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HS-EDEEC: An Energy-Efficient Transmission Model for Route Probability of Heterogeneous WSN-Based on IoT Networks

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Wireless sensor network (WSN) is often used for monitoring, collecting data, and facilitating communication in internet of things (IoT) environments. However, traditional energy-efficient routing protocol methods fall short in ensuring low energy consumption (EC) and high fault tolerance (FT), especially in heterogeneous IoT-based WSNs due to the failure of one or more cluster heads.*

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ABSTRACT

In internet of things (IoT)-based wireless sensor networks (WSNs), sensor nodes are distributed across a designated area to collect and transmit data. However, communication failures in WSNs, caused by the failure of one or more cluster heads, can disrupt data transmission and processing. The study proposes the hybrid optimized harmony search enhanced distributed energy-efficient clustering algorithm that optimizes route selection, detects faults, and calculates probability values to identify reliable communication paths, thereby enhancing fault tolerance (FT) and energy consumption (EC) efficiency. The model's performance has been evaluated using a Matrix Laboratory (MATLAB) simulator in the context of an IoT-based WSN network, demonstrating its effectiveness in improving computational delays and EC by 12% ($P < .02$) and minimizing average computation time (CT) with an improved 16% FT rate compared to existing models such as Efficient Fault-Tolerant routing using Path graph flow modeling with Marchenko-Pastur Distribution (EFT-PMD), energy-efficient secure-based IoT, distributed cognitive maps, and energy efficient data communication.

Index Terms—Energy-efficient (EE), fault tolerance (FT), harmony search enhanced distributed energy-efficient clustering (HS-EDEEC), Internet of Things (IoT), wireless sensor network (WSN)

I. INTRODUCTION

Wireless sensor networks (WSNs) are being used more often in the fields of smart cities, health care, agriculture, and industry as the use of internet of things (IoT) expands [1]. These self-configured, infrastructure-free networks of wireless devices monitor environmental and physical factors such as temperature, vibration, pressure, and sound. The data collected by the sensor nodes (SNs) is wirelessly transmitted to a central hub for analysis [2]. These nodes not only gather data but also act as routers to relay information across the network and to the internet through a coordinator, enabling WSNs to be seamlessly integrated with the IoT [3]. The IoT refers to a system where everyday objects—ranging from household devices to industrial machines—are embedded with sensors and computing capabilities to send and receive data without human intervention. With the growth of IoT, WSNs are increasingly deployed in applications such as smart cities, healthcare, agriculture, and industry.

However, the integration of WSNs with IoT systems presents several challenges, particularly regarding energy efficiency, network longevity, and reliable data transmission [1, 4, 5].

Traditional WSNs generally rely on homogeneous SNs with similar capabilities. However, modern IoT systems often incorporate heterogeneous WSNs (HWSNs) [6], where nodes have varying energy levels, computational capabilities, and communication ranges. This diversity introduces both opportunities for improved performance and cost-effectiveness, a s w ell a s c hallenges related to network management and energy consumption (EC). The use of energy-efficient (EE) routing in HWSNs is necessary since SNs are powered by limited battery capacities and inefficient routing causes quick depletion of energy thereby shortening the lifetime and reliability of the network [7-9].

WHAT THIS STUDY ADDS ON THIS TOPIC?

- *This research proposes and implements an optimized fault-tolerance method through a hybrid optimized harmony search enhanced distributed energy-efficient clustering (HS-EDEEC) algorithm, designed for routing in IoT-based WSNs.*
- *The proposed method demonstrates significant improvements, achieving up to 6.7 joules in EC and an average computation time (CT) of 1.2 seconds, while enhancing FT. Additionally, it shows a 12% reduction in EC, offering an effective approach to minimize both energy usage and CT in WSN-based IoT networks.*
- *The research empirically validates the HS-EDEEC model as a promising solution, positioning it as an energy-efficient transmission model for route probability in heterogeneous WSNs within IoT networks.*

Several strategies, such as clustering and multi-hop communication, have been proposed to optimize energy usage. Clustering reduces EC by organizing nodes into groups with designated cluster heads (CHs) that aggregate and transmit data, while multi-hop communication breaks down long-distance transmissions into shorter, less energy-intensive hops. Despite the advantages of these techniques, challenges remain in ensuring the fault tolerance (FT) and security of WSNs in IoT applications. The need for optimized fault-tolerance methods that can handle the constraints of WSNs while improving energy efficiency is becoming more urgent. The paper focuses on an optimized fault-tolerance method using a hybrid optimized harmony search enhanced distributed energy-efficient clustering (HS-EDEEC) based on a routing method for IoT-WSN. It presents the HS-EDEEC method and existing model issues in IoT-based WSNs. It proposes a fault detection and tolerance model concerning choosing and optimizing the given route responses to detect faults and provide a probability value for the best route. The proposed model tolerates the faults by developing a minimum average computation time (CT) or an EC value.

- The proposed HS-EDEEC approach integrates HS with EDEEC to enhance fault detection, EC, and tolerance in IoT networks through dynamically adjusting the selection of (CHs).
- By incorporating probability values, residual energy (RE), and network performance metrics, the HS-EDEEC approach optimizes route selection in IoT networks. This helps in improving fault detection accuracy and reduces the likelihood of selecting unreliable routes, thereby enhancing network performance and stability.
- The decision-making process in the proposed approach is significantly enhanced through the evaluation and comparison of probability sets. Routes are classified into optimal and worst-case scenarios, with the worst-case routes being eliminated.
- This ensures that only the most reliable routes are selected, contributing to better overall network performance and energy-aware FT.

The proposed article is prepared as a trial: Section I defines an overview of WSN and IoT with FT. In Section II, the existing FT routing and optimization methods are described. Section III illustrates the proposed work. Section IV shows the performance metrics with outcomes and graphical representations. This proposed work is determined by defining the further improvements in Section V.

A. Related Works

An EE routing method based on grid cells (GCs) or clusters to enhance the network lifetime of WSN-based IoT was presented in [10]. In the EE routing method based on GC, the complete network area was divided into virtual groups, and the number of SNs was managed between cells. So, a CH node was selected according to the RE and the distance between the destination nodes in each cell. However, to determine the routes for data delivery inside and their CH node into the minimum spanning tree. In the future, the ant colony optimization (ACO) will be used to search the paths of data transmission packets from CH nodes to sink to optimize energy utilization. The experiment outcomes indicated that the EE routing method's performance is better than other methods such as power efficient gathering in sensor information systems, low-energy adaptive clustering hierarchy (LEACH), power efficiency grid-chain routing protocol, etc.

A heterogeneous network with a huge network lifetime and maximum throughput while utilizing maximum electricity was discussed in [11]. Requirements like the field, nodes, destination position, etc., must be defined. Network throughput, data transmission rate, analysis of live nodes, and optimization in EC node were all parameters in this approach CH selection. So, creating an embedded IoT system was difficult. The proposed adaptive distributed energy-efficient clustering model results in a network throughput of 19% compared to other methods.

The previous issues of resource allocation and routing procedures for IoT networks based on scheduling and optimization approaches are analyzed in [12]. They have studied several routing methods that measured safety evaluations and improved the network metrics. Resource allocation approaches elaborated the queue-based method for selecting the best route for further paths based on the number of constraints, which enhances the way of discovering structure.

The EE ultra-scalable ensemble clustering method designed to cluster nodes to manage huge amounts of data effectively in [13]. The flamingo search method was employed for CH selection due to its minimum complexity and maximum stability. Lastly, the q-learning approach was adopted to choose the small route between CHs and base station (BS) as it was reliable for route

selection in difficult network situations. The simulation outcomes with existing methods include alive nodes (ANs), time consumption, last node dead, first node dead, half node dead, network throughput, and total RE.

The hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) reptile optimization method for verifying the optimized path from cluster to destination was developed in [14]. Then, the tuned supervision-based FT plan can be carried out to diagnose the distinct faults such as RE, communication, and sensing faults in IoT-WSN.

IoT-based WSNs for smart agriculture, developed a novel IoT-based WSN framework [15]. Wireless sensor networks are widely used in agriculture to monitor crop conditions, automate precision farming, and collect data on temperature, humidity, and irrigation. However, sensor constraints like limited processing power, energy, and memory can hinder performance, while security threats from malicious adversaries remain a concern. The proposed framework includes a multi-criteria decision function for cluster head selection and uses the signal-to-noise ratio to ensure efficient data transmission. Data security is enhanced through the recurrence of the linear congruential generator. Simulation results show significant improvements, including a 13.5% increase in network throughput, a 38.5% reduction in packet drop ratio, a 13.5% decrease in latency, a 16% reduction in EC, and a 26% decrease in routing overheads compared to existing solutions. This framework offers a robust approach to enhancing productivity and efficiency in smart agriculture.

To address resource limitations and security challenges in IoT-based WSNs for smart agriculture, proposed a novel IoT-based WSN framework [16]. The proposed algorithm begins with node identification assignment and utilizes distributed fuzzy cognitive maps (DFCM) to select CHs based on energy levels, proximity to the BS, and neighbor count, ensuring balanced CH distribution for optimal energy usage. Secure data transmission is achieved through the earthworm-based deer hunting optimization algorithm and blockchain-based integrity checking. Comparative analyses with existing techniques, including genetic algorithm-particle swarm optimization (GA-PSO), chaotic improved-reptile search algorithm, accelerated cultural independent-group search optimizer, and parallel water wave optimization (P-WWO), demonstrate the superiority of the proposed method. At varying node densities, the approach achieves a 60% increase in network lifetime over GA-PSO, sustaining an average of 3200 rounds. Energy consumption is reduced by 33.3% compared to GA-PSO at 100 nodes, while the packet delivery ratio (PDR) reaches 98%, a 4% improvement over P-WWO. Throughput at 500 nodes increases by 33.3%, reaching 0.8 Mbps. Additionally, the method sustains 66.7% more active nodes at the three thousand five hundredth round, with a higher detection rate (75%-90%) and faster convergence. This optimized secure cluster-based routing protocol with blockchain presents a comprehensive solution for enhancing the efficiency, resilience, and security of WSNs in smart agriculture. To address the challenges of energy efficiency and scalability in WSNs and the IoT, presented an energy efficient data communication (EEDC) scheme utilizing a "Region-based Hierarchical Clustering for Efficient Routing (RHCER)" framework [17]. Wireless sensor networks and IoT have emerged as transformative technologies with applications in environmental monitoring, agriculture, manufacturing, smart health, home automation, wildlife monitoring, and surveillance. However, issues such as population growth, climate change, and resource constraints pose significant challenges for modern IoT applications. For example, in agriculture, IoT-based WSNs are used to monitor yield conditions, automate precision farming, and collect data on crop health, soil moisture, temperature, and irrigation systems. Despite their potential, sensors face limitations such as finite, non-rechargeable batteries and restricted memory capabilities, which can negatively impact network performance, particularly when deployed over large areas.

A fault-tolerant clustering approach using the cat optimization algorithm to improve target tracking in WSNs was suggested [18]. The method minimizes target loss, reduces EC during recovery, and prevents data loss. Simulations in optimized performance network show significant improvements over existing protocols; it reduces end-to-end delay by 84.93%, lowers media access delay by 15.08%, and improves throughput by 3.84%. Compared to dynamic capacitated road routing problem, it enhances media access delay by 2.90%, throughput by 2.02%, and reduces EC by 0.30%. While the approach shows trade-offs in energy and delay when compared to existing approaches, it outperforms other protocols in several key metrics, confirming its effectiveness in target tracking optimization.

A hybrid strategy enhancing LEACH by integrating balanced relay and backup cluster head selection with improved CH mechanisms are presented [19]. It incorporates the base station reachability factor and link reliability period for EE clustering. The backup CH selection, using dual-density factor and RE, ensures FT. A PSO-based relay node strategy boosts communication and reduces EC through Link Quality Indicator and data propagation time. Results show the approach improves network lifespan, FT, and load balancing, achieving 3.98 joules of energy and 0.38 seconds delay in a 250-node setup. The Selection of Wireless Active Routing Algorithm using Metaheuristics (SWARAM), which is based on the Osprey Optimization algorithm, was utilized to perform energy-efficient cluster head (CH) selection in wireless sensor networks (WSNs) deployed for Internet of Things (IoT) applications [20]. The SWARAM approach involves two phases: cluster formation using Euclidean distance and CH selection using the SWARAM technique. Simulations in MATLAB2019a show that the SWARAM algorithm reduces EC to 0.35 J, compared to 0.59 J for energy-efficient cluster head selection-artificial rabbits optimization, 0.54 J for HSWO, and 0.45 J for EE cluster head selection in WSNs Using an improved grey wolf optimization over 4000 network rounds. SWARAM reduces EC by 24%, 20%, and 10% compared to these methods, while also achieving faster convergence in CH selection due to its use of residual energy ratio (RER) and distance parameters in the fitness function.

The squirrel search algorithm (SSA) for optimal CH selection in WSN, with modifications to addressed the specific CH selection needs [21]. The improved squirrel search algorithm integrates enhancements like adaptive population initialization, dynamic step size control, and a local search algorithm to improve convergence and solution quality. The goal function considers CH balance, sink distance, RE, and intra-cluster distance. Simulations show that the ISSA-C method achieves a PDR of 88%, outperforms GWO, sparrow search algorithm, and multi-agent pathfinding using ant colony optimization (MAP-ACO), reduces EC to 210 mJ, and improves bit error rates. It also reduces cluster formation and head selection times to 82 seconds and 67 seconds, respectively.

The camel series elephant herding optimization (CSEHO) algorithm, which combines the Camel algorithm's exploration capabilities with the EHO algorithm for optimal cluster head selection (CHS) was introduced [22]. The Camel algorithm mimics the scavenging behavior of camels, improving exploitation efficiency, while EHO enhances exploration through its clan and separator operators. Simulations show that the CSEHO algorithm outperforms existing CHS algorithms, achieving 21.01%, 31.21%, 44.08%, 67.51%, and 85.66% better performance than EHO, CA, PSO, LEACH, and decision tree, respectively.

II. MATERIAL AND METHODS

Internet of Things platforms are putting much work into conserving energy in WSNs. Many IoT devices send data to facilitate IoT connectivity in WSNs. A significant amount of energy is needed to execute the IoT system and transfer the massive amounts of data generated by IoT devices. As a result, IoT system energy usage remains a significant concern. In addition, data transmission delays are a major issue for wireless sensor systems. They can occur due to data traffic issues or other unwanted circumstances in the transmission medium. The existing techniques need to be more efficient in managing the transmission of packets, which causes timeouts or packet drops. Fig. 1 shows the general scheme of the work of the proposed HS-EDEEC algorithm of fault detection and route optimization in IoT networks. The two sequential phases of the workflow are presented. Phase I involves the configuration of the route response database (RDB) and parameters related to the node are obtained to build the route health database (RH-DB). On the basis of these parameters, candidate routing solutions are initially generated randomly, and selection and replacement operations take place to assist in optimization. Phase II is concerned with testing the solutions generated. Candidate routes are evaluated, compared, and allocated optimized probabilities of the routes to aid in decision-making. The routes are categorized as the worst-case or the best-case routes based on predefined fitness criteria. The worst-case routes are removed, and the optimum routes are sent through the termination check, and the final optimum route is selected. The proposed approach enhances fault detection by optimizing route selection based on probability values, RE, and network performance metrics. Unlike traditional clustering-based approaches, HS-EDEEC integrates HS with EDEEC to dynamically adjust CH selection based on RE, node density, and fault probability metrics. The HS algorithm plays a key role in optimizing routing decisions. It utilizes a harmony memory (HM) structure to store candidate solutions, where each solution represents a potential routing path. The HM size determines the number of stored solutions. New solutions are generated using the HM considering rate (HMCR) and pitch adjustment rate (PAR), which control memory usage and fine-tuning, respectively. This improvisation process iteratively refines routing paths based on network conditions. Unlike ACO, which relies on pheromone updates, HS employs a memory-based stochastic optimization mechanism, making it more suitable for dynamic IoT-based WSN environments. The process begins with configuring the RDB. If the RDB exists, node parameters such as packet drop rate, computation capacity, and network congestion status are extracted. These parameters are used to construct a RH-DB, which helps evaluate the reliability of different routes. The next phase involves initializing random solutions and selecting potential routes based on the extracted parameters. If a selected route is not suitable, replacement mechanisms are applied to refine the options. In parallel, an evaluation and comparison process is performed to optimize probability sets, ensuring an efficient decision-making process. The system then classifies routes into optimal and worst-case scenarios. The worst-case routes are eliminated, while the optimal ones proceed to the termination check. If an optimal route is found, the process stops; otherwise, it loops back to refine selections until an optimal route is determined.

It is concerned with choosing and optimizing the given route responses to detect faults and provide a probability value for the best route. It enhances the performance of the workings of the proposed architecture and offers a high transmission rate in IoT network

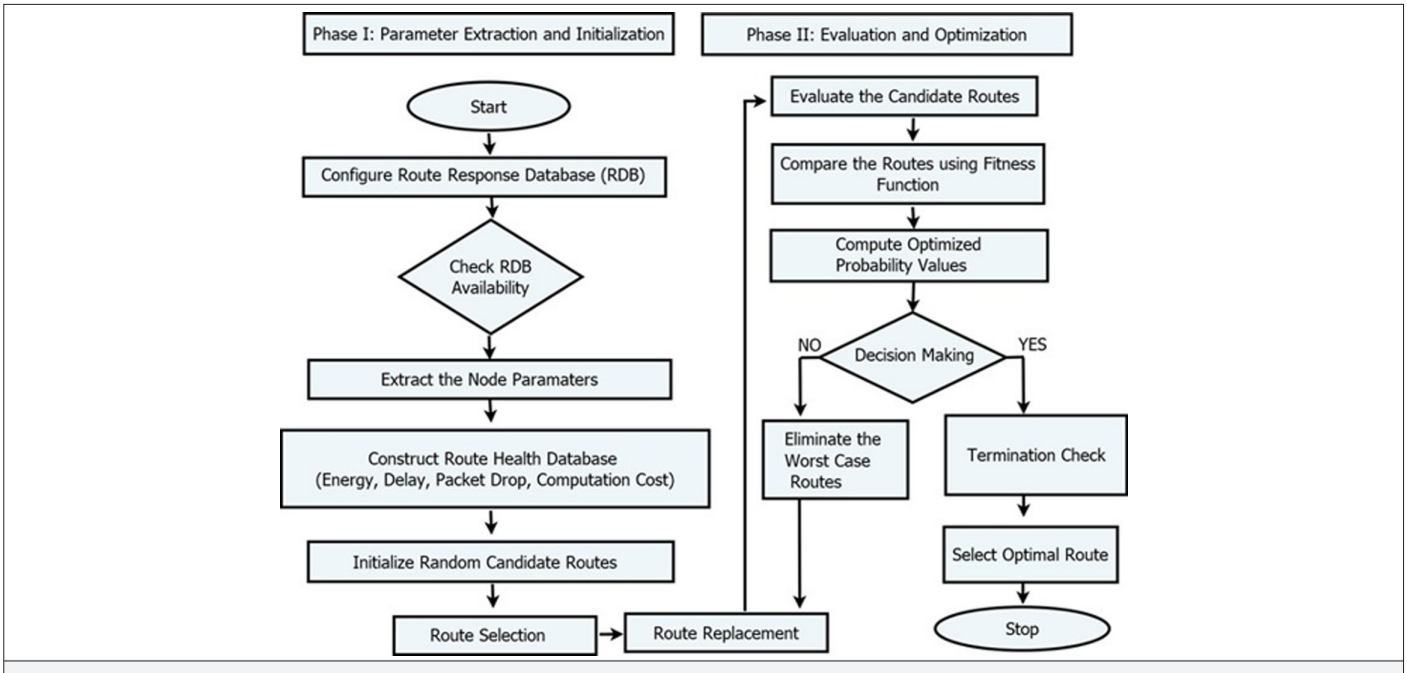

Fig. 1. Proposed routing architecture.

communications. The processed RDB is the initial input for the fault identification process, given in (1).

$$RDB = \sum_{i=0}^{R} R_i \tag{1}$$

Where, R_i indicates the response of the i-th candidate route, and R denotes the total number of route responses in the database. Only in the case when the RDB is available in the network repository and has valid route responses, the fault detection and optimization modules are activated.

The selection criteria for probability values in route selection are now empirically justified based on RE, transmission success rate, and historical fault data. These parameters lead to selecting and establishing a better communication route between the network nodes. The wrong node parameters can create a fault in the network transmission and degrade the transmission performance of the IoT networks. The extracted parameters of the network nodes create a dependency model and are loaded into the optimization process as the initial population. The optimization process executes various operations while keeping the random upper and lower bounds in mind. Let x_i denotes the i-th decision variable as a routing parameter (e.g., RE, delay, or packet drop rate). The starting value of every variable is produced within stipulated minimum and maximum limits as follows in (2).

$$x_i^{'} = x_i^{lower} + rand \times \left(x_i^{upper} - x_i^{lower} \right) \tag{2}$$

Where, x_i^{lower} and x_i^{upper} denotes the total possible maximum and minimum values of the decision variable x_i, respectively, and rand$\in$ [0,1] and is a uniformly distributed random number.

The optimization process performs various operations like selecting instances, evaluations, and comparisons for the best fitness calculation of the node's health toward the faults. It processes and evaluates the final probability calculations toward the best and worst-case scenarios, assisting in the selection of the best transmission route for the packets.

In order to statistically prove the performance improvement of the proposed HS-EDEEC model, the pairwise comparison of the model was done with the current methods using a two-tailed t-test on 20 independent simulation runs. To help in choosing the routing paths within the HS framework, a probabilistic evaluation function is proposed. This operation prioritizes candidate routes stored in the HM on the basis of several performance indicators, such as RE, link quality, as well as transmission reliability. In contrast with classical models based on the use of pheromones, this model is formulated in such a way that it supports the improvisation process of HS on (3).

$$P_{kl}^{m}(u) = \frac{\left(\mathcal{T}_{kl}^{\alpha} \cdot \eta_{kl}^{\beta} \cdot E_l^{\gamma} \right)}{\sum_{s \,\epsilon\, allow_m} \left(\mathcal{T}_{ks}^{\alpha} \cdot \eta_{ks}^{\beta} \cdot E_s^{\gamma} \right)} \tag{3}$$

Where,τ_{kl} denotes the HM quality of the route between nodes k and l. η_{kl} denotes the heuristic desirability factor associated with the route, and E_l is the RE of node l. The set $s \,\epsilon\, allow_m$ includes all feasible candidate routes at iteration m. The paramterss α,β, and γ are weighting factors that regulate the effects of memory of harmony, heuristic desirability, and RE respectively. η denotes heuristic desirability calculated from link quality such as delay and packet success rate, and E denotes RE of nodel I.In this context, HM acts as a repository of candidate routing paths, and the probability function in (3) is used to rank and refine these candidates during the improvisation process rather than guiding path construction as in ACO. Fig. 4 illustrates the routing architecture of the proposed HS-EDEEC algorithm. It represents the fault detection and tolerance process in the proposed HS-EDEEC approach for IoT networks. The process begins with the deployment of SNs in a specific network area, where each node is assigned properties such as location, initial energy, and other communication parameters. The deployed nodes are then grouped into clusters, and a threshold value is generated to facilitate the selection of CH based on RE and fault probability. Once the clusters are processed, the network initiates a route request, and RDB is collected to determine potential transmission routes. Before transmitting data, the system gathers routing information to ensure optimal path selection. If data packets fail to transmit, the process loops back to collect updated routing details. If transmission is successful, performance metrics such as EC, throughput, and network lifetime are evaluated. The final processed RDB is updated with optimized modules to enhance route selection, ensuring efficient fault detection, energy optimization, and improved reliability in IoT communication.

The routing algorithm collects information from the network and delivers it to the appropriate destination. Before the routing in the simulation environment, the system needs some nodes and network routes for communications. The initial step for an IoT network formation is to deploy nodes with some specifications in the particular network area. The deployed nodes can have various parameters, like energy, coverage areas, network location, etc. Once the network node deployment is executed, the system defines network CHs according to the parameters and coverage details. The central aspect of the CH selection is shown in (4)

$$\frac{P_i}{1 - P_i \left(\frac{r_{mod}}{1 / p_i} \right)} \tag{4}$$

If $s_i \in G$.

Here, in (4), the G belongs to the deployed nodes in the network area and the calculated threshold of the node vector. P_i is the probability associated with node i being he CH and r_{mod} is the threshold modification factor for the selection. It indicates whether or not the node in the network area is suitable for the CH. The CH selection procedure in the network divides the nodes and places of transmission. Now the network protocol generates the initial request for the packet transmission and generates a response as RDB for the fault detection and tolerance module. An intelligent best-fit selection module provides better route selection with lower minor fault and packet drop probabilities. The network protocol initializes the route, transmits data over the network, and monitors side by side to find the best processing results. At the end of the transmission, the network calculates some performance parameters like accuracy, loss, throughput, etc., to validate the performance of the protocols and overall transmission quality.

ALGORITHM 1: HS-EDEEC ROUTING OPTIMIZATION

Input: SNs, network parameters

Output: An optimal path.

1. Add SNs and set parameters (RE, delay, packet drop rate)
2. Produce route request (RREQ) messages and create RDB.
3. Derive node features, construct RH-DB.
4. Initialize candidate routes (2) and values of pheromones of ACO.
5. Use ACO to build routes and rebuild pheromone according to the fitness.
6. Optimize paths with HS (HMCR, PAR) and score with (3).
7. Prioritize routes, eliminate worst-case routes, choose good route R and update RDB/RH-DB

III. RESULTS

The experiment was conducted in a WSN network with various scenarios involving changing sensor populations ranging from 100 to 500 SNs and randomly organizing sensors across a 1000 × 1000 meters area. However, the next research work will include the test cases based on the different nodes (100, 500, 1000, etc.). The fixed workload of five sources and one destination is utilized. The sensors' energy distribution is measured in the data packet. According to the metric, the nodes are organized to dissipate energy. For an experimental analysis of the proposed work, the network's simulator tool MATLAB version 2018a was utilized and further will use network simulator (NS2) and objective modular network testbed in C++ (OMNeT++) for comparison analysis. All proposed parameters' initial values are shown in Table I such as initial energy, transmission and receiving energy, amplification energy for short_dist., amplification energy for long_dist., etc.

Therefore, the HS-EDEEC model has been submitted and calculated with the following parameters:

A. Energy Consumption

This is the proportion of total frictional losses to node count based on (5).

$$EC = E_{idle} + \sum_{v \in V} \sum_{p \in P} w(p) * A * E(u,p) \quad (5)$$

B. Computational Time

Computational time refers to the total time required to execute a given process or algorithm, including data processing, transmission, and reception within the network based on equation (6).

$$CT = T_{end} - T_{start} \quad (6)$$

TABLE I. SIMULATION PARAMETERS

Parameters	Values
E0 (initial_energy)	0.5 joule
Eelect (transmitting and Receiving energy)	5nj per bit
Efs (amplification energy for short_dist)	10 pJ per bit per m^2
Emp (amplification energy for long_dist)	0.013 pJ per bit per m^2
Eda (data aggregation_energy)	5 nj per bit per signal
m (percentage of advance nodes)	0.1
Advanced node energy	E0 (1+a)
Metrics	Energy and computation time

Where: T_{end} = Time when the process or computation finishes and T_{start} = Time when the process or computation begins.

In order to statistically prove the performance improvement of the proposed HS-EDEEC model, the pairwise comparison of the model was done with the current methods using a two-tailed t-test on 20 independent simulation runs.

IV. DISCUSSION

The network performance metrics are discussed in the Section V. The research work has calculated two metrics, average CT, and EC. The remaining parameters, such as (PDR, throughput, and delay) are discussed in detail and the proposed model has achieved the minimum energy and delay as compared to the other routing protocols. The comparative analysis is shown in Table II.

The deployment and route selection within the network are presented in Fig. 2. It communicates between nodes using the routing method. The transmission performed in this network is dependent on the nodes, and CH nodes are used both within and outside the cluster.

The lines show the connections between several nodes and the data transmission between them. The proposed model has defined the transmission process in the deployment network and the message of data packets from the source to the destination node. In this network, search the source node for signal broadcasting and the destination node for the end of the communication.

Fig. 3 shows the comparison of EC performance metrics between HS-EDEEC and existing models to evaluate the network cost. The maximum EC defines the network's high price and minimum lifetime. The network lifetime is automatically reduced if the EC is high. The EC of the network is the highest compared to the other methods. The proposed HS-EDEEC model has reduced the EC by 12% ($P < .02$) compared to the existing EFT-PMD, EESIoT, DFCM, and EEDC model.

Fig. 4 shows the comparison of CT between HS-EDEEC and the existing model. It usually consumes time to select CH during the broadcast. This time slot defines the execution speed and evaluation of several network characteristics and searches for a better CH to restart the network performance metric. The proposed method has

TABLE II. COMPARATIVE ANALYSIS OF PROPOSED MODEL

Method	Energy Consumption (Joules)	Average Computation Time (Seconds)	Fault Tolerance Rate (%)
Proposed (HS-EDEEC)	6.7	1.2	95
EFT-PMD[23]	17.9	3.1	80
EESIoT[24]	26	13.5	60
DFCM	33	—	50
EEDC	31	—	55

DFCM, distributed fuzzy cognitive maps; EEDC; energy efficient data communication; EESIoT, energy-efficient secure-based internet of things; EFT-PMD, ; HS-EDEEC, hybrid optimized harmony search enhanced distributed energy-efficient clustering.

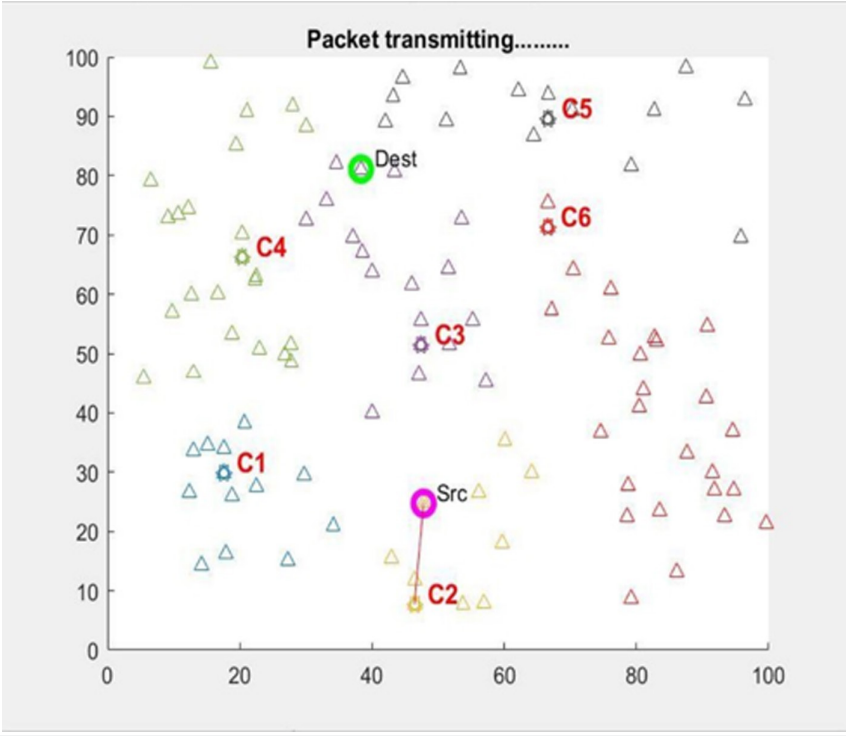

Fig. 2. Deployment and route selection within the network.

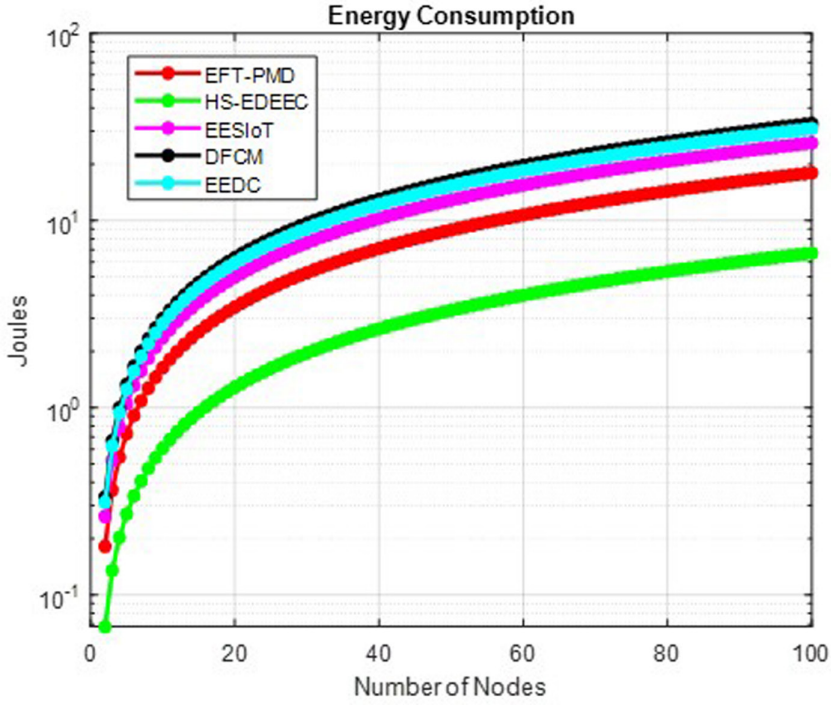

Fig. 3. Comparison of energy consumption.

achieved minimum CT, resulting in better network performance. The proposed HS-EDEEC model has produced better output by reducing average CT compared to the existing EDEEC, existing EFT-PMD, and EESIoT model.

Fig. 5 shows that the HS-EDEEC method outperforms the other approaches in FT, with a rate of 95%. It is more effective in handling network faults compared to EFT-PMD (80%) and EESIoT (60%). Both DFCM (50%) and EEDC (55%) show lower FT, indicating their reduced

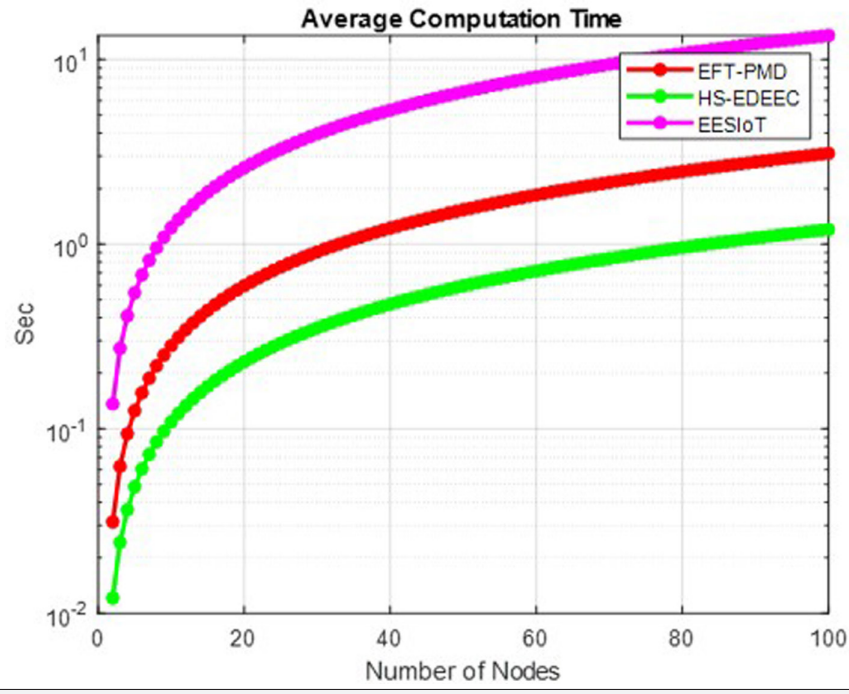

Fig. 4. Comparison of average computation time.

resilience in fault-prone environments. Overall, HS-EDEEC demonstrates superior reliability for IoT networks.

Statistical significance was confirmed with a two-tailed t-test with *P*-values of .018, .011, .009, and .013 when compared with EFT-PMD, EESIoT, DFCM, and EEDC, respectively. The improvements are statistically significant since all the values are less than 0.05.

VI. CONCLUSION

The proposed HS-EDEEC method and existing model issues in IoT-based WSNs are being investigated. The proposed model of fault detection and tolerance is divided into different phases. The initial phase belongs to the fault detection and tolerance process, with the help of various parameters and optimized decision-making

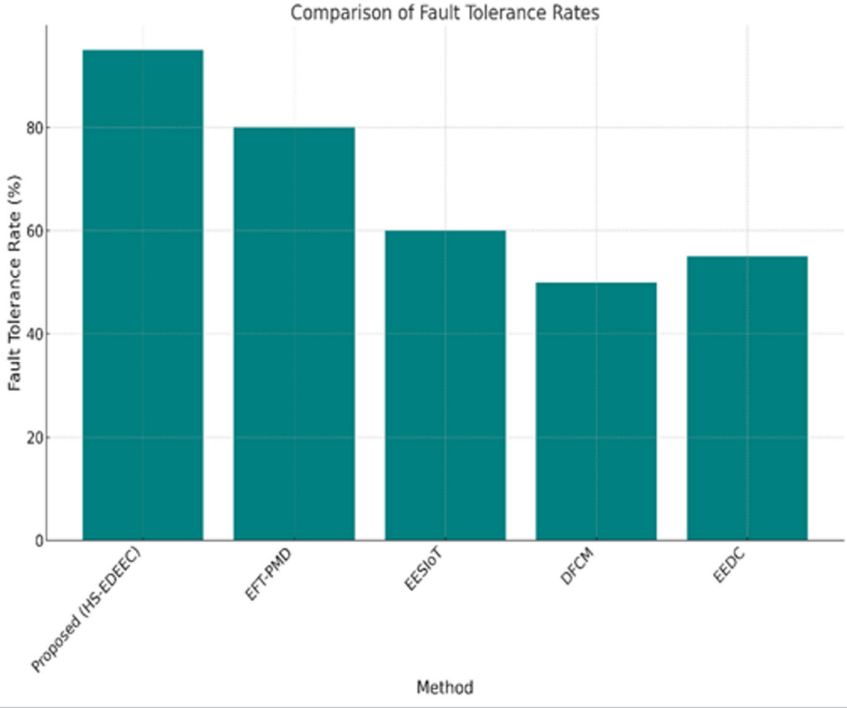

Fig. 5. Comparison of fault tolerance rate.

techniques. The second flow belongs to network working and the validation of the proposed architecture. It is concerned with choosing and optimizing the given route responses to detect faults and provide a probability value for the best route. It enhances the performance of the workings of the proposed architecture and offers a high transmission rate for IoT network communications. The research model has used the HS-EDEEC model and adequate tolerance of the failure of CH. It is explored whether the research model can be fault-free and improve EC and time. The proposed HS-EDEEC model has better FT than current routing protocols like LEACH, EEDC, and EFT-PMD, with probability-based route selection and better energy efficiency via HS optimization. Compared to the traditional approaches, which use static clustering, HS-EDEEC dynamically changes according to the network conditions, which leads to improved robustness and reliability.

As an outcome, the research model has tolerated the faults by developing a minimum average CT and EC value. Improving network performance by enhancing FT through homogeneous and hybrid routing methods can be beneficial further.

Although the performance of the proposed HS-EDEEC model is promising, there are some limitations. The existing solution lacks adaptive machine learning-based clustering or mobility-aware solutions, which could restrict its usefulness in dynamic and large-scale IoT settings. Also, security and privacy factors have not been properly discussed and the model has emphasized more on EC and CT with limited assessment of other parameters like PDR, throughput, and delay. Future development will be aimed at enhancing scalability, incorporating advanced security measures, and better network performance.

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