

Original Article

Transformer-Enabled Digital Twin for Predictive Energy-Aware Lifespan Enhancement in Wireless Sensor Networks

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Abstract - Wireless sensor networks are extensively employed for empirical and monitoring purposes. Their performance is severely constrained by limited node energy, making network lifetime maximization a critical challenge. Clustering-based communication has been extensively adopted to reduce energy consumption, yet most existing protocols rely on reactive decisions derived from instantaneous or historical network conditions, often leading to unbalanced energy depletion and premature node failures. To overcome this restriction, this study exploits a Transformer-Enabled Digital Twin (TEDT) framework for predictive energy-aware clustering in WSNs. The proposed approach maintains a virtual replica of the physical network to continuously model energy dynamics and traffic behavior. A Transformer neural network is employed to predict future residual energy of sensor nodes using historical energy sequences, enabling a predict-then-cluster strategy. Cluster-head election is performed based on predicted power, communication distance, and node density, which ensures balanced energy utilization and reduced re-clustering overhead. Extensive simulations conducted and demonstrated that the proposed method achieves lower per-round energy consumption, delayed node death events, faster convergence, and significantly extended network lifetime in contrast to conventional clustering protocols involving LEACH, HEED, and DEEC. The results confirm the effectiveness of the proposed predictive clustering for sustainable WSN operation.

Keywords - Wireless Sensor Networks, Digital Twin, Transformer model, Energy-aware clustering, Network lifetime, Predictive optimization.

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as an essential component of many contemporary applications, including environmental monitoring, smart cities, precision agriculture, healthcare systems, and industrial automation. Such networks are composed of many inexpensive sensor nodes that work collaboratively to collect information, perform basic processing, and then transmit the detected data to a central BS [1]. Despite their benefits, sensor nodes are hampered by their short communication ranges, limited processing capability, and limited battery capacity. [2]. Accordingly, the two most important shortcomings in the construction and the operation of WSNs remain power utilization and network lifetime optimization [3].

Clustering has become a popular technique in WSNs to deal with energy constraints. Sensor nodes are grouped together in a clustering-based communication method, and a chosen node serves as the cluster head, collecting data from its members, compiling it, and forwarding the merged

information to the base station [4]. This method considerably lowers communication overhead and improves scalability. However, the performance of clustering protocols largely depends on effective CH selection, balanced cluster formation, and fair rotation of CH roles [5]. Conventional clustering methods such as LEACH, HEED, and DEEC typically rely on probabilistic, energy-aware, or heterogeneity-based mechanisms, which often operate reactively using current or past network information [6].

Reactive clustering decisions may lead to uneven energy depletion, frequent re-clustering, and premature node failures, especially in dynamic network conditions. Recent advances in intelligent techniques, including machine learning and deep learning, have attempted to improve clustering efficiency by learning network patterns. Nevertheless, most existing approaches still lack the ability to anticipate future energy trends during cluster formation. Motivated by this gap, this work introduces a Transformer-Enabled Digital Twin framework that enables predictive energy-aware clustering. By continuously modelling the physical network within a



virtual environment and anticipating upcoming energy usage, the proposed approach enables well-informed cluster-head decisions, promotes uniform energy distribution across nodes, and increases the network's total operational lifetime.

Below is an inventory of this work's main contributions:

- By enabling forward-looking and data-driven cluster-head selection decisions, a Transformer-enabled Digital Twin framework is suggested to increase the effectiveness of energy and increase network lifetime.
- Instead of using current network conditions, the suggested design uses supervised learning using a transformer model to dynamically find the best cluster heads based on past and present energy consumption trends.
- In addition, the integration of a Digital Twin facilitates proactive energy balancing and load-aware clustering. This effectively reduces the uneven energy depletion, premature node failures, and prolongs the network's aliveness.
- An improved cluster formation and rotation strategy is studied to balance intra-cluster load and minimize communication cost. This structure controls re-clustering frequency and achieves more stable energy harvesting across network rounds.
- Comprehensive simulation experiments confirm that the anticipated approach delivers prominent progress in energy competence, network stability duration, convergence behavior, and overall lifetime when evaluated against traditional clustering protocols such as LEACH, HEED, and DEEC under the same network settings.

This document is organized in a sequential fashion throughout the rest of it. An overview of pertinent studies and earlier research is depicted in Section 2. Section 3 describes the suggested methodology. Section 4 discusses the simulation findings. The study, concluded in Sections 5 and 6, presents study limitations and future research directions.

2. Related Works

Various related research relevant to this study is discussed in this section. Classical clustering procedures, efficient energy management, and novel strategies relevant to this study are discussed. A predictive, transformer-enabled digital twin-based clustering approach is motivated by the outcome of this analysis.

In [7], to optimize the operational lifespan of sensory networks, an energy-efficient technique is described. The proposed approach focuses on optimizing node energy utilization that balances communication load and reduces redundant transmissions. By dynamically adjusting transmissions using residual energy levels and network conditions, the approach considerably diminishes node

exhaustion, thus prolonging network stability. Experimental evaluations indicate that the method lowers energy consumption and sustains network operation for a longer duration than conventional clustering techniques.

In [8], an energy-efficient optimal tree-structured clustering is introduced to improve reliable data transfer in WSNs. The method organizes sensory nodes into an optimized tree-structured cluster that minimizes communication overhead and assures secure data transmission. This method reduces unwanted transmissions and energy depletion among nodes by considering a clustering structure with security restraints. Experimental analysis shows that the proposed tree-clustering strategy greatly increases network lifetime and energy conservation compared to the conventional clustering mechanisms.

In [9], a centralized clustering protocol is proposed to enable energy-aware multi-hop communication between clusters. The approach forms energy-aware clusters at the BS and ascertains multi-hop inter-cluster routing paths to reduce the transmission period. Residual energy and communication cost during cluster formation and routing are considered to balance energy depletion across the network. Simulation outcomes expressed that the introduced approach achieves lower energy utilization and prolongs network life when compared with traditional single-hop routing methods.

In [10], the study intends to prolong the lifespan by optimizing the CH selection in the LEACH-based approach, specifically when the BS is situated at the network destination. The improved LEACH mechanism increases network lifespan by adjusting the CH selection, node distances, and residual energy. These enhancements reduce premature node death caused by uneven energy depletion near the sink. Experimental results show notable improvements in the network's lifetime and stability period compared to the traditional LEACH technique.

In [11], an energy-aware data transmission mechanism is proposed that emphasizes data fusion to reduce unwanted transmissions in networks. This method organizes sensor nodes into energy-aware clustering structures and applies in-network data fusion to minimize overall transmission cost. It lowers energy depletion per round by diminishing the transmission count near the sink. Simulation results demonstrate prolonged network lifetime and enhanced data transmission compared to conventional approaches.

In [12], clustering techniques have been explored to further extend the lifetime of sensory networks by addressing the issue of energy imbalance among sensor nodes. This study offers a comparative analysis of classical and improved clustering techniques. Moreover, it also highlights how energy consumption, depending on cluster head selection and intra-cluster communication design, was affected. Further, it shows

the use of adaptive clustering that anticipates both residual energy and node distribution to avoid node failures and network lifespan. The reported results demonstrate that stable clustering appreciably improves stability and lifetime compared to static clustering schemes.

In [13], a machine learning based clustering method is developed to improve energy efficiency and extend the operational lifetime. The proposed approach identifies suitable cluster heads by considering node energy levels and communication costs. Furthermore, this method minimizes unnecessary re-clustering and distributes energy consumption more evenly across nodes. The proposed clustering techniques reveal notable improvements in network longevity and stability over the traditional heuristic-based approaches.

In [14], an ensemble-based and optimal type-2 fuzzy logic is integrated to propose a secure and energy-conscious routing approach. To select the reliable and energy-efficient communication path, the proposed model fuses multiple routing criteria, including residual energy, trust, and link quality. Type-2 fuzzy logic enables effective handling of ambiguity in network conditions, whereas the ensemble strategy improves routing sturdiness. Simulation outcomes prove the improvement in terms of energy conservation and lifetime maximization compared to conventional routing approaches.

In [15], an energy-aware clustering method using Graph Neural Networks (GNNs) is studied for dense networks. This method assumes a network as a graph structure and guides the process of CH selection. The GNN-based model improves energy balance and reduces unnecessary sensing coverage by learning spatial and associated relationships among sensor nodes. Experimental results demonstrate that the proposed study enhances network lifetime and improves clustering quality, especially in high-density network scenarios.

In [16], a Digital Twin-based model is introduced to increase the energy efficiency of wireless multimedia sensor networks for environmental monitoring applications. The proposed system maintains a virtual representation of the physical sensor network to optimize data transmission approaches. This approach ensures reliable multimedia data transmission by matching the digital twin with network dynamics. The obtained results demonstrate the visible improvements and highlight the potential of digital twin technology for managing complex sensor networks.

In [17], an improved form of the LEACH protocol regarding the clustering protocol has been introduced for better energy harvesting. Using such an improved protocol, the choices regarding CHs that can be used and the balanced proliferation of energy depletion in the sensory nodes can be achieved. In achieving this, the model uses the distance of the node from the BS and the residual energies. This improved

LEACH protocol ensures efficient network stability with reduced energy usage via the optimization of intra-channel and inter-channel communications.

In [18], an advanced version of the HEED clustering technique is developed for heterogeneous networks. This technique leverages the benefits of neural networks for assisting CH selection from complex interactions involving different energy levels of nodes, communication costs, etc. The DL-HEED technique provides better energy depletion and network lifetime compared to the existing HEED techniques. The results reveal that deep learning can improve the performance of cluster head selection in energy-aware networks significantly.

In [19], an integrated clustering technique is proposed based on a combination of fuzzy technology and the DEEC protocol. A fuzzy inference system is utilized, considering several constraints such as residual energy, proximity, and communication expense, allowing effective election of cluster heads. The potency of the recommended scheme is verified, reducing the problem of energy imbalance and stability by incorporating the fuzzy concept into the traditional DEEC protocol. Simulation results show a better performance of the suggested integrated method over the existing DEEC protocols.

In [20], to develop smart city applications, an energy-efficient clustering method is proposed. A node energy status and spatial dispersion-based efficient clustering method is developed to improve cluster head selection efficiency and minimize communication overhead. Balanced cluster formation and distance minimization during data transmission enable the corresponding system to increase system longevity and energy efficiency, especially in larger-scale network scenarios. Better performance is achieved over traditional cluster head selection methods, as shown in the analysis in this study.

In [21], deep reinforcement learning's suitability for energy-aware routing in wireless Internet of Things networks is investigated. In this study, a deep Q-network is utilized for dynamic path routing, which allows the network to make adaptive decisions based on network metrics and node energy status. The suggested approach uses less energy and improves data transmission efficiency by interacting with the network to learn efficient routing paths. When compared to conventional rule-based approaches, the simulation results showed that this method improves the routing system's lifetime and performance.

An integrated tactic for cluster head selection is proposed in [22] to enhance energy efficiency and maximize wireless sensor network life. To exploit their complementary aspects, various decision-making models are hybridized by the authors to make cluster head selection more reliable and fairer. The

hybrid approach tackles uncertainty and WSN dynamics effectively using variables such as remaining node energy, node dispersion, and communication costs. Compared to traditional single-approach-based clustering methods, simulation results prove that this hybrid approach improves network stability and reduces node energy inequality.

To efficiently choose the cluster heads in heterogeneous wireless sensor networks, an optimized Pelican Optimization Algorithm is described in [23]. In order to explore energy-efficient and evenly distributed cluster heads while addressing nodal heterogeneity, it leverages both exploration and exploitation aspects of the pelican optimization technique. It reduces irregular energy consumption and improves stability by accounting for both residual energies and communication distances. Compared with traditional clustering algorithms, results clearly prove that this optimized solution offers enhanced lifetime and efficiency of energy consumption of the network.

A special type of routing protocol that is adaptive to a wireless sensor network used for energy harvesting has been developed in [24]. The routing protocol keeps changing its clustering and routing decisions according to the available harvesting energy and battery life. The approach improves the sustainability and longevity of networks by allowing more energy to be received to handle the communication load. The approach has advantages of improved longevity and balancing of energy, but on the other hand, it has disadvantages because it is harder to maintain a sustainable cluster due to varying patterns of harvesting.

In [25], fuzzy logic and a quantum annealing algorithm were proposed to develop an energy-efficient cluster-based routing scheme in wireless sensor networks. Although the proposed quantum annealing algorithm was intended to optimize cluster-head formation and routes, fuzzy logic was responsible for dealing with uncertainties associated with network parameters such as residual and communication distances. Thus, the proposed model reduces the chances of untimely failures within nodes and proper balancing of energy, but its real-world implementation within sensor nodes is prone to increased computation costs associated with the former.

In terms of energy-harvesting-based wireless sensor networks, a novel and efficient clustering strategy is proposed in [26]. In this strategy, the formation and selection of clusters are dynamically influenced by the remaining battery energy and the collected energy. This strategy reduces the energy consumption in battery-powered sensor nodes by allocating more communication tasks to the sensor nodes with high and stable energy harvesting rates. The re-clustering algorithms are used for adapting to dynamic changes in the network environment as well as the available energy. This improves the efficiency of the network in terms of energy. Therefore,

the network can continue running indefinitely. Using the frequent change of the available energy data under this strategy may present a challenge of ensuring an efficient cluster. Although the prediction efficiency of the energy may be a challenge, it is unlikely to influence the efficiency of the clustering strategy.

In [27], an energy-efficient cluster head selection algorithm, FEECS, has been proposed based on the application of fuzzy logic for increasing the lifetime of wireless sensor networks. This algorithm depends on the application of a fuzzy inference system for selecting appropriate cluster heads during vague network environments based on certain input attributes like energy level, proximity, and communication costs of nodes. By the application of fuzzy logic, the proposed technique can maintain energy balance among sensor nodes, thus avoiding failure and decreasing the failure possibility during cluster head selection. It can increase the value of the lifetime with the proper adjustment of appropriate parameters for implementing the fuzzy rule and membership function.

A novel energy-efficient cluster head election protocol has been proposed in [28] for optimizing the LEACH protocol used in common wireless sensor networks. By incorporating the use of residual energies and distances as an input for decision-making in the proposed protocol, the effectiveness of the existing protocol can be overcome. In this way, the potential risks of node death due to energy exhaustion can be reduced. Although this proposed protocol enhances the stability of the network and lifetime enhancement over the existing LEACH protocol, its efficiency is affected by factors such as accurate energy estimation as well as overhead costs of periodic re-clustering.

Overall, with fuzzy logic, machine learning, deep learning, reinforcement learning, and digital twin-based strategies, as well as enhanced clustering and routing techniques, prior research has made significant progress in increasing energy effectiveness and prolonging the network's operational span. However, most of these methods rely on reactive or instantaneous network information and lack the ability to anticipate future energy depletion during cluster formation. This limitation motivates the proposed Transformer-Enabled Digital Twin framework, which introduces a predictive, simulation-driven clustering strategy to achieve a longer lifespan of the network and more balanced energy usage.

3. Proposed Methodology

To maximize network lifetime in WSNs, this work presents a Transformer-Enabled Digital Twin (TEDT) model that supports predictive energy-aware clustering. The suggested method integrates predictive mechanisms into the clustering process, in contrast to traditional clustering

protocols that base their choices on current or previously observed network conditions. The proposed approach in TEDT uses a predict-then-cluster scheme in which sensor node future energy consumption is predicted before performing a clustering scheme.

With the ability to forecast the changing patterns of node energies, the design minimizes the probability of any nodes with rapidly depleting energies being allocated energy-demanding roles such as cluster heads. This foresighted approach to the management of node energies allows for the equitable usage of energy and significantly reduces the probability of premature node failures.

In order to accomplish this, the design consists of three interrelated components. A digital twin module is employed to constantly maintain a digital copy of the network and its operational states. A Transformer-based prediction model is utilized to forecast the residual energies of sensor nodes in the future, based on historical patterns of energy.

An energy-aware clustering mechanism then uses these predicted energy levels to direct cluster-head selection and cluster formation. These elements work together to make adaptive, proactive clustering decisions that improve network stability and increase the wireless sensor network's lifespan. While the Transformer forecasts future node energy trends, the Digital Twin continuously uses simulation data to reflect the current network state. To distribute energy consumption evenly and extend the network's lifespan, clustering operations like CH election and cluster formation are proactively carried out using these forecasts. Figure 1 shows the architecture of the TEDT model under study.

3.1. Initialization

To mimic the realistic and unsupervised network, the sensory units are placed erratically within the two-dimensional sensing region. In order for the nodes within the sensor network to have an equal and balanced connection, the sensor nodes are all assumed to have the same amount of energy, the same communication range, and the same sensing ability. The base station, or the key node where the main administration of the acquired information happens, is considered stationary and placed at a fixed location, either inside or outside the sensing region.

3.2. Network State Collection

The status information is exchanged among sensors at the start of each round of operations to represent the status of the network at any given time. The status information comprises the residual energy contained within each node, traffic information on data transmission, and communication distances with neighboring nodes or with the base node. The information is pivotal in aiding analysis for making decisions regarding clustering, based on an assessment of the status of the entire network.

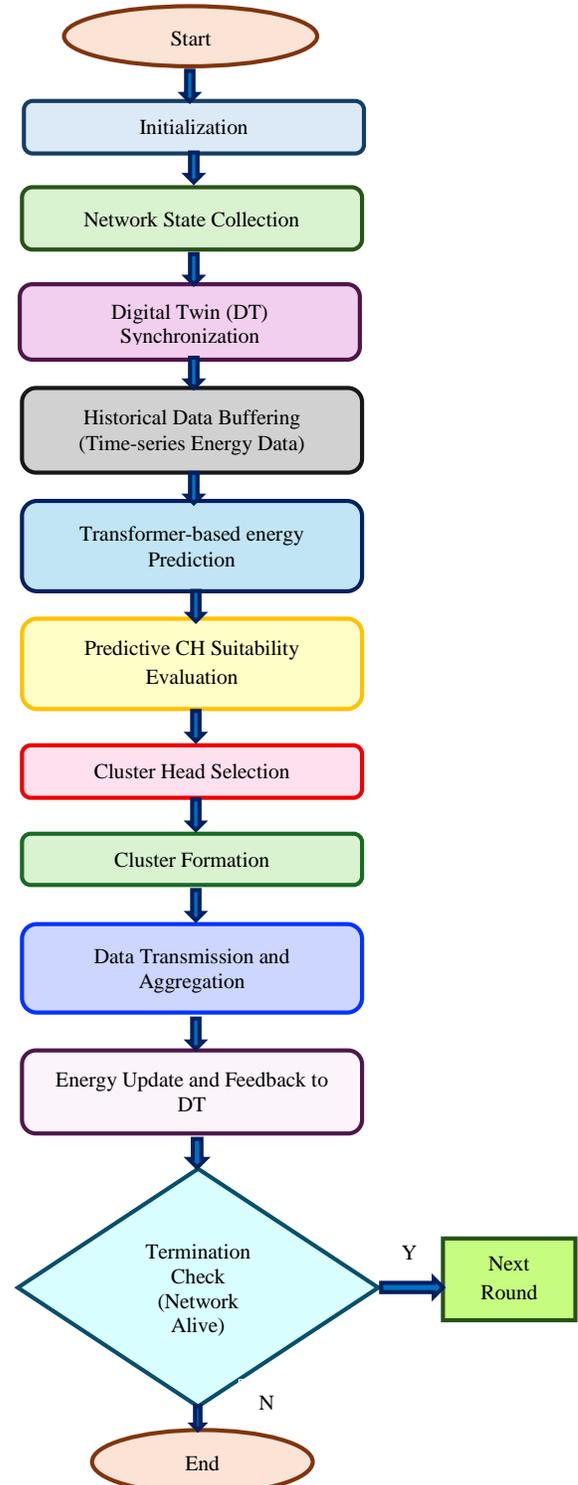


Fig. 1 Workflow of the proposed TEDT approach

3.3. Digital Twin

For a particular implementation and control of a virtual version of a wireless sensor network like this, Digital Twins step into the scene. With a particular update of critical

parameters like energy levels within nodes of a sensor network like this, alongside an evolution of the topology structure and consequently a corresponding situation of the traffic, there is a synchronization of a Digital Twin with a physical system like this. The phenomenon happens to be a precise and dependable platform with a focus on monitoring.

3.4. Historical Data Buffering

With time, all the remaining energy for each sensor node is recorded. Wave by wave, all these pieces of information create patterns that look like timelines. One by one, all those timelines display the gradual decline of energy that takes place through cycles. It is a gradual decline that can be seen; it is not steep.

Historical information like that aids prediction models down the line. Guesses become clearer for expected levels of energy. Decisions for forming groups for nodes can be made beforehand.

3.5. Transformer-based Energy Prediction

A neural network, termed a Transformer, is employed to analyze the past energy data from the sensor nodes and predict the residual energy of the sensor nodes in the future.

The Transformer neural network is employed to analyze the past data from the sensor nodes to make predictions about the residual energy of the nodes in the future. It utilizes a self-attention mechanism to understand the past connections present in the data.

3.6. Predictive CH Suitability Evaluation

The suitability of every sensory node for assuming the role of a cluster head (CH) is evaluated using a set of energy and topology-aware criteria. These include the following:

- Predicted residual energy
- Proximity to BS
- Local node density

Nodes that are anticipated to undergo rapid energy depletion are deliberately excluded from CH selection to prevent excessive energy drain. This selection strategy ensures that cluster head responsibilities are assigned to nodes with sufficient energy reserves and favorable network positions, thereby promoting balanced energy depletion across the network.

3.7. Cluster Head Selection

Those sensor nodes that receive the highest scores are selected to act as cluster head nodes for the cycle. To avoid sensor nodes exhausting their power, a cluster head rotation mechanism is designed. It is ensured that the sensor nodes are assigned the task of being the cluster head nodes after a fixed interval. By this means, equal distribution of power in the network is ensured, which is the key to an extended lifetime of the network.

3.8. Cluster Formation

The sensory nodes that will not be chosen as CHs independently join an appropriate cluster by picking a neighboring CH that has less transmission overhead. The process is based on efficiency, meaning that there is minimal energy used when data is exchanged. Additionally, there is a mechanism that maintains a balance of members per cluster, thereby preventing a situation where a cluster head is overloaded. It is for this reason that there is a balanced cluster that prevents bottlenecks in wireless communication while maintaining cluster head energy.

3.9. Data Transmission and Aggregation

The member nodes then employ short-range communication to forward their information to the appropriate related cluster heads after having formed clusters. Just before sending aggregated data to the BS, each cluster head then aggregates the received data from member nodes in such a way that it eliminates any repeated data and thus reduces the amount of data sent to the BS in each communication round. This ends each communication process, after which all nodes involved in a communication process update their energy cost based on sensing, transmitting, and receiving functions in each communication round.

3.10. Feedback and Adaptive Loop

The updated values of the residual energies are then fed back into the Digital Twin, representing the most recent conditions of the network. The Digital Twin is then synchronized with the updated state of the simulated environment. The prediction and clustering of the energies are then processed again based on the updated information in the next round.

3.11. Termination Condition

The above process is done iteratively through multiple rounds, and when a certain criterion on the network lifetime is achieved, the process stops. The network lifetime is measured through different performance metrics, which include the round when the first sensor dies (First Node Death), the round when half the nodes in the network have died (Half Node Death), and the round when all the nodes have died (Last Node Death). All these metrics give a comprehensive network lifetime.

3.12. Pseudocode of the Proposed TEDT Method

Input:

N - number of sensor nodes; E_θ - initial energy of each node; BS - base station; R_{max} - maximum number of rounds; K - history length for energy sequences; α , β , γ - weighting coefficients

Output:

Network lifetime metrics (FND, HND, LND); Clustering structure for each round

Begin
 Deploy N sensor nodes randomly in the sensing area
 Initialize energy $E_i \leftarrow E_\theta$ for all nodes n_i
 Initialize Digital Twin DT with network state
 for round $r = 1$ to R_{max} do
 Collect current state from all nodes:
 residual energy, traffic load, distances
 Synchronize DT with the collected network state
 for each node n_i do
 Update historical energy buffer S_i
 if length $S_i \geq K$ then
 Predict future energy \hat{E}_i using the Transformer model
 else
 $\hat{E}_i \leftarrow E_i$
 end if
 end for
 for each node n_i do
 Compute distance d_i to BS
 Estimate local node density ρ_i
 if $\hat{E}_i < \text{energy_threshold}$ then
 Suitability $\Phi_i \leftarrow \theta$
 Else
 $\Phi_i \leftarrow \alpha \cdot \hat{E}_i + \beta \cdot (1/d_i) + \gamma \cdot \rho_i$ (1)
 end if
 end for
 Select nodes with the highest Φ_i as Cluster Heads
 Apply cluster head rotation constraint
 for each non-CH node n_j do
 Join the nearest Cluster Head based on the minimum cost
 end for
 Enforce cluster size limits for all clusters
 for each cluster do
 Member nodes transmit sensed data to the CH
 CH aggregates data and forwards it to BS
 end for
 Update energy E_i of all nodes based on communication cost
 Feed updated energy values back to DT
 Check network lifetime conditions:
 FND, HND, LND
 If the termination condition is satisfied then
 break
 end if
 end for
 Output lifetime metrics and clustering history
 End

4. Simulation Results and Discussion

4.1. Experimental Configuration

The proposed framework is tested using a simulation environment created using MATLAB (R2022a). The simulation model includes a 200 m \times 200 m square sensing area, where 100 sensor nodes are distributed for testing the efficiency of the communication process. The description of parameter assumptions for the simulation results is represented in Table 1.

Table 1. Simulation setup

| S.No | Specifications | Values |
|------|--|-----------------------|
| 1 | Coverage area | 1000m x 1000m |
| 2 | Units count | 100 |
| 3 | Preliminary energy of units | 1 Joules |
| 4 | Sink | x = 100, y = 100 |
| 5 | Data packet size | 4000 bits |
| 6 | Power aggregation | 5 nj/bit |
| 7 | (ϵ_{fs}) | 10 (Pj/bit/m2) |
| 8 | Power amplifications (ϵ_{mp}) | 0.0013 (Pj/bit/m4) |
| 9 | Energy transmitted and received | 50 (nj/bit) |
| 10 | Count of rounds | 14000 |

4.2. Performance Comparison

To assess the efficacy of the proposed Transformer-Enabled Digital Twin framework, its performance is compared with three popular clustering schemes in wireless sensor networks: LEACH, HEED, and DEEC. LEACH acts as the baseline hierarchical clustering algorithm, which uses a randomized rotation algorithm among the clusters to consume energy evenly. HEED optimizes energy consumption by incorporating the characteristics of the residual energy and the proximity among nodes in the process of selecting the cluster heads. The DEEC protocol describes an energy-aware hierarchical clustering algorithm extended to support heterogeneous wireless sensor networks, which takes the standard power value of the network compared to the residual energy among the nodes. The proposed algorithm differentiates itself by the support it provides to the forecast energy consumption using a Transformer algorithm within a Digital Twin framework. The comparison study considers the important parameters specified below.

4.2.1. Energy Consumption per Round

An analysis of the mean energy consumption per round is carried out to determine the efficiency of the clustering protocols. Figure 2 highlights the energy consumption per round comparison of the proposed technique and the traditional techniques. A probabilistic selection of the cluster head in LEACH consumes more energy because of the resulting unequal clusters and the large transmission distances. HEED reduces energy consumption by considering the energy and communication costs. DEEC enhances the energy efficiency by adapting the selection of the cluster head according to the energy consumption. All the protocols are reactive in nature and based on the existing or previous conditions.

Conversely, the proposed design of the Transformer-Enabled Digital Twin system sustains a reduced and constant level of energy consumption per iteration around 0.19 J at 10,000 iterations and even around 0.13 J at 14,000 iterations. The selection of the cluster head based on the predicted future

available energy through the usage of the Transformer component of the Digital Twin system promotes nodes that continuously have available energy. The proposed system enhances the network performance through optimized utilization and prolongation of the lifetime compared to LEACH, HEED, and DEEC.

- Half Node Death (HND): A measure of the mid-term energy balance of the network that occurs when half of the sensor nodes cease to operate.
- Last Node Death (LND): The network’s lifetime is represented by the round in which the final sensor node runs out of energy.

4.2.2. FND, HND, and LND

Network lifespan is further estimated using First Node Death (FND), Half Node Death (HND), and Last Node Death (LND) metrics.

- First Node Death (FND): The simulation round when network instability begins when the first sensor node runs out of energy.

Figure 3 above illustrates the functional evaluation for FND, HND, and LND in LEACH, HEED, and DEEC protocols. In LEACH, nodes experience early deaths due to the random rotation of cluster-heads, resulting in the shortest FND.

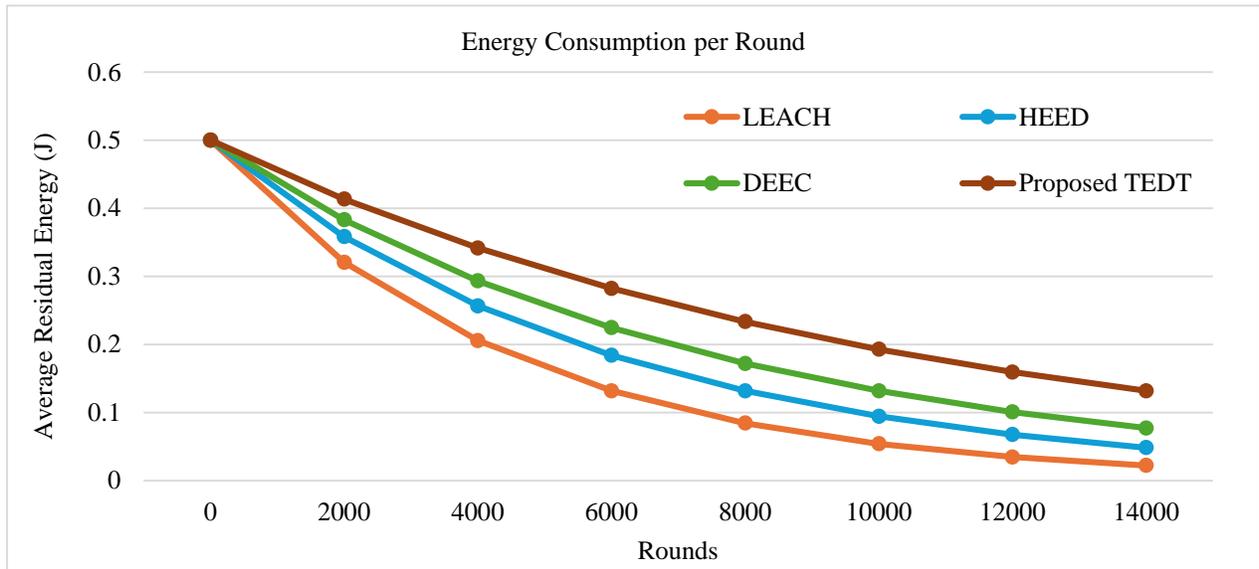


Fig. 2 Comparison of energy consumption per round

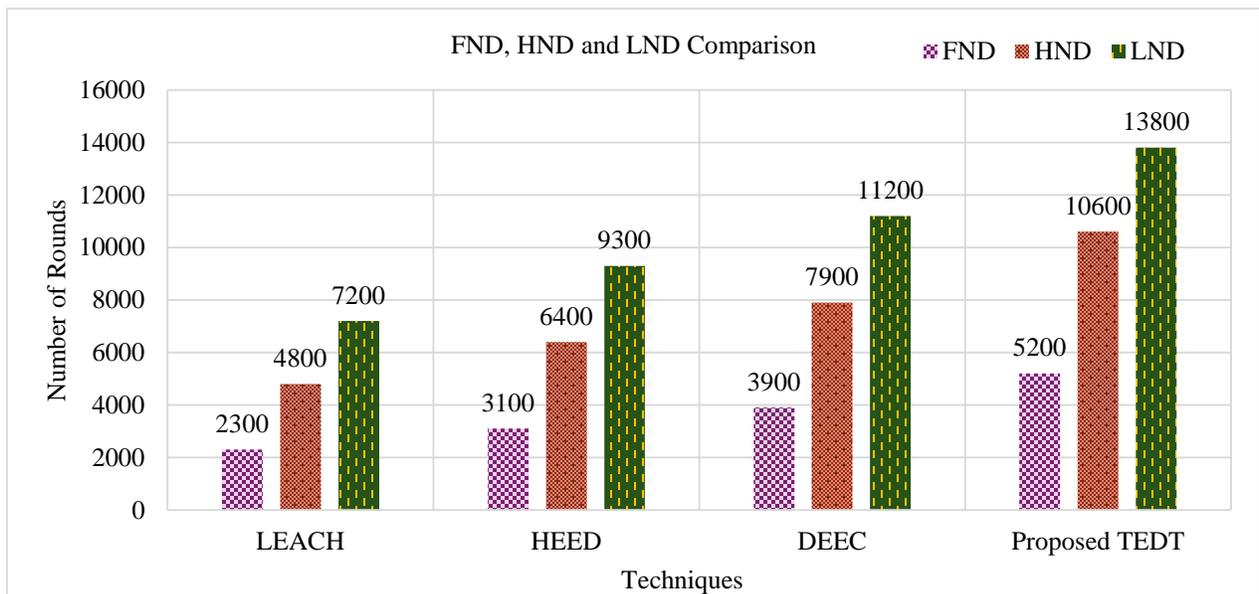


Fig. 3 FND, HND, and LND comparison

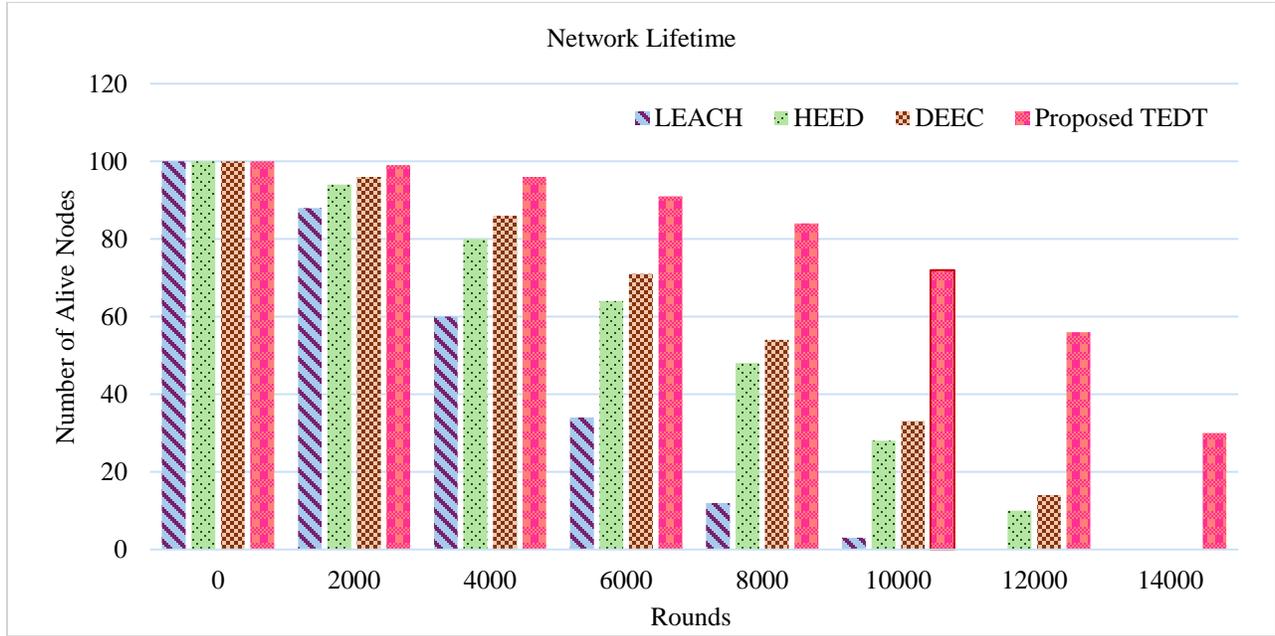


Fig. 4 Network lifetime comparison

HEED increases the network lifetime through residual energy, while DEEC does so through adaptive clustering based on energy variations in nodes. Regarding the proposed framework involving the Transformer-Enabled Digital Twin, the network possesses good sustainability values at all stages of evaluation. The first death event of the nodes takes place around 5200 rounds, signifying the well-established balance of energy and formation of clusters. The average sensor nodes last for around 10600 rounds. This shows that all nodes evenly dissipated their energy.

The network continues functioning up to nearly 13800 rounds, marking a significantly prolonged operational lifetime. These results confirm that predictive energy-aware forecasting enabled by the Digital Twin and Transformer-based forecasting effectively prevents premature node exhaustion and maintains long-term network stability. Consequently, node failures are delayed across all lifetime stages, demonstrating a clear improvement in network stability and longevity compared to LEACH, HEED, and DEEC.

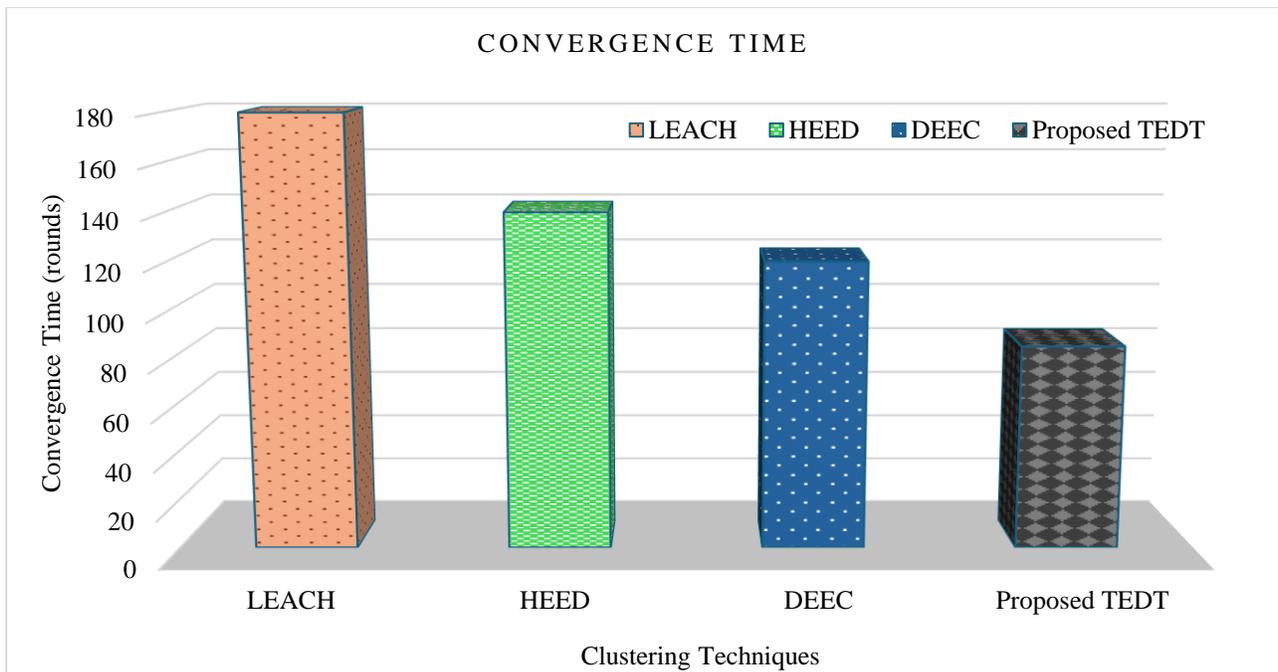


Fig. 5 Convergence time comparison

4.2.3. Network Lifetime

Network lifespan is assessed by tracking the sum of active sensor nodes across simulation rounds under the same network conditions. Figure 4 presents a comparison of the network lifetime achieved by the proposed method against existing approaches. Conventional clustering protocols, such as LEACH, exhibit a rapid decline in active nodes due to uneven energy consumption, leading to early network degradation. HEED and DEEC show gradual improvements by incorporating residual energy into cluster-head selection; however, their decisions remain reactive to current network states. For the proposed Transformer-Enabled Digital Twin framework, more than 90 sensor nodes remain active up to around 6,000 rounds, indicating stable and balanced energy consumption. At 10,000 rounds, nearly 70 nodes are still operational, demonstrating sustained network functionality. Even beyond 13,000 rounds, the network continues to operate with approximately 30 active nodes at 14,000 rounds. These results confirm that the proposed predictive energy-aware clustering strategy effectively delays node failures and extends the overall network lifetime.

4.2.4. Convergence Time

The minimal number of rounds is known as the convergence time, required for the clustering process to reach a stable state, where successive clustering configurations show negligible variation. Let $C^{(r)}$ denote the cluster configuration at round r . Convergence is achieved when the difference between two consecutive configurations falls below a predefined threshold ϵ , expressed in equation (2).

$$T_{conv} = \min\{r \mid \|C^{(r)} - C^{(r-1)}\| \leq \epsilon\} \quad (2)$$

Where $\|\cdot\|$ represents a suitable distance or dissimilarity measure between clustering states, and ϵ is a small positive constant. Figure 5 demonstrates the convergence time comparison of the proposed TEDT method.

Convergence time is analyzed to examine how quickly different clustering protocols stabilize their cluster formation and energy consumption patterns. Conventional approaches such as LEACH require a larger number of rounds to reach stability due to their probabilistic cluster-head selection, which causes frequent changes in cluster structure. HEED improves convergence by incorporating residual energy and communication cost, yet multiple iterations are still needed before a stable configuration is achieved. DEEC further reduces convergence time by adapting cluster-head selection based on node energy levels, resulting in a comparatively faster but still reactive stabilization process.

The proposed Transformer-Enabled Digital Twin framework achieves significantly faster convergence than the existing methods, stabilizing within approximately 85 rounds. This improvement is attributed to the predictive capability of the Digital Twin, where future energy states are estimated

before clustering decisions are made. By selecting cluster heads with sustained energy availability from the initial rounds, the proposed method minimizes repeated re-clustering and avoids unstable cluster transitions. As a result, the clustering structure converges rapidly and remains stable over subsequent rounds, demonstrating superior convergence performance compared to LEACH, HEED, and DEEC.

5. Conclusion

This work presented a Transformer-Enabled Digital Twin framework for predictive energy-aware clustering aimed at enhancing network lifetime in wireless sensor networks. Unlike conventional clustering procedures that rely on instantaneous or historical network information, the proposed approach adopts a predict-then-cluster strategy, in which future energy depletion is estimated before cluster formation. By integrating a simulation-driven Digital Twin with a Transformer-based energy prediction model, the framework enables informed selection of cluster heads and balanced energy utilization across the network. Extensive simulations conducted under identical network conditions demonstrate that the proposed method achieves lower energy consumption per round, faster convergence, and a significantly prolonged network lifetime when compared with well-known clustering protocols such as LEACH, HEED, and DEEC. The delayed occurrence of First Node Death, Half Node Death, and Last Node Death confirms the effectiveness of predictive clustering in preventing premature node exhaustion. Moreover, the reduced convergence time highlights the stability of the proposed clustering mechanism from the early stages of network operation. Overall, the results validate that incorporating Digital Twin-assisted prediction with Transformer-based modelling offers a promising direction for energy-efficient, scalable WSN design. Future work may focus on extending the framework to heterogeneous networks, incorporating real-time data streams, and exploring lightweight prediction models to further enhance its applicability in resource-constrained environments.

5.1. Study Limitations and Future Research Directions

A Transformer-Enabled Digital Twin framework for predictive energy-aware clustering in wireless sensor networks is presented in this work. Nevertheless, a few drawbacks should be noted. Initially, the suggested method is assessed by simulation-based trials, which, while thorough, might not accurately represent environmental variables, communication noise, and hardware flaws found in real-world deployments. Second, the Transformer model's accuracy may be impacted by extremely dynamic traffic patterns or sudden changes in network conditions because it depends on historical energy data for the forecast. Furthermore, although controllable in the simulated environment, the computational expense of model training and Digital Twin synchronization may present difficulties for large-scale or resource-constrained sensor platforms.

This work can be expanded in several ways by future research. To verify the usefulness and resilience of the suggested framework under actual operating circumstances, real-world testbed implementations might be investigated. To cut down on communication and computational overhead, lightweight or distributed learning models should be studied.

Additionally, using adaptive model updates or online learning can improve forecast accuracy in dynamic contexts. To further enhance the usability of the suggested method in various wireless sensor network applications, future research may further consider security limitations, energy harvesting capabilities, and mobile sink scenarios.

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