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Towards Self-Sustainable and Intelligent WSNs: A Survey of Energy Harvesting and Cognitive Radio Technologies

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Abstract: ***Wireless Sensor Networks (WSNs) have gained significant attention due to their wide range of applications in environmental monitoring, smart agriculture, healthcare, industrial automation, and Internet of Things (IoT) systems. The current WSNs have limitations such as limited battery capacity, low network lifespan, spectrum scarcity, scalability problems, and poor communication quality. To address the constraint of limited energy, several technologies have been proposed for energy harvesting (EH) to ensure an operation of self-sustainable networks, which makes possible to tap into various sources of environmental energy, including sun, vibration, or radio frequency signals. Cognitive Radio (CR) technology has similarly proved to be a beneficial approach to spectrum utilization through dynamic spectrum access and intelligent channel selection. EH and CR technologies are combined to form Energy Harvesting Cognitive Wireless Sensor Networks (EH-CWSNs), which enable better energy efficiency, better spectrum utilization and longer network lifetime. However, the routing complexity, clustering efficiency, spectrum sensing, scalability, communication reliability and resource management are some of the problems that still remain with EH-CWSNs. This survey provides an exhaustive analysis of the existing routing protocols, clustering, optimization and energy management techniques in WSNs and their benefits and drawbacks, with emphasis on EH-WSNs, Cognitive WSNs, and EH-CWSNs. In addition, some current challenges and future research directions are outlined for the development of efficient and intelligent wireless sensor networks.***

Keywords: Wireless Sensor Networks, Energy Harvesting, Cognitive Radio, Routing Protocols, Spectrum Management

1. Introduction

The Wireless Sensor Networks (WSNs) consist of large number of sensor nodes that work collaboratively to track physical or environmental parameters like temperature, humidity, pollution, pressure, motion etc. and report the obtained information to some target sink or a base station for analysis [1]. WSNs have received significant attention in several applications including environment monitoring, smart agriculture, smart industrial automation, healthcare, military surveillance, and Internet of Things (IoT) systems due to their ability to self-organize and be deployable at a low cost [2,3].

A typical WSN is composed of the sensing, processing, wireless communication and power sources [1]. Conventional WSNs are facing several limitations even though they were widely used, such as low battery capacity, limited network lifetime, scalability issues, unreliable communication, and spectrum scarcity. Often these sensor nodes must be deployed in a remote location or in hostile environments where frequent replacement of batteries becomes impractical and increases the cost of maintaining the system [4].

To tackle this limitation, Energy Harvesting (EH) techniques, which allow sensor nodes to tap energy from the environment, including solar energy, vibration, thermal energy, wind, and radio frequency signals, have been found effective [5,6]. EH technologies enhance the sustainability of the network and prevent reliance on the limited battery resources, which increases the operational lifetime of the network [7]. The spectrum shortage issue is another challenge associated with energy limitations, created by growing demands on wireless communication. To enable DSA, CR technology has been developed as an intelligent mechanism that enables sensor nodes to dynamically exploit the available spectrum resources, while causing acceptable interference levels to the licensed services users [8]. The integration of cognitive capabilities into WSNs results in Cognitive Wireless Sensor Networks (CWSNs), which improve spectrum utilization and communication efficiency [9].

As a result of the above combinations, the field of Energy Harvesting Cognitive Wireless Sensor Networks (EH-CWSNs) [10] has emerged. EH-CWSNs provide self-sustainable network operation by simultaneously overcoming both energy limitation and spectrum utilization challenges. These networks have shown a lot of interest due to their applications in smart cities, environmental monitoring, disaster management, industrial automation, and large-scale IoT deployments [11,2]. A number of routing, clustering, optimization, and resource management techniques have been suggested for EH-WSNs, CWSNs, and EH-CWSNs that can enhance the energy efficiency, network lifetime, throughput, and communication reliability. However, various issues like routing complexity, scalability, spectrum sensing overhead, resource allocation, communication reliability and network adaptability have yet to be resolved [12]. This survey provides a comprehensive review of the WSN-based approaches in detail focusing on Energy Harvesting WSNs, Cognitive WSNs and Energy Harvesting Cognitive Wireless Sensor Networks by analyzing techniques, benefits, challenges, and further research directions.

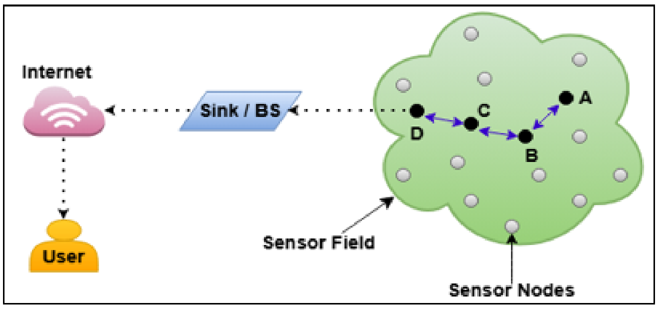

Figure 1: Illustration of Wireless Sensor Network architecture

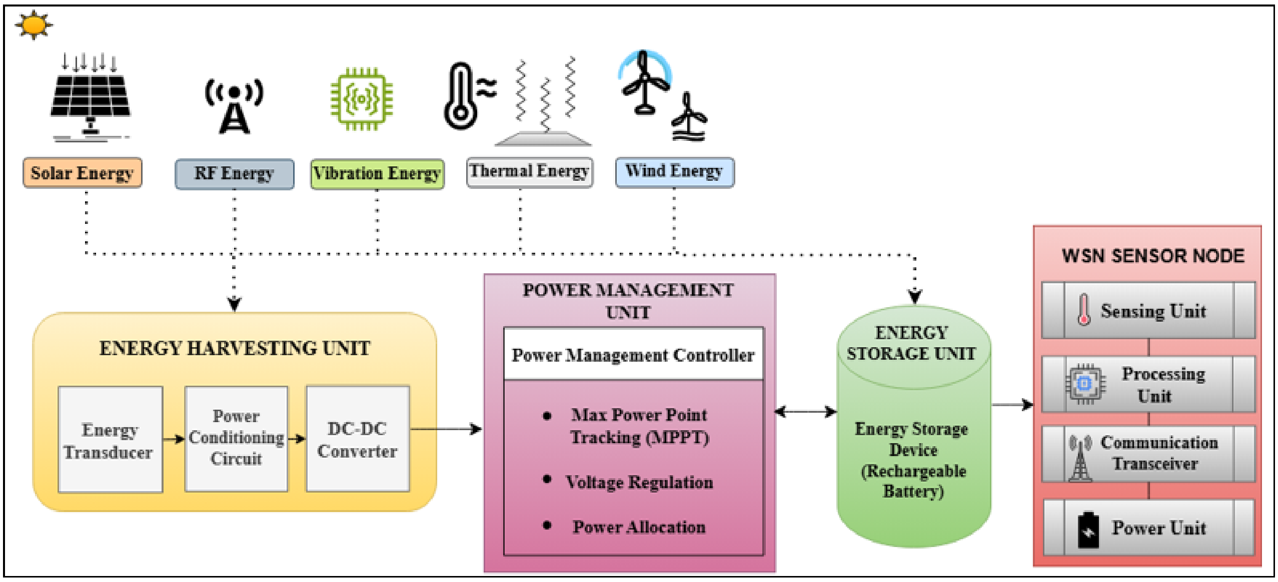

Figure 2: Illustration of Energy Harvesting Sources in WSN

2. Review on WSN Based Approaches

2.1 Energy harvesting WSN

Sah et al., [7] developed an Efficient Routing Awareness Scheduling (ERAS) algorithm for energy harvesting Wireless Sensor Networks (WSNs) to combat energy scarcity and network performance. This technique added a solar energy harvesting scheme and a hierarchical clustering routing protocol, to improve energy efficiency. The scheme was dynamic altering the node states according to sensed data and residual energy, which provided efficient use of harvested energy. It was used synchronization-based TDMA scheduling to regulate communication among every cluster-head (CH) and cluster-members (CMs) to avoid data collision and ensure higher transmission reliability. In the cluster head selection process, both residual energy of the nodes and harvested energy were taken into account along with the number of active nodes in a cluster for maximizing throughput and spread of energy.

Zeb et al., [13] presented a Location-Centric Energy Harvesting-Aware (LCEHA) routing protocol for IoT-based Wireless Sensor Networks (WSNs) to save energy, improve network lifetime and routing performance. This method mitigated various challenging issues, including energy scarcity, routing delay, and packet loss, by incorporating energy harvesting mechanisms into the network. A location-based routing strategy was used which was to select routing paths towards the destination subject to angular proximity, thereby making routing towards an efficient node. The protocol included distributed neighbour discovery and routing processes, that leverage neighbour data to establish routes. The method combined energy harvesting techniques to increase energy use in all the sensor nodes and to make the sensors more sustainable.

Jalalinejad et al [14] introduced a novel multi-hop clustering and renewable energy-based routing framework named NERY to enhance energy harvesting wireless sensor network (EHSN) network efficiency and stability in the limited energy harvesting environment. At first, the framework applied for hybrid clustering by dividing between centralized and decentralized clustering according to the node status of energy and harvesting energy levels. The protocol was implemented in three main stages: forming a cluster, data transfer, and centralized management to enhance communication efficiency. In order to save all the energy and enhance the performance of the packet transmission, multi-hop real-time routed was applied between sensor nodes, cluster heads (CHs) and base stations (BSs). The framework dynamically analysed harvested energy levels and chose routing paths and cluster structures to allow for optimum energy distribution across network nodes.

Asiedu et al., [15] investigated spectrum-sharing network, where primary device-to-device networks operate in dual-band, and secondary Wireless Sensor Networks (WSNs) are assisted by the energy harvesting system. A multi-stage rectenna energy harvesting circuit model was incorporated in this new model to increase network energy efficiency. A new multi-hop routing problem was worked out to improve the overall performance of the network by optimizing the routing, sensor node transmits power control, and clustering of energy transmitters while considering the effects of interference, power budget, and rate. A combination of centralized and distributed routing schemes was implemented to solve these inter-related tasks effectively.

Taghizadeh et al., [16] introduced a learning-based routing approach that is named LANTERN for energy harvesting IoT networks in order to maximize packet delivery performance. The framework reported a first approach using Routing Protocol for Low-Power and Lossy Networks (RPL) as a basis for routing decision-making, and added energy harvesting awareness to solve the shortcomings of conventional routing policies. The recommended method is based on Q-learning for learning energy harvesting behavior and predicting energy consumption due to communication and computation requirements of sensor nodes. Besides, a new routing metric named Energy Exponential Moving Average (EEMA) was developed to decide the path selection based on harvested energy, energy consumption rate and the remaining node energy. Dynamic adaptation of routing had been performed according to the varying harvesting conditions to overcome energy hole issues and enhance the network reliability.

Sheikh & Joshi [17] Developed WSNs for improving the network performance, energy efficiency and reliability. In this approach, each sensor node had been incorporated with a wireless energy harvesting (WEH) unit to prolong network lifetime and enhance the quality of service under dynamic IoT conditions. The protocol used clustering techniques to minimize control overheads in order to enhance inter-node connectivity: Cluster head (CH) and Cluster gateway (CG) selection is based on evaluation of cost function, which incorporates distance to the sink, link quality estimation, residual energy and total energy. Also, a cooperative node (CN) mechanism was added to identify suspicious or undesirable node behavior and improve network security. This also guaranteed fault tolerance, as some nodes could fail partially and continue to be a part of the network for data transmission.

Hao et al., [18] introduced a Biodynamics-inspired energy-efficient routing algorithm for Energy Harvesting (EH)-aided three-dimensional Wireless Sensor Networks (3-D WSNs), to address energy efficiency and buffer blocking problem. First, the model was built to calculate the energy state of sensor nodes using classification of the channel conditions in a 3-D space. Then, it was developed a new buffer queuing model to analyze the buffer congestion level and blocking conditions in the network. The IEEE 802.11b MAC protocol, node energy status and buffer conditions were then added to the idle energy prediction mechanism to dynamically control the states of data reception and the power level of the transmission to maximize energy utilization. Additionally, an approach inspired by hemodynamics was used to establish the routing strategy and procedure for selecting an optimum path.

Yoon [19] suggested an energy-efficient dual-mode data collection scheme for energy harvesting Wireless Sensor Networks (WSNs) by integrating Long Range Wide Area Network (LoRaWAN) and Bluetooth Low Energy (BLE) technologies. This approach reduced sensing intervals dynamically according to the prediction of harvested energy and stored energy for critical data sending to achieve network efficiency. Environmental data like temperature, humidity, and light intensity is reported to the cloud via LoRaWAN single-hop to conserve energy. Urgent data generated during abnormal events (e.g., intrusion detection, real-time monitoring) was transmitted via BLE using multi-hop routing and multiple pathways to guarantee timely and reliable delivery. The scheme applied an adaptive sensing rate and has a buffer of energy to be used for high-priority transmissions.

2.2 Cognitive WSN

He et al., [20] suggested an optimization-based routing protocol named Whale Optimization Routing Protocol (WORP)for Cognitive Radio Wireless Sensor Networks (CR-WSNs) to tackle the energy constraints and routing issues. In this approach, whale foraging behavior is used for determining optimal routing paths and residual energy and total node energy are considered for energy-aware routing. To optimize network efficiency and minimize transmission delay, WORP chose routes based on fitness values. The protocol emphasized minimizing network cost, maximizing Quality of Service (QoS), and optimizing routing cost performance in CR-WSNs with limited battery supplies.

Wang et al., [21] introduced an IMO-based clustering routing protocol (IMOCRP) for Cognitive Radio Sensor networks (CRSNs) for the selection of cluster heads and approaches to energy efficiency issues. This protocol used Ions Motion Optimization (IMO) algorithm to optimize the number of cluster and cluster head automatically and to reduce the average energy consumption and the balance of the remaining energy among the nodes. IMOCRP adopted centralized cluster formation and channel allocation strategies to decrease the overhead, collision of primary users, and increase the success of information transmission. This protocol specifically adapted the available channel information at the sensor nodes so as to effectively adapt to dynamic spectrum environments.

Panbude et al., [22] presented an optimal cluster head (CH) selection algorithm: Cosine Sand Cat Optimization (CSCO) to facilitate efficient communication for clusters in Cognitive Radio Sensor Networks (CRSNs) with minimum energy consumption. This CRSN environment was simulated and spectral allocation performed on a LeNet based spectral feature extractor model. Then, Primary User (PU) aware optimal CH selection was performed with the suggested CSCO algorithm by taking into account various objective fitness parameters. After the cluster selection, the optimized cluster structure was used for data communication between sensor nodes.

Kamatham & Sunehra [23] suggested a Node Grade Factor (NGF)-based multi-path routing protocol named NGFMR for Cognitive Sensor Networks (CSNs) to improve energy efficiency, reliability, and overall network performance. This approach resolved several critical issues like mobility of nodes, spectrum variations, and shortage of resources by allowing adaptive routing in dynamically changing wireless communication environments. Several Quality of Service (QoS) metrics like distance to the sink, spectrum accessibility, communication cost, and node delay were incorporated into the protocol to help with the selection of the route. The method was designed to introduce NGF, to provide a node-disjoint multi-path routing and minimize route interference in order to improve load balancing across the network. In addition, multiple paths were used to distribute traffic to improve stability and avoid early node depletion.

Faris et al. [24] investigated the enhancement of Wireless Sensor Networks (WSNs) for natural disaster prediction through the integration of neural network-based cognitive radio technology. The goal of this approach was to enhance the performance, resilience, and efficiency of the network, with a particular focus on optimizing its ability to support and manage disasters by leveraging advanced routing protocols and machine learning techniques. To assess the effectiveness of the method and examine different key performance metrics, including energy consumption, network lifetime, and prediction accuracy, simulations were performed with different scenarios. Moreover, clustering-based hierarchical topologies and energy-efficient routing were determined as effective efficient solutions for employing efficient network operations.

Al-Ibraheemi et al., [25] presented a Levy Flight fine-tuned Red Deer Optimization (LFRDO) algorithm for minimizing energy consumption and transmission data loss in WSNs. This method applied the Red Deer Optimization and Levy Flight mechanisms to optimize routes, minimize energy consumption, minimize network delay and improve scalability. LFRDO controlled cognitive energy and reached intelligent routing decisions to achieve better packet delivery and network lifetime in dynamic network conditions. Moreover, it is an effective routing that enables large scale WSN environments and provides reliable communication and minimum end to end delay.

2.3 Energy Harvesting-Cognitive Radio Sensor Networks

He et al., [26] investigated a Hybrid Game Theory Routing and Power Control (HGRPC) algorithm to investigate power control and routing issues in Energy Harvesting (EH) multi-hop Cognitive Radio Networks (CRNs). The proposed method involves relay selection, routing decision, residual energy, distance of communication, hop count and energy availability to gain optimum performance of the network. HGRPC used game theory to control cooperation and competition between the secondary user nodes and select optimal secondary user nodes to be the next hop for data forwarding. The routing process involved in these services were the route discovery, route selection, route reply and route maintenance to enable effective multi-hop communication.

Obaid et al., [27] developed RMAC-M, a mobility-aware cluster-based MAC protocol for RF cognitive wireless sensor networks (CWSNs) to address energy limitations and topology changes resulting from the mobility of nodes. This protocol incorporated RF wireless energy harvesting with a multi-tier clustering architecture and utilized an R-factor-based cluster head selection mechanism considering residual energy, residual data, and node speed. It did not need neighbor discovery, but used a three-layer super cluster head routing mechanism to transmit data. Moreover, in order to minimize the loss of clusters due to node mobility, a reserve-cluster-head scheme was implemented. This protocol adopted recursive frame design, spectrum sensing schemes to enhance the energy efficiency and to control the access to the spectrum. Wang et al., [28] developed a Simultaneous Wireless

Information and Power Transfer (SWIPT)-based Multi-hop Clustering Routing Protocol (SMCRP) to optimize energy balance and maximize network lifetime in RF Energy Harvesting Cognitive Radio Sensor Networks (RF EH-CRSNs). Energy gathered from the ambient radio frequency (RF) energy as well as energy retrieved by SWIPT was taken into consideration for cluster head selection, cluster formation and inter-cluster routing, under the protocol. But the assumption was perfect spectrum sensing and linear energy harvesting, making it agnostic in practical. Errors in the spectrum sensing would result in interference with a primary user, and non-linearity of the spectrum harvesting would cause the power harvested to saturate.

Mortada et al., [29] explored the integration of Location Information-based Routing (LIBRO) protocol in Energy Harvesting based Cognitive Radio Wireless Sensor Networks (EH-CWSN) in addressing the problems of energy consumption and operation of the network in a sustainable manner. This method developed LIBRO to enable CR functionalities, such as spectrum sensing, and optimized the network parameters to minimize energy consumption, collision wavelet with PUs, packet delivery delay, and network throughput. The protocol was designed to reduce the exchange of information among the nodes and help them reduce the disruptions they cause PUs and way of energy consumption, providing greater sustainability.

Giang et al., [30] analyzed a deep reinforcement learning (DRL) method to optimize both the phase shifts of RISs and the transmission power through a joint optimization, in RIS-enabled NOMA CRNs. The system was parameterized as a Markov Decision Process (MDP) to maximize the sum-rate of cognitive users under dynamic network conditions such as channel uncertainty, energy harvesting constraints and user mobility. To address high-dimensional continuous state and action spaces, a Deep Deterministic Policy Gradient (DDPG) algorithm was used to make adaptive decisions in time-varying environments. The approach achieved higher spectral efficiency and network performance compared to other conventional benchmark schemes, that included OMA and myopic optimization. The results showed that for practical constraints, the optimization of communication efficiency in CRNs was significantly improved by the use of RIS-assisted DRL-based optimization technique.

Mer: Improved sum-rate and spectral efficiency in RIS-assisted NOMA communication.

Dem: Needs correct channel and system state information, which can be difficult in real networks.

3. Comparative Analysis

Tables 1, 2 and 3 show the comparison between reviewed WSN-based approaches, such as Energy Harvesting WSN, Cognitive WSN, and Energy Harvesting Cognitive Radio Sensor Network approaches. This comparison emphasizes strengths and weaknesses, methods employed, environments for simulation, and performance measures to compare current methods.

Table 1: Energy harvesting WSN

Ref	Techniques Used	Merits	Demerits	Performance Metrics
Sah et al., [7]	ERAS	Significant packet-loss reduction and operational network lifetime increase in Wireless Sensor Networks	High control message overhead increased energy consumption due to frequent data exchange for monitoring node distribution and residual energy	No of nodes=100, PDR=3, Network lifetime= 4900, Energy consumption=8500, Network sustainability in linear and varaiable weather condition = EH Rate(EHR)=5.8, Energy consuming rate (ECR)=5 and EHR=5.5, ECR=5
Zeb et al., [13]	EH technique, LCEHA	The network reduced the need for manual battery swapping with ambient energy available locally (solar, wind and vibration).	LCEHA protocol causes uneven energy depletion across nodes because localized spatial energy predictions are involved (can cause early node failures).	Energy Consumption: 0.277, Throughput:69.64, Packet Loss Ratio (PLR) = 0% up to 80 nodes
Jalalinejad et al [14]	AEHAC and CRBS protocols	This approach increases the network stability by decreasing the amount of energy used for unnecessary operations and increases the overall network lifetime	Prone to higher routing complexity and computation expense for several hops to transmit and hybrid centralized-decentralized clustering mechanism	No of alive nodes =200, Total Time (hour)= 3:36, Network Stability = 48 min-816.9 packets (95%), Avg energy of alive nodes=6, Total Time=72 hrs, Energy consumption=374.9j, Throughput=94. Packet loss=0.
Asiedu et al., [15]	CSDRMandD SDRM methods	The routing and clustering solutions yielded better performance than the benchmark solutions in terms of network efficiency and system performance	Increased computational and coordination overhead due to the jointly optimized routing, power control and clustering functions, which may limit scalability and processing complexity in large scale networks	Total Transmit power range=14 No of routing SNs(K)=16 Avg NEE= 350, SN's avg achievable rate (Rk) =1.6, SN's average transmit power=2, Performance of CRM: K=10, Avg NEE=320, Rk=1.1, avg Transmit power= -29.
Taghizadeh et al., [16]	EEMA, DODAG	Improved network lifetime, increased packet delivery ratio, reduced energy consumption per successfully delivered packet, and enhanced routing efficiency in dynamic energy-harvesting IoT environments	It has a high computation overhead and an initial learning latency	Homogeneous and Heterogeneous battery capacity for Packet Delivery Ratio (PDR) =59% and 49%, Energy Consumption =1.9 and 2.9, End to End Delay (E2ED) =220 and 330.
Sheikh & Joshi [17]	ISERP	The ISERP protocol enhanced energy efficiency, reduced packet delay, increased network lifetime and lowered energy consumption of the cluster heads	ISERP increased network lifetime but nodes located close to the base station drained their energy source quickly in comparison to others	No of nodes=2000, Network Lifetime=1900, Residual energy= 27, Energy usage=2330, active nodes =40, Delay analysis= 120, Throughput=9.2
Hao et al., [18]	3-D WSN, MAC protocol, BDRA-TD	The computational complexity and convergence of the algorithm have been investigated to assess its effectiveness and stability	The system experienced higher complexity in handling real-time data queues and spatial constraints in decentralized deployments, which reduced scalability and operational efficiency	No of nodes=300, Avg E2ED(s)= 0.15 Avg energy dissipatation(J)=0.13, Avg residual energy=11, PDR= 0.89, Energy variance=20
Yoon [19]	MDT algorithm	LoRaWAN enables long-range technology, low power consumption, long battery life and has a high indoor penetration rating without the need for a license	But, LoRaWAN has suffered from low bandwidth, slow data rates, strict payload limits, and requires infrastructure setup for high-density data and data streaming applications	No of nodes=300, cumulative no of gathered sensory data=3.4 × 106, urgent data arrival rate=0.9

Table 2: Cognitive WSN

Ref	Techniques Used	Merits	Demerits	Performance Metrics
He et al., [20]	EHR-QL, POMDP	The random prey search mechanism helps the algorithm explore various sections of the network and steer clear of sub-optimal search routes	Resource-poor nodes consume more power due to excessive computation	No of episodes=60, Total E2ED=1000 ms, Avg Throughput=11.5 Avg E2ED=900 ms No of EH-Sus= 20, Toatl network lifetime =25s Avg Throughput=8.5

				Network lifetime=21s
Wang et al., [21]	IMO algorithm	Protocol worked well in various scenarios and conditions regarding the different number of primary users, lowered number of collisions and enabled reliable communication in higher CRSN settings.	The algorithm can get stuck in the local optimum, which leads to lower rates on global optimization.	No of collisions with Pus=100, no of rounds= 8000, collision with PUs=15, PDR=0.969,
Panbude et al., [22]	fuzzy logic approach	It dynamically balances global exploration and local exploitation without needing strict parameter tuning	Slow convergence of the SCSO algorithm sometimes led to local optima, degrading the quality of the globally acquired solution	Static Analysis: Throughput=48.04, PDR=93.36, Delay=0.0271, Overhead=2.588, Energy Consumption=0.02993, Dynamic Analysis: Throughput=46.49, PDR=84.37, Delay=0.0276,Overhead=3.366, Energy Consumption=0.03049.
Kamatham & Sunehra [23]	Node Grade Factor, node-disjoint multi-path routing protocol	Using the multi-criteria scoring system they took the best routes for transmission	NGFMR can lead to the quick depletion of energy in high quality nodes through continuous workload forwarding and load imbalance	Energy Consumption=1.71j, Dealy=0.015ms, Energy Overhead=1.5%, Throughput=355.
Faris et al. [24]	WOA	It was found that neural networks along with cognitive radio lead to a considerable increase in network reliability and forecasting ability	High computational complexity, and real-time application is challenging in resource-limited WSN nodes	Energy consumption=2500,Network lifespan=1750,Diasaster prediction accuracy=93
Al-Ibraheemi et al., [25]	RDO	The system possesses better scalability, reliable communication and less end-to-end delay in large-scale WSN environment	Random long jumps can cause convergence slowdown and decrease the accuracy of optimization at the final stage of search	Throughput=0.9, Packet Delivery ratio=96, Energy Efficiency=95, Network Lifetime=38

Table 3: WSN-Energy Harvesting-Cognitive Radio Sensor Networks

Ref	Techniques Used	Merits	Demerits	Performance Metrics
He et al., [26]	MDP	Regulates energy consumption dynamically to avoid early death of nodes, significantly extending the battery life	A lot of control information being exchanged makes the overhead higher and it can extend communication time too	No of episodes=60, Network Lifetime=21, Throughput=11.7
Obaid et al., [27]	MACprotocol, RFWEHmechanism	Enhances energy efficiency and optimizes spectrum access, thereby improving network performance	Heavy interference and packet collisions can occur in overloaded or unlicensed frequency bands in traditional RF protocols	Throughput=175, PDR=0.21, Delay =0.84s
Wang et al., [28]	SWIPT	Achieved better network lifetime with energy harvesting balanced using SWIPT.	There may be practical interference and sensing errors which lead to performance degradation	No of surviving nodes=500, Total no of rounds=7000, No of rounds in first node death=989, Total network energy consumption =0.0030, Energy consumption=0.0018, No of duration for effective data collection=120, Duration of effective data collection=106.8
Mortada et al., [29]	LIBRO	It is also highly tolerant to node movement and is efficient in handling large and dense networks.	A lot of position reporting also makes communication redundant and energy use more expensive, which degrades the network's efficiency	No of nodes= 3000, PDR=99, Collision Porbability=0.08, Packet Delivery Dealy=9, Energy Consumption= 1.3
Giang et al., [30]	MDP, DDPG, DRL approach	Improved sum-rate and spectral efficiency in RIS-assisted NOMA communication	Needs correct channel and system state information, which can be difficult in real networks	Total Energy efficiency=75, Energy efficiency=56, No of RIS elements= 12, Avg Rate=5.4

4. Performance Evaluation

In this section evaluates the energy efficiency performance of the WSN, EH-WSN, CWSN, and EH-CWSN approaches. For wireless sensor networks, lower energy consumption is better usage of resource, longer network life, and better network sustainability, especially because energy usage is among most important performance factors of WSNs. This comparative analysis demonstrates the ability of several routing, clustering, optimization and resource management approaches proposed for improving energy efficiency in various WSNs.

Figure 3 shows the comparison of the amount of energy used for various approaches based on Energy Harvesting WSN. LCEHA, as one of the evaluated methods, reduced energy consumption as low as 0.0027 Joule, whereas the ERAS,

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AEHAC, ISERP and BDRA-TD methods have consumed 85 Joules, 1.875 Joules, 1.165 Joules and 4.3 Joules, respectively. The meaningful reduction in energy consumption realized by LCEHA suggests the effectiveness of energy-aware harvesting and resource management mechanisms to maximizing network lifetime and reducing battery dependency. Figure 4 depicts the energy consumption performance of Cognitive Wireless Sensor Network approaches. The outcome shows that DFPC consumed the minimum energy [0.000145 J] in comparison to NGFMR [0.0171 J], LFRDO [0.2375 J] and WOA [25 J]. The efficiency of its spectrum utilization, intelligent channel selection, and optimal communication strategy allows for minimization of unnecessary energy expenditure during data transmissions, which is the reason for the superior performance of DFPC.

Figure 5 shows the comparison of energy consumption of Energy Harvesting Cognitive Wireless Sensor Network (EH-CWSN) approaches. The considered methods showed that SWIPT consumed the minimum energy with the value 1.428 J whereas LIBRO and DDPG consumed 4.3 J and 6.2 J respectively. For the results, it is found that the simultaneous integration of wireless information and power transfer mechanisms greatly enhances energy efficiency while sustaining successful communications.

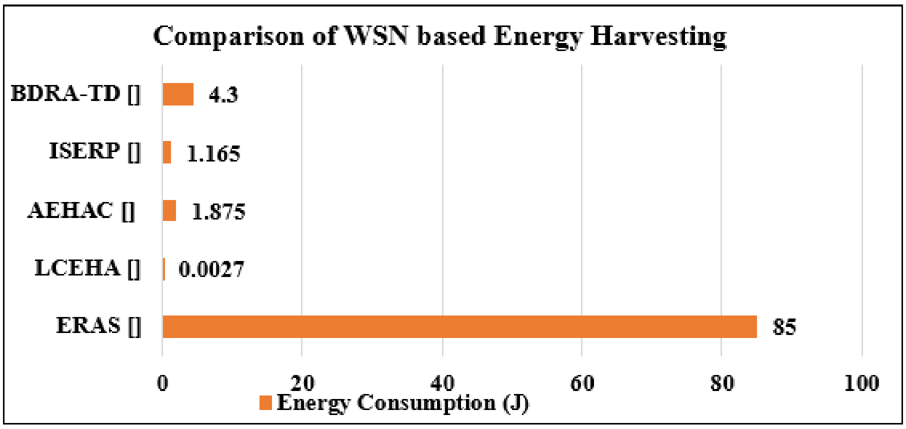

Figure 3: Comparison of WSN based Energy Harvesting

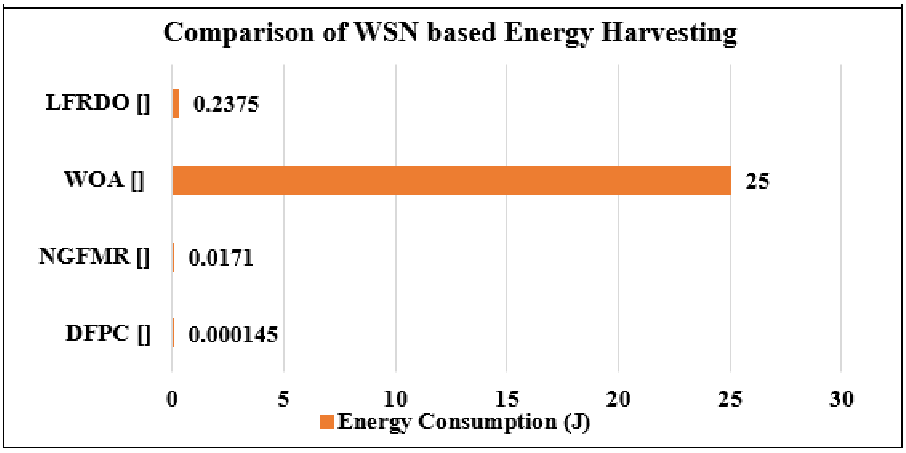

Figure 4: Comparison of WSN based Cognitive

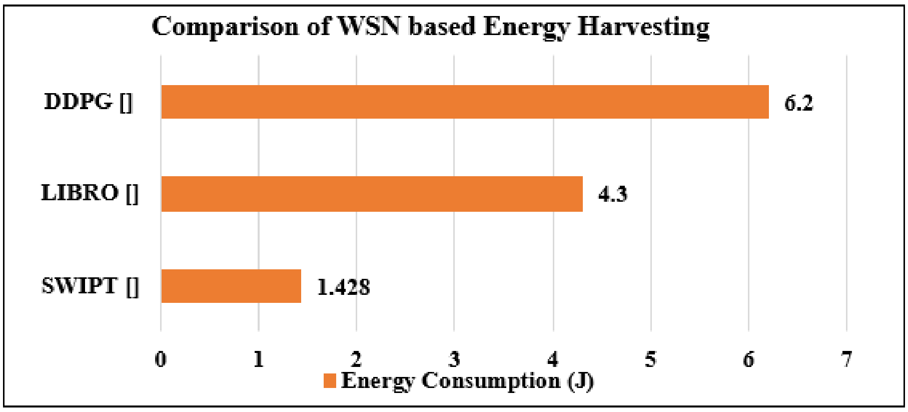

Figure 5: Comparison of WSN based Energy Harvesting with Cognitive

The comparative analysis highlights that advanced energy harvesting and cognitive radio-based techniques save a significant amount of energy and hence improve network life, network utilization, and sustainability in the next generation wireless sensor networks.

5. Conclusion

In this survey, WSN-based methods were surveyed specifically for EH-WSNs, CWSNs and EH-CWSNs. The traditional WSNs have several drawbacks such as limited battery capacity, limited network life, narrow spectrum availability, and spectrum reliability problems. Both energy harvesting and cognitive radio technology aim to mitigate the energy constraints and help achieve self-sustained operation and better spectrum utilization, respectively. The combination of these technologies has enhanced network lifetime, energy efficiency, throughput, and communication performance. This survey discussed different routing, clustering, optimization and resource management strategies, their pros and cons as well as their performance. However, several scalabilities, routing, spectrum sensing overhead, resource allocation, and network adaptability issues still exist. Future work will emphasize novel, adaptive, and energy-efficient methods that will enable robust, scalable, and sustainable wireless sensor network deployments.

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