International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 24s, 2025
https://theaspd.com/index.php

Integrated Context-Aware Duty Cycling And Clustering For Sustainable Wireless Sensor Networks In Environmental Monitoring Applicatrions

Eman K. Elqassas[1*], Osama Imam[1], Hossam Eldein Shamardan[1]
[1] Faculty of computers and artificial intelligence, Helwan university, Helwan, Egypt

Abstract
Wireless Sensor Networks (WSNs) face a critical trade-off between data fidelity and network lifetime. Conventional duty cycling protocols, which rely on fixed schedules or residual energy alone, often cause premature node depletion and network instability. This paper introduces a novel, lightweight, context-aware duty cycling (CA-DC) mechanism that significantly extends network lifetime by dynamically adjusting sleep-wake schedules. Our primary innovation is the integration of three parameters: residual energy, local traffic load, and data entropy. Using data entropy as a control parameter allows nodes to remain active when sensing high value information, thereby maximizing the intelligence gathered per unit of energy. Unlike computationally intensive machine learning or optimization-based solutions, our mechanism employs a simple adaptive rule to balance energy conservation with data quality and traffic management. This prevents premature node death, mitigates congestion, and prioritizes the collection of meaningful data. Simulations validate that our proposed CA-DC protocol demonstrates significant improvements in both stability and lifetime. In terms of stability, CA-DC achieves gains of 45.1% over LEACH, 18.1% over VDC, and 6.9% over TDC-MAC, while in terms of lifetime (Last Node Dead) (LND), it outperforms LEACH, VDC, and TDC-MAC by 51.8%, 33.1%, and 24.1%, respectively. These results confirm the effectiveness of CA-DC in enhancing energy efficiency, stability, and overall network sustainability. By achieving enhanced network longevity with minimal computational overhead, our proposed mechanism offers a practical and effective solution for resource-constrained WSN deployments, ensuring both stability and efficiency.
Keywords: *Cluster Head Selection, Duty Cycling, Energy Efficiency, Sleep Nodes, WSN Lifetime.*

I. INTRODUCTION

Sustainable environmental monitoring is a cornerstone for addressing today's global challenges such as climate change, water scarcity, soil degradation, and urban air pollution. These monitoring systems depend heavily on WSNs to provide reliable, long-term data for environmental decision making. However, in practice, many large-scale WSN deployments suffer from early node failures and short lifetimes, which compromise the continuity and reliability of environmental datasets. Such disruptions can reduce the accuracy of climate models, impair pollution tracking, and weaken the effectiveness of environmental management strategies. Empirical studies show that in conventional clustering protocols, a large fraction of nodes deplete their energy shortly after the first node death (FND), resulting in a sharp decline in sensing coverage and monitoring stability. Hence, designing energy-efficient communication and scheduling mechanisms remains a critical research challenge for sustainable environmental sensing. Clustering has been widely recognized as an effective strategy for prolonging WSN lifetime, where Cluster Head (CH) nodes are responsible for data aggregation and transmission to the base station. Classical protocols such as Low Energy Adaptive Clustering Hierarchy (LEACH) [1] and LEACH-C [2] employed probabilistic or centralized CH selection but often neglected spatial density and node centrality, leading to uneven energy consumption. Subsequent enhancements, such as energy aware clustering [3] and fuzzy-based CH selection [4], incorporated residual energy and network topology but still struggled with balancing stability and adaptability. More recent studies (2020 2024) have introduced hybrid approaches—such as entropy-aware clustering that integrates hesitant fuzzy logic and data fusion [7], deep reinforcement learning-based duty cycling [8], and soft-k-means clustering aimed at energy-balanced CH rotation [9]. While these demonstrate improvements, they often incur high computational complexity or require global knowledge, limiting their practicality in resource-constrained WSNs deployed for environmental monitoring. In parallel, duty-cycling mechanisms, including TDC-MAC [5] and Variable Duty Cycle (VDC) [6], focused on reducing idle listening and overhearing by adjusting node activity according to traffic load or energy levels. While effective in reducing communication overhead, these schemes often treated CH selection and duty-cycling as separate processes, thereby limiting their synergy and their ability to adapt to the spatiotemporal dynamics of environmental data streams. To overcome these limitations, this work introduces the Context-Aware Duty Cycling (CA-DC) protocol, which integrates both clustering and adaptive duty-cycling into a unified framework. In CA-DC, CH selection is performed using residual energy, node concentration, and node centrality, ensuring well-distributed and energy-efficient cluster formation suitable for monitoring large scale environmental systems. Subsequently, nodes adjust their duty cycles by jointly considering residual energy, sensed data entropy, and traffic load, thereby reducing redundant transmissions and balancing energy consumption across the network. In particular, entropy serves as a lightweight indicator of data redundancy common in environmental sensing (e.g., repeated temperature or soil readings), ensuring that nodes remain active only when their sensed readings add informational value. Simulation results demonstrate that CA-DC achieves superior performance compared with LEACH, TDC-MAC, and VDC, particularly by achieving a higher FND, an extended stable region, and improved overall lifetime—making it highly suitable for long-term environmental monitoring applications.

2. RELATED WORK

The extension of network lifetime remains a fundamental challenge in WSNs, as energy constraints directly limit the stability and performance of such systems. Numerous re- search efforts have focused on designing energy-efficient clustering and duty-cycling strategies, with varying levels of success. This section reviews representative approaches and highlights the research gap that motivates the development of the proposed CA-DC protocol.

2.1 CLUSTERING-BASED PROTOCOLS

Clustering has been widely recognized as a key mechanism to enhance energy efficiency in WSNs by reducing long- distance transmissions and balancing the load among nodes. The seminal LEACH protocol [1] introduced randomized cluster-head (CH) rotation to distribute energy consumption. However, its random selection often produced uneven CH placement, leading to unstable clusters and reduced lifetime. Several variants were developed to address these short- comings. DE-LEACH [10] improved stability by incorporating both residual energy and distance to the base station into CH selection, while HEED (Hybrid Energy-Efficient Distributed Clustering) [3] introduced a hybrid strategy combining residual energy with intra-cluster communication cost to avoid randomness and create balanced clusters. Later enhancements, such as H-HEED [11], adopted fuzzy logic and heterogeneity awareness to further improve adaptability under variable energy distributions.

More recent protocols emphasize heterogeneity. Enhanced Distributed Energy-Efficient Clustering (EDEEC) [12] ac- counts for normal, advanced, and super nodes, distributing load more fairly across heterogeneous environments. In parallel, machine learning–enhanced clustering, reinforcement learning–based clustering algorithms (e.g., RLDCSSA- CDG)[13] have emerged to dynamically integrate clustering and duty-cycling, adapting to network conditions in real time

2.2 DUTY-CYCLING MECHANISMS

While clustering reduces transmission energy, idle listening and overhearing also contribute significantly to energy waste. To mitigate this, duty-cycling protocols have been extensively investigated. Schemes such as SPAN [14] and GAF [15] selectively activate a subset of nodes to preserve connectivity while others remain in sleep mode, effectively reducing energy consumption at the MAC layer. Moreover, protocols like TDMA-based scheduling scheme [16] that strikes a balance between energy-saving and end-to-end de- lay. This balance is achieved by scheduling the wakeup intervals appropriately, so that data packets are delayed by at most one sleep interval for the end-to-end transmission from the sensors to the gateway. More advanced duty-cycling protocols such as TDC-MAC [5] and VDC [6] adjusted node activity based on traffic load and residual energy, effectively mitigating overhearing and channel contention. However, these mechanisms were typically designed independently of clustering, limiting their impact on overall network stability.

2.3 ENTROPY AND CONTEXT-AWARE APPROACHES

Entropy has recently gained traction as a lightweight indica- tor of information redundancy in sensor readings.

Entropy- based duty cycling [17] allows nodes with low-variance data to remain in sleep mode, suppressing redundant trans- missions and conserving energy. Similarly, hesitant fuzzy entropy clustering [18] integrates entropy into cluster forma- tion, ensuring that only information-rich nodes contribute to CH roles.

In [19], entropy was applied at the MAC layer to ad- just sleep schedules according to redundancy levels, while in [20], entropy was combined with traffic awareness to balance load distribution and avoid overburdening nodes in high-traffic regions. Despite these advances, entropy-based strategies are often implemented in isolation—either at the clustering or duty-cycling layer—without full cross-layer integration, limiting their potential to maximize stability.

2.4 HYBRID CLUSTERINGDUTY CYCLING APPROACHES

Recognizing the limitations of separate clustering and duty- cycling strategies, several hybrid approaches have been pro- posed. such as HADC [21], which integrates adaptive duty cycling into clustering, represents promising steps toward combining the two mechanisms into one unified protocol. Another recent example is the work by Anees and Zhang [17], which integrates thermal entropy, cluster formation, and asynchronous sleep–awake decisions to suppress redundant traffic. These schemes demonstrate that combining clustering and duty cycling can yield longer stable periods. However, many still rely on synchronous scheduling or assume global knowledge of traffic, making them less feasible for highly constrained WSN environments.

These hybrid solutions demonstrate promising improvements by aligning clustering with duty-cycling decisions. However, many rely on computationally heavy optimization or centralized coordination, making them unsuitable for large-scale or highly resource-constrained WSN deployments.

2.5 RESEARCH GAP AND MOTIVATION

Although clustering-based protocols such as LEACH and HEED improve network scalability and energy distribution, they fail to incorporate temporal data redundancy or node- level traffic variations in their energy management. Conversely, duty-cycling mechanisms effectively reduce idle energy waste but often ignore higher-level cluster dynamics. This separation leads to suboptimal performance when net- works face high data redundancy or uneven load distribution. To bridge this gap, the proposed CA-DC protocol intro- duces a context-aware duty-cycling mechanism integrated with clustering. By jointly considering residual energy, entropy of sensed data, and traffic forwarding load, CA-DC ensures that nodes dynamically adjust their duty cycles according to both network state and data relevance. This unified approach enhances stability periods while preserving overall energy efficiency, thereby outperforming traditional clustering-only or duty-cycling-only solutions.

3. SYSTEM MODEL

This section examines sensor nodes according to the network model, analyzing their energy consumption using a radio- based energy framework.

3.1 NETWORK MODEL

Assume that sensor nodes are distributed randomly inside a square-shaped two-dimensional region. These sensors continuously gather data within this region. The collected data must be received, aggregated, and forwarded to BS. The CH has multiple responsibilities depending on its energy levels. Communication between CMs, CHs, and the BS adheres to standard multi-hop protocols. The network model is char acterized by the following: 1) The sensor network is static, meaning nodes cannot be relocated once deployed. 2) Each CM is equipped with a GPS device to store its location. 3) After deployment, the position of the BS is stationary and known to all CMs and it has an unlimited energy supply.

3.2 ENERGY MODEL

Unlike the routing algorithms used in wired networks, which focus primarily on optimizing data transmission, wireless network routing algorithms emphasize minimizing overall energy consumption. In this work, we adopt a simple energy model where the transmitter consumes energy for radio electronics, power amplification, and signal transmission, while the receiver expends energy for the radio electronics operation. The wireless energy transfer model utilized in this research is referenced in the power attenuation in wire- less communication relies on the (d) distance between the transmitter and receiver. For relatively short distances, signal loss follows an inverse-square relationship (d^2), whereas for longer distances, it follows an inverse-quartic relationship (d^4). Power regulation can mitigate these losses by adjusting the amplifier power at the receiver to maintain a required signal strength. Consequently, the radio system transmits a k-bit message over a distance (d). This energy dissipation model for wireless communication is illustrated in Fig.1.before transmission, The electronic energy consumption (E_{elec}) is influenced by several factors, including modulation, digital coding and signal filtering. To ensure the received signal strength remains above a predefined threshold ($P_{r\text{-thresh}}$), the parameters E_{fs} and E_{mp} are determined based on receiver sensitivity and noise levels. The minimum necessary trans- mission power can be determined by tracing back from this power threshold. Given a radio bit rate R_b, the transmission power (P_t) is expressed as:

$$P_t = E_{Tx} - \text{amp}\,(1, d)\,R_b \tag{1}$$

The energy consumed to transmit a k-bit across a distance d is defined by:

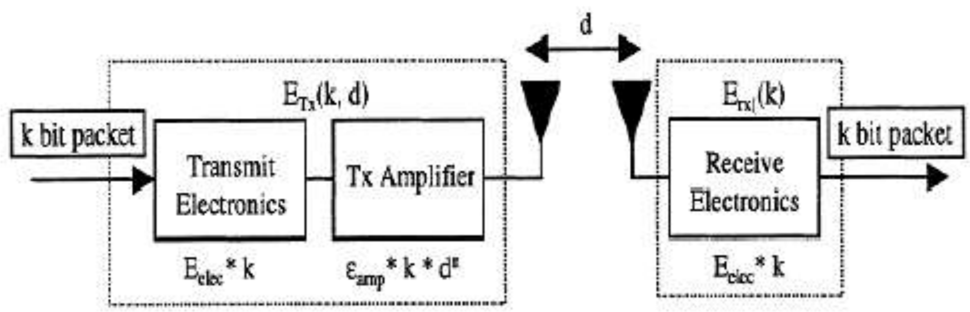
$$E_{\text{Tx}}(k\,,\,\text{d}) = \begin{cases} E_{elec}\cdot k + E_{fs}\cdot k \cdot d^2, & x < 0 \\ E_{elec}\cdot k + E_{mp}\cdot k \cdot d^4, & x \geq 0 \end{cases} \tag{2}$$

Similarly, the receiver's energy consumption for receiving a k-bit message is:

$$E_{Rx}\,(k) = E_{elec}\cdot k \tag{3}$$

Where E_{Tx} (k, d) represents the energy consumed by the transmitter to send a k-bit message over distance d, ERx denotes the energy consumed by the receiver to process the k-bit message, and E_{Tx} includes the energy used by the wireless transceiver circuit. The parameters E_{mp} and E_{fs} refer to the amplification energy required under the multi-path and free-space propagation models, respectively. d0 is the threshold distance which determines the point at which the energy model transitions from free-space to multi-path propagation, and is computed as:

$$d_0 = \sqrt{\frac{E_{mp}}{E_{fs}}} \tag{4}$$



The radio energy depletion model
Figure 1

3.2.1 Transition Energy Costs

In duty-cycled WSNs, nodes frequently switch between sleep and active states. Each transition incurs overhead in powering up oscillators and stabilizing the radio chain. We model this as:

$$E_{\text{Transition}} = \alpha\,.\;E_{\text{elec}} \tag{5}$$

where α is a protocol-dependent factor (0.1–0.2 in typical low-power radios). This cost is added whenever a node transitions between sleep and active states.

3.2.2 Synchronization Overhead

Time synchronization is necessary to align duty cycles across nodes. The cost per synchronization event is modeled as:

$$E_{sync} = \beta \cdot E_{elec} \cdot K_{sync} \quad (6)$$

where β represents protocol efficiency, and K_{sync} is the size (in bits) of synchronization beacons. This overhead is incurred periodically, typically every frame or super frame.

3.2.3 Cluster Head (CH) Selection and Responsibilities

In the proposed CA-DC framework, CHs are selected based on a composite metric that considers residual energy, node concentration, and centrality:

$$CH_{score}(i) = w_1 \cdot \frac{E_0}{E_i} + w_2 \cdot \frac{N_{max}}{N_i} + w_3 \cdot d_i \quad (7)$$

where:

E_i: is the residual energy of node i,
N_i: is the number of neighbors (density factor),
d_i: is the average distance to neighbors (centrality factor),
w_1, w_2, w_3: are normalized weights.

The node with the highest CH_{score} in its local neighborhood becomes the CH.

Responsibilities of CHs include:

A. Collecting and aggregating intra-cluster data.
B. Scheduling sleep–wake cycles of member nodes to minimize redundancy.
C. Transmitting aggregated data to the BS. D. Managing synchronization overhead within the cluster.

Thus, the total energy cost of a CH in one round is:

$$E_{CH} = \sum_{j \in c} E_{RX}(K_j) + E_{agg}(K_{tot}) + E_{Tx}(K_{agg} + d_{BS}) + E_{sync} + n_{trans} \cdot E_{\text{Transition}} \quad (8)$$

where:

E_{agg}: is the per-bit aggregation cost,
K_{agg}: is the aggregated packet size, and
n_{trans}: is the number of state transitions.

4. PROPOSED PROTOCOL (CONTEXTAWARE DUTY CYCLING (CA-DC))

4.1 Algorithm

Algorithm 1: Context-Aware Duty Cycling (CA-DC)
Input: Number of nodes N, max rounds R_{max}
Output: Lifetime metrics: FND, (Half Node Death) HND, LND

```
foreach node i ∈ {1, . . . , N} do
    E_i ← E_0;  D_i ← D_min;
    Initialize entropy window X_i ← ∅ of size B; Mark node as alive;
for r ← 1 to R_max do
// CH Selection: Complexity O(N^2)
        foreach alive node i do
            En(i) ← E_i/E_0;
            density(i) ← |neighbors(i)|/N ;
            centrality(i) ←
            1/(avg. distance to neighbors);
            Normalize density(i), centrality(i) ∈ [0, 1];
            CH_score(i) ←
            w_1. En(i)+w_2 . density(i)+ w_3 . centrality(i);
Select top-scoring nodes as CHs;
```

Each non-CH node joins nearest CH;
// Duty Cycle Decision:
Complexity $O(N)$

foreach *alive node i* **do**
Update entropy window $\mathcal{X}_i$ every Δ rounds;
$H(i) \leftarrow entropy(\mathcal{X}_i, B)/\log B$; $En(i) \leftarrow E_i/E_0$;
$T_n(i) \leftarrow (generated + forwarded)/T_{\max}$; $S(i) \leftarrow \beta_E(1 - En(i)) + \beta_H H(i) + \beta_T T_n(i) + \beta_C(1 - C_{norm}(i))$;
$D^*(i) \leftarrow clamp(1 - S(i), D_{\min}, D_{\max})$; $D_i \leftarrow (1 - \eta)D_i + \eta D^*(i)$;
// Data Transmission and Energy
foreach *alive node i* **do**
if *i is CH* **then**
Receive from members;
Aggregate data;
Transmit aggregated packet to BS;
else
Transmit to CH with probability D_i;
Deduct energy
$E_{Tx}, E_{Rx}, E_{agg}, E_{sync}, n_{trans} \cdot E_{transition}$;

if $E_i \leq 0$ **then**
Mark node as dead;

Update alive nodes, residual energy;
Record FND, HND, LND if thresholds reached

4.2 Overview

The proposed CA-DC protocol is designed to extend the life- time of WSNs by combining energy-aware CH selection with an adaptive duty cycling mechanism. Unlike conventional clustering protocols that rely solely on residual energy or random selection, CA-DC integrates residual energy, node concentration, and centrality to elect stable CHs. After cluster formation, a duty cycle mechanism is applied, where each node dynamically adjusts its active and sleep schedules based on residual energy, sensed data entropy, and traffic load. This dual-stage approach ensures both balanced energy consumption and reduced redundancy in transmissions, leading to prolonged network stability and lifetime.

4.3 CLUSTER HEAD(CH) SELECTION PHASE

At the beginning of each round, the protocol evaluates all alive nodes to determine suitable CHs. The decision process considers three factors:

Residual Energy (E_n): Ensures that nodes with higher remaining energy are prioritized for CH roles, preventing pre- mature death of weaker nodes.

Node Concentration (Density): Nodes with a higher density of neighbors are favored, as they can form well-balanced clusters with reduced communication overhead.

Node Centrality (centrality): Computed as the inverse of the average distance to neighboring nodes, centrality guarantees that selected CHs are topologically well-positioned, minimizing intra-cluster communication costs. Each node calculates a CH score as a weighted combination of these factors. Nodes with the highest scores are selected as CHs, and all other nodes join the nearest CH to form clusters.

4.3 DUTY CYCLE DECISION PHASE

Once clusters are established, each node decides its duty cycle, i.e., the proportion of time spent in active or sleep states. The decision is based on four inputs:

Residual Energy (E_n): Nodes with depleted energy are allowed more sleep time to preserve longevity.
Entropy (H): Measures the information content of recently sensed data. If consecutive readings are redundant (low entropy), the node reduces activity.
Traffic Load (T_n): Nodes forwarding a high number of packets (either self-generated or relayed) require longer active periods, while nodes with low traffic can remain asleep longer.
The sleep tendency score S(i): is derived from a weighted combination of these parameters, and the new duty cycle is updated using a smoothing factor to avoid abrupt state changes. This ensures a balance between energy efficiency and reliable data delivery.

4.4 DATA TRANSMISSION AND ENERGY UPDATE

During transmission, only active nodes participate in communication. CMs forward their sensed data to their respective CHs based on their duty cycle probability. CHs then aggregate the received data and forward it to the BS. The energy of each node is updated according to the radio energy model. Dead nodes with energy $<$ 0 are excluded from subsequent rounds.

4.5 LIFETIME METRICS

The protocol evaluates performance using the following key indicators:
FND: Indicates the start of instability.
HND: Represents the point when 50% of nodes are depleted.
LND: Marks the complete depletion of the network.
CA-DC is expected to achieve higher FND, HND and LND values due to balanced energy distribution.

4.6 COMPLEXITY ANALYSIS

This section analyzes the computational, communication, and memory complexity of the proposed CA-DC protocol.

4.6.1 Computational Complexity

The CH selection phase requires each node to compute its score based on residual energy, concentration, and centrality, followed by a comparison among all nodes. This leads to a complexity of $O(N^2)$ per round, where N is the number of sensor nodes. In contrast, the duty cycle computation involves only local parameters (residual energy, entropy, and traffic load), resulting in a linear cost of O(N). Therefore, the overall per-round computational complexity of CA-DC is:

$$O(N^2 + N) \approx O(N^2) \tag{9}$$

4.6.2 Communication Complexity

During the setup phase, nodes broadcast their status and metrics to facilitate CH selection, which incurs $O(N^2)$ message exchanges. In the steady-state phase, each member node transmits data to its CH, and each CH forwards aggregated data to the base station, leading to O(N) message transmissions per round. Thus, the communication complexity is dominated by the setup phase but remains efficient during data transmission.

4.6.3 Memory Requirements

Each node maintains a neighbor list and an entropy calculation window. The neighbor information requires O(log N) storage per node under standard adjacency-list representations, while the entropy window requires a fixed buffer size B. Consequently, the per-node storage requirement is O(log N), leading to a total network memory requirement of O(N log N).

5. SIMULATION RESULTS

In this study, simulations were conducted for two different network scenarios using MATLAB 2018 to evaluate the performance of the LEACH, TDC-MAC, VDC, and the proposed CA-DC protocols. The comparison was divided into three categories: alive nodes versus rounds, energy consumption versus rounds, and network stability versus rounds. Each category included two scenarios. In the first scenario, 100 nodes were deployed in a 50 × 50 m^2 area with the base station located at (25, 100). In the second scenario, 100 nodes were deployed in a 100 × 100 m^2 area with the base station located at (50, 125). The simulation parameters are summarized in Table 1.

Parameter Name	Parameter Value

Number of Nodes	100
Network Size	(50 x 50) m^2 , (100 x 100) m^2
BS's Location	(25,100) , (50,125)
Initial Energy	0.5 J
Size of The data	4000 bits
Radio Electronics Energy	50 nJ/bit
Radio Amplifier Energy (free space model)	10 pJ/bit/m^2
Radio Amplifier Energy (multi-path model)	0.0013 pJ/bit/m^4
do	87.7
Data Aggregation Energy	50 nJ/bit

TABLE 1. the simulation parameters

5.1 SIMULATION RESULTS OF SCENARIO 1

According to the proposed protocol, the findings demonstrate a substantial enhancement in network lifetime. As illustrated in Fig. 2, CA-DC is evaluated against LEACH and TDC- MAC, and VDC. The results reveal that the proposed protocol achieves superior performance in terms of network lifetime, defined as the period until the network becomes inoperative.

From Fig. 3 and Table 2, it is evident that the LND in the proposed CA-DC protocol occurs after 2,356 rounds, compared to 1,552 rounds for LEACH, 1,898 rounds for TDC-MAC, and 1,770 rounds for VDC. Moreover, the CA- DC protocol achieves the highest HND value, surpassing that of the other protocols. These outcomes clearly demonstrate that CA-DC sustains network operation for a longer duration, thereby improving stability and extending overall network functionality. The higher HND reflects that nodes in CA-DC remain active for a longer period, ensuring more balanced energy consumption, while the superior LND indicates that the protocol maintains functionality until later stages of the network's lifetime. Collectively, these results confirm the reliability and robustness of the proposed protocol in com- parison with conventional approaches. Figure 4 illustrates the residual energy per round for the proposed CA-DC protocol in comparison with LEACH, TDC-MAC, and VDC. As expected, the overall energy consumption of nodes increases with the number of rounds; however, CA-DC demonstrates superior energy conservation, resulting in higher efficiency and an extended network lifetime. Specifically, CA-DC re- quired 2,356 rounds to consume 50 J, whereas LEACH, TDC-MAC, and VDC reached the same consumption level at 1,552, 1,898, and 1,770 rounds, respectively. These results highlight the ability of CA-DC to balance energy usage more effectively across nodes, thereby delaying energy depletion and enhancing network stability. From a practical perspective, such efficient energy utilization makes CA-DC particularly advantageous for energy-constrained Wireless Sensor Network applications, including environmental monitoring, precision agriculture, and healthcare systems, where pro- longed operation and reliable data transmission are critical.

Finally, Table 3 presents the energy consumption in each round for each protocol.

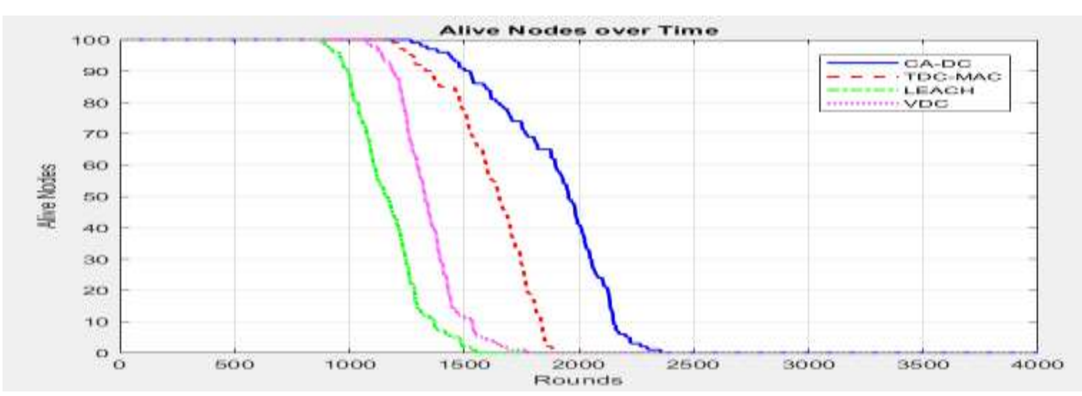


FIGURE 2. Number of alive nodes versus the round number of the network for scenario 1

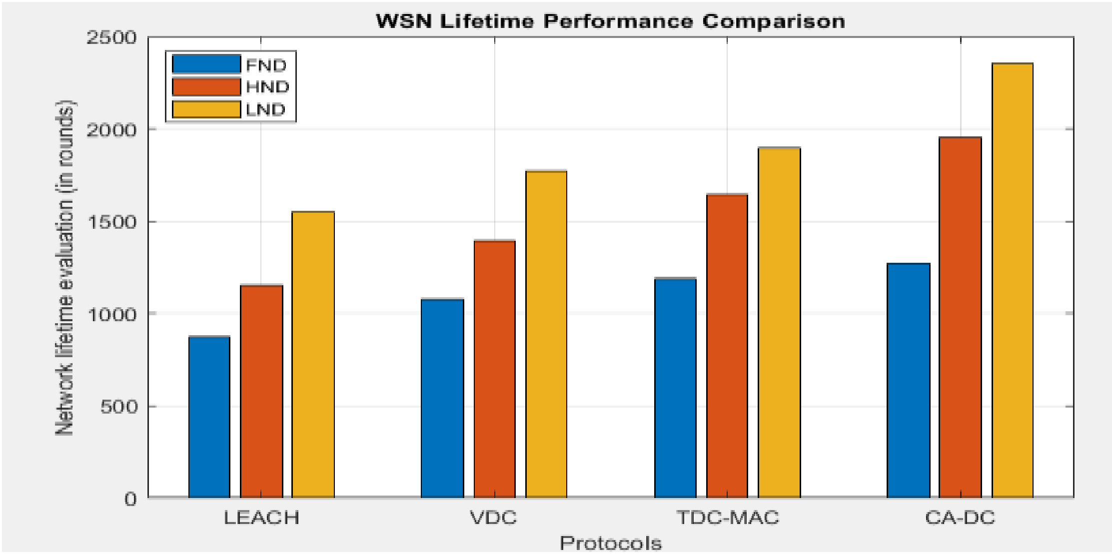


FIGURE 3. FND, HND, and LND for scenario 1

Protocol	FND	HND	LND
LEACH	876	1153	1552
VDC	1076	1329	1770
TDC-MAC	1189	1647	1898
CA-DC	1271	1955	2356

TABLE 2. Comparison of FND, HND, and LND for Different Protocols in scenario 1

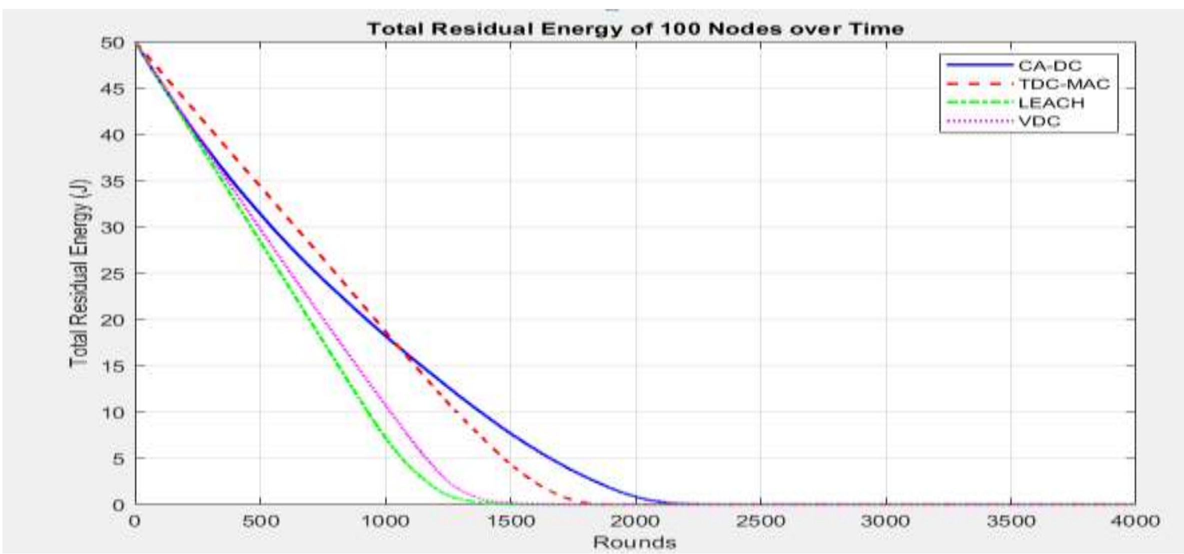


FIGURE 4. Remaining Energy Comparison for scenario 1.

Rounds	LEACH	VDC	TDC-MAC	CA-DC
100	4.32	4.12	3.32	4.33
200	8.63	8.21	6.27	8.33
300	12.93	12.25	9.40	11.99
400	17.24	16.26	12.53	15.43

500	21.55	20.21	15.62	18.59
600	25.85	24.12	18.75	21.59
700	30.15	27.97	21.85	24.34
800	34.45	31.78	24.98	26.91
900	38.72	35.53	28.13	29.39
1000	42.79	39.24	31.28	31.77
1300	49.43	48.43	40.45	38.38
1600		49.95	47.63	44.06
1800			49.81	47.01
2000				49.16
2200				49.93
2350				49.99

TABLE 3. Energy consumption of LEACH, VDC, TDC-MAC, and CA-DC over various rounds for Scenario 1.

5.2 SIMULATION RESULTS OF SCENARIO 2

As depicted in Figure 5, the proposed CA-DC protocol is compared with LEACH, TDC-MAC, and VDC. The results clearly demonstrate that CA-DC achieves the highest LND, with the final node depleting after 4,429 rounds. In contrast, the LND values for LEACH, TDC-MAC, and VDC occur at 1,256, 2,081, and 1,509 rounds, respectively, as summarized in Table 4 and illustrated in Figure 6. Similarly, Figure 7 presents the energy consumption patterns of the protocols. The proposed CA-DC protocol consumes its full initial energy budget of 50 J only after 4,429 rounds, whereas LEACH, TDC-MAC, and VDC exhaust their energy much earlier, at 1,256, 2,081, and 1,509 rounds, respectively. Table 5 provides a detailed comparison of residual energy across different rounds. These findings confirm that CA-DC achieves superior energy efficiency and significantly extends network stability compared to the benchmark protocols. By delaying both complete energy depletion and the last node death, CA-DC ensures more balanced energy distribution among nodes, prolonged operational lifetime, and more reliable data delivery in energy-constrained WSN applications.

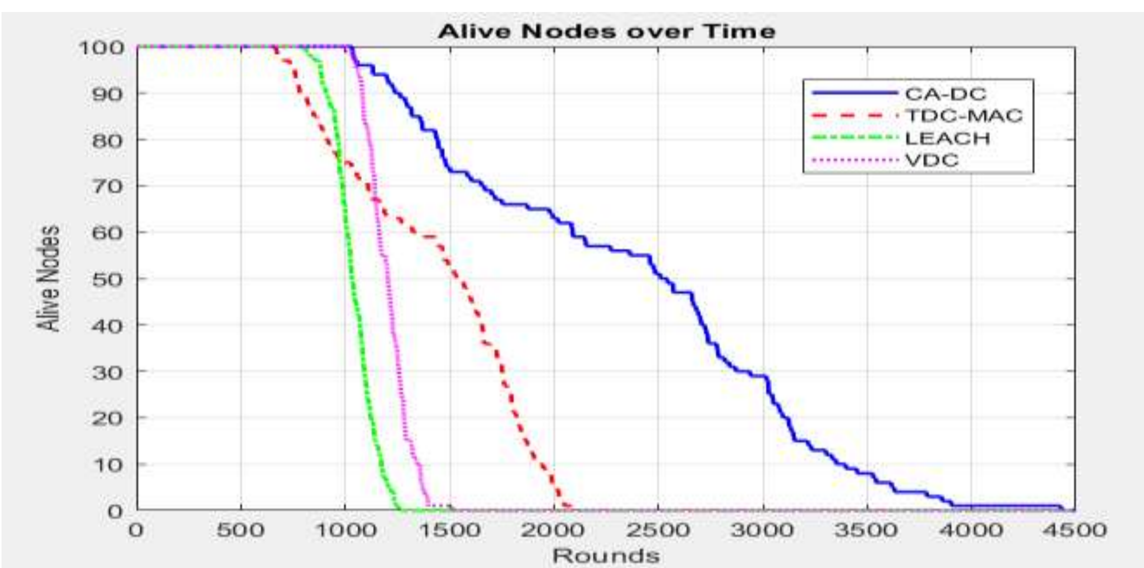


FIGURE 5. Number of alive nodes versus round number of network for scenario 2.

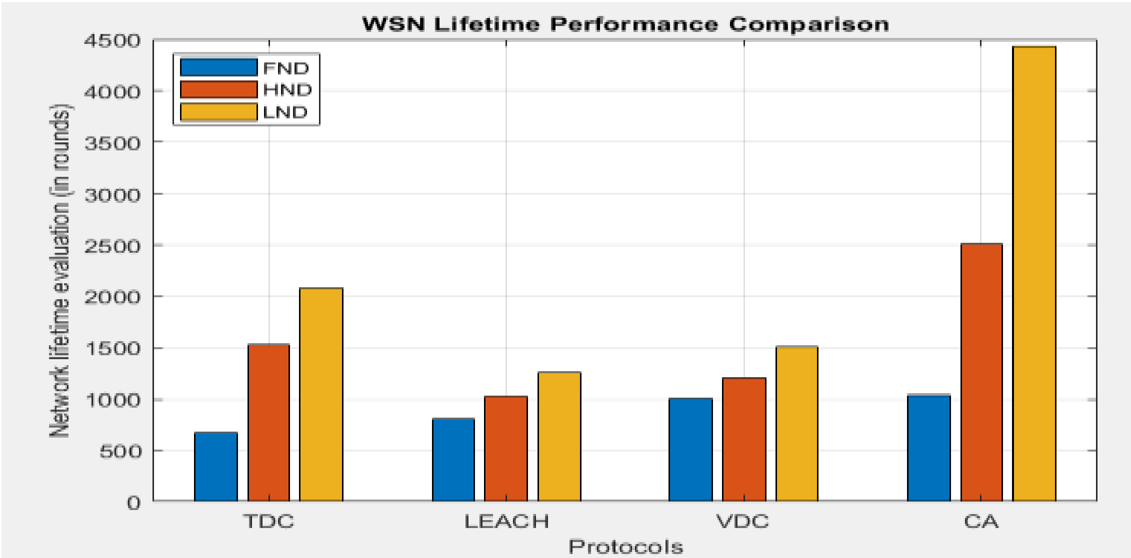


FIGURE 6. FND, HND, and LND for scenario 2.

Protocol	FND	HND	LND
LEACH	810	1031	1256
VDC	1003	1204	1509
TDC-MAC	670	1532	2081
CA-DC	1035	2510	4429

TABLE 4. Comparison of FND, HND, and LND for Different Protocols in scenario 2.

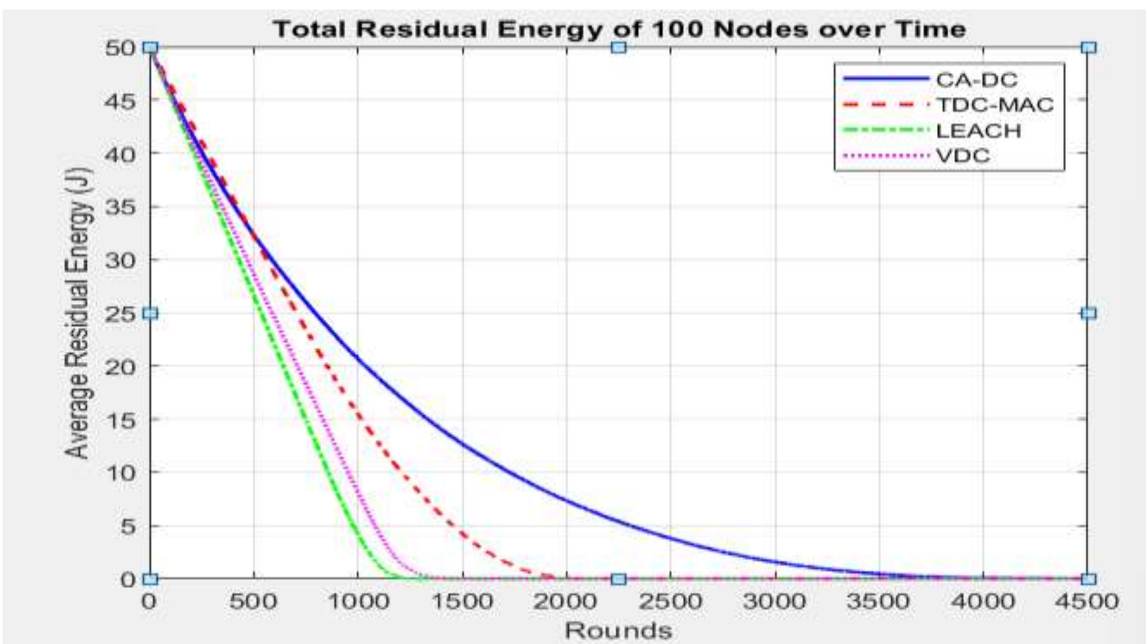


FIGURE 7. Residual Energy Comparison for scenario 2.

Rounds	LEACH	VDC	TDC-MAC	CA-DC
100	4.75	4.48	3.95	5.09
200	9.56	8.90	7.89	9.54
300	14.36	13.27	11.86	13.48

400	19.10	17.56	15.74	17.03
500	23.87	21.79	19.64	20.32
600	28.60	25.99	23.59	23.30
700	33.43	30.14	27.47	26.02
800	38.16	34.29	31.08	28.49
900	42.38	38.47	33.97	30.83
1000	46.75	42.64	36.50	32.94
1250	49.99	49.43	41.72	37.44
1500			47.63	40.72
1750			48.90	43.21
2000			49.95	45.07
2500				47.90
3000				49.41
3500				49.88
4000				49.97
4400				49.99

TABLE 5. Energy consumption of LEACH, VDC, TDC-MAC, and CA-DC over various rounds for Scenario 2.

6. DISCUSSION

6.1 PROTOCOL ADVANTAGES AND PRACTICAL IMPLICATIONS The CA-DC protocol provides several advantages over traditional clustering-based WSN protocols. By incorporating entropy alongside fuzzy logic metrics such as residual energy, concentration, and centrality, the protocol ensures more balanced CH selection. This results in reduced energy dissipation, improved load balancing, and extended network lifetime. Furthermore, the integration of a dynamic duty cycle mechanism allows nodes to conserve energy during low-traffic periods without sacrificing overall connectivity. Together, these design choices enable CA-DC to achieve superior stability and reliability compared to classical protocols such as LEACH, TDC-MAC, and VDC. Beyond its technical efficiency, CA-DC has direct implications for environmental sustainability. By conserving node energy and prolonging the lifetime of WSNs, the protocol ensures continuous collection of high-quality environmental data, which is critical for applications such as long-term climate observation, soil moisture monitoring, water resource management, and air quality assessment. Extending the operational lifespan of sensor deployments reduces maintenance costs, minimizes the carbon footprint of sensor redeployment, and ensures uninterrupted datasets for environmental decision-making.

6.2 LIMITATIONS AND CONSTRAINTS

Although the CA-DC protocol demonstrates significant improvements in energy efficiency and stability, it is not with- out limitations. The computational overhead associated with entropy evaluation and fuzzy logic-based CH selection is higher compared to lightweight clustering protocols. While the complexity remains polynomial $O(N^2)$ for CH selection and $O(N)$ for duty cycle updates), this may become a bottleneck in very large-scale WSNs with thousands of nodes. Additionally, the protocol requires synchronization during duty cycle transitions, which introduces coordination overhead that may affect latency in time-critical applications. Another constraint lies in the assumption of static deployment with uniform initial energy among nodes. While CA-DC is effective for static networks, variations in energy heterogeneity can influence fairness in CH selection and potentially lead to unbalanced energy consumption across the network. Furthermore, the entropy-based mechanism requires nodes to maintain a history of sensed data, which increases memory usage. In resource-constrained devices, this may limit scalability unless storage efficiency techniques are applied. These constraints highlight that while CA-DC performs well in static WSN scenarios, careful consideration is needed when deploying in extremely resource-limited or large-scale environments.

6.3 FUTURE WORK AND EXTENSIONS

There are several directions in which CA-DC can be extended and refined. First, mobility-aware enhancements could be incorporated, enabling adaptive CH selection in scenarios where nodes or sinks are mobile. This would broaden the applicability of the protocol to vehicular networks, disaster recovery, and mobile healthcare monitoring. Second, the incorporation of machine learning techniques could further optimize duty cycle decisions and CH selection by learning from network traffic patterns, thereby reducing dependency on manually tuned fuzzy parameters. Future research will focus on applying CA-DC to real-world environmental datasets and exploring integration with energy-harvesting sensors, thereby enabling self-sustaining monitoring infrastructures that support next-generation environmental management and climate resilience strategies.

REFERENCES

[1] Wendi Rabiner Heinzelman, Anantha Chandrakasan and Hari Balakrishnan, “Energy-Efficient Communication Protocol for Wireless Microsensor Networks,” in Proc. 33rd Annu. Hawaii Int. Conf. Syst. Sci., Maui, HI, USA , pp. 3005–3014, 2000.

[2] S. S. Hegde, S. Guruprasad and S. M. Kulkarni, “Energy efficient LEACH- C protocol for Wireless Sensor Network," 2014 International Conference on Advances in Electronics, Computers and Communications (ICAECC), Bangalore, India, pp. 1-5, 2014.

[3] O. Younis and S. Fahmy, “HEED: a hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks,” IEEE Transactions on Mobile Computing , vol. 3 , no. 4, pp. 366 - 379, 2004.

[4] S. Lata, S. Mehfuz, S. Urooj and F. Alrowais, “Fuzzy Clustering Algorithm for Enhancing Reliability and Network Lifetime of Wireless Sensor Networks,” IEEE Access, vol. 8, pp. 66013-66024, 2020.

[5] Umashankar Pandey, Saroj Kumar Chandra and, Gulshan Soni, “Enhancing Sensor Node Lifespan in WSNs through Traffic-Adaptive Duty Cycle MAC (TDC-MAC) Protocol,” J. Electrical Systems, pp. 6209-6218, 2024.

[6] Chauhan, Vinith and Soni, Surinder, “Variable duty cycle aware energy efficient clustering strategy for wireless sensor networks,” Journal of Ambient Intelligence and Humanized Computing, vol. 14 , no. 2, 2022.

[7] Anees, J., Zhang, H.-C., Baig, S., Guene Lougou, B., and Robert Bona, T. G., “Hesitant Fuzzy Entropy-Based Opportunistic Clustering and Data Fusion Algorithm for Heterogeneous Wireless Sensor Networks,” Sensors, vol. 20 , no. 3, 2020.

[8] Mohammadi, Razieh and Shirmohammadi, Zahra, “DRDC: Deep reinforcement learning based duty cycle for energy harvesting body sensor node,” Energy Reports, vol. 9 , no. 12, pp. 1707-1719, 2023.

[9] Botao Zhu, Ebrahim Bedeer, Ha H. Nguyen, Robert Barton, and Jerome Henry, “Improved Soft-k-Means Clustering Algorithm for Balancing Energy Consumption in Wireless Sensor Networks,” IEEE Internet of Things Journal, 2020. doi: 10.1109/JIOT.2020.3031272.

[10] Kumar, Surender, Prateek, Manish, Ahuja, Nidhie, and Bhushan, Bharat, “DE-LEACH: Distance and Energy Aware LEACH,” International Journal of Computer Applications, vol. 88, no. 9, 2014.

[11] Juwaied, A., Jackowska Strumillo, L., and Majchrowicz, M., “Enhanced Distributed Energy-Efficient Clustering (DEEC) Protocol for Wireless Sensor Networks: A Modular Implementation and Performance Analysis,” Sensors, vol. 25, no. 13, 2025.

[12] El-Shenhabi, A. N., Abdelhay, E. H., Mohamed, M. A., and Moawad,
I. F., “A Reinforcement Learning-Based Dynamic Clustering of Sleep Scheduling Algorithm (RLDCSSA-CDG) for Compressive Data Gathering in Wireless Sensor Networks,” Technologies, vol. 13, no. 1, 2025.

[13] Chen, B., Jamieson, K., Balakrishnan, H., “pan: An Energy-Efficient Coordination Algorithm for Topology Maintenance in Ad Hoc Wireless Networks,” Wireless Networks, vol. 8, pp. 481–494, 2004.

[14] Grover, J., Shikha, S., and Sharma, M., “A Study of Geographic Adaptive Fidelity Routing Protocol in Wireless Sensor Network,” IOSR Journal of Computer Engineering, vol. 16, pp. 88-96, 2014.

[15] Aasem Ahmad and Zdenek Hanzalek, ‘An Energy-efficient Distributed TDMA Scheduling Algorithm for ZigBee-like Cluster-tree WSNs,” ACM Trans. Sen. Netw , vol. 16 , no. 3, 2020.

[16] Junaid Anees and Hao-Chun Zhang, “Thermal entropy based hesitant fuzzy linguistic term set analysis in energy efficient opportunis- tic clustering,” istributed, Parallel, and Cluster Computing , 2021. doi: https://doi.org/10.48550/arXiv.2111.15130

[17] Liu, Yang, Xiao, Jing, Li, Chaoqun, Qin, Hu, Zhou, Jie„ “Sensor Duty Cycle for Prolonging Network Lifetime Using Quantum Clone Grey Wolf Optimization Algorithm in Industrial Wireless Sensor Networks,”Sensors, 2021. doi: https://doi.org/10.1155/2021/5511745.

[18] Hassan, E. S., Madkour, M., Soliman, S. E., Oshaba, A. S., El-Emary, A., Ali, E. S., and El-Samie,“ Energy-Efficient Data Fusion in WSNs Using Mobility-Aware Compression and Adaptive Clustering,” Technologies, vol. 12 , no. 12, 2024.

[19] Wang, J., Tawose, O. T., Jiang, L., and Zhao, D, “A New Data Fusion Algorithm for Wireless Sensor Networks Inspired by Hesitant Fuzzy Entropy.,” Sensors, vol. 19, no. 4, 2019. doi: https://doi.org/10.3390/s19040784.

[20] Adnan Ismail Al-Sulaifanie and Bayez Khorsheed Al-Sulaifanie, “Hybrid access and adaptive duty cycle clustering protocol for ultra-low power wireless sensor networks,” IET Communications, vol. 15, pp. 1158–1173, 2021.

[21] Deepika Agrawal and Sudhakar Pandey, "Optimization of the selection of cluster-head using fuzzy logic and harmony search in wireless sensor networks," International Journal of Communication Systems, vol. 34 , 2020.
[22] Kai, Z., Sharaf, M., Wei, S. Y., Al Shraah, A., Le, L. T., Bedekar, A. A., & Ahmad, A. Y. B. (2024). Exploring the asymmetric relationship between natural resources, fintech, remittance and environmental pollution for BRICS nations: New insights from MMQR approach. Resources Policy, 90, 104693
[23] Liang, P., Guo, Y., Nutakki, T. U. K., Agrawal, M. K., Muhammad, T., Ahmad, S. F., ... & Qin, M. (2024). Comprehensive assessment and sustainability improvement of a natural gas power plant utilizing an environmentally friendly combined cooling heating and power-desalination arrangement. Journal of Cleaner Production, 436, 140387.
[24] Liang, P., Guo, Y., Chauhdary, S. T., Agrawal, M. K., Ahmad, S. F., Ahmad, A. Y. A. B., ... & Ji, T. (2024). Sustainable development and multi-aspect analysis of a novel polygeneration system using biogas upgrading and LNG regasification processes, producing power, heating, fresh water and liquid CO2. Process Safety and Environmental Protection, 183, 417-436..
[25] Mohsin, H. J., Hani, L. Y. B., Atta, A. A. B., Al-Alawnh, N. A. K., Ahmad, A. B., & Samara, H. H. (2023). The impact of digital financial technologies on the development of entrepreneurship: evidence from commercial banks in the emerging markets. Corporate & Business Strategy Review, 4(2), 304-312.
[26] Ramadan, A., Alkhodary, D., Alnawaiseh, M., Jebreen, K., Morshed, A., & Ahmad, A. B. (2024). Managerial Competence and Inventory Management in SME Financial Performance: A Hungarian Perspective. Journal of Statistics Applications & Probability, 13(3), 859-870.
[27] Almestarihi, R., Ahmad, A. Y. A. B., Frangieh, R., Abu-AlSondos, I., Nser, K., & Ziani, A. (2024). Measuring the ROI of paid advertising campaigns in digital marketing and its effect on business profitability. Uncertain Supply Chain Management, 12(2), 1275-1284.
[28] Daoud, M. K., Al-Qeed, M., Al-Gasawneh, J. A., & Bani Ahmad, A. Y. (2023). The Role of Competitive Advantage Between Search Engine Optimization and Shaping the Mental Image of Private Jordanian University Students Using Google. International Journal of Sustainable Development & Planning, 18(8).
[29] Yahiya Ahmad Bani Ahmad (Ayassrah), Ahmad; Ahmad Mahmoud Bani Atta, Anas; Ali Alawawdeh, Hanan; Abdallah Aljundi, Nawaf; Morshed, Amer; and Amin Dahbour, Saleh (2023) "The Effect of System Quality and User Quality of Information Technology on Internal Audit Effectiveness in Jordan, And the Moderating Effect of Management Support," Applied Mathematics & Information Sciences: Vol. 17: Iss. 5, Article 12.
[30] C. Verma, V. P, N. Chaturvedi, U. U, A. Rai and A. Y. A. Bani Ahmad, "Artificial Intelligence in Marketing Management: Enhancing Customer Engagement and Personalization," 2025 International Conference on Pervasive Computational Technologies (ICPCT), Greater Noida, India, 2025, pp. 397-401, doi: 10.1109/ICPCT64145.2025.10940626.
[31] N. Parihar, P. Fernandes, S. Tyagi, A. Tyagi, M. Tiwari and A. Y. A. Bani Ahmad, "Using Machine Learning to Enhance Cybersecurity Threat Detection," 2025 International Conference on Pervasive Computational Technologies (ICPCT), Greater Noida, India, 2025, pp. 387-391, doi: 10.1109/ICPCT64145.2025.10939232.
[32] A. Y. A. Bani Ahmad, P. Sarkar, B. Goswami, P. R. Patil, K. Al-Said and N. Al Said, "A Framework for Evaluating the Effectiveness of Explainability Methods in Deep Learning," 2025 International Conference on Pervasive Computational Technologies (ICPCT), Greater Noida, India, 2025, pp. 426-430, doi: 10.1109/ICPCT64145.2025.10939073.