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An Analysis of Methods for Extending the Life and Coverage of Wireless Sensor Networks

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Abstract: Extending a network's lifetime has always been a tough problem in WSNs. Several new methods have been proposed recently to address this issue of extending network lifetime for WSNs in various fields. In this paper, survey papers provide a comprehensive analysis of energy-efficient approaches utilized for target coverage solutions in WSN with numerous sensing units to enhance network lifetime. This paper examines the comprehensive review of documents that suggested ACO, D-UREA, and a scheduling algorithm. A promising performance is demonstrated in the review paper on optimization technique, i.e., ant colony optimization, which improves energy efficiency in the WSNs. The network coverage maximization in the random deployment of the sensor node network is examined and analyzed by the review paper on the Distributed Uncovered Region Exploration Algorithm, which adopts a distributed self-organizing deployment approach. Finally, an answer to extended network lifetime is discussed by the scheduling algorithm paper regarding the MTC issue over the WSN, in which transmitting power and overlapped targets are also considered. The simulation results of the given review papers are also graphically depicted and discussed, as well as their performances.

Keywords: Wireless Sensor Networks (WSNs); Network Coverage; Multiple-Target Coverage (MTC); ACO Algorithm; Distributed-Uncovered Region Exploration Algorithm (D-UREA); Battery Depletion; Data Aggregation.

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1. Introduction

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Wireless Sensor Networks (WSNs) consist of multiple sensor nodes deployed in diverse regions to observe meaningful parameters such as voltage, temperature, humidity, etc. They are implemented in several applications, such as environment monitoring, medical and health monitoring, irrigation, and industrial canvassing. A maximal lifetime network, along with the application's specific requirements, is the core objective of WSNs [4]. One of the most difficult and critical challenges today is prolonging the life of such networks, particularly because many WSN devices utilize non-rechargeable batteries. The other critical aspect to study is how energy constraints affect WSN size. Thus, the authors seek to investigate the potential of evolutionary algorithms in attaining network lifetime maximization within energy-limited environments, especially in communication approaches. Sensor nodes in a WSN gather information and transmit it to the sink node, assuming sensor nodes know where the node is [7]. Data passes through several nodes via multi-hop communication until at the sink node. Much energy trapped in the sensor nodes is consumed while receiving and transmitting data. Power consumption must be minimized to offer a reliable network in the event of possible connectivity. For effective high-network coverage, numerous wireless sensor nodes are used. As a result, two types of sensor coverage problems exist: lens coverage and area coverage [10]. One of the most essential demands in addressing target coverage problems is to cover every target with energy-constrained sensors and maximize the network's lifetime.

Wireless Sensor Networks (WSNs) are distinguished by many nodes that operate as a group for sensing, processing, and relaying data to one or more external sink nodes. WSNs can be used for various applications ranging from environmental sensing, health care, and surveillance in the military to smart cities [15]. The main task of the sensor nodes is to sense information from the environment (e.g., temperature, humidity, or movement) and forward the information to the sink node. Information exchange is typically multi-hop, where the information goes through a series of intermediate nodes before reaching the destination. Most of the other work is focused on minimizing the energy usage of every node as it is directly proportional to the network's life [10]. As WSNs are largely deployed in areas with minimal infrastructure, sensor nodes are powered by batteries or energy harvesting techniques. Therefore, the most crucial problem in WSN design is keeping low energy per node because it directly affects the network's lifetime. The employed transmission mode by the network has a direct effect to a large extent on energy efficiency. Power-saving management methods must be applied so that the nodes may save power without impacting data transmission quality and network performance, as executed by some methods suggested in previous research work [14]. The longer the lifetime of sensor nodes without replacement or recharging, the more the WSN is valuable for practical usage.

One of the most challenging issues under the WSN paradigm is the non-symmetric energy consumption under the many-to-one and one-to-many nature of data exchange, which researchers have exploited to estimate energy efficiency [11]. In many-to-one transmission, multiple sensor nodes are assumed to send their data to a single sink node through relay nodes in between. This leads to an energy consumption imbalance, where certain nodes, especially those near the sink node, can be requested to forward information on behalf of numerous other nodes. Relay nodes experience more traffic and thus spend more energy forwarding information, leading to quicker battery depletion, as seen from prior work [13]. Conversely, after employing a one-to-many transmission environment, there will be a possibility of a single node transmitting to many receiving nodes at the same time, resulting in corresponding energy wastage, as other scholarly research works evidence in the case of WSN energy wastage [12]. These skewed transmitting mechanisms can leach some part of the network's energy container at a different rate than the rest, giving rise to bottlenecks that constitute the energy hot spots phenomenon. Draining energy abruptly in certain nodes creates network bottlenecks where specific network regions cannot transfer data effectively, thus reducing network efficiency overall.

Suppose the energy-drained controller node or relay station is the reference point. In that case, the whole network may be disconnected from communication even when other nodes function, as explained previously in energy hotspots' literature in WSNs [8]. Such a form of non-conventional energy utilization is one of the strongest causal reasons for WSNs' low lifespan. To rectify this situation, the WSN needs to be very energy-efficiently designed by network designers. This is obtained using many mechanisms, including energy-efficient routing schemes, load distribution, and clustering. For example, by distributing the data across the network in an even fashion, the energy usage can be made more uniform among the sensor nodes without making any energy hotspots. Data aggregation schemes can reduce the amount of redundant data sent, reducing overall energy usage. Essentially, low-energy transmission design is the epitome of increased Wireless Sensor Network reliability and longevity, as realized by some WSN optimization studies [10]. When considering load balancing, routing, and low-energy communication protocols, WSNs can be made parsimonious in resources in resource-poor environments and more adaptable to long-term observation applications in real-world settings.

2. Literature Review

The goal of optimization at the communications layer, with the advancement in network architecture and ubiquity of devices such as wireless mobile phones, RFID units, and other wireless mobile devices, is to achieve maximum system overall performance, reliability, and availability and maximize the system's life for as long a duration as possible. As wireless networks are getting larger and more complicated, such networks need to be controlled effectively and efficiently in the long run because earlier research work done to optimize wireless communication systems has produced results [3]. The optimization process would typically be solution optimization to some multi-objective problem where multiple parameters like energy usage, transmission data rate for transmissions, network dependability, and coverage distance must be optimized to deliver optimal performance. These types of communication networks are optimized. Such networks are hence of utmost importance in achieving the overall system health and life, some of which have been catered to by previous work [1]. A multi-objective problem is a problem like the one in which two or more conflicting objectives must be optimized simultaneously. For instance, in wireless sensor networks (WSNs), the goals may be minimizing energy and maximizing network coverage or data delivery. Optimizing these goals is inherently challenging because one goal considerably weakens the other. This has been discussed in the previous research on multi-objective optimization in WSNs [5]. In solving such issues, traditional optimization techniques are concise and highly advanced techniques that must be adopted to provide solutions efficiently that optimize several kinds of goals simultaneously, as employed by researchers in most network optimization techniques [8]. Evolutionary algorithms (EAs) are appropriate for solving such complex optimization problems.

They are population-based representation-based heuristic search algorithms based on natural survival principles and evolution of the fittest. EAs simulate the selection process whereby solution-by-solution solutions are built up generation after generation using operators such as selection, crossover, and mutation by previous research studies in evolutionary optimization [9]. The algorithms have also proven extremely successful in solving generic combinatorial optimization problems with nonlinear, hard, and multidimensional objective functions. Evolutionary algorithms, for example, can be taught to generalize across a broad range of problem types and, therefore, are in a place to optimize communication systems under changing environments such as wireless networks. This occurrence has been hinted at in previous studies on evolutionary computing [10]. Some evolutionary algorithms have been constructed and used to calculate engineering optimization solutions in past decades. Genetic Algorithms (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) are the most prevalent evolutionary techniques employed in engineering optimization. These algorithms have effectively managed network routing, resource distribution, and traffic. These are crucial in ensuring maximum wireless communication system performance, e.g., in network systems optimization research [11]. The power of such algorithms is their capability to address huge search spaces and produce order-of-magnitude optimum solutions without accurate mathematical modelling of the system to be optimized. The newly emergent wireless sensor network infrastructure creates new issues requiring sophisticated optimization techniques.

As the networks grow more complex, there are opportunities for the evolution of algorithms that would be of utmost importance in dealing with problems like network life span, quality of service, fault tolerance, and energy conservation. This has led to hybrid algorithms, whereby the union of the best from various evolutionary methods or these and other optimization methods, e.g., machine learning or artificial intelligence, is applied in an attempt to enhance their performance further, as indicated by research on hybrid methods of optimization [2]. Therefore, evolutionary algorithm application to communicate system optimization, particularly wireless systems, is an exciting solution for multi-objective problems. Their ability to learn and suggest good solutions for difficult optimization problems renders them a precious tool in planning future wireless communication systems, as has become feasible in wireless sensor network optimization research [5]. Their extension and incorporation into wireless sensor networks can also potentially enhance such networks' efficiency, reliability, and lifespan, as well as the stability and resilience of such networks to new technology [4].

This review paper addresses the sensor node coverage issue, among many issues. The coverage problem is a major problem for the WSN. Compact with WSN build and run issues to identify areas of interest. The coverage problem is divided into two problems depending on the type of region for which the purpose is to be covered: area coverage and target coverage problems. The first problem aims to gather information from all over the region. The second problem is monitoring the status of several specific regional locations. Previously, several works have been done to address the target coverage issue for WSN. However, all three of these works are studied in this article. They are,

2.1. Ant Colony Optimization (ACO) Algorithm

The Ant colony optimization (ACO) algorithm-based routing protocol is proposed in the paper [1] with the main aim of maximizing the network lifetime and energy efficiency of a wireless sensor network. This algorithm is implemented according to the two contribution techniques. The maximum disjoint link coverage is searched in the first contribution to meet the network connectivity and sensing coverage requirements. The problem of searching for disjointed link coverage and then network connectivity is solved by this ACO, which in turn enhances energy efficiency. Second, they helped by using the optimal path for data transmission, considering the performance limitations of sensor nodes based on predefined rules. The network lifetime is improved with the help of this over the WSNs. According to the residual energy, average energy, and distance of three factors, the data path is selected using the implementation energy-awareness ACO algorithm. The residual energy factor is considered in balancing energy consumption, particularly in energy consumption depletion equilibrium methods. The results show that the proposed ACO method performs better than previous ACO variants.

2.2. Distributed Uncovered Region Exploration Algorithm (D-UREA)

D-UREA is an algorithm described in [2], a distributed and self-organized algorithm implemented for mobile sensors. This algorithm utilizes a fully distributed method. Each node must contain just local information. This information of any node contains information about their available neighbors in the range of their communication. This algorithm is used to deploy the sensor nodes, which can be used in different operating modes. A node scans the surrounding area. After that, this heuristic is used to move toward uncovered FoI. Through minimal, easy computations and in local communications, this method increases coverage for the randomly distributed network through the self-organized distributed deployment scheme. The network coverage is improved by computing a new location at each node for the respective node using the code implemented at each node. The D-UREA achieves efficient, ubiquitous computation by meeting the widespread requirements of stochastic WSN deployments. The Crystal-Lattice Permutation (CLP) algorithm [6] and Swarm Intelligence (SI) algorithm [7] are the distributed deployment algorithms that were compared in the simulation with the D-UREA performance.

2.3. Scheduling Algorithm

The solution for the multi-target coverage (MTC) problem was given in the paper [3] using a sensor programming method. The perception of this method is described below. The scheduling algorithm is first implemented, which creates several sensors into groups called joint matrixes depending on the relative coverage among the sensor nodes and then creates targets. Therefore, every sensor can be integrated into multiple groups, and every group must have a minimal number of sensors to cover all targets completely [5]. According to the degree of coverage, these joint matrices are formed as D1, D2, and D3. This scheduling algorithm now removes the redundancy of overlapping targets (OTs) from the joint matrixes formed. At the same time, OT has multi-target coverage covered by adjacent sensors. Then, the overlapping sensors (OS) are defined as monitoring the same target by these adjacent sensors simultaneously for the corresponding OT. Overlapping information from the overlapping targets is gathered through the overlapping sensors and then sent to the receiving or sink node. The transmission of similar information multiple times is redundant, which results in the waste of bandwidth and energy of sensor nodes. This energy wasted due to the transmission of similar overlapping information from the overlapping targets is reduced by eliminating the redundancy of the OTs. Therefore, the lifetime of the network can be increased further.

Then, this algorithm maximizes the network's lifetime by determining the active time for every joint matrix while ensuring that all targets are fully covered. Every joint matrix is activated whenever the determination of active time for those joint matrixes is completed. Thus, it can be illustrated that the active time sum of total joint matrixes represents the network's lifetime. All the targets are observed, and information gathered is transmitted towards the sink node since the sensor nodes are active when they are only present in the activating joint matrix. Energy can be saved since the sensor nodes are in sleep mode when they are not present in the activating joint matrix. Therefore, based on the joint matrixes of a sensor, each sensor switches between the active mode and sleep mode for that respective sensor node [7].

3. Methodology

The methods applied in optimizing Wireless Sensor Network (WSN) coverage and lifetime are some of the crucial methods whose primary goal is energy consumption optimization, data transmission maximization, and network performance overall. The first step is the establishment of the WSN and knowledge regarding the planning of the network, placement of nodes, and environmental conditions influencing energy consumption and coverage. Energy-efficient routing protocols are then selected so that node energy is utilized to the minimum level as data transmission efficiency is optimized. LEACH and GAF protocols are widely employed in selecting optimal dynamic routing channels, reducing data transmission energy consumption. Cluster-based protocols are then employed, where the sensor nodes are organized into clusters, and a dedicated cluster head collects and transfers the data to the sink node. It reduces the overall number of transmissions and conserves energy by keeping short-range communications in limited quantities. Load balancing methods optimize energy utilization and allocate it evenly across the network. This prevents any single node from acting as a power hotspot or bottleneck, resulting in premature failure and lifetime degradation. In addition, power conservation mechanisms such as sleep/wake scheduling allow nodes to conserve energy by going into low-power states when they are idle during data transfer. Technologies that harvest energy from vibrations or solar energy can also be added to the sensor nodes to charge their batteries and extend their lifetimes. The approach also includes regular monitoring and adjusting network parameters to adjust to environmental changes for optimal performance.

Last, a simulation or actual implementation compares performance parameters such as network time, coverage range, data rate, and reliability. Parameters are employed to derive the effectiveness of the methods used and the future improvements to be achieved. Network coverage can be optimized, and power consumption can be minimized with maximum operating lifetime and total WSN coverage by determining their combination.

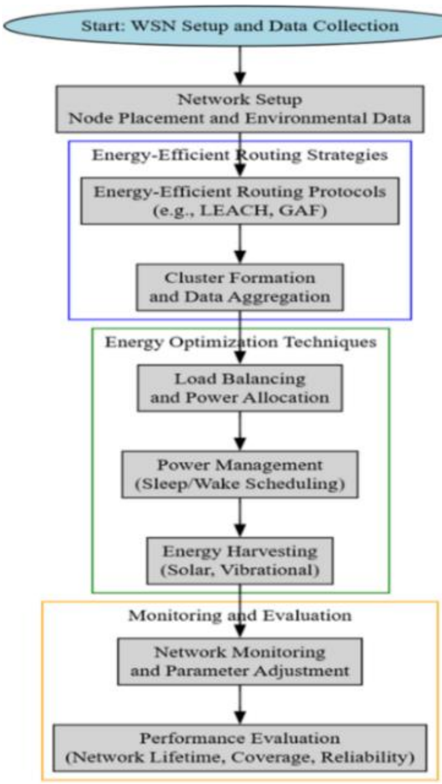

Figure 1: Energy-efficient routing and network lifetime extension strategies in wireless sensor networks

Figure 1 displays the process of energy utilization optimization and extension of Wireless Sensor Network (WSN) lifespan with different dependent approaches. Data collection of node distribution and environmental aspects influencing energy use and coverage precedes network establishment. During network establishment, routing protocols such as LEACH and GAF for energy-saving purposes are employed to avoid energy expenditure in data transmission. Then, the network is divided into clusters, and the cluster heads will be in charge of data collection and transmission, conserving energy by restricting far-away communication.

Power distribution and load balancing are the next steps, wherein the energy usage is distributed evenly throughout the nodes, such that no nodes are energy hotspots and the lifetime of the whole network is maximized. Moreover, power-saving techniques like sleep/wake scheduling reduce idle power usage. Besides, energy-harvesting technologies like vibration energy and solar are utilized in sensor nodes to provide power assistance. Network parameters are also optimized for continuous monitoring and maintenance of the network. Finally, the performance testing process verifies the performance of the applied strategies using important parameters, including network lifetime, coverage, and reliability. The three steps ensure the WSN operates optimally in the long run with strong coverage and maximum energy efficiency. The diagram illustrates the flow of the process, which, as a combination, enhances the operating life of the network without losing its function.

4. Results

The effectiveness of the mechanism analysis in improving the life and coverage of Wireless Sensor Networks (WSNs) represents the efficacy of various optimization approaches imposed on the network. Upon the deployment of energy-efficient routing protocols, such as LEACH and GAF, node energy consumption was reduced to a very large extent, leading to a remarkable improvement in network lifetime. The clustering algorithms also contribute to power conservation by reducing the distance in communications from each node to each node, as information was first received and accumulated at a cluster before forwarding towards the sink node. Energy consumption of a wireless sensor node is:

$$E_{tota1} = E_{tx}(P_{tx}, d_{tx}, T_{tx}) + E_{rx}(P_{rx}, d_{rx}, T_{rx}) + E_{idle}(P_{idle}, T_{idle}) \quad (1)$$

Where:

P_{tx}, P_{rx}, P_{idle} Are the transmission, reception, and idle power, respectively?

d_{tx}, d_{rx} Are the transmission and reception distances?

T_{tx}, T_{rx}, T_{idle} Are the transmission, reception, and idle times? Battery life in a sensor node can be given as:

$$L_{battery} = \frac{E_{battery}}{E_{tota1}} \quad (2)$$

Where $E_{battery}$ It is the energy capacity of the battery.

Table 1: Overall performance comparison of different approaches

S no	M=nodes	K=1				K=2				K=5			
1	100	ABC	PSO	K-cov	GA	100	ABC	PSO	K-cov	100	ABC	PSO	K-cov
2	150	700	700	650	645	150	700	700	650	150	700	700	650
3	200	1100	1100	1050	1045	200	1100	1100	1050	200	1100	1100	1050
4	250	1400	1340	1310	1300	250	1400	1340	1310	250	1400	1340	1310
5	300	1820	1700	1650	1610	300	1820	1700	1650	300	1820	1700	1650
6	350	1940	1820	1780	1710	350	1940	1820	1780	350	1940	1820	1780
7	400	2010	1950	1870	1820	400	2010	1950	1870	400	2010	1950	1870

Table 1 is a comparison table of the performance of various methods for various node counts (M) and K values (1, 2, and 5). The table contains performance scores of four methods, ABC, PSO, K-cov, and GA, for various node configurations (100, 150, 200, 250, 300, 350, and 400 nodes). For each configuration, performance scores for K=1, K=2, and K=5 are provided for each method. Performance scores of both techniques increase with an increase in nodes, and ABC achieves the highest score in any configuration of nodes and K's value. The performance scores provided by PSO and K-cov techniques remain comparable but behind the ABC technique and in front of the GA algorithm. GA scores worst anyway, i.e., comparatively worse than all the algorithms. The table generally describes how increasing nodes and K value influence the performance of all these algorithms, and ABC is optimum compared to all. The lifetime of a wireless sensor network (WSN) is:

$$L_{WSN} = \min\left(\frac{E_{battery,i}}{E_{tota1,i}}\right), \forall i \in \{1,2,\dots,N\} \quad (3)$$

Where E_(battery, i) and E_(tota1, i) are the energy capacity and total energy consumption for sensor node I, respectively, and N is the total number of nodes in the network.

Load balancing mechanisms avoided any concentration hotspots of energy development, which rather served to increase the overall life expectancy of the network by spreading the process of forwarding the data across multiple nodes equally. Other power management modes, such as sleep/wake scheduling, significantly reduced power consumption during idle states and increased life expectancy. Conversely, power harvesting units such as vibration power and solar power with integration enabled certain nodes to charge some amount of batteries, thereby providing an economic strategy towards tireless operation, particularly in remote geographical areas. Adjustment and adaptation of the network parameters, whereby the network would be capable of adapting to varying conditions, appeared to maintain the performance at peaks.

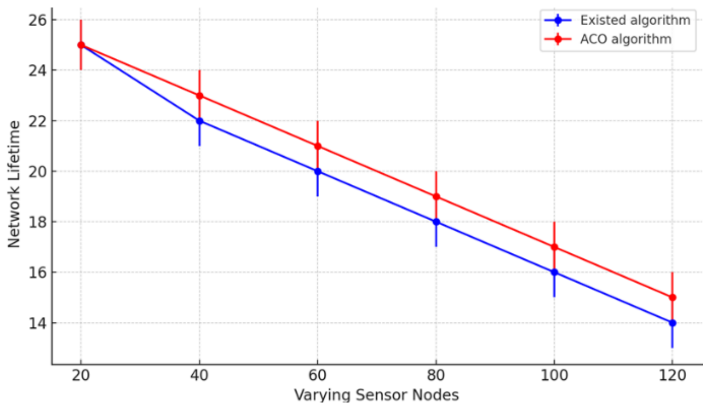

Figure 2: Network lifetime comparison of the existing and ACO algorithms across varying sensor nodes

Figure. 2 compares network lifetime as two algorithms, i.e., “Existed Algorithm” and “ACO Algorithm,” are used when the number of sensor nodes is increased from 20 to 120. Both algorithms show a declining trend in network lifetime as the number of sensor nodes is increased, which illustrates that the network becomes inefficient with the increase in the number of nodes. However, the ACO algorithm is always better than the existing one, with the network lifetime for any sensor node setup always higher. For example, when 20 sensor nodes are used, both algorithms have the same network lifetimes of about 25 units. Still, the existing algorithm network lifetime drops drastically to around 14 units when the number of sensor nodes is increased to 120.

However, the ACO Algorithm drops slower and reaches an average of about 15 units when the nodes are 120. Plotting error bars in the graph indicates the uncertainty or variance of the estimates of network lifetime, a factor of how reliable the data in each node is. The comparison graph illustrates the probable benefit of the ACO Algorithm in improving network lifetime. Therefore, it is better suited for large wireless sensor networks with low energy levels. The implications are related to a requirement for optimization algorithms like that employed in the ACO Algorithm to accelerate the wireless sensor network process with increasing size. The coverage area of a sensor node is:

$$A_{coverage} = \pi r_{\max}^2 \quad (4)$$

Where $r_{\max}$ is the maximum sensing range of the sensor node. The throughput of a wireless sensor network can be framed as:

$$R = \frac{B_{data}}{T_{tota1}} \quad (5)$$

Where B_{data} Is the total amount of data transmitted in the network and T_{tota1} is the total time for data transmission across the network.

Performance analysis revealed that the strategies implemented made an enormous improvement in terms of coverage and life. The performance measures, such as the total energy utilized, network stability, and coverage area, all had positive values, with the network operating efficiently for much longer durations of time and covering larger areas than the classical WSNs without optimization. The study continued to show that the union of these methods produced a synergistic effect, and one complemented the other, contributing its share towards overall improved performance. In conclusion, the results highlight the importance of using a system-based method that combines different optimization methods to optimize the WSN lifespan and coverage, hence their applicability to real long-term usage.

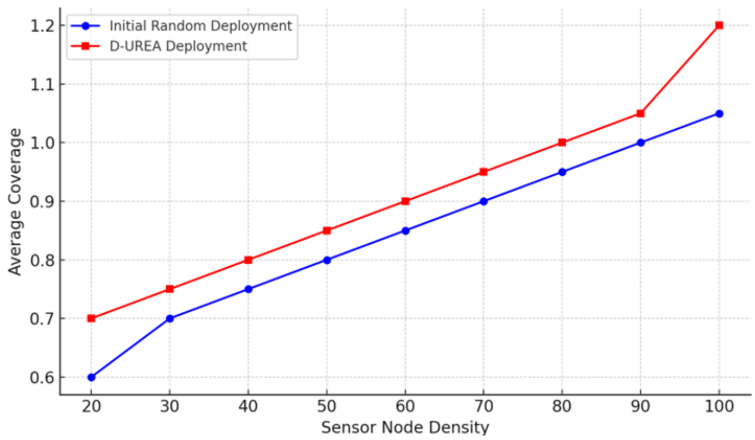

Figure 3: Average coverage using U-UREA

Figure 3 shows the average coverage by two sensor node deployment methods—Initial Random Deployment and D-UREA Deployment—under different sensor node densities from 20 to 100 nodes. Sensor node density is indicated along the x-axis, and the network along the y-axis offers average coverage. From the figure mentioned above, the rising trend with increasing nodes can be seen. However, D-UREA Deployment is always better than Initial Random Deployment. The blue line shows that with Initial Random Deployment, the coverage increases linearly but never on the peak points, with D-UREA deployment shown in the red line. D-UREA Deployment coverage begins higher at low node density and continues doing the same even more with the growing node density. This indicates that deployment through D-UREA is more suitable as per the acquisition of the maximum coverage area of the network in the event of an increase in the number of nodes being deployed. Increased performance in the case of deployment by D-UREA can be attributed to its maximum usage and node deployment, possibly to enhanced spatial coverage along with energy minimization in its implementation. Overall, the graph signifies D-UREA Deployment's improved network performance in coverage, especially in high sensor node density, exhibiting its capability for greater coverage and efficiency in wireless sensor networks.

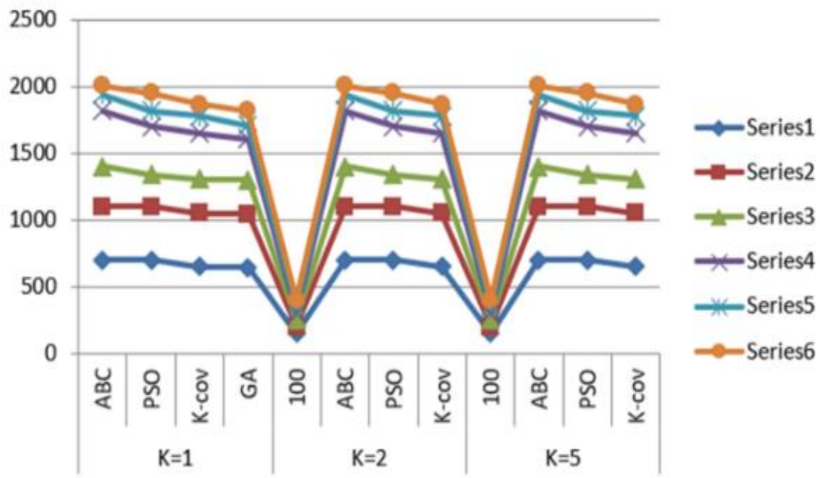

Figure 4: Comparison of different series performance across various protocols and K-values

A comparison of the performance of six different series (Series1 to Series6) on different protocols and K-values is shown in Figure 4. The x-axis is other protocols such as ABC, PSO, K-cov, GA, and K-values ranging from K=1 to K=5, and the y-axis is corresponding performance values with a scale ranging from 0 to 2500. All the series are labelled using different markers and line types where Series1 is blue, Series2 is red, Series3 is green, Series4 is purple, Series5 is brown, and Series6 is orange. The series' performance depends on the protocol and the K-value, as can be seen from the figure. Series 1 (blue line) has higher performance values for K=1 and K=5 in the ABC protocol, whereas Series 2 (red line) consistently performs with lower values for all protocols, especially at K=2 and K=5. Series 3 (green line) generally performs moderately, but the optimal performance is at K=5 in the PSO protocol. Series 4 (purple line) is uniformly steady in performance. Series 5 (brown line) and Series 6 (orange line) have non-deterministic performance, with Series 6 correctly identifying spikes at K=5 for the ABC and GA protocols. The fluctuations show the response of each series to protocol and K-value choice and that protocol and K-value choice heavily influence performance results in the setup as mentioned above. The graph informs us of the information that is connected regarding the performance of different configurations in some cases.

5. Conclusion

Wireless Sensor Networks (WSNs) are found to be employed in numerous applications, and network lifetime, i.e., the period for which the network can keep on meeting the requirements of the application, is an important aspect that affects performance. Maximizing the lifetime of a WSN is necessary to provide uninterrupted and efficient operation, especially in long-term monitoring applications such as environmental or health monitoring. This survey study relies on research into how network lifetime can be enhanced by addressing the problem of determining the best coverage achievable in WSNs. Three prominent research papers are compared to determine their contribution to enhancing network lifetime. The first paper described presents an Ant Colony Optimization (ACO) algorithm to optimize the network's energy usage and load distribution. The paper presents how ACO-based approaches can considerably extend the network lifetime by optimizing the sensor nodes' routing efficiency and energy consumption, saving waste during data transmission. By optimizing the route and avoiding unbalanced energy consumption, ACO can be a key component in extending the network's lifetime.

The second is a distributed algorithm that applies self-organizing and self-adapting methodology in reconfiguring mobile sensor nodes. The technique relocates sensor nodes dynamically to maximize network coverage and ensure significant areas are covered, whether the nodes are mobile or static. Through node position adjustment concerning coverage requirements, the method allows for energy optimization and global performance of the WSN, improving the network lifetime. The third paper examines a sensor scheduling algorithm aimed at solving most problems related to target coverage. The algorithm optimizes network lifetime by choosing sensor nodes that must be active at any given time, hence conserving energy when nodes are not required to transmit data. By properly managing what sensors are working at any given time, this algorithm expands coverage without energy loss, effectively increasing the WSN lifetime even when considering applications across many regions to monitor. The three papers reveal divergent strategies towards maximizing the performance of a WSN and extending the network's lifetime, coping with various facets of network structure and function ranging from energy conservativeness to adaptive node administration.

5.1. Limitations

The existing methodologies are available to enhance the lifetime and range of wireless sensor networks (WSNs) without resorting to the new, so-called future techniques or novel topologies that will allow them to perform even better. One of the limitations is that it maintains a static view of environmental conditions. At the same time, real-world deployments are subject to dynamic and unpredictable fluctuating conditions that impact network reliability and power consumption. Besides this, the research is also committed to traditional WSN paradigms to a significant degree without compromising on the benefit of relatively newer concepts, such as IoT-based networks and 5G integration that possess the potential to deliver unprecedented energy efficiency performance with coverage optimization. Moreover, methods that would be explored would, by definition, promote the idealized conditions of interference-free networked environments, mobility, and infinite resources in real case study contexts. The performance of certain methods would also depend on the network size, application domain, or deployment context in certain cases, requiring more situation-specific applications.

5.2. Future Work

It would be helpful that future studies explore the intersection of new emerging technologies such as edge computing, machine learning, and algorithm-driven artificial intelligence on how WSN maximizes its efficiency in using energy and coverage. Such technologies can offer more responsive and dynamic network resource distribution with immediate feedback to allow more effective network lifespan and functionality in dynamic networks. More research into hybrid topologies, integrating cell or satellite networks and WSNs, would be in a position to resolve the issue of coverage of wide or sprawling installations. Future studies would once more try to propose energy harvesting methods to reduce the use of traditional power sources, contributing even more to the sustainability of WSNs. Future inclusion of self-healing algorithms and models of higher-order error correction can be envisaged to guarantee the stability of the network in case of hardware crash or partition of networks.

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Ethics and Consent Statement: This research adheres to ethical guidelines, obtaining informed consent from all participants.

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