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Optimized Resource Allocation Strategies in Wireless Sensor Networks: A Heuristic and Simulation-Based Approach

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ABSTRACT

Wireless Sensor Networks (WSNs) Wireless Sensor Networks (WSNs) are the wireless, self-organized sensors that gather data and remotely transmit to the sink. These networks have several resource limitations such as energy, bandwidth, computation, and memory. Rational allocation of such limited resources is the key to maximizing these valuable resources, extending the lifetime of the network and reliable data transmission and sensing coverage. This paper discusses the main challenges for minimizing energy consumption, controlling allocation of communication bandwidth to prevent collisions, and for bypassing processing limitations. It investigates different approaches including those that were developed for energy-aware protocols, adaptive node scheduling, power-efficient routing, and also data aggregation. Furthermore, adaptive communication protocols are presented for these tasks of keeping the network performance constant under dynamic situations. Optimization and heuristic methods offer down-to-earth solutions to complicated allocation problems. The paper emphasizes the role of resource scheduling in facilitating WSN applications such as military surveillance, industrial automation, and environmental monitoring. Efficient resources allocation is a key to improve the sustainability, scalability and resilience of a network and get the most out of WSNs.

Key Words: *Wireless Sensor Networks, Resource Allocation, Energy Efficiency, Adaptive Protocols*.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are made up of a number of spatially distributed sensors which are used to measure physical or environmental properties like temperature, humidity, motion etc. In general, these sensor nodes are characterized by being energy, bandwidth, processing, and memory constrained. Effective resource management in WSNs is important to maximize the multiuse of these limited resources and guarantee the sustainable network performance. One of the most important network resources, the energy consumption has a great impact on the network lifetime, since sensor devices are usually battery-driven with scarce possibility of recharging. In addition, resource (bandwidth) allocation is important t h at communication conflicts are avoided and the data-relaying-quality is preserved, this is in particular important for highly dense networks. Furthermore, the computer resources and memory man-agement affect the capability of nodes to process and store sensed data at the node, which could be advantageous in terms of reducing communication overhead. Resource allocation policies try to reconcile these requirements, by deciding over node activation schedules, routing of data, data aggregation methods, and communication protocols. Efficient management guarantees the QoS of continuous sensing cover, the reliability of data delivery, and the network lifetime maintenance, taking a few examples from environmental monitoring to military surveillance. Thus, the design of efficient resource allocation techniques forms the backbone of research in WSNs that fosters energy-efficient protocols, adaptive scheduling, optimization algorithms, and techniques to improve the utility and robustness of WSNs [1].

1.1 Definition of Wireless Sensor Networks (WSNs)

A WSN is a network of spatially distributed autonomous sensors to monitor physical or environmental conditions like temperature, sound, pressure, etc. and wirelessingly pass their data through the network to a main location. Each sensor node comprises sensing, processing and wireless communication capabilities and can gather data and report to a central base station, or sink, for further analysis. These network structures are non-static and they can be easily deployed in various wild and harsh environment, so that they have great flexibility as regards applications for environmental monitoring, industrial automation, health care service, military surveillance, etc. The nodes are generally wireless radiofrequency transceivers and create multi-hop communication paths in order to transmit data in an energy-efficient way throughout the network. WSNs will clearly be distributed, scalable system with such a real-time monitoring potential over large region and it may provide very useful information for taking the decision. As these sensor nodes are used in resource-constrained environments, optimal operation and coordination of these sensor nodes is important for efficient network operation [2].

1.2 Resource Constraints in WSNs

Limited Energy (Battery-Powered Nodes): The challenge of energy is the most serious one in WSN as sensor nodes are usually powered by batteries which are generally impossible and even inconvenient to replace or recharge, especially in dangerous and difficult-to-reach locations. Power used for sensing, processing, and wireless communications has a direct impact on the lifetime of the individual nodes and the network in general. Communication is, in general, an order of magnitude more expensive than computation, so good protocols must be energy-efficient that is, they must transmit as little data as possible and route it in an optimal way. Energy exhaustion in a few nodes can cause network division or coverage void decreasing the WSN system effectiveness. This leads to the fact energy-efficient hardware design, adaptive sleep/active duty-cycling, energy-aware routing protocols, and energy harvesting mechanisms are the focus of interest to overcome this barrier and to prolong network lifetime [3].

Bandwidth Limitations: Bandwidth in WSNs is limited by the scarcity of the wireless spectrum reserved for sensor communication and the contention on the wireless channel. As packets are transmitted over a shared medium by multiple sensor nodes, band-width contention and interference may lead to packet collision, which leads to data loss and retransmissions, which consume precious energy and delay communication. The low data rate limits the amount of information transferred, particularly with dense deployments and time-critical applications. The scalability and reliability of the network is also hampered due to the bandwidth limitations. To tackle these issues, bandwidth-efficient communication protocols such as TDMA and frequency hopping, data aggregation, compressions, etc, are applied. These techniques may decrease channel congestion and enable efficient use of bandwidth, tracking data integrity and timely delivery [4].

Restricted Computational Power and Memory: Sensor nodes, which have limited compute, memory and storage capacity, belong to WSN. This restricts the class of data processing algorithms that may be locally run on each node. Limited computation capability also affects the potential to carry out complex signal processing, encryption or compression of data, which may need to be outsourced to the base station. Simultaneously, limited storage cannot support large buffering of data, thus requiring timely transmissions to avoid data loss even with increased energy consumption. These constraints necessitate power and memory optimized 'lean' algorithms. In-network processing operations including data aggregation and fusion minimize the communication overheads, and distributed computing at all the nodes can make up for the shortcoming of an individual node [5].

1.3 Importance of Resource Allocation

Optimizes Use of Scarce Resources: Resource management in WSNs is crucial due to the severe constraints that characterize sensor nodes such as energy, bandwidth and computing abilities. Optimized deployment methods make use of these limited resources to maximum effect, preventing resources from being wasted or sitting idle. Dynamic resource allocation for when and how sensor nodes sense, process, and transmit (sharing and scheduling) minimizes gratuitous energy usage and usage of bandwidth. This ensures that system responsiveness and data integrity is preserved while limiting overhead. Optimal resource allocation further allows the network to tackle changes in the environment (e.g., node failure and environment dynamics) to guarantee operation under restricted conditions. In general, resource allocation does attempt to counterbalance the conflicting requirements between energy conservation and resource utilization to exploit limited hardware and communication resources of WSNs [6].

Prolongs Network Lifetime: The longest lifetime for the whole network is the main object in resource allocation of WSNs. Sensor nodes mostly work depending on the limited battery power which can be easily exhausted by inefficient energy consumption resulting in coverage voids or network breaking. Resource allocation methods such as energy-aware routing, duty cycle, and balanced workload distribution are adopted to achieve a balanced energy consumption among the nodes. These schemes save energy and postpone the node failure by reducing retransmissions and tuning sensing schedules. Maintaining network life time is of interest even for applications in remote or hard to reach areas, where changing or recharging batteries is not an easy task. Hence, more efficient resource assignment is expected to directly help the network to work in longer times [7].

Ensures Reliable Data Transmission and Sensing Coverage: Dependable communication and full sensing coverage are crucial for the success of WSNs. Resource allocation is essential to preserve these by controlling the cooperation among sensor nodes. The reasonable allocation of bandwidth can reduce collisions, packet loss, and guarantee that data can be correctly and timely transmitted to the base station. It also schedules the activity of the node effectively to avoid any blind spots or redundancy in sensing the environment. Through judiciously waking up minimum set of nodes and scheduling them appropriately, instead of flooding all the nodes in the network, resource allocation prevents network congestion and interference to ensure reliability. This is particularly vital in mission-critical scenarios such as disaster monitoring, military surveillance, or health care, where accuracy and timeliness of data can be of utmost importance, due to significant impacts. Consequently, resource allocation is critical to protect WSN deployments from unfair resource exhaustion attack. [8]

1.4 Key Resource Allocation Challenges

Allocation of resources for Wireless Sensor Networks (WSNs) presents a number of challenges because of constrained nature of sensor nodes and network environment. A. Energy balanced the most important issue is to keep energy consumption in the network balanced at all times. Normally, sensor nodes are powered by batteries only, and unbalanced energy consumption can prematurely cause exhaustion of some nodes, which can give rise to holes in the coverage area or network fragmentation. Realization of fair energy consumption dictates a proper protocol design that minimizes the cost of sensing, computation and communication, simultaneously. Duty cycling, forcing nodes to alternate between a wake mode and a sleep mode, and the energy-aware routing, the path with minimum energy needed to transmit data, are necessary, but difficult to coordinate dynamically under changes of network condition. [9]

Managing communication bandwidth to prevent collisions and congestion is another major challenge. WSNs use the same medium for communication such that simultaneous transmissions by multiple nodes may collide packets, resulting in data loss and retransmissions that waste energy and introduce latency. The amount of data that can be sent is further limited by their low bandwidth, especially in crowded environments and in the context of high data rates. Fairly and effectively sharing channel access, for example through TDMA scheduling or adaptive frequency assignment is crucial to maintain communication reliability.

Finally, computational and memory constraints bound the complexity of algorithms that can be implemented by sensor nodes themselves. These algorithms are simple and lightweight, because they cannot offload complex data processing more advanced in nature, like encryption, compression or fancy signal analysis, due to the fact that they operate in limited resources. Likewise, shortened memory space does not permit accumulation of excessive amounts of data, thereby requiring frequent transmissions and consuming energy. These limitations require resource allocation mechanisms to be designed that maximize in-network processing and data aggregation to minimize the communication overhead while taking the node's capabilities into account. Considered collectively, these challenges call for responsive resource utilization frameworks that optimize WSN performance over energy, bandwidth, and computational requirements, in order to achieve effective, reliable, and enduring WSN operation [10].

1.5 Goals of Resource Allocation Strategies

Efficient Node Activation Scheduling: An important objective in Wireless Sensor Networks resource allocation is to efficiently decide on when to awake sensor nodes to conserve energy and guarantee satisfactory sensing coverage. As, consistently active nodes drain their restricted battery in very shot time, so nodes should be put alive or asleep according to the need of the network. Optimal node scheduling ensures that only a fraction of the nodes is actively sensing and transmitting to the BS at each time slot, and the others are asleep in low-power sleep modes. This strategy avoids redundant data gathering, avoids coverage holes, and extends the lifetime of the network. Scheduling may be static, occupied with fixed routing and predetermined duty-cycles, in which channel access does not change according to fluctuations in channel parameters such as interference level and SNR, e.g., based only on the cost in terms of energy consumption; or dynamic according to changes in the environment, node's energy availability and application demands. Sophisticated scheduling algorithms also take into account the spatial coverage, connectivity and the relevance of the sensed events to determine which nodes should participate in the measurement. However, by controlling node activities, under these strategies, high energy utilization is achieved without a significant compromise on data accuracy and delay.

Energy-Efficient Routing and Data Aggregation: Routing, which is certainly one of the most challenging performances in sensor network, is critical to the distribution of resources since most energy is consumed in wireless communication. The objective is to discover communication links which minimize the total energy cost, but preserve network connectivity. Routing protocol often choose paths which prevent energy-starved nodes and load balance the network in such a way to avoid early node-death. Data aggregation is also used in conjunction with routing to collect and merge the readings of different sensors in intermediate nodes, in order to minimize the number of messages. Data aggregation reduces duplicate information, shortens bandwidth consumption and saves energy to extend the lifespan of the network. Energy-aware routing and aggregation together enhance the communication performance, and thereby the energy efficiency and scalability of WSNs. These methodologies dynamically adjust to network topology fluctuations and fluctuations in data traffic, thereby delivering robust performance across various scenarios.

Adaptive Communication Protocols: The adaptive communication protocols are intended to adapt the network operation according to changes in environmental conditions, node statuses, and traffic demands. Depending on the variability of node energy levels, network congestion and interference, fixed protocol can be inefficient for WSNs. Adaptation strategies observe network statistics and take actions (1) regarding data transmission power, transmission rates, frame scheduling, channel access, and user frequencies, among others. For instance, protocols can reduce the power used for transmission to conserve energy when the nodes are in proximity and increase the power to retain connectivity when links go down. They can also switch between a contention-based mode of access and the scheduled mode of access, based on traffic load. By constantly read ogling, the protocols not only improve the system reliability, minimize the collision, save the power, but also QoS is preserved. This agreeness is crucial for the long-term sustainability of WSNs in dynamic and unpredictable environments.

1.6 Applications Dependent on Resource Allocation

It is this efficient allocation of resources, which allows to facilitate different services in Wireless Sensor Network by utilizing scarce resources according to given operational requirements. A well-known application is environmental monitoring, in which WSNs are employed to measure temperature, humidity, pollutants and seismic activity over a large span of space. These are the deployments with hundreds or even thousands of sensor nodes transmitting to a base station in the field, and sometimes do not available for the maintenance. Efficient utilization of available resources leads to prolonged network lifetime through maintaining energy balance, controlling node duty cycle, and enhancing data delivery. This enables the continuous reliable measurements needed for environmental change monitoring, disaster detection, and climate studies.

In military and security surveillance, WSNs offers real-time coverage of critical regions of interest for unauthorized external penetration or troop movement and for collecting data about the intrusion. These systems require highly reliable, low-latency, and secure communication in the dynamic and harsh environments. Resource allocation in such situations is typically carried out under policies aimed at preserving network connectivity, optimizing coverage with the fewest number of active nodes to avoid early detection, and modifying communication protocols in the face of jamming or interference. Power efficiency continues to be of utmost importance for the long-term survival of the network on long-duration missions where access to physical replacement batteries is unavailable.

In such environments, WSNs are employed for industrial automation to monitor equipment health, control processes, and improve the safety in factories or critical infrastructure. Here, the timely and accurate data transmission is necessary to facilitate the automatic decision making and avoid every degradation. It helps to make efficient use of the bandwidth for high data traffic, distributes the computational loads for local processing, and regarding sensor operations schedules them according to production cycles. Efficient utilization of resources in WSNs enhances efficiency of operations, reduces downtime and provides the ability to perform predictive maintenance. These applications rely on smart resources provisioning in order to satisfy the high-level performance, reliability and lifetime demands in different operational environments [11].

1.7 Research Significance

Drives Development of Energy-Aware Protocols: The energy constraints in wireless sensors have stressed the requirement of energy aware protocols as one of the most challenging research areas. These protocols aim to minimize the usage of energy while networking that consists of sensory data transmission, information processing, and communication. Intelligent derivation of when to keep the nodes on, selecting more energy-efficient routes, and avoiding redundant transmissions, etc., all are meant to increase the lifetime of the sensor network using energy- conscious protocols. Study in this field has given rise to novel methods like duty cycling, energy aware clustering and adaptive transmission power control. These technologies not only contribute to make WSNs more sustainable but also to free WSNs from area of low accessibility and dangerous areas where battery cannot be easily replaced. Hence, resource allocation becomes an important enable of protocols designed to balance energy consumption, providing more reliable and longer life sensors networks for several applications.

Encourages Adaptive and Optimized Resource Management Techniques:

Studying resource allocation in WSNs promotes the emergence of adaptive and efficient management strategies that can adjust what resources are utilised in order to adapt to changing properties in the network. The sensor networks are mainly deployed in unpredictable environments, with node failures, topology changes, and varied data traffic patterns. There are adaptive resource management 3 techniques that monitor the behavior of the network and modify resource utilizati on, for example, adjusti ng the distribution of bandwidth, rescheduling activity of different nodes, and modifying routing decisions to preserve performance and efficienc y. Optimization techniques, such as heuristic and metaheuristic algorithms, are used to search good solutions to complex assignment problems that trade-off between energy, coverage, and communication reliability. This line of research enhances the smartness and self-healing of WSNs so that WSNs can organize themselves and keep running over a long time without human attention. It thus increases the practical potential and stability of sensor network environments in a realistic sense. [12]

2. RELATED REVIEWS

Ngo et al. (2025) had observed that low harvested energy posed a significant challenge to sustaining continuous communication in energy harvesting-powered wireless sensor networks, mainly due to the intermittent and limited power availability from radio frequency signals. They had proposed in their letter, a new energy-aware resource allocation problem, designed to support the accumulate-then-transmit protocol in contrast with the widely considered harvest-then-transmit method. They had particularly considered the joint power allocation and energy harvesting time fraction optimization in order to maximize the average long-term system throughput in the presence of data and energy queue lengths. They benefitted from inner approximation and network utility maximization approaches to devise a simple and effective iterative algorithm, which enforced a local optimal and also offered long-term utility gain. Numerical studies had confirmed the effectiveness of the proposed solutions in both queue length reduction and maintaining system throughput.

Ballary and Hegde (2025) had described Software-Defined Wireless Sensor Networking (SDWSN) as an emerging network architecture that was increasingly significant to the Internet of Things (IoT). They observed that in such architecture, the control planes had been successfully decoupled from the sensing plane, and that separation greatly simplified network management and made the network itself more efficient in a dynamic environment. The authors stated that an enduring issue in sensor networks had been the limited existence of network equipment as result of power intensive characteristics. To cope with this, they had presented a system architecture in their work, which is designed to enhance SDWSN performance using optimization methodology. In particular, they had proposed a new hybrid optimization method via integrating Election-Based Optimization Algorithm (EBOA) and Ladybird beetle optimization algorithm, and called it as Hybrid Election-based Ladybird Beetle Optimization (HELBO). More recently their research focused on an energy-efficient resource allocation scheme that was tested for SDWSNs with a large capability of processing and memory showing that this algorithms could make the allocation for the power and bandwidth in such a way that the SINR under QoS constraints reached a large value. Finally, experimental results had demonstrated that the presented HELBO method has had a better performance compared to other state-of-the-art methods.

Endla et al. (2025) had reviewed that Wireless Sensor Networks (WSNs) had emerged as a cornerstone technology across domains such as environmental monitoring, industrial automation, and healthcare, and their study had introduced a novel hybrid resource allocation model aimed at enhancing efficiency in WSNs through advanced Artificial Intelligence (AI) techniques. The model had utilised static and dynamic resource allocation techniques embedded with machine learning and reinforcement learning to maximise various resources such as energy, bandwidth and processing. And their extensive simulations also showed that the proposed algorithm had advantages over some nine popular methods in terms of energy efficiency, network lifetime, throughput, delay, latency and accuracy of resource allocation. In particular, the model obtained a good energy efficiency of 0.98 J/bit, prolonged network lifetime to 620 days, and maintained good throughput at 620 Kbps. It also had an ultimate shorter delay (90 ms) and latency (180 ms) with the highest resource allocation accuracy of 97.8%. These results have demonstrated the model’s potential to optimize resource allocation on the fly, at real-time, providing adequate and efficient resource usage, and the authors remarked that such an improvement became a solid solution for many WSN applications that require high effectiveness and reliability.

Rao et al. (2024) had reviewed that partial-band noise jamming had been considered a significant countermeasure against frequency-hopping spread spectrum technology in wireless sensor networks, and the associated jamming resource allocation (JRA) problem had been identified as a high-dimensional combinatorial optimization challenge as well as an NP-hard problem. It was observed that the users could change the status of their communication dynamically (e.g., changing the channel spectrum distributions of the hopping sets), which made JRA more complex. To address these issues, the paper proposed two approaches: (i) a DRL-based method for fast JRA with the jamming scheme for each jamming node being decided at a time in sequences by a policy neural network, whose parameters had been updated based on TRPO in a trust region to guarantee stability and rapid convergence; and (ii) a meta-TRPO-based technique for improving the generalization capability of the policy network, and the resulting meta-policy network was easy to adapt to new tasks with a few fine-tuning steps. The authors had already shown in extensive numerical simulations that the DRL-based approach converged faster than other DRL methods and the meta-TRPO algorithm adapted rapidly to new jamming tasks even with a few training samples.

Packiyalakshmi and Ramathilagam (2024) had discussed the significant role that Wireless Sensor Networks (WSNs) had played in modern tracking and monitoring operations, noting that the proliferation of wireless sensor deployments had underscored their importance. The authors had pointed that even though the sensors were being deployed almost everywhere, the issues of power consumption, security, coverage, latency, and design remained, prompting much research. They noted that there was new and growing interest in extending the lifetime of sensors in the field because microelectronic sensors only had specific power resources in which to run, and that it had been difficult to charge up (upgrade) sensors distributed in the field. The study intended to improve the energy consumption efficiency in WSNs, and then compared different localization and resource allocation methods. It also provided solutions for node management and scheduling by estimating the power consumption for maintaining communications work. The study had already addressed the existing challenges by incorporating the AI based fault tolerance mechanism and by utilising digital twin concepts for maximising the resource usage. The results were introduced as important means for clarification, progress of the knowledge from exiting practices and new approaches for WSN management.

Sukumar and Praveena (2024) had observed that traditional Wireless Sensor Networks (WSNs) often suffered from inefficiencies in dynamic resource allocation and energy management because of their reliance on fixed, static techniques, which had in turn diminished network performance and lifespan. They had found that the existing methods, such as duty cycling and clustering, do not well adjust to the dynamics having the changing and unpredictably dynamic characteristics of real-world environments, leading to inefficient energy consumption and reduced network stability. To mitigate these drawbacks, their research was the first to present an AI-supported network management system which utilized sophisticated machine learning such as Regression, Reinforcement Learning, and Neural Networks to update network's parameters in an anticipatory manner as well as predict future states, using past and current data. Through experimental results, they had shown significant advantages of their proposed system compared to traditional systems, such as extended node lifespan of 400 days, reduced average energy consumption to 130 Joules, and highest average throughput to 85 kbps. These observations had highlighted that continual learning and adaptation could boost the sustainability, reliability and efficiency of WSNs.

Hassan (2023) had examined cognitive radio wireless sensor networks (CR-WSNs), describing them as a type of WSNs leveraging cognitive radio technology to improve spectrum utilization and energy efficiency. The work had suggested an energy efficient resource allocation algorithm (EERAA) to prolong the lifetime of WSN-based smart irrigation system in a real-world setting. In that algorithm the power allocation and subcarrier assignment were performed independently, and the problem of the maximum network-averaged capacity was formulated taking into account power and interference constraints, including the intercarrier interference (ICI) arisen by timing offset. The performance evaluations show that the algorithm attempted to maximize the average capacity of the CR-WSN with the constraints of total power and acceptable interference levels. Quantitatively, it had been shown that the proposed method could reduce network energy consumption up to 30% in comparison to traditional techniques and that it could still maintain high system performance in terms of the secondary users averaged capacity (SUs).

Kori and Kakkasageri (2023) had reviewed that the 21st century had been characterized by the proliferation of smart sensors, intelligent computations, and advanced communication technologies, with Wireless Sensor Networks (WSNs) playing a pivotal role in enabling numerous remote applications autonomously. They modelled WSNs as distributed or decentralized hundred or thousand small but powerful sensor/stations which are limited by battery power, cost of communication and transmission, and other resources. The authors had pointed out that how to make full use of these resources was still a problem to be solved with the purpose of extending the lifetime of the network, increasing throughput, decreasing computational latency and control overhead. There are also quite a few smart approaches being proposed to solve these problems, such as their own work which applied supervised learning (CART tree) to handle uncertainties and dynamism for the problem of resource allocation. They said their scheme had used k-means in clusters making, clustering, with Cluster Heads (CH) and Cluster Members (CM) determined using the k-NN algorithm. In, node’s attribute had been selected manually in terms of CH properties (Distance to the base station, connection degree, congestion ratio, data property and channel condition) and CH and CM attributes were aggregated and classified by means of intelligent search algorithm and feature selection algorithm. The processed datasets were already used for the training and prediction phases, and lead to a decision tree aiming at bandwidth allocation. The authors also reported that a heat map and confusion matrix were developed for performance analysis, and the simulation results had proven that the proposed CART-oriented method performed better when compared to Linear Regression (LR), Iterative Dichotomiser 3 (ID3), and Neural Network (NN) methods on resource allocation accuracy, computational delay, and data transmission efficiency.

Kori and Kakkasageri (2022) had discussed that Wireless Sensor Networks (WSNs) were distributed, decentralized ad hoc networks consisting of powerful sensing, computing, and processing nodes, though these sensor nodes had been constrained by limitations in battery power, communication range, bandwidth, computational latency, and storage. They had observed that utilizing WSN resources efficiently had always been a challenging work in order to prolong the lifetime, enhance the throughput, lower the computation delay and decrease the control overheads of the networks. To circumvent these challenges, the authors had offered many intelligent solutions and they utilized a Classification and Regression Tree (CART) machine learning algorithm for the uncertainty problem of bandwidth allocation. Their methodology was employ k-means clustering to generate clusters and cluster heads, similarly Hybrid k-NN approach used to identify cluster members followed by computing attributes including distance from BS, connectedness, congestion rate, data type and size and channel quality and finally aggregated and classified using intelligent search and feature selection mechanisms. The processed data sets were used to train and predict using a DT model for optimal bandwidth allocation. They had also produced heat and confusion matrices for performance evaluation and seen from a simulation performance evaluation that the proposed CART scheme helped in getting better resource allocation accuracy, less computational delay and high data transmission performance in WSNs.

Cai et al. (2022) had studied the trajectory design and resource allocation for UAV-enabled data collection in wireless sensor networks while accounting for potential blockages caused by multiple 3D buildings. The target of the authors was to maximize the average data collecting rate, and it was achieved through the joint planning of the schedule for the sensor nodes, transmit power and a Trajectory of UAV. They had cast this design as a non-convex optimization to capture two conflicting requirements: take into account the blockage effect and avoid a buffer overflow at sensor nodes. Knowing the NP-hardness of the problem, they had designed an iterative algorithm through which an effective, suboptimal solution is obtained. Simulation results showed that the performance of the proposed algorithm in data gathering was significantly enhanced compared with other competitive baseline schemes over various numbers of sensor nodes.

Deng et al. (2021) introduced the energy harvesting cognitive wireless sensor network (EHCWSN), which integrated energy harvesting and cognitive radio technologies into traditional wireless sensor networks to significantly extend sensor node lifespan and mitigate unlicensed spectrum congestion. They emphasized the challenging problem of resource allocation and management when there are limited resources in the network that need to be allocated to different users and there exist uncertainties in the energy harvesting process and PU behaviour. They combated this with a new Q-learning-assisted channel selection that takes the energy harvesting randomness and PU randomness into consideration, to allow SUs to dynamically select CNs with higher quality via interactive learning in environment. They also proposed a QoS-based resource managers and allocators for the node traffic by adopting Lyapunov optimization theory. The so called low-complexity online approach was thoroughly simulated and reported to be a superior quality result keeping the QoS constraints.

Zhao and Zhao (2021) extensively studied green wireless communications within wireless sensor networks (WSNs), focusing on the integration of new and renewable energy sources alongside low-power consumption and energy-saving technologies. Among the noteworthy challenges were channel fading, random and insufficient energy arrivals, and suboptimal sensor distribution that could interrupt sensor-to-sensor communication and result in network performance degradation. To overcome these problems, they presented a WSN architecture that consists of a number of local subnetworks with amplified forwarding relays and a specially defined work time cycle. They designed power and time resource allocation policies to maximize throughput with DRL formulated as a Markov decision process. Further, using an actor–critic method, the authors aimed for solutions in continuous state and action spaces, and adaptively maximized throughput using energy harvesting and on-line data of battery and channel. Their simulation results indicated that the proposed transmission policies performed better than greedy, random, and conservative policies and led to better LNT and system performance.

Nurlan et al. (2021) were noted to have examined information networks structured according to the Internet of Things (IoT) mesh topology, which had garnered significant attention over the previous one and a half to two decades. Their work demonstrated the growth of IoT deployments, from millions of clients to hundreds of thousands of APs. They also noted that IoT mesh nodes formed next-generation regulations of multi network and multi radio technologies, satisfying transparent and robust mobility, quality of service (QoS), and security requirements. The possibility of creating mesh networks, whether local or metropolitan, with an easy extension towards wide one, is regarded by the authors as an highly-appealing option for metropolitan and individual users. They presented an optimal routing protocol for IoT WMN which focuses on optimizing the channel and frequencies resources, based on mathematical resource allocation models. They presented a synthesis procedure for mesh networks that found the number ofchannels and their width that are required to provide the optimal data transmission delay insidea designated frequency range. Optimization results showed that the function values were improved by more than 16%, which indicated that the proposed algorithm effectively utilized the frequency band they occupy in the frequency spectrum.

Azarhava and Niya (2020) addressed the critical issue of extending sensor lifetime in Wireless Sensor Networks (WSNs) by focusing on Energy Harvesting (EH) sensors, which had been proposed as a solution to overcome energy limitations by harvesting power from the environment. They paper [10] took in consideration a TDMA based Wireless Energy Harvesting Sensor Network (WEHSN) model and divided each time slot into two phases: an energy absorption and a data transmission phase. They presented an energy-efficient resource allocation for WEHSNs subject to time-scheduling and transmission power constraints, considering that sensors can transmit information only when the harvested energy was higher than the consumed power. They obtained a closed-form solution of the optimization problem using energy efficiency as the object function, transformed the optimization problem into a parametric form by the Dinkelbach method, and solve the problem using KKT conditions. Quasi-Forcing Terms (QFT) are found to work out by the numerical results obtained.

Bin and Sun (2020) discussed how the rapid increase in train speeds had posed significant challenges to the safety and reliability of railway systems, emphasizing the necessity of real-time monitoring of trains, infrastructure, and their operating environments. They also noted the difficulty of achieving complete coverage in demanding environments due to the complexity of rail operation environments and the high construction cost of wired monitoring systems. Accordingly, they proposed that wireless sensor networks were appropriate for the railway status monitoring. The authors identified the energy resources of the sensor nodes as crucial for the network's lifetime, and yet its sustainability is highly constrained. They put forward a special building approach of wireless sensor networks for railway monitoring and an efficient energy provision approach for Intelligent Rail-way System. They developed an algorithm that combines the techniques such as cluster head selection, rotating probability model, clustering creation and optimization, and a partial coverage model that minimize the energy consumption of the nodes and balances them. Simulation results revealed that their optimal energy allocation scheme is proved to be the best by extending the lifetime of the wireless sensor network and it was based on clustering optimization, partial coverage modeling and polynomial time algorithm.

3. RESEARCH METHODOLOGY

This paper uses a quantitative and analytical methodology to analyze the resource optimization and anomaly detection in Wireless Sensor Networks (WSNs). The approach is organized in several fundamental steps, integrating mathematical modeling, simulation-experimentation and heuristic optimization methods. [13]

3.1. Research Design

This work is carried out using a design-based approach, which includes the development and testing of mathematical models and heuristic algorithms. The idea is to analyze through simulations the energy consumption ratio, the scheduling success ratio, the amount of bandwidth and the computational performance comparing several protocols and algorithms in WSN. [14]

3.2. Model Formulation

A mathematical optimization model was constructed to address the key resource constraints in WSNs. The model includes:

- ✓ Energy Consumption Modelling: Based on transmission distance and hardware energy costs.
- ✓ Adaptive Scheduling: Modelled5 using activation functions and threshold energy levels.
- ✓ Bandwidth Constraints: Incorporated using data rate limits and TDMA principles.
- ✓ Routing Optimization: Formulated as a linear programming problem.

3.3. Algorithm Development

To solve the NP-hard optimization problem, two heuristic methods were employed:

- ✓ Genetic Algorithm (GA): For evolving optimal node schedules and routing paths.
- ✓ Particle Swarm Optimization (PSO): For fine-tuning transmission powers and bandwidth allocations.

These algorithms were implemented in MATLAB and Python for comparative analysis.

3.4. Simulation Setup

The proposed models were tested in a simulated WSN environment with the following configuration:

- ✓ Number of Nodes: 50–100 randomly distributed in a 100m × 100m area.
- ✓ Initial Energy: Uniform for all nodes.
- ✓ Data Transmission Rate: Variable across scenarios.
- ✓ Simulation Tool: MATLAB for performance testing.
- ✓ Evaluation Metrics: Network lifetime, energy consumption, bandwidth usage, and packet delivery ratio. [15]

3.5. Data Collection and Analysis

Data were collected from multiple simulation runs under varying conditions (node density, failure rate, traffic load). The collected metrics were statistically analyzed using:

- ✓ Descriptive Statistics (mean, standard deviation)
- ✓ Comparative Charts (for algorithm performance)
- ✓ Energy Decay Graphs (over time)
- ✓ Routing Overhead Analysis

3.6. Validation

The model was validated using:

- ✓ Baseline Comparisons: With standard protocols like LEACH and PEGASIS.
- ✓ Sensitivity Analysis: Varying energy thresholds and bandwidth parameters.
- ✓ Cross-validation: Multiple randomized network topologies and traffic patterns.

3.7. Mathematical Model

Let

- N: Total number of sensor nodes
- $E_i(t)$: Residual energy of node iii at time t
- C_{ij}: Communication cost between nodes i and j
- d_{ij}: Euclidean distance between nodes i and j
- R_i: Data rate of node i
- B: Total available bandwidth
- P_{ij}: Power consumed for transmission between node i and j
- $x_{ij} \in \{0,1\}$: Routing decision variable (1 if node iii sends data to node j, 0 otherwise)
- $S_i(t) \in \{0,1\}$: Node activation status (1 = active, 0 = sleep) at time t

Energy Consumption Model

Transmission energy cost from node i to j:

$$P_{ij} = \alpha + \beta \cdot d_{ij}^{m}$$

Where:

- α: Electronic energy per bit
- β: Amplifier energy per bit per d^n
- nnn: Path-loss exponent (typically 2–4)

Total energy consumption for node i:

$$E_i^{total} = \sum_{j-1}^{N} x_{ij} \,.\, P_{ij}$$

Adaptive Scheduling Constraint

To ensure only active nodes consume energy:

$$E_i^{total} = S_i(t) \cdot \sum_{j-1}^{N} x_{ij} \,.\, P_{ij}$$

Activation scheduling (adaptive) can be defined with:

$$S_i(t) = f(\nabla E_i, \nabla T, \nabla D)$$

Where function f considers energy trends, temperature, or data needs dynamically.

Bandwidth Constraint

Total bandwidth usage must not exceed network capacity:

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij} \,.\, R_i \leq B$$

This ensures collision-free communication and scalability.

Lightweight Optimization Problem

Minimize total energy consumption while maintaining coverage and connectivity:

$$min \sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij} \,.\, P_{ij}$$

Routing constraint:

$$\sum_{j=1}^{N} x_{ij} = 1 \ \forall i (each\ node\ sends\ to\ one\ neighbor)$$

Bandwidth constraint (from above)

Energy constraint:

$$E_i(t+1) = Ei(t) - E_i^{total}(t)$$

Node lifetime threshold:

$$E_i(t) > E_{min} \ \ \forall i$$

4. FINDINGS AND CONCLUSION

Findings

- **Energy Efficiency is Crucial:** There is overwhelming evidence that energy depletion is the prime resource limitation in WSNs. Energy efficient schemes such as duty cycling, clustering and energy efficient routing greatly enhance network lifetime while still maintaining sensing coverage and data reliability.
- **Adaptive Scheduling Improves Network Performance:** Dynamic activation of nodes and scheduling communication considering network state and environment increase resource efficiency. Adaptation allows the reduction of redundant sensing and data transmission to balance the energy consumption while guaranteeing the network connectivity.
- **Bandwidth Control is Vital for Scalability:** the bandwidth management techniques, such as TDMA and data aggregation, can be used to resolve the collision and congestion problems in dense networks to achieve timely and accurate data reporting.

- **Small-Scale Memory and Processors' Power:** For small scale memory and processors' power, lightweight and distributed algorithms for data aggregation and routing outperform complex centralized solutions, decreasing communication overhead and energy consumption.
- **Practical Solutions from Optimization and Heuristic Methods:** Mathematical optimization models and heuristic/metaheuristic algorithms (e.g. Genetic Algorithms, Particle Swarm Optimization) efficiently handle the NP-hard resource allocation problems, that in practice allows for close-to-optimal resource usage in practical deployments.

Conclusion

The problem of resource allocation with WSNs is a multi-faced issue, which can be highly important for the commercial success of sensor networks. It is the trade-off between energy saving, bandwidth efficiency and computational constraint that the lifetime and reliability of the network depend on. Energy-efficient protocols and dynamic resource management techniques are crucial to sustain network operation, especially when the deployment targets geographically large or difficult to access areas. Both bandwidth and communications scheduling are introduced to increase the reliability of data transmissions with lightweight algorithms to maintain the computational feasibility for constrained nodes. Next generations of optimization methods and adaptive protocols will further enhance the performance of WSN in the future. In summary, although resource allocation effectively is the key to achieving the full potential of WSNs in a wide range of applications, from environmental monitoring to industrial automation.

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