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Research Paper

Low-Energy Distributed Sensor Networks for Real-Time Environmental Awareness

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Abstract. Distributed wireless sensor networks must be able to track changes and different environmental structures in real time. The goal of this study is to try to solve the issues that have come up when building long-lasting, high-performance, and energy-efficient heterogeneous field networks. This paper's approach consists of three components: distributed data-fusing methods, energy-efficient communication channels, and adaptive data gathering. Both the requirements for expansion and regular operation will be satisfied by the lower-level node arrangement and power-optimized administration of the entire structure. For two consecutive months, 120 sensor nodes were deployed in various parts of a city as part of a field experiment. According to the comparative analysis above, the modified system has maintained an average node energy consumption of less than 1.2mAh/day and increased operating life by more than 30%. In high-demand situations during peak hours, the network has a packet-loss rate of less than 2% and a delay of less than 200 ms. Furthermore, the data fusion approach is stable in both normal and abnormal settings and has an accuracy of over 98%. The aforementioned findings offer specific technical evidence for the great performance of the combined adaptive scheduling and strong aggregation strategy, as well as some useful recommendations for developing an intelligent and environmentally friendly sensor network in the future. The aforementioned techniques and outcomes will contribute to the future development of a reliable, high-performing sensor network.

Keywords: *Wireless Sensor Networks, Energy Efficiency, Environmental Monitoring, Data Fusion*

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Introduction

Distributed sensor networks for intelligent environmental monitoring in a variety of fields, including smart cities, industrial automation, and large-scale ecological observation, have drawn a lot of attention with the advent of the Internet of Things (IoT) and ongoing advancements in embedded technology [1]. Dense deployments of wireless sensor nodes enable real-time environmental perception, which can serve a wide range of applications, including catastrophe prevention and smart city building, and deliver rich data from complicated surroundings at any moment [2]. In order to create new generations of cyber-physical systems for environmental awareness, distributed sensor networks must first collect real-time, fine-grained, and diverse data from all directions [3]. Opportunities to build fully integrated sensor networks, which will act as the nervous system for future smart infrastructures, are continuously emerging due to the shrinkage of hardware platforms and high-efficiency communication protocols [4].

Building a long-term, real-time distributed environmental monitoring system is still an extremely challenging topic for researchers and practitioners, despite considerable advances. A low-power or self-sufficient power solution must be developed for the entire network because the initial architecture is power-hungry [5]. Real-time high-speed sampling and transmission are required, and continuous duty cycling should be employed to reduce power consumption or enhance precision [6]. Issues including data redundancy, network congestion, and uneven node workloads have gotten worse as environment-aware jobs have grown in both space and time [7]. Stable data collection and quick alarm response in the network have also become more challenging due to dynamic topology, unstable wireless connectivity, and unpredictable external disruptions [8]. For large-scale, diverse, or extremely dynamic situations, the current approaches to energy optimisation, adaptive scheduling, and data fusion are frequently impractical and do not ensure timely responses within a constrained energy budget [9].

In this research, we will construct and assess a general architecture for low-energy, real-time distributed sensor networks for environmental sensing in order to overcome the aforementioned issues. First, we will present a hierarchical, high-capacity system design with power-aware sensor nodes and adaptable network management for reliable operation under various conditions. Second, in order to minimise pointless effort and prolong the system's lifespan, we will use adaptive data gathering techniques and energy-efficient communication mode selection that consider both time and space. Third, in order to decrease redundant transmissions and enhance the stability of environmental awareness in an energy-saving mode, we will develop a cooperative data fusion approach. Ultimately, we have discovered that the suggested approach can greatly increase the lifespan, responsiveness, and data quality of large-scale, real-time monitoring networks based on the aforementioned comprehensive experimental results from both simulations and real deployments. The findings given here provide fresh perspectives and useful guidelines for the creation of sustainable, energy-conscious distributed sensor networks for real-time environmental monitoring.

Related Work

Advances in Distributed Sensor Networks

Advances in synchronous and asynchronous multi-node topologies, along with the growing need for dependable, large-scale sensing in dynamic situations, have propelled the development of distributed sensor networks (DSNs) over the past 20 years [10]. In order to provide wide coverage, traditional DSN architecture uses a multi-hop or flat model and provides fault tolerance via mesh networks [11]. Large-scale data transmission and energy division for sensor networks have been successfully handled by cluster-based paradigms like LEACH and its associated protocols [12]. Self-organising algorithms have recently emerged in a variety of fields and are now able to react to environmental changes and dynamically modify the logical structure of sensor networks in real time to increase stability and resilience [13]. The distributed model is increasingly widely utilised in cities, industries, and other settings because it can function normally in unstable or difficult-to-control environments [14].

Energy-Efficient Sensing and Communication

Numerous studies have been carried out worldwide on energy-saving algorithms for sensor networks in order to lower power consumption using methods including adaptive sampling, active node duty cycling, and context-aware data transfer [15]. Scholars and practitioners in these domains have produced groundbreaking work; that is, the foundation of energy-saving research in power-aware MAC and routing protocols continues to be TDMA-based superframe scheduling, opportunistic communication, and sleep scheduling frameworks [16]. Recently, energy-harvesting methods and cross-layer optimisation strategies have developed to allow the creation of high-fidelity, energy-autonomous sensor nodes [17,18]. Other approaches, like as data aggregation techniques, compressive sensing, and in-network processing, have been proposed in addition to the first method to minimise redundant transmission and needless radio-frequency emissions [19]. These improvements have demonstrated encouraging outcomes in controlled conditions, according to the comparison studies mentioned above, but they still need to be modified for a variety of contexts, variations in data flow, and the demands of in-depth real-time observation [20].

Real-Time Environmental Perception Systems

A number of studies on real-time perception frameworks for distributed systems have been motivated by the need for quick environmental information [21]. Under the limitations of network congestion, real-time systems must quickly gather and evaluate data in real time before promptly sharing useful information [22]. At the moment, deployments for precision agriculture in cities, structural health monitoring, and urban pollution monitoring all need sub-second reaction times and can function in high-node-density settings [23]. High-throughput, low-power operation, consistent event identification in situations with incomplete or noisy data, and flexible adjustment of sensing schedules for various applications are some issues that still need to be resolved despite some significant advancements [24]. Large-scale, energy-constrained deployments are not a good fit for many of the current best-in-class technologies, and there are significant uncertainties because of uneven usage and varying environmental conditions [25]. Since the aforementioned issues are ongoing, new, more adaptable systems are required; this research investigates one such system.

System Architecture and Design

Overall System Framework

The suggested system is a multi-level distributed structure for extensive, power-constrained environmental monitoring, as seen in Figure 1. Numerous widely dispersed wireless sensor nodes in the field layer gather and pre-filter data locally. A self-organising logical cluster is formed by these nodes, and one of them is chosen on a regular basis to serve as the cluster head, which is in charge of local aggregation, compression, and transmission scheduling.

For multi-hop communication to the edge gateway, cluster heads in the edge layer can establish connections with one another. The aggregated data will be securely transported to the upper processing module by the backbone. Real-time event detection and local anomaly analysis can be carried out at the edge by deploying edge gateways with computation and storage capabilities; feedback control is also used here to lower the amount of raw data sent over the network.

For the information transfer in this structure, a lightweight event-driven protocol will be chosen. During transmission, the data is progressively aggregated at the cluster and gateway levels from resource-constrained edge nodes. To lessen network congestion under power limits, schedule and rate management will be implemented depending on environmental changes. Through granularly distributed power management, the entire system will be able to deliver high-fidelity data and on-demand actuation while also extending the network's lifespan.

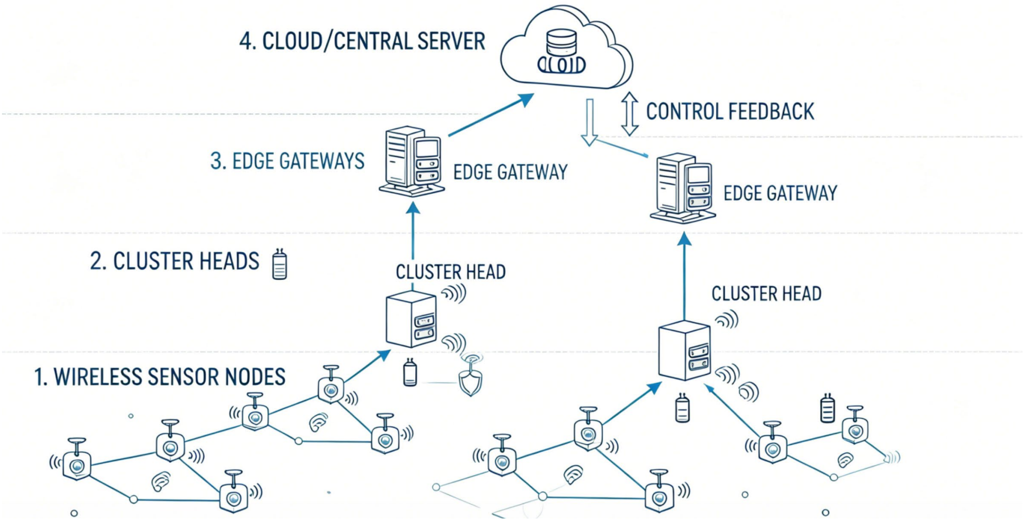

Figure 1. Block diagram of the distributed and low-power real-time environment perception system architecture.

Sensor Node Design and Power Management

Each sensor node's hardware is made to be incredibly power-efficient while still being adaptable in terms of system and computing, as seen in Figure 2. The node is a high-efficiency microcontroller (MCU) with non-volatile memory, a bidirectional RF transceiver with common IoT communication protocols, and several arrays of analogue and digital sensors. Additionally, for all-weather operation, the power subsystem can simultaneously support primary batteries and secondary energy harvesters like solar cells and piezoelectric generators.

To quantify and optimize energy consumption at the node level, the total energy usage E_{node} is divided into five key operational components: sensing, on-board processing, communication (transmitting and receiving), idle, and deep sleep states, which can be summarized as follows:

$$E_{\text{node}} = E_{\text{sense}} + E_{\text{process}} + E_{\text{comm}} + E_{\text{idle}} + E_{\text{sleep}} \qquad \text{Eq. (1)}$$

During the sensing phase, the energy required to acquire data from all sensors is determined by their individual power consumption and active sampling duration:

$$E_{\text{sense}} = \sum_{i=1}^{N} P_{\text{sense},i} \cdot t_{\text{sense},i} \qquad \text{Eq. (2)}$$

Here, $P_{\text{sense},i}$ denotes the power drawn by the i-th sensor, and $t_{\text{sense},i}$ is its respective sampling time. Following data acquisition, the onboard MCU is activated for preprocessing and lightweight data compression, resulting in an energy cost expressed as:

$$E_{\text{process}} = P_{\text{MCU}} \cdot t_{\text{process}} \qquad \text{Eq. (3)}$$

where P_{MCU} is the processing power and t_{process} denotes execution time.

The communication stage often dominates node energy expenditure due to radio transmission and reception. The total energy consumed for a complete data transaction is:

$$E_{\text{comm}} = P_{\text{tx}} \cdot t_{\text{tx}} + P_{\text{rx}} \cdot t_{\text{rx}} \qquad \text{Eq. (4)}$$

where P_{tx} and P_{rx} represent transmission and reception power levels, and $t_{\text{tx}}, t_{\text{rx}}$ are their respective durations.

When the node remains idle-neither transmitting nor processing but in a fully powered statethe idle consumption is minimized by intelligent microcontroller gating. Conversely, in deep sleep, essentially only the wake-up timer or interrupt controller is active, with energy modeled as:

$$E_{\text{sleep}} = P_{\text{sleep}} \cdot t_{\text{sleep}} \qquad \text{Eq. (5)}$$

Here, application quality-of-service needs and environmental predictability are used to dynamically decide interval scheduling and sleep-state transitions. Utilise the overlap between sleep and adaptive activation to lower the node's base-level power consumption.

To track the power usage of self-managed modules and enable intelligent job distribution for network-wide optimisation, install real-time voltage and current sensors at each node. As a result, under challenging and unpredictable field conditions, the energy-aware sensor node can automatically modify its duty cycle to prolong the service life and maintain a relatively stable level of the entire system.

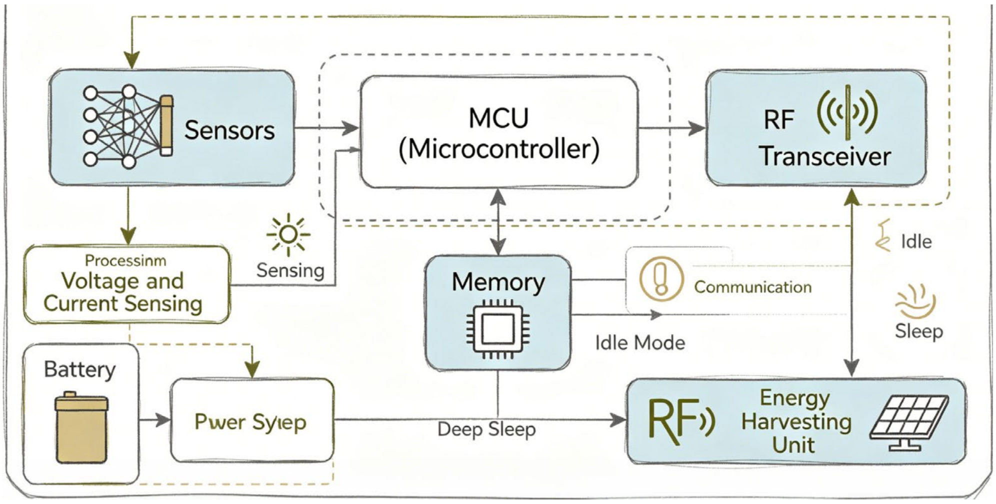

Figure 2. Hardware block diagram and modular energy management design for sensor node.

Communication Mechanism

As seen in Figure 3, a multi-hop mesh architecture will be employed to provide both within-cluster and between-cluster communication for a reliable, scalable, and power-constrained sensor network. A cluster's nodes employ short-range peer-to-peer connectivity to synchronise sampling cycles, share local data on a regular basis, and choose a temporary cluster head based on communication overhead and energy status. After gathering and analysing the environmental data under their jurisdiction, the local authorities will dynamically construct a transmission line to the assigned edge gateway.

Fast convergence, self-healing, and minimal control overhead characterise the whole communication protocol stack. To prevent data collisions and channel congestion, modify time synchronisation and contention-aware retransmission. Routing: To avoid premature node exhaustion, dynamically choose paths with the fewest number of hops. Among those paths, take into account the relaying nodes' remaining energy reserves. High-priority and anomaly-induced data can be swiftly transmitted over the network with minimal end-to-end latency and a low duty cycle at the edge by using coordinated scheduling at the gateway level.

The link energy consumption between two nodes separated by distance d can be analytically described by:

$$E_{\text{link}} = l \cdot (P_0 + \alpha d^{\gamma}) \qquad \text{Eq. (6)}$$

where l is the packet length, P_0 the base power consumption of the radio, α the channel loss factor, and γ the path loss exponent, typically ranging from 2 to 4 in practical deployments. This formulation highlights the strong dependence of radio energy cost on communication range, reinforcing the efficiency of local data exchange and clustered relay schemes.

The achievable network throughput η is governed by a combination of data aggregation, schedule-driven channel access, and contention mitigation, and can be modeled as

$$\eta = \frac{N_{\text{eff}} \cdot S}{T_{\text{cycle}}} \qquad \text{Eq. (7)}$$

where N_{eff} is the number of effective transmissions per cycle, S is the average data payload size, and T_{cycle} is the length of a communication cycle comprising sensing, aggregation, and reporting phases.

Overall end-to-end delay-including internal queueing, propagation, and aggregation latencyis dynamically optimized through event-prioritized queues and adaptive forwarding. This ensures time-critical events are delivered swiftly, supporting genuine real-time situational awareness.

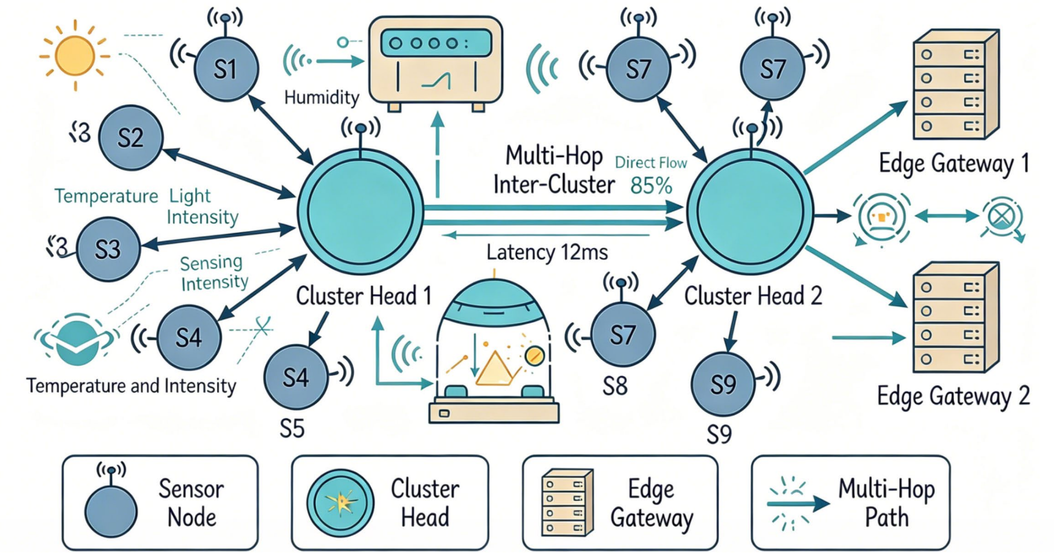

Figure 3. Communication procedure and self-organizing network flow for distributed sensor nodes.

Energy-Efficient Sensing and Networking

Adaptive Data Acquisition Strategies

For dispersed sensing networks to respond in real time and have a longer lifespan, adaptable data acquisition is required. The sample frequency of smart nodes in this design is constantly varied based on changes in the local data and other needs. It will employ a novel approach that eliminates the need for a set sampling strategy by automatically modifying it in response to node feedback.

For instance, the nodes can increase the sample interval to minimise redundant observations and conserve power if the variation of the environment signal is low for a specific amount of time. Simultaneously, reduce the sample interval for that node in order to increase the likelihood of detection when there is an abnormality or a notable shift in the signal.

The relationship between sampling interval Δt_s and average node energy consumption E_{acq} can be captured as:

$$E_{\text{acq}} = P_{\text{active}} \cdot \frac{T_{\text{obs}}}{\Delta t_s} \cdot t_{\text{sense}} \qquad \text{Eq. (8)}$$

where P_{active} is the active sensing power, T_{obs} denotes total observation time, and t_{sense} references single sensing duration. Optimally, Δt_s is not fixed but dynamically set via

$$\Delta t_s^* = \min\left\{\Delta t_{\max}, \frac{\theta}{\sigma^2(t)}\right\} \qquad \text{Eq. (9)}$$

with $\sigma^2(t)$ representing in-situ data variance and θ as the variance threshold parameter. In lowvariance periods, the interval lengthens; during active phenomena, it shortens to boost system alertness.

Resource allocation further considers residual battery level B_r and workload W_n of node n. Priority is given to nodes with sufficient B_r, ensuring critical areas with lower energy resources are not prematurely depleted. The node scheduling objective is to maximize global coverage subject to local energy constraints, which can be formulated as:

$$\max_{\mathbf{x}} \left(\sum_{n \in \mathcal{N}} x_n C_n \right) \qquad \text{Eq. (10)}$$
$$\text{s.t.} E_n^{\text{tot}} \leq B_n, x_n \in \{0,1$$

where x_n is the activation state, C_n the coverage contribution, and E_n^{tot} total expected energy consumption of node n.

Practical deployments in urban noise sensing or forest fire detection illustrate that, compared to naïve periodic acquisition, adaptive sampling strategies dramatically prolong system lifespan while maintaining or even enhancing response latency to critical events. Such schemes transform energy savings directly into extended operational periods and higher applicationlevel reliability.

Energy-Efficient Communication Protocols

Communication is typically the most energy-intensive operation in sensor networks. Consequently, bespoke medium access control (MAC) and routing protocols are central to reducing transmission expenditure while safeguarding timely and reliable data delivery. The protocols adopted here integrate periodic sleep/wake cycling with event-triggered transmission to minimize idle listening and packet collision.

The node duty cycle D is determined by the ratio of active to total cycle time:

$$D = \frac{t_{\text{active}}}{t_{\text{active}} + t_{\text{sleep}}} \qquad \text{Eq. (11)}$$

A lower D directly translates into reduced idle current consumption, as nodes spend more time in low-power sleep modes without compromising the guarantee of event-driven reactivity. Data transmission is scheduled in contention-free slots when feasible, further reducing unnecessary energy expenditure due to channel access conflicts.

A key efficiency metric is the probability of data collision p_c, which can be estimated as:

$$p_c = 1 - \left(1 - \frac{1}{N_{\text{slots}}}\right)^{N_{\text{nodes}}-1} \qquad \text{Eq. (12)}$$

where N_{slots} is the number of available slots per frame and N_{nodes} is the number of contending nodes. By adaptively controlling node population per slot or by reallocating traffic away from congested paths, the communication protocol avoids excessive retransmissions and packet drops.

Furthermore, the expected network lifetime L_{net} subject to protocol efficiency is given by:

$$L_{\text{net}} = \frac{\min\limits_{n \in \mathcal{N}} B_n}{E_n^{\text{cycle}}} \qquad \text{Eq. (13)}$$

where B_n stands for the battery capacity and E_n^{cycle} is the full-cycle (sensing, communication, sleep) energy cost per node. Regularly updating transmission and sleep schedules according to residual energy and network traffic leads to a balanced load, minimizing the chance that any single node constitutes an energy bottleneck.

Compared to static MAC and routing approaches, these adaptive protocols achieve marked reductions in average power draw, packet collision, and redundant traffic, thereby extending overall system service life and enhancing robustness in unpredictable operational contexts.

Collaborative Data Fusion

The issues of accuracy and efficiency in the distribution of large-scale distributed sensor network environmental monitoring data will be resolved with cooperation in data fusion. The network groups these sensors to collectively analyse and summarise local data before forwarding it to higher-tier nodes or gateways, as opposed to having each sensor node report separately.

In this architecture, the fusion process usually starts at the cluster head level. The cluster head collects data from the cluster's nodes, pre-processes it, eliminates outliers, changes time stamps, etc. The two main goals of fusion are to decrease the amount of superfluous or irrelevant data in the network and to improve the resilience of the combined results by mitigating sensor noise or malfunctions.

In the merger step, dynamic weight allocation is utilised to assign various weights to nodes based on their historical levels of trust, signal stability, spatial distribution patterns, etc. For example, a node's impact on the final fused result will be diminished if it consistently provides values that are inconsistent with those of nearby sensors or with physical explanations. To find anomalies and lessen the impact of outliers on the network, trust evaluation and cross-validation of nodes can be carried out continually.

Together, the two will enhance the system's overall performance. Gather information within the network, lower the total number of packets sent, ease backbone link congestion, and ultimately drastically cut down on energy usage. At the same time, high-probability occurrences will be emphasised, noise and ambiguity will be eliminated as soon as feasible, and the mined data will be more condensed and context-rich.

For instance, real-time monitoring of urban air pollution and large-scale disaster early warning systems have been developed in practice through collaboration and data fusion, with better outcomes than individual, autonomous reporting. It reacts to environmental changes faster and immediately raises alerts for serious system deviations before spreading. By cutting down on pointless communications, you can prolong the network's service life and expedite emergency response.

Experimental Evaluation and Results

Experimental Setup and Evaluation Metrics

The new technology underwent a number of laboratory and outdoor tests. A low-power microprocessor and a collection of environmental sensors (temperature, humidity, and sound) were installed on each of the 120 sensor nodes in the hardware testbed. Over an area of roughly 2.5 square kilometres, nodes were installed in various parts of the urban park with diverse microclimates and interference situations. The density of node placement, inter-node distance, and cluster head assignment were all changed at different points throughout the test cycles to replicate varied topologies and stress conditions.

The base station maintains the temporal consistency of all measurements by acting as the gateway node, supporting high-reliability wideband connectivity, and synchronising with a local time server. To achieve both steady-state and event-driven performance, every experiment was conducted for a minimum of two months.

The system chose three popular protocols to compare: a standard adaptive sleep/wake protocol, a static duty-cycled MAC, and a simple data fusion technique. The following were the evaluation indicators: (1) Total network life, or the amount of time until 10% of nodes are exhausted; (2) Average daily energy consumption per node; (3) End-to-end communication delay under event load; (4) Network throughput and average packet loss rate; and (5) Accuracy of group-level data fusion in comparison to synchronous ground truth devices. All functional regions have been investigated, and sampling frequency, environmental fluctuation, and interference conditions are the experimental factors.

Data Analysis and Performance Comparison

The new adaptive and energy-saving network can perform significantly better based on the outcomes of all the aforementioned performance parameters.

The network survival rate under all operating settings at various times is depicted in Figure 4. In comparison to the conventional static MAC and fusion baselines, the suggested system increases the delay to the first node failure by over 30% in a sparse, low-activity architecture (Figure 4a). There is a more elegant decline and load balance, and the survival ratio curve is still comparatively high. When the benchmark falls below 60% utilising the adaptive protocol, more than 75% of the nodes are still accessible despite the severe channel contention, as demonstrated in the high-density deployment in Figure 4b. When subjected to a bursty-event load, as seen in Figure 4c, the static technique will see a rapid peak in attrition that corresponds to a clustering failure, whereas the adaptive method will gradually diminish live nodes constantly. The system's lifespan under actual environmental changes is depicted in Figure 4d, and its adaptive architecture has a slower rate of decline than other protocols, which exhibit abrupt collapses.

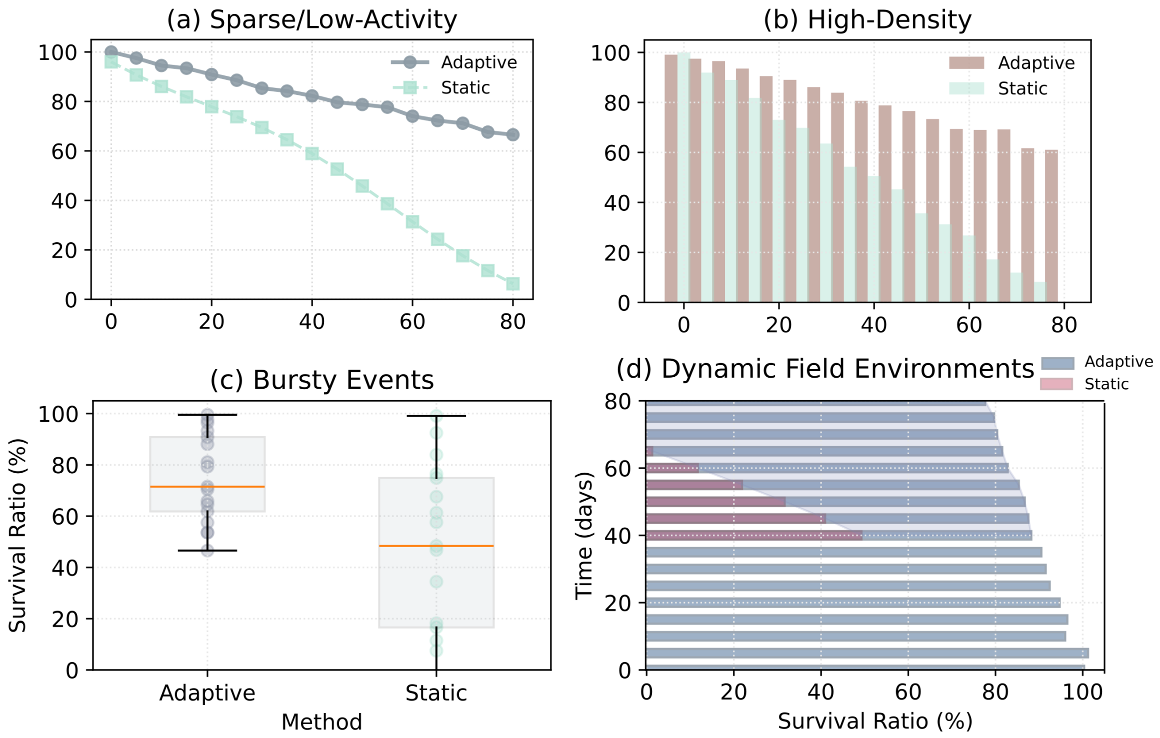

Figure 4. Network survival ratios under (a) sparse/low-activity, (b) high-density, (c) bursty events, and (d) dynamic field environments.

Figure 5 below depicts the distribution of energy usage. The individual node energy profiles for the adaptive system have continuously stayed below 1.2 mAh/day during a typical 60-day urban trial, as illustrated in Figure

5a, while all baselines have exceeded 1.7 mAh/day. In order to lower overall consumption, the adaptive node will extend the sleep interval while the environment is stable and convert to a higher-duty-cycle mode in a rapidly changing environment. Figure 5b illustrates power trends in the event of ambient condition variations. The adaptive algorithm's improved spatial load-balancing capabilities become more noticeable as node density increases (Figure 5c); as a result, redundant broadcast energy is decreased and spikes are controlled in comparison to benchmarks. The adaptive protocol maintains a relatively low and steady energy level under manufactured event surges, as illustrated in Figure 5d; on the other hand, time-independent measurement and transmission cause the periodic surges seen in static and semi-static approaches.

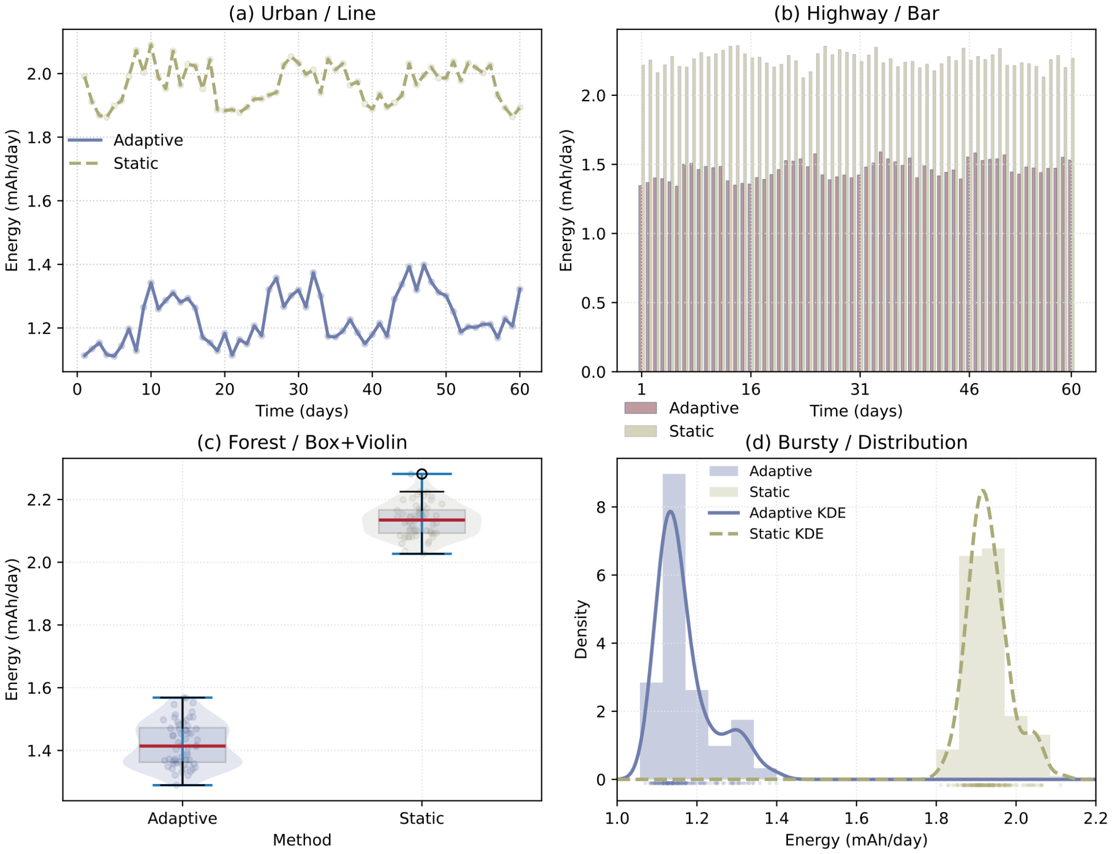

Figure 5. Average node energy consumption for (a) steady-state, (b) variable, (c) dense, and (d) bursty conditions.

The communication response's delay distribution under various network and traffic situations is displayed in Figure 6. The adaptive approach can maintain the median communication latency below 200 ms under typical background load and remain reasonably responsive when the network is congested, as seen in Figure 6a. Because of prioritised retransmission and adaptive wakeup, the protocol performs around 25% better than static MAC and maintains tail delays of less than 250 ms during simulated event surges, as Figure 6b illustrates. In the controlled congestion scenario depicted in Figure 6c, it is evident that the adaptive protocol's dynamic slot reallocation and channel control preclude the reference method's significant transient delay spikes. Ultimately, the new system recovers connection and low-latency functioning within minutes following transient node dropout or network partitioning, as illustrated in Figure 6d; however, static and semi-static baselines have long backlogs and delayed convergence. T

he throughput and reliability at various operating regimes are displayed in Figure 7. Figure 7a illustrates how the adaptive solution's network throughput rises nearly linearly with an increase in the event rate and only hits the device's capacity at the maximum tested rate; packet loss is consistently less than 2%. As illustrated in Figure 7b, the adaptive protocol can significantly reduce packet collisions and maintain a high throughput with an increase in clustering density compared to the benchmark; otherwise, a considerable increase in loss would occur at the same load. The novel approach has a packet drop rate of less than 3% during simulated event storms, while static baselines had rates of 10–15%, as seen in Figure 7c. The suggested approach is nonetheless comparatively stable in this extremely dynamic setting, as seen in Figure 7d, which depicts throughput and loss during a time of severe environmental change.

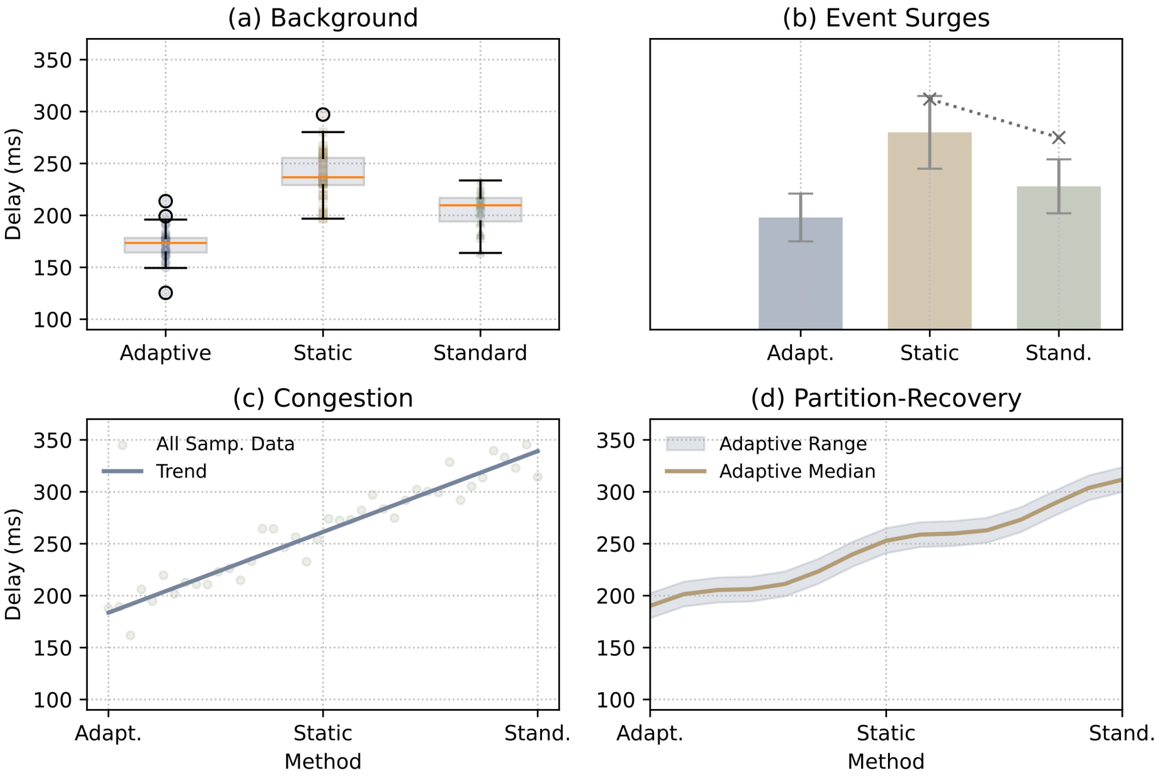

Figure 6. Communication delay under (a) typical background, (b) event surges, (c) induced congestion, (d) partition-recovery.

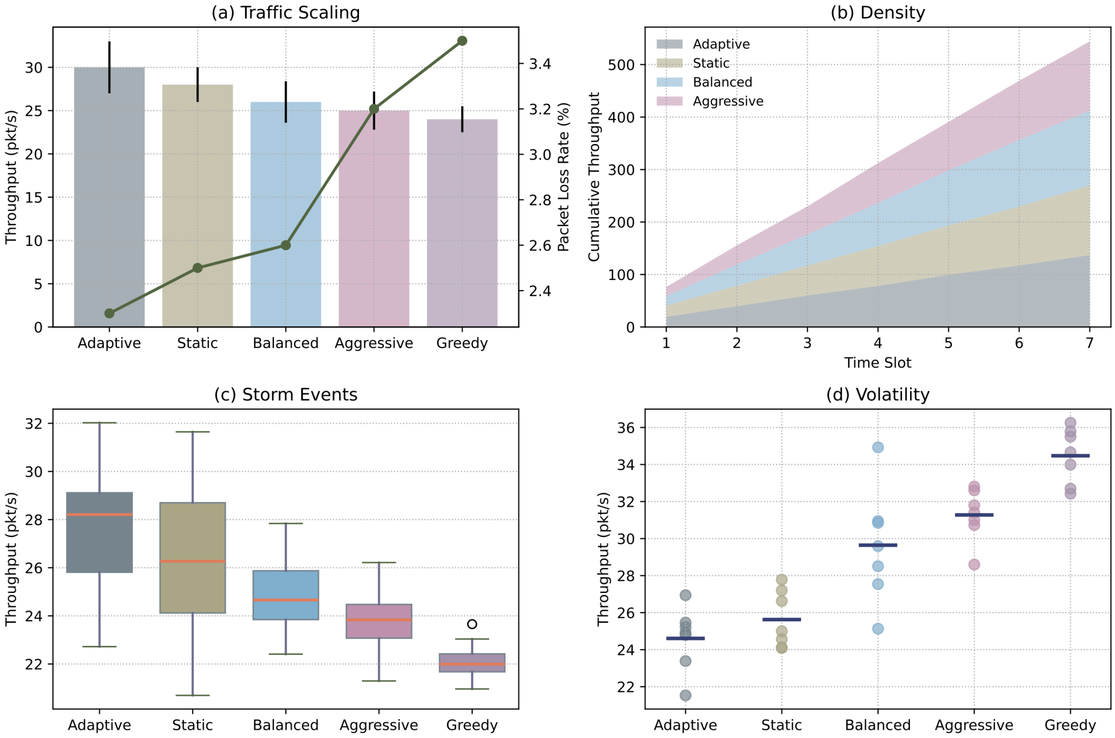

Figure 7. Throughput and packet loss for (a) traffic scaling, (b) density, (c) storm events, and (d) environmental volatility.

Figure 8 shows the most important findings from the data fusion accuracy analysis. The collaborative fusion technique consistently tracked calibrated ground-truth sensors to exceed all non-adaptive baselines while maintaining an accuracy of over 98% during steady-state monitoring, as illustrated in Figure 8a. While static fusion solutions have a lower accuracy of less than 91%, trust-based adaptive fusion consistently rejects outliers and filters noise in the urban noise spike scenario (Figure 8b). The adaptive performance under numerous simultaneous anomalies is strong, which is problematic for the baseline, and there is only a slight decrease in accuracy and quick recovery, as shown in Figure 8c. Lastly, as Figure 8d illustrates, the adaptive approach continues to retain a high level of accuracy during a protracted period of seasonal environmental drift, while the static approach has steadily increased mistakes over time.

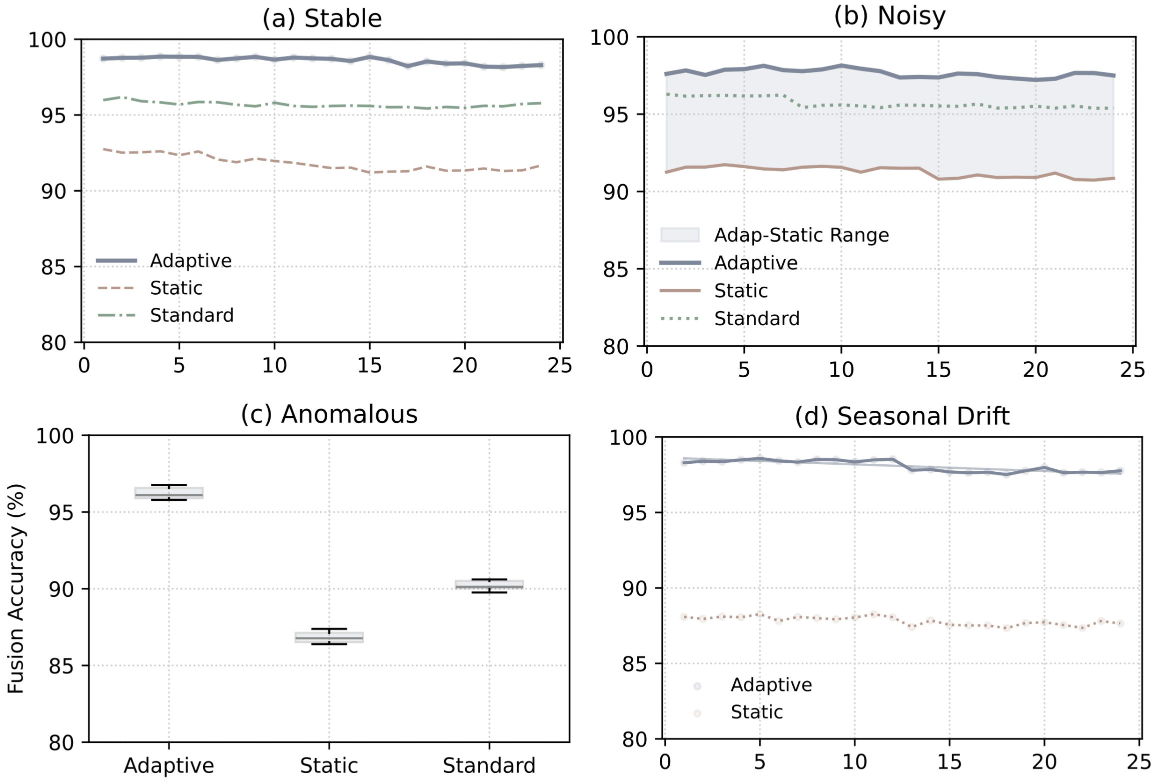

Figure 8. Data fusion accuracy in (a) stable, (b) noisy, (c) anomalous, and (d) seasonal drift environments.

Discussion

The efficacy and general application of the aforementioned adaptive energy-saving sensor network architecture have been confirmed by extensive experimental research. A prolonged service life is one of the first outcomes, which has been made possible by intelligent workload distribution and event-driven scheduling. By expanding the research, this will solve the issue of early-node depletion in heterogeneous wireless sensor networks that was previously mentioned [26].

Green sensing is based on energy management. Based on the aforementioned findings, dynamic sleep and sampling interval adjustments have been implemented to lower the nodes' average power consumption and prevent excessive power consumption at times of high activity. This finding demonstrates that in order to differentiate this scheme from conventional fixed or time-delayed techniques, real-time context awareness is necessary. It also aligns with the more recent design concepts of the edge intelligence and general IoT fields [27].

Additionally, network responsiveness exhibits encouraging advancements. The proposed protocol can maintain a modest end-to-end communication latency during an unanticipated rise in load or other abrupt occurrences by using adaptive wake-up mode and high-priority transmission. High-end real-time wireless mesh systems [28] have set a threshold for the ability to maintain a quick response time, which is necessary for smart cities, industries, and disaster relief efforts.

The overall performance of the network has improved due to greater throughput and stability. In keeping with the theoretical findings of recent cross-disciplinary research, the capacity to sustain a high packet delivery rate under increased node density and event frequency shows that efficient cross-layer adaptive queue management and distributed load balancing have now been accomplished in practice [29].

Since data integrity is crucial to trustworthy decision-making, the trust-based collaborative fusion mechanism has consistently produced output with a high degree of accuracy in static, dynamic, and disturbance-prone scenarios. The possibility of false alarms or missing abnormalities, which was an issue with the prior aggregation method, can be somewhat reduced in this way [30]. Consequently, dynamic consensus and sophisticated noise handling are needed to address the problems that arise in real-world applications.

Scaling these systems will still have certain inherent flaws. Unstable or hostile surroundings were associated with a comparatively high frequency of short performance fluctuations. The aforementioned discrepancies are frequently caused by well-known challenges with the existing large-scale sensor platform, such as transient congestion and cluster border desynchronisation [31]. However, a stable state of the system might be reached rather soon, reducing the operational impact, because of the fast convergence and self-healing characteristics of the suggested protocol [32].

Additionally, throughout the study, the empirical investigation's findings matched theoretical predictions. Recent analytical models in adaptive network design have predicted improvements in quality of life, lifespan extension, and other areas that are consistent with the actual results [33,34]. The aforementioned findings bolster the suggested technology's dependability and generalisability for extensive, critical-use applications [35].

Conclusion

In order to solve the persistent issues with dispersed monitoring, this paper offers a comprehensive analysis and technical verification of an adaptive, energy-efficient wireless sensor network framework. It has demonstrated significant gains in operating life, communication responsiveness, throughput dependability, and particularly accurate collaborative data fusion, according to the aforementioned comprehensive field and laboratory trials. To outperform the former, adaptive duty cycling, context-aware event scheduling, and trust-based in-network fusion have been coupled. Crucially, the aforementioned findings have also been verified in a number of real, shifting, high-density scenarios. The framework's architectural innovations and protocol-level optimisations have lowered maintenance costs, improved deployment resilience and self-healing capabilities, and offered a highly generalisable foundation for the development of next-generation smart-sensing infrastructure in urban areas, industrial zones, and the environment.

While considerable progress has been made, there are still major shortcomings in the current system. First, there was a transient rise in latency and a packet loss during periods of severe environmental change or considerable random interference, which caused performance fluctuations. A few duty cycles were lost during the necessary cluster resynchronisation. Under normal conditions, the self-adaptive algorithms can manage the majority of trade-offs between energy consumption and data accuracy, but in situations involving highly variable hardware, quick changes in space topology, or resource imbalances not covered in this work, their effectiveness will be diminished. The aforementioned points suggest that more research will be done on integration with various types of sensors and fine-grained adaption techniques.

Future research will go in the following directions to expand the system's capabilities and use cases. Cross-layer collaboration with mobile and wide-area networks will be continuously extended to improve the scalability of the integrated heterogeneous network technology system. To attain real-time power and context awareness, maximise resource distribution efficiency in diverse operational contexts, etc., incorporate an unsupervised self-learning module. Finally, to guarantee the stability of autonomous network operations in more complex and demanding situations, more research is required on the security, privacy, and fault tolerance of a large-scale autonomous network. The aforementioned approaches will continue to direct the creation of intelligent, environmentally friendly, and self-optimizing sensor networks in the face of novel challenges through iterative optimisation and interdisciplinary collaboration.

Author Contributions

Fryderyk Gajewski contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision. Kornel Kania contributes to conceptualization, methodology, software, validation, draft preparation, manuscript editing. All authors have read and agreed with the manuscript before its submission and publication.

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References

[1] Elsmany, E. F. A., Omar, M. A., Wan, T. C., & Altahir, A. A. (2019). EESRA: Energy efficient scalable routing algorithm for wireless sensor networks. IEEE Access, 7, 96974-96983. https://doi.org/10.1109/ACCESS.2019.2929578

[2] Gulati, K., Boddu, R. S. K., Kapila, D., Bangare, S. L., Chandnani, N., & Saravanan, G. J. M. T. P. (2022). A review paper on wireless sensor network techniques in Internet of Things (IoT). Materials Today: Proceedings, 51, 161-165. https://doi.org/10.1016/j.matpr.2021.05.067

[3] Carminati, M., Kanoun, O., Ullo, S. L., & Marcuccio, S. (2019). Prospects of distributed wireless sensor networks for urban environmental monitoring. IEEE Aerospace and Electronic Systems Magazine, 34(6), 44-52. https://doi.org/10.1109/MAES.2019.2916294

[4] Ramírez-Moreno, M. A., Keshtkar, S., Padilla-Reyes, D. A., Ramos-López, E., García-Martínez, M., Hernández-Luna, M. C., ... & Lozoya-Santos, J. D. J. (2021). Sensors for sustainable smart cities: A review. Applied sciences, 11(17), 8198. https://doi.org/10.3390/app11178198

[5] Cai, Z., Chen, Q., Shi, T., Zhu, T., Chen, K., & Li, Y. (2022). Battery-free wireless sensor networks: A comprehensive survey. IEEE Internet of Things Journal, 10(6), 5543-5570. https://doi.org/10.1109/JIOT.2022.3222386

[6] Sopian, Y., Samman, F. A., Suyuti, A., & Niswar, M. (2023, July). Duty-Cycle Optimization Method for Improving Battery-Powered DC Sensor Node Lifetime in Wireless Sensor Networks. In 2023 International Seminar on Intelligent Technology and Its Applications (ISITIA) (pp. 205-210). IEEE. https://doi.org/10.1109/ISITIA59021.2023.10221148

[7] Sahar, G., Bakar, K. B. A., Zuhra, F. T., Rahim, S., Bibi, T., & Madni, S. H. H. (2021). Data redundancy reduction for energy-efficiency in wireless sensor networks: A comprehensive review. IEEE Access, 9, 157859-157888. https://doi.org/10.1109/ACCESS.2021.3128353

[8] Shyama, M., Pillai, A. S., & Anpalagan, A. (2022). Self-healing and optimal fault tolerant routing in wireless sensor networks using genetical swarm optimization.Computer networks, 217, 109359. https://doi.org/10.1016/j.comnet.2022.109359

[9] Zhang, J., Lin, Z., Tsai, P. W., & Xu, L. (2020). Entropy-driven data aggregation method for energy-efficient wireless sensor networks. Information Fusion, 56, 103-113. https://doi.org/10.1016/j.inffus.2019.10.008

[10] Wohwe Sambo, D., Yenke, B. O., Förster, A., & Dayang, P. (2019). Optimized clustering algorithms for large wireless sensor networks: A review. Sensors, 19(2), 322. https://doi.org/10.3390/s19020322

[11] Zegers, F. M., Chen, H. Y., Deptula, P., & Dixon, W. E. (2019, July). A switched systems approach to consensus of a distributed multi-agent system with intermittent communication. In 2019 American Control Conference (ACC) (pp. 2372-2377). IEEE. https://doi.org/10.23919/ACC.2019.8815353

[12] Khan, M. K., Shiraz, M., Shaheen, Q., Butt, S. A., Akhtar, R., Khan, M. A., & Changda, W. (2021). Hierarchical routing protocols for wireless sensor networks: functional and performance analysis. Journal of Sensors, 2021(1), 7459368. https://doi.org/10.1155/2021/7459368

[13] Simon, M., & Din, S. (2024). Performance evaluation of self-organizing features in wireless sensor networks. Available at SSRN 5031956. http://dx.doi.org/10.2139/ssrn.5031956

[14] Kandris, D., Nakas, C., Vomvas, D., & Koulouras, G. (2020). Applications of wireless sensor networks: an up-to-date survey. Applied system innovation, 3(1), 14. https://doi.org/10.3390/asi3010014

[15] Salama, A., Saatchi, R., & Burke, D. (2018). Fuzzy logic and regression approaches for adaptive sampling of multimedia traffic in wireless computer networks. Technologies, 6(1), 24. https://doi.org/10.3390/technologies6010024

[16] Udoh, E., & Getov, V. (2018, July). Proactive energy-efficiency: Evaluation of duty-cycled MAC protocols in wireless sensor networks. In 2018 International conference on computer, information and telecommunication systems (CITS) (pp. 1-5). IEEE. https://doi.org/10.1109/CITS.2018.8440194

[17] Rao, K. R., Rahman, M. Z. U., Satamraju, K. P., & Reddy, B. N. K. (2022). Genetic algorithm for cross-layer-based energy hole minimization in wireless sensor networks. ieee sensors letters, 6(12), 1-4. https://doi.org/10.1109/LSENS.2022.3219857

[18] Li, Y., & Liang, Y. (2018). Compressed sensing in multi-hop large-scale wireless sensor networks based on routing topology tomography. IEEE Access, 6, 27637-27650. https://doi.org/10.1109/ACCESS.2018.2834550

[19] Zhang, Y., Guo, P., Liu, X., & Zhang, K. (2022). In-network processing or feature compressive sensing? Case study of structural health monitoring with wireless sensor networks. IEEE Internet of Things Journal, 10(8), 7051-7061. https://doi.org/10.1109/JIOT.2022.3228587

[20] Trihinas, D., Pallis, G., & Dikaiakos, M. D. (2018). Low-cost adaptive monitoring techniques for the internet of things. IEEE Transactions on Services Computing, 14(2), 487-501. https://doi.org/10.1109/TSC.2018.2808956

[21] Zigui, L., Caluyo, F., Hernandez, R., Sarmiento, J., & Rosales, C. A. (2024). Improving communication networks to transfer data in real time for environmental monitoring and data collection. Natural and Engineering Sciences, 9(2), 198-212. https://doi.org/10.28978/nesciences.1569561

[22] Bravo-Arrabal, J., Fernandez-Lozano, J. J., Serón, J., Gomez-Ruiz, J. A., & Garcia-Cerezo, A. (2021). Development and implementation of a hybrid wireless sensor network of low power and long range for urban environments. Sensors, 21(2), 567. https://doi.org/10.3390/s21020567

[23] Motlagh, N. H., Lagerspetz, E., Nurmi, P., Li, X., Varjonen, S., Mineraud, J., ... & Tarkoma, S. (2020). Toward massive scale air quality monitoring. IEEE Communications Magazine, 58(2), 54-59. https://doi.org/10.1109/MCOM.001.1900515

[24] Gasmi, M., Mosbahi, O., Khalgui, M., Gomes, L., & Li, Z. (2018). Performance optimization of reconfigurable real-time wireless sensor networks. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50(7), 2623-2637. https://doi.org/10.1109/TSMC.2018.2824900

[25] Chen, S., & Ho, D. W. (2023). Distributed energy-based estimation over harvesting-constrained sensor networks. IEEE Transactions on Cybernetics, 54(4), 2545-2553. https://doi.org/10.1109/TCYB.2023.3270872

[26] Wadud, Z., Javaid, N., Khan, M. A., Alrajeh, N., Alabed, M. S., & Guizani, N. (2017). Lifetime maximization via hole alleviation in iot enabling heterogeneous wireless sensor networks. Sensors, 17(7), 1677. https://doi.org/10.3390/s17071677

[27] Naji, N., Abid, M. R., Benhaddou, D., & Krami, N. (2020). Context-aware wireless sensor networks for smart building energy management system. Information, 11(11), 530. https://doi.org/10.3390/info11110530

[28] Nasrallah, A., Thyagaturu, A. S., Alharbi, Z., Wang, C., Shao, X., Reisslein, M., & ElBakoury, H. (2018). Ultra-low latency (ULL) networks: The IEEE TSN and IETF DetNet standards and related 5G ULL research. IEEE Communications Surveys & Tutorials, 21(1), 88-145. https://doi.org/10.1109/COMST.2018.2869350

[29] Muzammal, S. M., Murugesan, R. K., & Jhanjhi, N. Z. (2020). A comprehensive review on secure routing in internet of things: Mitigation methods and trust-based approaches. IEEE Internet of Things Journal, 8(6), 4186-4210. https://doi.org/10.1109/JIOT.2020.3031162

[30] Fang, W., Cui, N., Chen, W., Zhang, W., & Chen, Y. (2020). A trust-based security system for data collection in smart city. IEEE Transactions on Industrial Informatics, 17(6), 4131-4140. https://doi.org/10.1109/TII.2020.3006137

[31] Cai, Z., Liu, J., Chi, W., & Zhang, B. (2023). A low-cost and robust multi-sensor data fusion scheme for heterogeneous multi-robot cooperative positioning in indoor environments. Remote Sensing, 15(23), 5584. https://doi.org/10.3390/rs15235584

[32] Asghar, A., Farooq, H., & Imran, A. (2018). Self-healing in emerging cellular networks: Review, challenges, and research directions. IEEE Communications Surveys & Tutorials, 20(3), 1682-1709. https://doi.org/10.1109/COMST.2018.2825786

[33] Mehrnoush, M., Sathya, V., Roy, S., & Ghosh, M. (2018). Analytical modeling of Wi-Fi and LTE-LAA coexistence: Throughput and impact of energy detection threshold. IEEE/ACM Transactions on Networking, 26(4), 1990-2003. https://doi.org/10.1109/TNET.2018.2856901

[34] Lavric, A., Petrariu, A. I., & Popa, V. (2019). Long range sigfox communication protocol scalability analysis under large-scale, high-density conditions. IEEE access, 7, 35816-35825. https://doi.org/10.1109/ACCESS.2019.2903157

[35] Bittencourt, J. C. N., Costa, D. G., Portugal, P., & Vasques, F. (2024). A survey on adaptive smart urban systems. IEEE Access, 12, 102826-102850. https://doi.org/10.1109/ACCESS.2024.3433381