International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7436
Article Received: 15 May 2023 Revised: 02 July 2023 Accepted: 27 July 2023

A Review of Wireless Sensor Networks with Cognitive Radio Techniques and Applications

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Abstract— The advent of Wireless Sensor Networks (WSNs) has inspired various sciences and telecommunication with its applications, there is a growing demand for robust methodologies that can ensure extended lifetime. Sensor nodes are small equipment which may hold less electrical energy and preserve it until they reach the destination of the network. The main concern is supposed to carry out sensor routing process along with transferring information. Choosing the best route for transmission in a sensor node is necessary to reach the destination and conserve energy. Clustering in the network is considered to be an effective method for gathering of data and routing through the nodes in wireless sensor networks. The primary requirement is to extend network lifetime by minimizing the consumption of energy. Further integrating cognitive radio technique into sensor networks, that can make smart choices based on knowledge acquisition, reasoning, and information sharing may support the network's complete purposes amid the presence of several limitations and optimal targets. This examination focuses on routing and clustering using metaheuristic techniques and machine learning because these characteristics have a detrimental impact on cognitive radio wireless sensor node lifetime.

Keywords- Wireless Senor Networks, Energy Optimization, Machine Learning, Metaheuristic Algorithms, Cognitive Radio.

I. INTRODUCTION

Wireless sensor networks (WSNs) are networks of interconnected sensor nodes that interact wirelessly in order to acquire data about the scattered environment while using minimum energy. [1], [2]. These sensor nodes that are also termed as data-centric nodes are in charge of gathering appropriate information in the targeted location and delivering it in a single-hop or multi-hop fashion to the sink node [3], [4]. The aim of this analysis is to explore methods that have produced novel cluster-based routing protocols and metaheuristic machine learning, especially with the intention of lowering WSNs energy consumption. On the path to the destination, the routes may include working with one or more router nodes. The final destination node is typically the nodes of destination or sink that is immediately linked to the (BS)base station.

These sensing devices are now used more often to monitor specific regions without routine supervision due to their reduction in size and cost. Although each node in WSNs has constrained resources, they work together to process information and communicate. It permits the distributed task execution of the application by the network. However, the fundamental issue with these networks is energy consumption, which reduces their ability to process and transmit data. As a result of the complexity of contemporary networks, routing algorithms for WSNs confront substantial difficulties. For example,

i) Centralized algorithms struggle with scaling,
ii) Static algorithms struggle with handling frequent modifications in network, and
iii) Algorithms that are distributed as well as dynamic-struggle with oscillation and stability.

The process of forwarding of packets by nodes consumes a significant amount of energy, limiting the energy and network lifetime, making it critical to optimize energy consumption in WSNs. Algorithms are created in order to minimize energy usage and also conserving energy resources. Using clustered routing algorithms to implement energy-saving measures is common. Due to the shorter communication distance, clustering has the inherent ability to optimize energy usage. One node serves as the Cluster Head (CH) in a cluster setup. Typically, the CH is the node that uses the most energy and processes data more efficiently than the other nodes. These are information-sensing nodes with very low energy and communicates with the CH. The difficulty of WSNs has been addressed by some clustered routing protocols using metaheuristic algorithms for optimization. "**A metaheuristic algorithm is a search strategy designed to detect, a good solving methodology to an optimization problem that is complicated and difficult to**

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optimize". These are iterative processes that use a variety of operators to explore and maximize the search space while intelligently guiding a subordinate heuristic. To handle challenging issues such as determining the shortest path and the best route for data to transfer through WSNs, metaheuristic algorithms have been put into place. Since there are still unresolved issues and open lines of research, the use of metaheuristic approaches in WSNs is a highly active area.

The following is the order of this study:

In Section 2, Clustering in Wireless Sensor Networks; in Section 3, Routing in WSN; in Section 4, Machine learning techniques are discussed, Section 5, Metaheuristic-based routing protocols are defined, in Section 6, Introducting Cognitive Radio In WSN and in Sect. 7 includes Conclusion.

II. CLUSTERING IN WIRELESS SENSOR NETWORKS

Algorithms like PRODUCE (Probability Driven Unequal Clustering Mechanism), EDUC (Energy Driven Unequal Clustering), LUCA (Location based Unequal Clustering Algorithm) and LEACH (Low Energy Adaptive Clustering Hierarchy) [5] has been discussed and probabilistic methods are simple and can be accommodated in wide range WSNs. Deterministic methodologies will be utilized in selective - consistent applications. These are the most effective options for the provided application environment, but load balancing is the basic issue opted from all the other nodes in the network. This methodology limits in the fact that clustering for moving nodes are not investigated with respect to swarm and machine learning. Various algorithms like HEED (Hierarchal Energy Efficient Distributed Clustering) with conventional [6] approach has been used for analysis, it gives a best solution to detect malicious nodes in a cluster. Typical problems arise during reliability and robustness. The selected cluster head does not support the network requirements all the time.

The author [7] describe the efficient usage of Genetic algorithm based optimized clustering (GAOC) protocol and multiple data sinks based GAOC (MS-GAOC) for optimized cluster head and MS-GAOC reduces the distance between the base station and nodes. But these methodologies are inefficient in finding the location and sensing the surrounding conditions. An optimal multi-hop route finding [8] approach that leverages the fitness function has been identified for lowering energy consumption and extending network lifetime. Eventually it does not handle multi hop nature of the dynamic wireless sensor networks.

A hybrid Fuzzy-Genetic method [9] has been used to find the varying input data. Apparently, the optimal solution is obtained in fuzzy, and the Genetic scheme is employed to treat it. This scheme leads to some matching between the time consumption and the distance it traversed. To monitor all the targets and to increase the lifetime of the network, a target-oriented GA based algorithm [10] makes sensors with different directions, but it lags to find the priority of the target based on the sensitivity.

The cuckoo search algorithm is employes in the Evolutionary multipath energy-efficient routing (EMEER) [11] technique for locating the correct cluster head but it does not inquire about the efficiency of alive node during data transmission. Particle swarm optimization-based [12] energy restricted clustering strategy is used to reduce the energy consumption but does not capable of working in heterogeneous WSNs.

The combination of [13] Ant colony optimization (ACO) and Butterfly optimization algorithm (BOA) is provided, to locate the best cluster head by butterfly optimization algorithm and the ant colony optimization technique is used to anticipate the path. Hence, the overall energy consumption is reduced and network lifetime is increased.

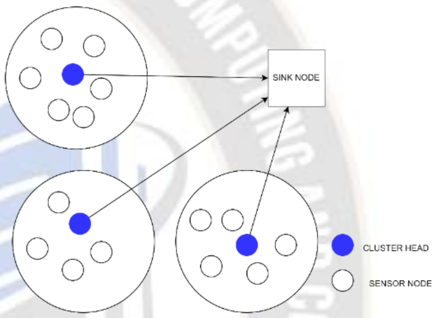

FIG.1 FORMATION OF CLUSTER HEAD IN WSN

The author [14] describes the fuzzy parameters are determined by Shuffled frog leaping algorithm (SFLA) and has three processes: preprocess, clustering and routing in the network. The input specifications are drawn out during pre-processing. SFLA then approximates and selects the parameter with the needed specifications, tunes the fuzzy scheme, and improves the network's performance metrics.

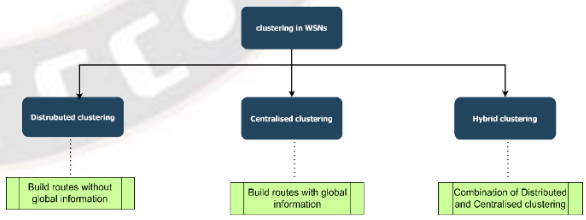

FIG.2 CLUSTERING METHODS

The clustering environment shown in the figure has been discussed by the authors [15], and it gives wide information about the methods of clustering environment.

Using machine learning technique, a Clustering based on energy with a fuzzified updates algorithm [16], the issues such as overhead due to messages and the transmission data complexity has been solved. It works under phases including fuzzy, data transmission by machine learning and change of CH.

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During the phase construction of the cluster, the clusters are formed and are modified using fuzzy inference system (FIS) scheme for clustering it again during improper conditions of the network. This is suitable for only static nodes. The CH is in charge of each and every node in the cluster, which impacts propagation distance.

For energy-efficient cluster-based defensive mechanisms, a deep learning technique [17] known as deep learning-based defense mechanism (DLDM) can be utilized in computing the DOS (Denial of service) attacks effectively. The cluster head retains the signal strength that varies dynamically for each and every node in a cluster that has an impact on the propagation limit or distance.

The Neuro-fuzzy rule-based cluster formation and routing protocol can meet criteria such as reliable routing and extending network lifetime [18]. Making decision to a single qualitative output for number of inputs can be achieved by the combination of Neuro-fuzzy inference system. Once if the training process gets completed, the data is transferred to sensor nodes through base station, but not all the sensor nodes are secure and security measures are needed.

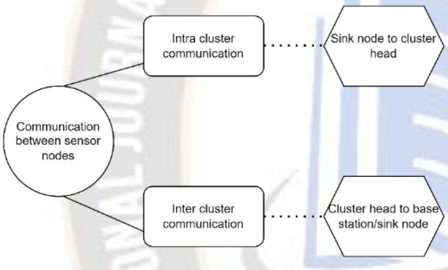

FIG.3 Communication between the sensor nodes has been classified [19] the figure depicts intra-cluster communication (between clusters) and inter-cluster communication (within clusters).

The first hierarchical cluster-based routing technique for WSNs is LEACH (Low Energy Adaptive Clustering Hierarchy) [20], it is distributed, hierarchical and probabilistic. Each sensor has a chance of becoming a CH in every round and uses a stochastic self-election technique.

Another distributed fuzzy clustering protocol is DFCR (Distributed Fuzzy Clustering-based Routing) [21]. Each node in the DFCR has a timer. A node determines its competition, after the timer expires, the radius is calculated using the node density, neighbor metric, and a competence function.

The author [19], describes the different clustering methods and it has different functionalities:

Hierarchal clustering: A top-down and bottom-up technique that is very adaptable for point-to-point communication.

Clustering based on partitions: Cluster is divided into divisions and this technique is used when there are few nodes.

Clustering based on spectral data: It uses similarity matrix.

Density based clustering: It is used in denser clusters, more number of clusters are used in dynamic clustering.

Grid based clustering: Clusters are divided into grids.

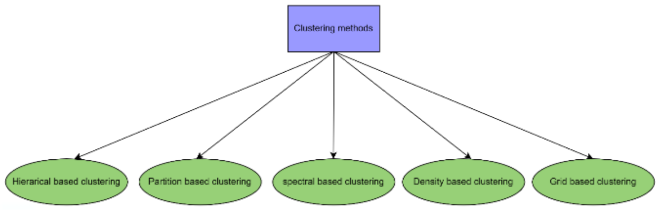

FIG.4 Different methods of clustering is explained by the authors in [19] and it is shown in the figure

The authors of [25] outline a coverage optimization technique that uses the Voronoi glowworm swarm (VGS) optimization based on K-means methodology and is energy-efficient. The coverage area is optimized utilizing the fewest available live nodes while accounting for the best sensing radius for well-organized sensor node placement in this technique.

Expanding energy balancing over all sensor nodes in clusters to decrease energy waste during network connections, the authors of [26] provide an improved technique for lowering energy usage and extending network longevity.

Authors in [27] present a plan that arranges sensor nodes for charging, in order to enhance systems for extending lifetime. To determine the sensor elements that require charging, an inspection algorithm is first developed to visit and inspect sensor nodes. Secondly, shortest distance can be determined by greedy approach.

Clustering algorithm evaluation metrics:

Various measures for assessing the effectiveness of routing protocols are covered in this section. The most popular metrics are throughput, standard deviation, packet delivery ratio, packet delay, energy consumption/energy efficiency, and network longevity [28, 29, 30&31].

When the first node's energy is exhausted, several authors determine the network lifetime. Other methods of defining network lifetime considering the time after the death of half the nodes, the final node, or when the rate of message loss reaches a specific level. [32] provides further meaning of the concerning network durability. Protocols such as LEACH or HEED can determine the number that are functioning nodes in a network during operation to measure its effectiveness.

The Energy Enhanced Routing Protocol (EERP) approach was recommended by Loganathan et al. [33]. The technique uses a firefly fault-free transmission that offers an intellectual cluster head selection mechanism. It targets network throughput, energy efficiency, and longevity but not emphasizes route deviation.

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Evaluation standards of WSN:
Consumption of energy and energy efficiency are the important parameters that are commonly utilized to analyze the performance of clustering algorithms. Energy efficiency is calculated by dividing the total energy consumed by sensor nodes by the amount of data packets sent to the sink node.

The total quantity of energy consumed by sensor nodes during network operation is referred to as energy consumption. The distance between the source and the destination, the retransmission rate, and the control messages all have an impact on these metrics. This ratio should be kept as low as possible in order to indicate efficient energy utilization. The overall network performance can be determined by:

- ***Ratio of packet delivery***
- ***Delay from beginning to end***
- ***Standard deviation and***
- ***Throughput***

III. ROUTING IN WIRELESS SENSOR NETWORK

Routing is the process which describes how algorithms control packet delivery and manage communication between the source and the destination. Based on energy optimization, network costs, or topology, there are several forms of routing. Routing makes it possible for nodes to communicate with one another through paths with metrics, and maintaining them by node connections that stabilizes the network topology. Proactive, reactive, and hybrid protocols are the three categories. In proactive protocol routes are determined before the data is transmitted, but in Reactive protocols determining the routes for the network is needed. There are no set routes. Both proactive and reactive methods are incorporated in hybrid procedures.

Routing in a cluster:
In WSNs, a routing protocol begins routing when a source node is unable to transfer the information directly to the destination. Routing is considered to be complex due to these factors:

- It is unable to create a global addressing system and cannot deploy sensor nodes using typical IP-based protocols.
- As a result of data collected by various sensor nodes, the resulting data traffic will be redundant.
- •Sensor nodes are constrained by transmission energy, computational ability, and storage space, consequently resource management is critical.

Structure of the network:
Routing methods are categorized based on network structure.

- Flat Routing,
- Routing can be either hierarchical or location-based.

Because all nodes have comparable functionality, flat routing combines sensing and routing responsibilities. To promote scalability and energy efficiency, hierarchical routing separates the network into clusters. The routing path in location-based routing is determined using node location information [34, 35].

Topology for Routing:
Routing algorithms are classified into topologies that are based on a chain, a tree, a grid, an area, or a cluster [36, 37]. Chains are used to build nodes for data movement in a chain-based routing design. The individual cluster chooses a CH to gather input from sink-like nodes. It is further subdivided into data-centric approaches and geographically-based methods. Because data-centric routing systems do not have global IDs, identifying sensor nodes for analysis is difficult. The geographical information protocol, on the contrary, makes use of location data to create a productive search that determines the most suitable path to the target.
The geographic protocol is beneficial for sensor networks and is employed for large and complex multi-hop wireless networks due to the accumulation of data, thereby minimizing the number of transmissions to the base station by reducing packet redundancy. [38].
Nodes are built in a tree-like pattern in tree-based routing. The information is sent from the leaf nodes to their parent nodes, and then it sends the data to the main node. Each node in the tree-structured structure gathers data.
The network is split into many grids by the grid-based routing design. The routing mechanism is used in this case without the need of a routing table.
Region-based routing topology is a more sophisticated topology that lets certain sensor nodes define a particular area and is used by mobile WSNs.
In a Cluster-based routing design, sensor nodes are grouped together to form clusters, and a CH from each cluster is chosen to act as a link between the members of the cluster and the BS.

Formation of path in a network:
Routing determines the path between the source and destination nodes. Path establishment approaches are classified into three types:
Proactive- Table-driven routing, also known as proactive routing, is a method in which each node selects an ideal path and provides data for the routing table.
Reactive- Reactive routing creates inefficiencies during route discovery since it lacks a specified path for route creation. The nodes react quickly to modifications in the detecting field.
Hybrid- In hybrid routing, nodes often send data and adapt to sudden shifts in perceiving events.

Principle of working Protocol:
There are five types of routing protocols: negotiation, query-related, multi-path, coherent, and QoS-based [39]. Prior to real data transfer, negotiation-based routing happens.

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Identifiers are used to negotiate amongst sensor nodes in order to eliminate duplicate data. In query-based routing, the source node responds to queries from the endpoint node. To increase network efficiency, multipath routing generates many paths from source to destination. Methods for lowering energy consumption during data processing include coherent and non-coherent routing. Quality of service characteristics like as data dependability, latency, and bandwidth are all ensured via QoS-based routing.

To defend against common routing assaults, the author develops [1], TAGA provides energy-aware and trust-based routing technology for wireless sensor networks that makes use of an adaptive evolutionary algorithm.

In this study [40], the author examines a two-tier heterogeneous wireless sensor system that involves N heterogeneity connection points (APs) capture monitoring data from a variety of sensors and transmit it to M heterogeneous fusion centers (FCs).

IV. MACHINE LEARNING

Artificial Intelligence is a study that includes soft computing and learning-based (machine learning) approaches, the three categories are:

- Supervised learning
- Unsupervised learning and
- Reinforcement learning

Supervised learning:

This is the fundamental machine learning approach when the framework provides labelled input and anticipated (desired) output. The major objective of this learning strategy is to create a mechanism which can automatically learn through the comparison of actual output to predicted output [52]. An error is defined as the difference among the actual and intended output. The two forms of supervised learning are regression and classification. Regression is perhaps the most basic machine learning approach, delivering reliable and exact results. This approach demonstrates how the Y attribute's value is affected by the X attribute's content. This strategy is primarily quantitative and continuous.

Methods for categorizing include:

- ANN (Artificial Neural Network),
- Bayesian,
- Decision Tree,
- k-Nearest Neighbour. (k-NN).
- RF (Random Forest) and
- SVM (Support Vector Machine).

Artificial Neural Network (ANN):

Human brain neurons influence the ANN approach. The objective of ANN is the processing of vast amounts of information with the aim to provide proper results. It is built on the notion of several levels. (There are three layers: input, output, and unseen).

Bayesian:

The study of statistics underpins the Bayesian method. It calculates the relationship among two datasets using dependent independence and a number of statistical methods.

Decision Tree (DT):

Rule-based learning predicts the output variable in decision tree method. The predictions about the output begin at the tree's root node [53]. Other characteristics are compared to the root node. This contrast results in the prediction of the following branch node.

k-Nearest Neighbour (k-NN):

The k-Nearest Neighbor is a mechanism for storing previously accessible values and subsequently categorizing new situations based on their similarity. It is a non-parametric, slow learning method that makes use of isolation functions, including hamming and Euclidian distance.

Random Forest (RF):

The process Random Forest is a machine learning system that works with large and diverse datasets. It works in two stages: creating the Radio Frequency classifier then calculating the results. A forest made up of several decision trees is built to attain exact results.

Support Vector Machine (SVM):

The most interesting methodology is support vector machine (SVM) which is highly interested in categorization difficulties. To classify coordinates, it uses hyper plane concepts. The support vector machine is trained using datasets to understand the genetic algorithm's behavioural pattern for optimizing the routing problem in diverse applications.

Unsupervised learning

The model works on itself in this technique by discovering or exploring hidden patterns in the provided data. Unlabeled data is only related with input data. This method discovers the connection between data points and organises them into clusters with comparable properties. It also produces unexpected results, and the primary goal of this learning approach is to reveal hidden patterns in the dataset. This data is divided into two categories: grouping and dimension reduction. Clustering is demonstrated using Principal Component Analysis (PCA), while dimensionality reduction is demonstrated using k-means.

K-means:

Another efficient technique is k-means method used for clustering that separates data points into clusters, then assigning each data point to the cluster with the least distance. This is how the method works:

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- Select a random mean number.
- Locate the nearest mean number and assign it to a certain cluster.
- Continue with steps 1 and 2 until the mean equals.

PCA (Principal Component Analysis):
The procedure is an empirical approach used to find significant patterns in a dataset. Variation and covariance determine it. It is a multi-variable extraction method that reduces dimensionality.

Reinforcement Learning:
It is a strategy of making decisions sequentially. The network has been intelligently trained to offer the best appropriate action inside a specific environment or scenario, enhancing efficiency and performance. The agent must have a feedback-reward mechanism, which can be favorable or negative. Positive reinforcement improves network performance, whereas negative reinforcement diminishes network performance. This feedback reward serves as a reinforcement indicator, assisting the agent in learning the network's function. Q-Learning is the technique's most promising application.

Nayak et al. [54] Machine learning-based routing was detected in numerous distinct existing routing systems. A communication algorithm that takes into account factors such as latency, energy, packet ratio, network durability, connection, and effectiveness. They proposed the development of new protocols for routing information and that are conscious of energy usage, delays, and network lifetime.

V. METAHEURISTIC OPTIMIZATION

The methods for optimization [55] can be heuristic and metaheuristic and these methods help to solve complicated issues. Selecting cluster head is done in random fashion in heuristic approach. As the network is homogenous, CH selection is unevenly disseminating and impacting network performance overall.

Meta-heuristics are easy and simple. Physical phenomena, animal behaviors, or evolutionary concepts are taken as the basic idea of these algorithms. Unknown parameters can also be sorted using Meta-heuristics and it is highly compatible for black box models.

The genetic algorithm [56] is a highly efficient algorithm that is mostly utilized in WSN clustering and routing responsibilities. By prolonging the lives of nodes or cluster heads, GA extends the network's long-term sustainability and its overall efficiency.

Swarm Intelligence (SI) [57] is a field that illustrates algorithms using animal, bird, and other nature-inspired characters, which includes ACO, PSO and Artificial Bee Colony (ABC). The merits of SI algorithms are:

It saves information of the search and stores the solution in memory, minimum number of operators is needed and it is easy to implement.

Few algorithms are listed below:

1. Bat-inspired Algorithm (BA) [58],
2. Artificial Fish-Swarm Algorithm (AFSA) [59],
3. Monkey Search [60],
4. Bee Collecting Pollen Algorithm (BCPA) [61],
5. Galaxy-based Search Algorithm (GbSA) [62].

Firefly algorithm [63] is an algorithm inspired by firefly, and the intensity is matched with the fitness values. It can be integrated with other WSN algorithms for cluster formation and CH selection and reduces the energy consumption when combined with harmony search algorithm.

A bird is considered to be a particle and thus it is called as Particle Swarm Optimization [63]. The particle will have the fitness value and that is responsible for the quality. It works by shortening the path between the cluster head and the base station. Ultimately, this methodology minimizes the total load of the network. To perform clustering and routing BPSO can be used.

An optimal node is discovered for resolving the node capture attack by fruit fly optimization algorithm [64]. Intruder will get the information such as energy needed for the transmission process parameters required for the network and the keys. It computes the correlation between the nodes and the path it transmits. For resolving such an issue, a trusted cluster head by honey bee algorithm is used.

HFAPSO (Hybrid Firefly Algorithm and Particle Swarm Optimization) is one of the metaheuristic clustering techniques that combines the firefly (FA) with particle swarm optimisation algorithm (PSO) [65]. The most efficient CHs are chosen to decrease total energy usage while also prolonging the lifetime of the network.
To improve energy efficiency in WSNs, MCH-EOR (Multi-objective CH-based Energy-aware Optimised Routing) [66] adopts a multi-hop cluster-based routing strategy based on Sailfish Optimizer (SFO). This approach selects the best CHs based on a multi-objective function to lower the total quantity of energy used and the number of inactive sensor nodes.

GA-FFO [67] is a hybrid routing strategy that employs GA and fruit fly optimisation (FFO) to improve the routing protocol by taking node degree, range to the sink, and proximity to the network's access point into consideration. After finding the primary CHs with GA-FFO, the final CHs are identified using a density adaptive approach. Following that, the Dijkstra algorithm is utilised to determine the best path from each CH to the sink.

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VI. COGNITIVE RADIO:

Joseph Mitola III and Gerald Q. Maguire came up with the concept of Cognitive Radio.
The Cognitive Radio (CR) strategy for wireless communicatio n involves a network or wireless
node altering its transmitting or receiving factors to interact eff ectively and reducing interventionfrom authorized or unauthor ized users.
This parameter adjustment relies on continuous tracking of sev eral types of factors in both withinand outside wireless environ ment, such as customer behavior, the electromagnetic spectru m, and connection stability.

A broad range of smart decisions can be offered by the cognitive radio. It can keep an eye on the electromagnetic spectrum and select frequencies to avoid interfering with currently used communication channels.

Additionally, the cognitive radio may display actions that are more obvious to the user:

1. Knowledge of its position,
2. Understanding of nearby networks and the services they provide.
3. Knowledge of the user and the biometric verification, the user uses to verify monetary transactions.
4. Knowledge of the user and emphasized targets.

Introducing Cognitive Radio In WSN:

When trying to gain control over the constraints imposed by traditional WSNs, cognitive approaches have been applied to wireless sensor networks. The process of knowing through sensing, arranging, deciding, acting, and continuously improving and upgrading with past experiences of learning is known as the cognitive technique. Difficulties in WSNs can be solved by cognitive radio if it can be combined with wireless sensors. The unutilized spectrum in a licensed or unlicensed spectrum band can be known by CR, and can take use of the opportunity to use the unutilized spectrum. it has primary user (PU) and secondary users (SU), primary users can use the spectrum at any time but the secondary users can use the spectrum only when the PU is not using the spectrum.

Spectrum sensing:

Spectrum sensing is an essential need for the development of CR networks, where a CR is built to be highly conscious of and adaptive to changes in its environment. By spotting spectrum gaps without interfering with the main network, spectrum sensing allows CR users to adapt to their surroundings. This can be done by using real-time spectrum monitoring to find weak the core signals across a large bandwidth.

The three categories of spectrum sensing methods are transmitter awareness, receiver tracking, and intervention tolerance.

Benefits of using CR in WSN:

A novel paradigm in the WS network domain called CR-WSN effectively uses the spectrum allocation for bursty traffic [77]. The structure has the ability of reducing transmission loss, reducing energy usage, effectively managing buffers, and enhancing communication quality.

- Spectrum efficiency and the availability of bandwidth for emerging innovations
- Utilizing several channels and being energy efficient
- Application-Specific Spectrum Utilization,
- Global Operational Capability,
- Financial Benefits to the bearer from Renting and
- Preventing Attacks

Applications Of CR-WSN:

Defense applications

Many military and public security applications use conventional WSNs, an opponent may broadcast jamming signals to disrupt radio communication channels on battlegrounds or in areas of dispute. When this occurs, CR-WSNs can switch to another frequency band to avoid the one with the jamming signal. Some military applications also need a lot of bandwidth, a narrow channel of access, and long communication delays. The use of CR-WSNs may be preferable for several applications.

Healthcare Application

Portable body-worn sensors are widely used in healthcare systems like telemedicine. On patients, several wireless sensor nodes are placed for collecting crucial data for healthcare professionals to monitor patients remotely. Medical data is time-sensitive, error-prone, and critical. If the operational spectrum band is crowded, a suitable degree of QoS may not be attained. By reducing these issues with spectrum, jamming, and worldwide operability, CR wearing body wireless sensors can increase efficiency.

Home applications

For many potential and new indoor applications to achieve an adequate QoS, a high density WSNs infrastructure is necessary. Due to the tremendous congestion of ISM bands indoors, conventional WSNs have a difficult time maintaining reliable communication [78]. Smart constructions, home surveillance systems, automated factories, personal entertainment, etc. are a few examples of interior uses for WSNs. The difficulties faced by traditional indoor WSN applications can be minimized by CR-WSNs.

The following tables provides the information given,

TABLE 1: Cluster head selection approaches

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TABLE 2: Benefits and drawbacks of various Machine learning approaches

TABLE 3: Literature Survey on Clustering Algorithms and

TABLE 4: Examples of optimization algorithms.

TABLE 1: Cluster Head Selection Approaches

REF	APPROACH	CH SELECTION METHOD	CRITERIA FOR CH SELECTION	CH ROLE	FEATURE	PARAMETERS	CHALLENGES
[22]	CONVENTIONAL	LEACH	Residual energy, RSSI parameter and number of hops.	Energy Distribution & traffic in nodes.	CH Selection depends on the importance of the parameter.	Network Throughput, energy ratio, Packet delivery ratio, alive nodes count, delay.	Every node is affected by Node Rank.
[23]	CONVENTIONAL	Multi-level trust evaluation method	Energy and distance.	Reliability.	Inspect and remove suspicious CHs.	Level of Trust, malicious nodes, False alarms.	Transmission and reception of the network and memory overhead traffic of the nodes.
[24]	CONVENTIONAL	Classical method	Availability of energy.	Reduces the energy exhaustion.	Decreases the energy during communications.	Lifetime of the network, Stability Period, CHs count.	Network throughput.

TABLE 2: Benefits and drawbacks of various Machine learning approaches

Techniques	Merits	Demerits
Decision Tree (DT)	The decision tree does not require domain expertise to construct.	Can provide only one output.
	It decreases the ambiguity associated with complex determinations.	Because it is dependent on the dataset, the decision tree classifier is unstable.
	Handling precise and numerical information.	Dataset is numerical and it generates complex DT
Support Vector Machine (SVM)	When compared to other ML techniques, it has the lowest overfitting problem. SVM provides better accuracy and reduces the complexity of non -linear data points.	Calculation is expensive. Choosing the right kernel function is difficult because different datasets has different kernel functions and produces different outputs. Time consumption is high.
K-Nearest Neighbour (KNN)	It has faster training speed. Implementing KNN is simple.	Highly sensitive to noise and more space is required in KNN.
	Data may be simply uploaded because no training time is required.	The testing speed is slow.
Bayesian	Computation is simple as well.	If the variables are dependent, it produces inaccurate results.
	Accuracy and processing speed is better.	Suitable for finding solutions for large data and provides comparative analysis easily.
k-Means	An efficient and highly converging algorithm for dynamic clustering.	Knowledge about the cluster and its attributes are needed.
	With recent scenarios, it becomes more adaptive.	Complicated to control improper clusters.
Principal Component Analysis (PCA)	Computations are faster.	Larger the data and high storage is required.
	Analyses multiple dimensions of the data.	Need correlation matrix to store the values of correlation.
	Highly employed in removing correlated features.	Independent variable interpretation is less.
Reinforcement Learning	Adapting and optimal usage.	Lags at local minima and it is expensive.
	Indexed data sets are not required.	Not suitable for simpler problems.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7436
***Article Received**: 15 May 2023 **Revised:** 02 July 2023 **Accepted:** 27 July 2023*

TABLE 3: Literature Survey on Clustering Algorithms

YEAR	TECHNIQUE/TITLE	DESCRIPTION	ADVANTAGES	LIMITATIONS	FUTURE WORK
2022[51]	**Aquila optimization**: Algorithm to Increase WSN Lifetime and Energy Efficiency.	In terms of life span, the AO method outperforms the other known algorithms, whereas LEACH and GA have the shortest.	Steady and efficient clustering.	No discussion about the data security.	The clustering term will improve data transmission security.
2022[41]	**TAGA:** Using an Adaptive Genetic Algorithm, we developed a safe routing system for wireless sensor networks that is energy-aware and trust-based.	Resist common routing and particular trust concerns while minimising data transit energy usage.	The impact of invading nodes is reduced, the amount of lost packets is reduced, and utilisation of energy is increased.	Malicious nodes with partially lost packets are more difficult to defend.	Higher energy optimization.
2021[40]	**Two-tier Heterogeneous wireless sensor network:** Deployment of Energy-Efficient Nodes in Heterogeneous Two-Tier Wireless Sensor Networks	Heterogeneous access points (APs) collect sensing data from widely spread sensors and transmit it to a network of M heterogeneous fusion centres (FCs).	Outperform the existing clustering methods.	Every access point must be located between the fusion centre to which it is connected and the geometric axis of its cell partition.	Communication range can further be increased
2020[42]	**Whale optimizer:** Method for Heterogeneous Wireless Sensor Networks, Relay Node Positioning and Energy-Efficient Routing Methods are Presented.	Energy efficiency and relay node location issues.	The AWO1 and AWO3 approaches can handle the relay placement problem in HWSN, with the AWO3 method outperforming the others.	Source and relay node distance is limited.	source and relay node distance can be increased
2022[43]	**Hybrid WOA-ABC CNN model:** WOA-ABC hybrid and proposed CNN intrusion detection system for WSN	New CNN model based on a WOA-ABC hybrid for feature selection and classification.	Increases the rate of detection, execution time, accuracy, and false alarms.	CNN model cannot be used without selection features	Intrusion detection with a powerful compact CNN architecture.
2022[44]	**CH selection and scalability:** A detailed assessment of recent advancements in clustering techniques for wireless sensor networks.	Threshold-based Timer that runs at random Only one metric Several metrics Probabilistic weighting Timer with weights Heterogeneous Techniques for WSNs and EH-WSNs Optimization.	Significantly reduces energy waste in vice-CH.	Not possible in using a predefined sensing rate.	Adaptive sampling is an effective strategy for adjusting the sensing rate unwanted measurements.

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2022[45]	**CMML**: Adaptable routing in cluster wireless sensor networks using combined metaheuristic and machine learning.	By varying the network size, number of nodes, aggregation factor, and lifespan specification, the CMML model and genetic algorithm are utilised to collect a comprehensive dataset from different WSNs based on the application criteria.	Prolonging network lifetime.	Only small and medium-sized network topologies can use the CMML protocol for routing.	The CMML framework can be modified to accommodate multi-hop higher size networks.
YEAR	**TECHNIQUE/TITLE**	**DESCRIPTION**	**ADVANTAGES**	**LIMITATIONS**	**FUTURE WORK**
2020[46]	**Mixed Integer Programming, log normal shadowing model:** Compressive sensing and energy harvesting for wireless multimedia sensor networks are investigated.	Increasing the amount of sparsity leads to longer execution times and lesser compression, resulting in a shorter network lifespan.	BCS offers better lifetime.	NO test bed implementation.	Investigate the consequences at the node and network levels.
2021[47]	**CR-IoTNet framework SU-IoT with GLRT detector**: Joint spectrum sensing and allocation Applying machine learning for cognitive radio empowered IoT cellular networks.	SVM for sensing data, Integration of cognitive radio with IoT and machine learning technologies.	Respond to altering network structure while also estimating spectrum availability with high accuracy and efficiency.	Many PUs in the network's channel conditions are not explored.	Multiple PU's are used.
2022[48]	**Yin–Yang PIO: WSN coverage enhancement**: Wireless Sensor Network area optimization for the Internet of Things using a Yin-Yang pigeon-inspired optimization method.	Improve the optimal solution and centre position, as well as the WSN coverage ratio.	PIO, PSO, and YYPO have better optimization ability and stability.	The technique is not used for WSN coverage enhancement in increasingly complicated environments situations.	Increase efficiency.
2021[49]	**Performance analysis of parameters**: A Comprehensive Examination Improving Quality of Service in Wireless Sensor Networks Applying Machine Learning for both Existing Achievements with Upcoming Opportunities.	QoS, collecting data, energy, event identification, and finding anomalies are all being investigated.	To get wide knowledge on the performance parameters.	Review of different algorithms.	Priority and deadline can be viewed.
2022[50]	**Pollard route deviations:** Optimized pollard route variation and choice of route in wireless sensor networks using Bayesian machine learning techniques.	Prior and posterior probability are used in Bayesian machine learning.	Pollarding, optimized route selection, minimal latency, and extended network lifespan are all very efficient.	Need improvement in Fail-over cluster.	Population simulation and harvesting approaches can be used to boost the overall network.

WSN-Wireless Sensor Networks
PRODUCE - Probability Driven Unequal Clustering Mechanism
EDUC - Energy Driven Unequal Clustering ,
LUCA - Location based Unequal Clustering Algorithm
LEACH Low Energy Adaptive Clustering Hierarchy
HEED - Hierarchal Energy Efficient Distributed Clustering
GAOC - Genetic algorithm based optimized clustering protocol
EMEER - Evolutionary multipath energy-efficient routing
ACO - Ant colony optimization
BOA - Butterfly optimization algorithm

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DLDM - deep learning-based defense mechanism
EERP - Energy Enhanced Routing Protocol
DFCR - Distributed Fuzzy Clustering-based Routing
ANN - Artificial Neural Network ,
SVM - Support Vector Machine .
BA - Bat-inspired Algorithm BA
AFSA - Artificial Fish-Swarm Algorithm AFSA
MS - Monkey Search
GA-Genetic algorithm
CR - Cognitive Radio
BCPA - Bee Collecting Pollen Algorithm BCPA
GbSA - Galaxy-based Search Algorithm GbSA
PSO - Particle Swarm Optimization
FA-Firefly algorithm.
GWO-Grey Wolf algorithm
GOA-Grasshopper optimization algorithm.
HFAPSO - Hybrid Firefly Algorithm and Particle Swarm Optimization
MCH-EOR - Multi-objective CH-based Energy-aware Optimised Routing
SFO - Sailfish Optimizer SFO

TABLE 4: Examples of optimization algorithms:

AUTHOR	TITLE	NATURE OF OPERATION	OPERATOR	FEATURES	CHALLENGES
Dorigo et al. [68]	ACO-Ant colony optimization	In search of food by ant.	Pheromone.	Finding the optimal path.	Consumption of energy is high.
Holland et al. [69]	GA-Genetic algorithm.	Genetics- deals with the characteristics of transfer of genes from parent to children.	Chromosomes.	Helps in finding optimal solution.	Dynamic nodes are complex.
Eberhart and Kennedy [70,71]	PSO-Particle swarm optimization	Search of food by birds.	Location and speed of travelling.	Provides solution for high energy consumption.	Network overhead is high.
Passino [72]	BFO-Bacterial foraging optimization	In search of nutrients by Bacteria.	Chemotaxis.	Provides solution for optimization issues.	When the area is large, it is unable to perform better.
Karaboga [73]	ABC-Artificial bee colony.	Searching of food source by Honeybees.	Amount of Nectar.	Solves low convergence issues.	Transmission efficiency is low.
Yang [74]	FA-Firefly algorithm.	In search of preys by Fireflies on its own flashlight nature.	Coverage distance.	Highly Useful in multi-dimensional issues.	Fails to detect weak path.
Seyedali Mirjalili et al,[75]	GWO-Grey Wolf algorithm.	Tracking, protecting, and the nature of social hierarchy.	Attempting prey and hunting.	Local optima avoidance and convergence.	It is necessary to create binary and multi-objective versions.
Saremi et al. [76]	GOA-Grasshopper optimization algorithm.	Food source searching by Grasshoppers.	Location finding vector.	Better in performing real time issues using random values.	Need high empirical data.

VII CONCLUSION

Wireless sensors are critical in today's fast-paced communication world. Generally, data must be collected even when no humans are present. Sensor energy is critical for monitoring and updating data. Given that clustering is an important strategy for minimizing energy usage in WSNs, this analysis focuses on clustering, routing metaheuristics, and machine learning. These algorithms provide details about forming a cluster, selecting the CH, unequal clustering routing, security and reliability. To examine the above features, many strategies employ conventional methodologies, machine learning approaches and optimization techniques. The dependable parameters with the relevant viewpoints are considered and provided for a more in-depth understanding of each perspective. The implementation of CR in WSNs is discussed in this study, along with its advantages and applications that can further reduce the energy of the network.

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