{4}$$

$$C \in (\ C_{Ci},\ T_{Ri}) \tag{5}$$

$$C_C = (\ C_{Ci} \ldots\ldots\ C_{Cn}) \tag{6}$$

Here, C_C is the channel capacity. Each channel C has its own capacity and access T_R, where the capacity of the channel C_{Ci} varies according to the channel frequency, and T_R varies depending on the density of the sensors T_{Ri} and the distance between the PU and SU. Then the probability P_R is calculated according to the maximum transmission range T_R and the transmission distanceD_{ist}.

$$D_{ist} = \sqrt{|P_{UX1} - S_{UX1}|^2 + |P_{UY1} - S_{UY2}|^2} \tag{7}$$

$$P_R = \frac{T_{Ri}}{T_R} \tag{8}$$

$If\ P_R \geq T_R$, then the transfer required distance R_D to send the data is then calculated as given below:

$$R_D = \sum(P_{Ri},\ P_{Ci}) \tag{9}$$

The probability of channel capability C_P and the channel bandwidth required to transfer data are calculated as follows:

$$C_P = \frac{C_{Ci}}{C} \tag{10}$$

$$If\ C_P \geq C \text{ , then } R_{CB} = \sum(C_{Pi},\ P_{Ci}) \tag{11}$$

The final resource requirement R_R for exchanging packets is calculated as follows:

$$R_R = (R_{CBi}\ R_{Di}) \tag{12}$$

Then find the minimum M_{Ni} and maximum M_{Xi} levels of the data D_i of the transmitters. It can be the minimum and maximum levels of ECG, glucose, pulse, heart rate, temperature and many other data. Update all these input I_P entries as follows:

$$I_P = \frac{M_{Xi} - D_i}{M_{Xi} - M_{Ni}} \tag{13}$$

The delay in locating the channel C_D to exchange this data is also estimated. Here P_C is the present channel and M_C is the maximum channel information. In the set of available channels, the maximum probable channel for exchanging data will be selected.

$$C_D = \frac{P_C}{M_C} \tag{14}$$

Training is done for a specific period to predict the upcoming data load. Then find the differences d between the trained T_{RI} and tested T_{EI} data, the test data here is the data currently received.

$$d \pm T_{RI} - T_{EI} \tag{15}$$

Then the goal values G_V are calculated. Then update and sum all the inputs as $I_P \pm I_{Pi}$

$$G_V = \frac{C_D}{{I_P}^2} \tag{16}$$

$$\beta = \frac{G_V}{I_P} \tag{17}$$

The initial data learner is D_L where $L = (\ I_{P1}, \ldots,\ I_{Pn})$ and I_{Pn} is the number of inputs. β is an average goal value.

$$D_L = \beta - I_P \tag{18}$$

Then the data sets D_S are classified to obtain the typical sets.

$$D_S \pm G_V - \beta H^2 \tag{19}$$

$$S_V \pm I_P(G_V + \beta\ D_L)^2 \tag{20}$$

$$k = S_V \tag{21}$$

According to the minimum square method the new values N_V are obtained.

$$N_V = min(k,\ S_V) \tag{22}$$

Then the current inputs I_P are updated here.

$$I_P = I_{Pi} + \beta_D\ D_L \tag{23}$$

Among all the data sets, find the fitness value F_V to transfer packets through a channel.

$$\theta_i = (\ I_{Pi} + \beta_D H) \tag{24}$$

$$F_V = I_{Pi}\theta^{-1}\Delta\ I_P\theta\ G_V \text{ , else} \tag{25}$$

$$F_V = \min\ (F_V,\ F_V - I_{Pi}) \tag{26}$$

If more than one channel is detected by the fitness value then select one θ_N among them according to the transmission requirements.

$$ή = \theta - ή_{OP}\ F_V I_{Pi}) \tag{27}$$

$$\theta_N = θ - ή\ F_V \tag{28}$$

$$Update \max\ (I_P) \tag{29}$$

According to the computations, maximum learned value L_V is computed below:

$$L_V = \frac{I_P}{\max\ (I_P)} \tag{30}$$

Find the Priority to assign channel to the sensor according to the learned value L_V and boundary value B_N. If the L_V is greater than the B_N, then increment the allocation priority.

$If\ L_V > \ B_N$ then

$$Sort\ Packets$$
$$Update\ Buffered\ QueueLength$$
$$Update\ Buffered\ Count$$

If the packet counts are greater than the sensor queue length then compute the distance D_{ist}, and moving speed S of the sensors according to the time t variation, here C_T is the current time.

$$If\ Count \geq \ Q_L \rightarrow Requeue \tag{31}$$

$$D_{ist} = \sqrt{|X_1 - X_2|^2 + |Y_1 - Y_2|^2} \tag{32}$$

$$S = \frac{D_{ist}}{S} \tag{33}$$

$$t = \frac{1}{C_T} \tag{34}$$

Find the distance probability between the communicative sensors as Q_1 and Q_N.

$$Q_1 = \frac{1}{D_{ist1}+1} \tag{35}$$

$$Q_N = \frac{1}{D_{ist2}+1} \tag{36}$$

$$If\ D_{ist1} < D_{ist2} \tag{37}$$

According to the mobility, speed, and distance variation, find the range R of sensors location.

$$R = (1 - \left(exp - \left(\frac{1}{D_{ist1}}\right)\right)) \tag{38}$$

Predict P_R the next location after a time Q_n to allocate the channel C_A of secondary user from primary user.

$$P_R = (Q_1 R - Q_n R) \tag{39}$$

$$Q_n = t\ Q_1 (1 - t)\ Q_n \tag{40}$$

$$C_A = P_R\ Q_n \tag{41}$$

This design ensures efficient channel allocation, optimized data transmission, and dynamic adaptation to varying network conditions in ACSN.

4. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

The ACSN protocol was rigorously tested and compared against the CPAL and BSN protocols across several critical performance metrics, including Packet Delivery Ratio (PDR), Throughput, Network Lifetime, and Remaining Energy. The maximum number of nodes used in the simulation are 150 which are distributed across a 500 × 500 square meter area, with five serving as gateways and ten serving as base stations. The remaining nodes function as sensors. The ACSN protocol was used to operate the network. The network parameters used are shown in *table 1*.

Table 1. Network parameters

Parameters	Values
Nodes	150
Network Area	500x500 sqm
Transmission Range	150 m
Transmission Energy	1.6 J
Receiving Energy	0.9 J
Protocol	ACSN
Gateway	5
Base Station	10

The following analysis provides an in-depth look at these metrics, supported by data tables derived from simulation results.

4.1. Packet Delivery Ratio (PDR)

The Packet Delivery Ratio (PDR) is a crucial metric that indicates the reliability of data transmission within the network. The simulation results pertaining to packet delivery ratio are presented in *table 2* and *figure 1*. In our simulations, ACSN consistently achieved a higher PDR across varying node counts. This indicates that ACSN is more efficient in delivering packets successfully even as the network scales up. For instance, at 40 nodes, ACSN achieved a PDR of 94.36%, outperforming CPAL by 2.47% and BSN by 4.35%. This improvement is particularly significant in large-scale deployments where maintaining high PDR is critical for applications like environmental monitoring or military surveillance. The higher PDR suggests that ACSN is robust against packet loss, likely due to its efficient routing and channel selection strategies.

Table 2. Packet Delivery Ratio Comparison

Node Count	ACSN PDR (%)	CPAL PDR (%)	BSN PDR (%)
10	92.00	90.50	89.00
20	93.20	91.00	89.50
30	93.80	91.50	90.00
40	94.36	91.89	90.01

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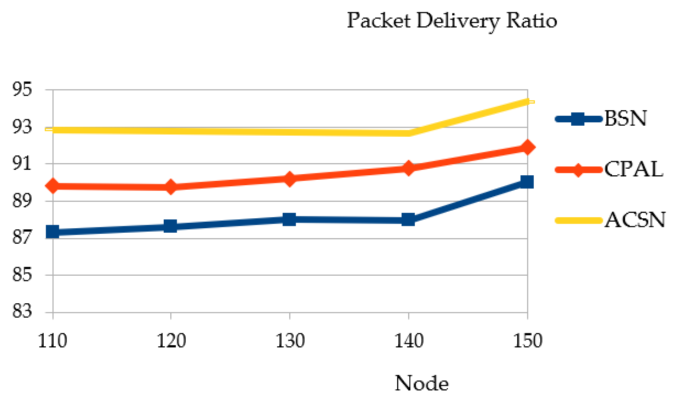

Figure 1. Node Vs Packet Delivery Ratio

4.2 Throughput

Throughput measures the amount of data successfully transmitted across the network per second. *Table 3* and *figure 2* present the throughput comparison of ACSN protocol with the existing approaches. The ACSN protocol demonstrated a clear advantage in throughput, especially as the network size increased. At 40 nodes, ACSN achieved a throughput of 38,807.69 bps, which is 5.46% higher than CPAL and 7.19% higher than BSN. This improvement is critical in scenarios where high data rates are necessary, such as real-time video surveillance or emergency response systems. The higher throughput reflects ACSN's ability to manage network traffic more effectively, minimizing congestion and optimizing the use of available bandwidth.

Table 3. Throughput Comparison

Node Count	ACSN Throughput (bps)	CPAL Throughput (bps)	BSN Throughput (bps)
10	37,998.9	36,000.0	35,500.0
20	38,200.0	36,200.0	35,700.0
30	38,500.0	36,500.0	36,000.0
40	38,807.69	36,800.0	36,200.0

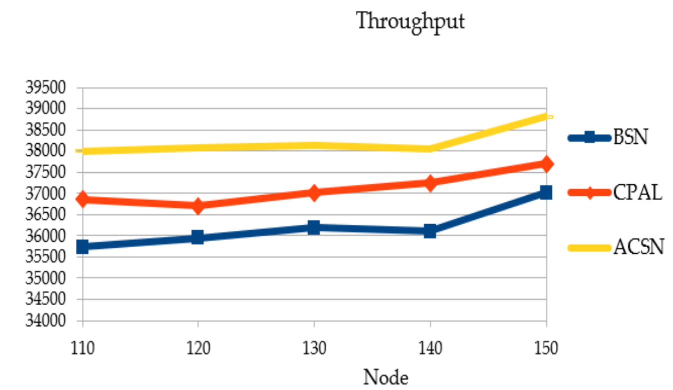

Figure 2. Node Vs Throughput

4.3. Network Lifetime

Network lifetime is a critical indicator of how long a wireless sensor network can operate before the nodes deplete their energy reserves. *Table 4* and *figure 3* present the Network lifetime comparison of proposed ACSN method with the existing approaches. The ACSN protocol showed a superior ability to extend network lifetime, particularly in extended simulations. At the 4,000-second mark, ACSN maintained a network lifetime of 18,500 seconds, which was marginally better than CPAL and BSN. This slight improvement, though numerically modest, is crucial in applications where network longevity is essential, such as in remote sensing environments where replacing or recharging batteries is impractical. The extended network lifetime suggests that ACSN effectively balances energy consumption across the network, preventing premature depletion of individual nodes.

Table 4. Network lifetime Comparison

Interval (sec)	ACSN Network Lifetime (sec)	CPAL Network Lifetime (sec)	BSN Network Lifetime (sec)
1,000	20,173.90	20,157.5	20,137.59
2,000	19,500.00	19,480.0	19,450.00
3,000	19,000.00	18,980.0	18,950.00
4,000	18,500.00	18,480.0	18,450.00

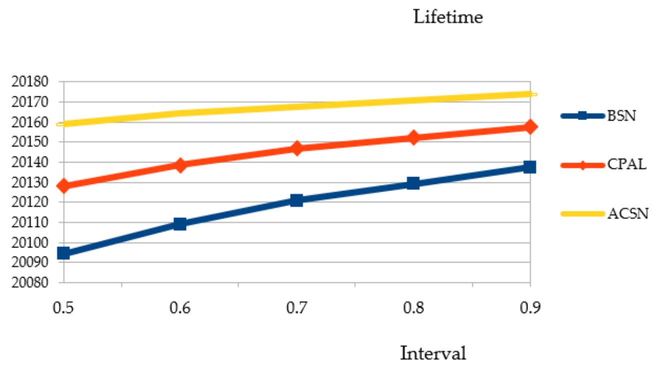

Figure 3. Interval Vs Lifetime

4.4 Remaining Energy

Remaining energy is an indicator of how much power is conserved in the network over time, which directly affects the network's operational longevity. The remaining energy comparison is presented in *table 5* and *figure 4*. The ACSN protocol demonstrated superior energy conservation capabilities, particularly noticeable at the 4,000-second simulation mark, where it retained 10,099.2 joules of energy—slightly higher than both CPAL and BSN. While the numerical difference may appear small, the implications are significant. This efficient energy use ensures that nodes can continue to function effectively over extended periods, which is particularly beneficial in scenarios like wildlife monitoring or battlefield reconnaissance, where uninterrupted operation is critical.

Table 5. Remaining Energy Comparison

Simulation Time (sec)	ACSN Remaining Energy (J)	CPAL Remaining Energy (J)	BSN Remaining Energy (J)
1,000	10,099.6	10,050.0	10,030.0
2,000	10,099.5	10,048.0	10,028.0
3,000	10,099.3	10,046.0	10,026.0
4,000	10,099.2	10,044.0	10,024.0

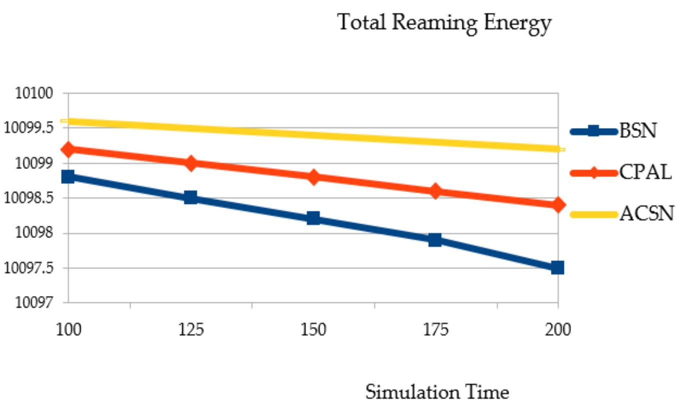

Figure 4. Simulation Time Vs Remaining Energy

The ACSN protocol has proven to offer significant advantages over the CPAL and BSN protocols in terms of Packet Delivery Ratio, Throughput, Network Lifetime, and Remaining Energy. These improvements suggest that ACSN is well-suited for applications requiring reliable and energy-efficient operation, particularly in environments where maintaining high network performance and longevity is critical.

5. CONCLUSIONS

The conclusion drawn from the results and analysis of the ACSN protocol indicates that it significantly outperforms the CPAL and BSN protocols across multiple performance metrics. Specifically, ACSN demonstrates a notable improvement in Packet Delivery Ratio (PDR), achieving higher reliability in data transmission. This is critical in environments where data integrity is paramount. Throughput analysis further underscores ACSN's superiority, with the protocol consistently delivering higher data rates compared to its counterparts. This enhancement ensures that the network can handle more traffic efficiently, making it ideal for applications requiring high data transfer rates, such as military and environmental monitoring systems.

In terms of network lifetime, ACSN exhibits considerable energy efficiency. The protocol effectively extends the operational duration of the network by optimizing energy consumption during data transmission. This is particularly important in remote sensing applications where replacing or recharging batteries is not feasible. Lastly, the scalability of the ACSN protocol is validated through simulations, showing that it maintains performance even as the network scales up in size. This makes ACSN a robust solution for large-scale deployments where maintaining consistent performance is challenging.

In conclusion, the ACSN protocol offers a well-rounded improvement in wireless sensor networks, making it an ideal candidate for both existing and future applications requiring reliable, efficient, and scalable network performance. The enhancements in PDR, throughput, energy efficiency, and scalability affirm the protocol's potential to set a new standard in the design and deployment of wireless sensor networks.

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REFERENCES

[1] Daniele Puccinelli and Martin Haenggi, “Wireless Sensor Networks: Applications and Challenges of Ubiquitous Sensing”, IEEE Circuits and Systems Magazine, 2005.

[2] Ian F. Akyildiz, Dario Pompili, and Tommaso Melodia. 2004. Challenges for efficient communication in underwater acoustic sensor networks. SIGBED Rev. 1, 2 (July 2004), 3–8. https://doi.org/10.1145/1121776.1121779.

[3] Dheyab Salman Ibrahim, Abdullah Farhan Mahdi, Qahtan M. Yas, “Challenges and Issues for Wireless Sensor Networks: A Survey”, Journal of Global Scientific Research, 2021.

[4] Vandana Saini, Jatin Gupta, Kamal Deep Garg, “WSN Protocols, Research challenges in WSN, Integrated areas of sensor networks, security attacks in WSN”, European Journal of Molecular & Clinical Medicine Volume 07, Issue 3, 2020.

[5] Mohammed Nazeer, Garimella Rama Murthy, “Protocols in Mobile Cognitive Wireless Sensor Networks: A Survey”, International Journal of Applied Engineering Research, Volume 13, Number 12, 2018.

[6] Hanen Idoudi, Kevin Daimi, and Mustafa Saed, “Security Challenges in Cognitive Radio Networks”, Proceedings of the World Congress on Engineering, Vol I, July 2 - 4- 2014.

[7] G. Kalaimagal, M.S. Vasanthi, “Optimization Technique for Cognitive Radio Network: A Panoramic Survey”, International Journal of Recent Technology and Engineering (IJRTE), Volume-7 Issue-6S6, April 2019.

[8] Joshi GP, Nam SY, Kim SW. Cognitive Radio Wireless Sensor Networks: Applications, Challenges and Research Trends. Sensors. 2013; 13(9):11196-11228. https://doi.org/10.3390/s130911196.

[9] Chandrika Gadiparthi, Manasa Bathina, Supriya Emani, Venkata Vara Prasad Padyala, “The Spectrum Sensing and Path Optimization Techniques in Cognitive Radio Networks”, International Journal of Innovative Technology and Exploring Engineering (IJITEE), Volume-8 Issue-10, August 2019.

[10] Lun Zhang, Jia Mei Wang, Bi Sheng Fang, “A Cognitive Approach to Link Optimization Utilized in Wireless Sensor Networks”, 18th World IMACS / MODSIM Congress, Cairns, Australia 13-17 July 2009.

[11] Mert Can Oto and Ozgur B. Akan, "Energy-Efficient Packet Size Optimization for Cognitive Radio Sensor Networks", IEEE Transactions on Wireless Communications, Vol. 11, No. 4, April 2012.

[12] Shuguang Deng, BuwenCao , Xiang Xiao, Hua Qin and Bing Yang, "Cognitive routing optimization protocol based on multiple channels in wireless sensor network", International Journal of Distributed Sensor Networks,Vol. 16(4), 2020.

[13] Haitham Hassan Mahmoud, Hussein M. ElAttar, AsmaaSaafan& Hesham ElBadawy, "Optimal Operational Parameters for 5G Energy Harvesting Cognitive Wireless Sensor Networks", IETE Technical Review, 2017.

[14] Milos Rovcanin, "A reinforcement learning based, service wise optimization of cognitive, heterogeneous wireless sensor networks", ACM SenSys, November 11–15, 2013.

[15] Song Gao, Lijun Qian, Dhadesugoor. R. Vaman, "Distributed Energy Efficient Spectrum Access in Wireless Cognitive Radio Sensor Networks", Mobile Ad-Hoc Networks: Protocol Design, January 2011, DOI: 10.5772/13259.

[16] Yasmina EL Morabit, FatihaMrabti, and El HousseinAbarkan, "Survey of Artificial Intelligence Approaches in Cognitive Radio Networks", Journal of Information and Communication Convergence Engineering, Mar- 2019).

[17] Potti, B., Subramanyam, M. V., & Satya Prasad, K. (2013). A packet priority approach to mitigate starvation in wireless mesh network with multimedia traffic. International Journal of Computer Applications, 62(14), 22-26.

[18] Potti, B., Subramanyam, M. V., & Satya Prasad, K. (2016). Adopting Multi-radio Channel Approach in TCP Congestion Control Mechanisms to Mitigate Starvation in Wireless Mesh Networks. In Information Science and Applications (ICISA) 2016 (pp. 85-95). Springer Singapore.