Grenze International Journal of Engineering and Technology, January Issue

An Adaptive Weather Resilient Systems using FBODCHS Algorithm

S.Mathavi[1], Dr.N.Uma Maheswari[2] and Dr.S.Jeyanthi[3]
[1]Assistant Professor Dept. of Electronics and Commnuication Engineering RVS College of Engineering and Technology Dindigul, Tamilnadu, India
Email: mathavi.2007@gmail.com
[2]Professor Dept. of Computer Science and Engineering PSNA College of Engineering and Technology Dindigul, Tamilnadu, India
Email: numamahi@psnacet.edu.in
[3]Lecturer Dept. of Computer Engineering Government Polytechnic College Karur, Tamilnadu, India
Email: sjeyanthigpt@gmail.com

***Abstract*—Internet of Things (IoT) has significantly transformed various aspects of human life. In this paradigm, sensor nodes connect multiple physical devices and systems over the network to collect data from remote places, such as precision agriculture, wildlife conservation and intelligent forestry. However, the limited battery life of sensor nodes affects the network's longevity and necessitates continuous maintenance, making energy conservation a critical issue. An Adaptive Weather Resilient System using the FBODCHS (Fuzzy-Based Optimized Dynamic Cluster Head Selection) algorithm is designed to enhance the performance and longevity of IoT networks, particularly in applications where weather conditions can impact sensor node efficiency and energy consumption. Clustering is crucial in IoT to optimize energy efficiency and extend network lifespan. Numerous clustering protocols have been introduced in recent years to address this, but networks often face an energy-hole issue due to the selection of inappropriate Cluster Heads (CHs). A CH manages and coordinates communication among nodes in a cluster, avoiding redundant data transmission by collecting and aggregating data. Thus, the CH plays a pivotal role in achieving efficient energy optimization and network performance. To tackle this problem, we propose an osprey optimization algorithm based on energy-efficient cluster head selection in a wireless sensor network-based IoT to identify the best CH in the cluster. Nodes are clustered using Manhattan distance before the CH is selected using the FBODCHS algorithm. Simulation of the proposed FBODCHS algorithm was conducted in the SCILAB tool. The performance of the SWARAM algorithm was compared with existing EECHS-ARO, HSWO, SWARAM and EECHIGWO. The suggested FBODCHS improves the packet delivery ratio and network lifetime, thereby enhancing the overall performance of the network.**

***Keywords*— Cluster Head selection, Internet of Things, Optimization, Weather resilience and Wireless Sensor Network.**

I. INTRODUCTION

Climate resilience refers to the ability to recover from or reduce vulnerability to climate-related shocks, such as floods and droughts.

Grenze ID: 01.GIJET.11.1.319_2

As transportation systems increasingly face the impacts of climate change and extreme weather events, their long-term reliability and functioning must adapt to these new conditions. Historically, these systems were designed for climate conditions that are now often exceeded. Modern planning for climate change emphasizes risk-based approaches and more robust infrastructure designs.

Wireless Sensor Networks are decentralized networks consisting of numerous sensors deployed in an ad-hoc manner. These sensors monitor physical, environmental, or system conditions and each sensor node includes an onboard processor for managing its specific area. Nodes communicate with a central Base Station, which processes and shares data over the internet. WSNs are employed for data processing, analysis, storage and mining with nodes gathering and wirelessly transmitting environmental data to destination nodes for analysis. These nodes pre-process data through electrical signals before communication. The effective transmission and reception of data are essential, supported by advancements in small, energy-efficient sensors.

WSNs have diverse applications in real-time scenarios across industries such as intelligent infrastructure, military systems and industrial automation. Some applications require extensive deployment of sensor nodes for real-time responsiveness. WSNs can dynamically restructure in response to factors like node mobility, environmental changes, and node additions or removals, optimizing network efficiency. However, ensuring the longevity of these networks is challenging due to the constraints of sensor nodes, including limited processing power, memory capacity and battery life.

Various strategies aim to extend the network's lifespan, focusing on conserving energy during data transmission. Effective routing is crucial as the number of sensor nodes grows, necessitating multi-hop communication [6]. Given the battery-powered nature of sensor nodes, effective energy management is essential. Hierarchical routing and clustering techniques are commonly used to address these energy concerns. Clustering protocols minimize energy consumption and enhance network lifespan by grouping sensor nodes into clusters managed by Cluster Heads that communicate with other cluster members.

Recent research has explored numerous optimization techniques for selecting the optimal CH such as particle swarm optimization, artificial bee colony, golden jackal optimization, coati optimization algorithm, marine predator optimization and whale optimization algorithm. However, these methods often have significant convergence times, leading to rapid battery depletion. To address this issue, the fuzzy based optimized dynamic cluster head selection algorithm has been proposed. FBODCHS offers faster convergence during the CH selection process, significantly improving the network's performance and adaptability compared to other optimization algorithms.

II. Related Works and Problem Formulation

In Wireless Sensor Networks, energy efficiency is crucial because sensor nodes are often battery-powered and located in remote, inaccessible areas. Selecting a cluster head is a key technique for maintaining network stability by organizing the network into clusters. Despite various CH selection methods [12] being proposed, optimizing energy consumption continues to be a significant challenge in WSNs. This chapter highlights the key drawbacks of existing approaches and provides an overview of current state-of-the-art algorithms, along with their strengths and weaknesses from different researchers' perspectives.

Abraham et al. [1] initiate Flamingo Search Algorithm (FSA) based approach for energy-efficient cluster head selection in Wireless Sensor Networks. It employed an ultra scalable ensemble technique to cluster nodes and manage extensive data within the network. Data packet transmission from Base Station to CH was optimized using the shortest path determined through Q-learning, mitigating challenges posed by complex network conditions. The results demonstrated that FSA-CHS significantly improved network performance through reduced energy consumption and efficient path selection.

Ambareesh et al. [2] proposed the Hybrid Jarratt Butterfly Optimization (HJBO) method for optimal route selection through CH. HJBO combined the FUZZY TOPSIS approach to identify the most efficient path, aiming to minimize energy consumption during data aggregation towards the Base Station. The performance of HJBO was evaluated using MATLAB 2018a, with metrics including energy consumption, delay, throughput, normalized overhead and network lifetime based on node count.

Arunachalam et al. [3] enhanced the squirrel search algorithm to create the Squirrel Search Algorithm-based Cluster Head Selection Technique (SSO-CHST), aimed at extending the lifespan of sensor networks. Incorporate a gliding factor to optimize Cluster Head selection. The fitness function calculated designated CHs and Cluster Members, with nodes showing higher fitness values chosen as CHs and those with lower values as CMs.

Chaurasia et al. [4] suggested Meta heuristic-based approach for cluster head selection (MOCRAW). This method consisted of two main processes: the Optimal Cluster Head Selection Algorithm (CHSA) and the Route

Search Algorithm (RSA). In CHSA, the Energy Level Matrix function was utilized to establish clusters, selecting CHs based on criteria including distance, residual energy, node density, and inter-cluster formation. RSA facilitated optimal path discovery between source and destination nodes, aiming to achieve loop-free routing and minimize communication overhead. MOCRAW's efficiency was evaluated using metrics such as energy consumption, node longevity, Packet Delivery Ratio, and latency. Cherappa et al. [5] introduced an efficient routing protocol-based energy-efficient clustering technique using the Adaptive Sailfish Optimization Algorithm (ASFO). ASFO utilized K-ASFO to select optimal Cluster Heads from suitable nodes, aiming to enhance data transmission efficiency through routing protocol.

Jaya Pratha et al. [7] proposed a hybrid cluster head selection approach in WSN aimed at enhancing energy stability and network longevity. Their study introduced the Hybrid Partha Mutualism Mechanism-inspired Butterfly and Flower Pollination Optimization Algorithm (HMMB-FPOA) for optimal CH selection based on multiple objectives including residual energy, network cost, proximity, and coverage. Ramalingam et al. [8] bring in the Energy-Efficient Cluster Head Selection based on Artificial Rabbits Optimization (EECHS-ARO) for WSN. This algorithm aimed to enhance network lifetime and reduce energy consumption by optimizing the selection of cluster heads. The EECHS-ARO method employed a fitness function incorporating parameters such as remaining energy (RE), distance, and cluster head balancing factors to determine the optimal CH within each cluster. It was noted that the algorithm required more time to converge during CH selection in the network.

Rami Reddy et al. [9] suggests Enhanced Grey Wolf Optimization Algorithm-based Energy Efficient Cluster Head Selection (EECHIGWO) technique for selecting cluster heads in WSN. This approach aimed to optimize the selection of cluster heads to enhance network lifetime, stability, energy efficiency, and average throughput in WSNs. During CH selection, parameters such as average intra-cluster distance, residual energy, distance to the sink node, and cluster head node balancing were considered crucial. Evaluations focused on metrics such as energy consumption, number of dead nodes, average throughput, and operational rounds.

Rama subba reddy et al. [10] proposed Osprey optimization algorithm based on energy-efficient cluster head selection (SWARAM). It improves packet delivery ratio and network lifetime by 10% respectively. SWARAM scheme will be tested with mobility, security, fault tolerance, and load balancing parameters.

Samiayya et al. [11] introduced the Hybrid Snake Whale Optimization (HSWO) technique for optimizing Cluster Head selection to enhance network lifetime in WSN. The method comprised three phases: CH selection, initialization, and route selection. During CH selection, HSWO was employed to select the optimal CH based on metrics such as distance and delay. In the initialization phase, models for distance, energy, and population were established. The route selection phase ensured that sensed data reached the destination via an optimal path without link breakages. HSWO demonstrated superior performance in terms of network energy, throughput, energy consumption, packet delivery ratio, network lifetime, and computational time.

Sindhuja et al. [13] proposed the MOCHSAPGAN-AVO approach for energy-aware multi-objective cluster head selection using African Vulture Optimization in WSN. This method facilitated secure data aggregation by employing a routing process through selected cluster heads, chosen based on a fitness function derived from a self-attention-based progressive generative adversarial network. The fitness function integrated factors such as throughput, delay, energy consumption, distance, and cluster density to determine optimal CHs.

Various optimization algorithms have been applied for Cluster Head selection in Wireless Sensor Networks. However, these methods often face significant limitations, including increased energy consumption, suboptimal CH selection and communication overhead. While numerous CH selection methods have been developed, employing diverse optimization techniques, they still encounter issues like energy inefficiency, improper CH selection and increased communication overhead. To address these challenges, this proposed work aims to develop an efficient adaptive weather resilience system model using the FBODCHS algorithm, focusing on overcoming the limitations of previous approaches and tackling future research challenges.

III. Proposed Work

The proposed adaptive weather resilience system utilizes the FBODCHS algorithm to improve the performance and reliability of IoT networks in weather-sensitive scenarios. It optimizes various parameters in real-time, ensuring efficient and long-lasting operation even in challenging weather conditions. Design of proposed adaptive weather resilience system shown in figure 1 which is divided into four phases as follows:

Phase 1: Sensor Network Model

In WSN individual sensor nodes that collect data from the environment. Nodes are grouped into clusters based on proximity in cluster formation. Clustering is a technique used to optimize energy consumption and extend the network's lifespan by organizing sensor nodes into clusters. Each cluster has a designated Cluster Head responsible for managing communication within the cluster, aggregating data and transmitting it to the central system. Cluster Head is selected for each cluster to manage communication in CH Selection Phase. Selecting an appropriate CH is crucial to prevent energy holes and ensure efficient data transmission. Clusters are formed using distance parameters among nodes in the network.

Phase 2: FBODCHS Algorithm
Cluster Head is selected using the FBODCHS within the nodes to enhance network lifetime and throughput. The fitness function is designed to include distance and residual energy parameters to achieve energy-efficient CH selection. Evaluation factors like energy levels and distance computed using fuzzy logic. Optimize the process of CH selection to enhance network performance using optimization techniques. Consider the environmental factors weather conditions to adapt the CH selection process.

Phase 3: Central Management System
Data aggregation involves collecting and processing information from the sensor network. Additionally, network management oversees the overall network, including node configuration and maintenance.

Phase 4: Adaptive Weather Resilience System
Adaptive weather resilience system focus three factors like energy, network longevity and data reliability. This were achieved using optimize energy use to prolong node lifespan, ensures the network remains operational over time and reduces data loss and ensures precise data transmission

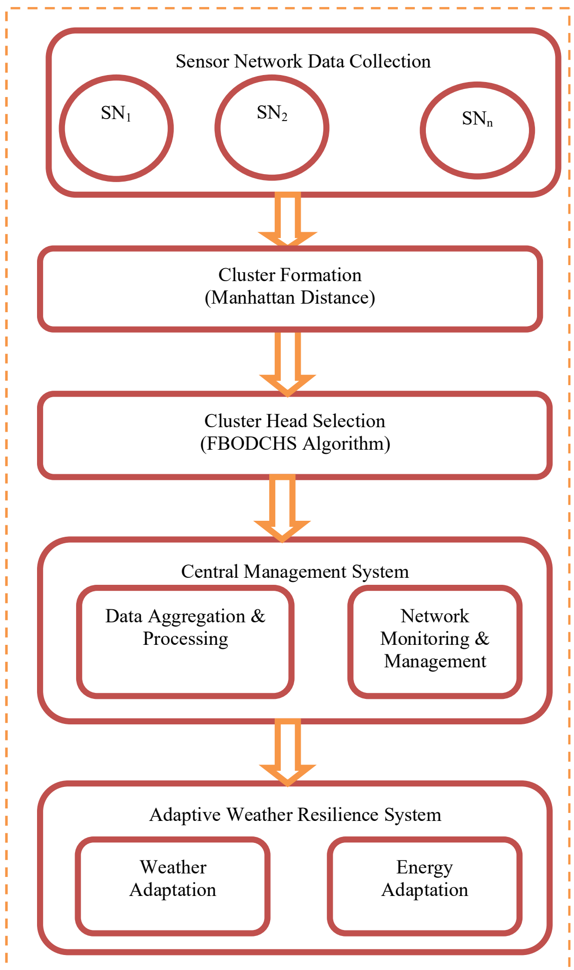

Fig.1. Design of the proposed adaptive weather resilience system

IV. PROPOSED FBODCHS ALGORITHM

The FBODCHS algorithm enhances the CH selection process by incorporating fuzzy logic and optimization techniques. It considers various factors such as node energy levels, distance to the base station and environmental conditions to select the most suitable CH. The algorithm adapts to changing weather conditions, ensuring that the selected CH can handle the additional energy demands imposed by adverse weather. This figure represents how the FBOCHS algorithm integrates into an adaptive weather resilient system to optimize IoT network performance in weather-sensitive applications.

A. Sugeno Fuzzy Inference Systems

Sugeno fuzzy inference uses singleton output membership functions that are either constant or a linear function of the input values. The input values are considered as network lifetime, energy consumption, communication overhead and packet delivery rate. In the proposed work follows four inputs and single output Sugeno fuzzy model. The figure below illustrates how each rule in a Sugeno system works. It depicts a four-input system with input values x_1, y_1, x_2 and y_2.

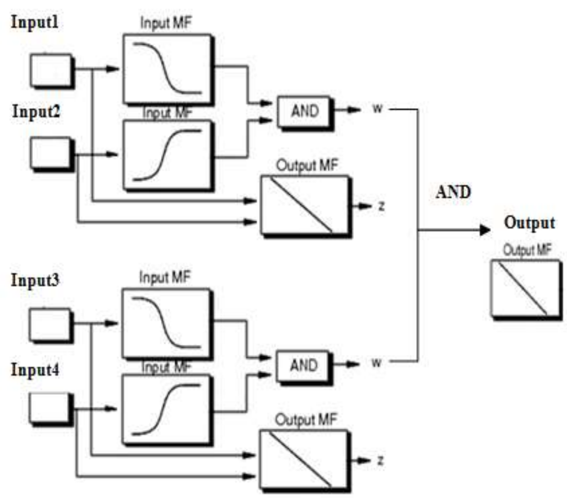

Fig.2. Sugeno model of four inputs with single output

Generally a rule-based framework has fuzzy sets in the antecedents and a crisp function in the consequent which is given below

$$\textit{if } x \textit{ is } A \textit{ and } y \textit{ is } B \textit{ then } z \textit{ is} = f(x, y)$$

where A and B stand in for linguistic variables (like high, medium, low) in the antecedent and consequent z is determines by a crisp function f(x, y). Membership functions that measure x and y's degree of membership in fuzzy sets A and B are used to characterize these sets. Using the provided inputs x and y, the consequent function returns an exact value.
In a Sugeno fuzzy model, a typical rule has the form

$$\textit{if } input_1 = x_1 \textit{ and } input_2 = y_1 \textit{ then output is } z_i = a_i x_1 + b_i y_1 + c_i$$

$$\textit{if } input_3 = x_2 \textit{ and } input_4 = y_2 \textit{ then output is } z_i = a_i x_2 + b_i y_2 + c_i$$

The output level z_i of a zero-order Sugeno model is constant where a=b=0. The firing strength w_i of each rule determines how much weight each output level z_i assigned.
Each rule weights its output level z_i, by the firing strength of the rule, w_i. For an AND rule with $input_1 = x_1$, $input_2 = y_1$, $input_3 = x_2$, $input_4 = y_2$ the firing strength is

$$w_i = AndMethod\,(F_1(x), F_2(y), F_3(y), F_4(y))$$

where $F_{1,2,3,4}(.)$ are the membership functions for inputs 1, 2, 3 and 4. The system's final output (F_o) is the weighted average of each rule's output, which is calculated as

$$F_o = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

where N is the number of rules.

if x_1 *is small and* y_1 *is small then* $z = -x+y+1$
if x_1 *is small and* y_1 *is large then* $z = -y+3$
if x_1 *is large and* y_1 *is small then* $z = -x+3$
if x_1 *is large and* y_1 *is large then* $z = x+y+2$
if x_2 *is small and* y_2 *is small then* $z = -x+y+1$
if x_2 *is small and* y_2 *is large then* $z = -y+3$
if x_2 *is large and* y_2 *is small then* $z = -x+3$
if x_2 *is large and* y_2 *is large then* $z = x+y+2$

The membership function is defined by the following

output = (-1) x *input+(-1)*
output = (1) x *input+(-1)*

V. SIMULATION RESULTS

In this section provides a comprehensive overview of the simulation setup and the parameters used for evaluating the performance of FBODCHS against benchmark techniques. The performance of the proposed FBODCHS approach is evaluated using SCILAB in a simulated network environment with dimensions of 750m × 750m. Fig.3. depicts simulation results of a Sugeno model with four inputs and a single output.

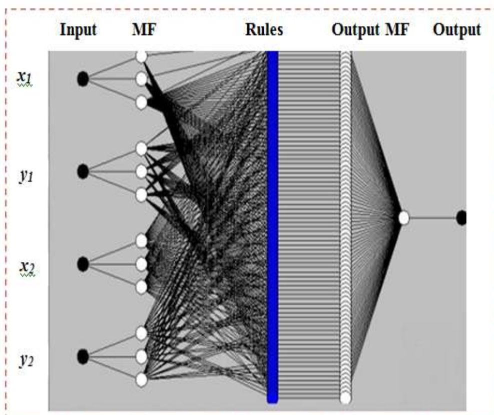

Fig.3. Simulation of four inputs with single output sugeno model

The simulation involves a flat network model where nodes are randomly distributed across the network area. The effectiveness of the FBODCHS technique is compared with several benchmark techniques: EECHS-ARO, HSWO, EECHIGWO and SWARAM. All benchmark techniques are tested with the same set of input parameters.

TABLE I PERFORMANCE METRICS

S.No	Performance Metrics
1	$N_{LT} = min_{i \in N}(T_i)$ - Duration from the start of network operation until the first sensor node exhausts its energy.
2	$A_{EC} = \frac{(E_i)}{N}$ - Total energy consumed by all sensor nodes divided by the number of nodes over a given period.
3	$A_{CO} = \frac{(O_i)}{N}$ - Average amount of additional communication, such as control packets, needed to maintain network operations.
4	$A_{PD} = \frac{P_{i,received}}{P_{i,sent}}$ - Average proportion of packets successfully delivered to the sink node compared to the total number of packets sent by all nodes.

To evaluate the performance of wireless sensor networks often use metrics such as network lifetime, average energy consumption, average communication overhead and average packet delivery to sink. The network is simulated with 1 Joule battery energy for all nodes over a total of 4000 rounds to assess performance and behavior. The sink node is positioned at the center of the network, specifically at coordinates (375m, 375m). In view of nature of node connectivity, each sensor node maintains at least one neighbor node. All nodes in the network are capable of sending data packets to the sink node using a single hop. All nodes have the same communication range but exhibit heterogeneity. Table 1 depicts the performance metrics were help in understanding and optimizing the performance of a wireless sensor network, especially in scenarios involving energy-constrained devices. In table NLT, AEC, ACO, APD presents network lifetime, average energy consumption, average communication overhead, average packet delivery to sink, Ti is the time at which node i runs out of energy, Ei is the energy consumed by node i, Oi is the communication overhead for node i, Pi, received is the number of packets delivered by node i to the sink and Pi, sent is the total number of packets sent by node i and N is the set of all nodes in the network. The performance of the proposed FBODCHS algorithm is evaluated through extensive simulations and compared with four benchmark CH selection algorithms: EECHS-ARO, HSWO, EECHIGWO and SWARAM. Figure 4, 5, 6 and 7 illustrates the network lifetime, energy consumption of nodes, communication overhead and packet delivery. The proposed FBODCHS approach is examined and compared with existing EECHS-ARO, HSWO, and EECHIGWO and SWAEAM approaches.

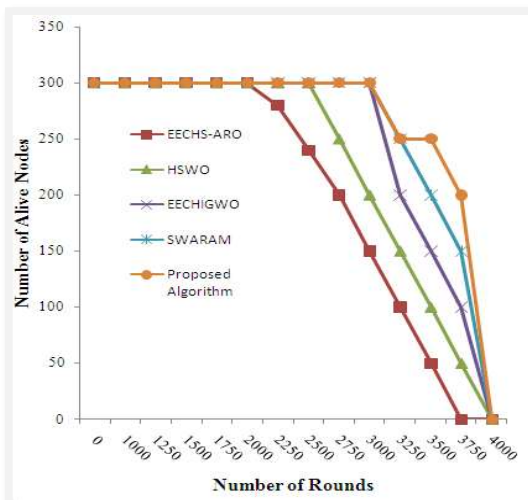

Fig.4 Analysis of Lifespan of the network

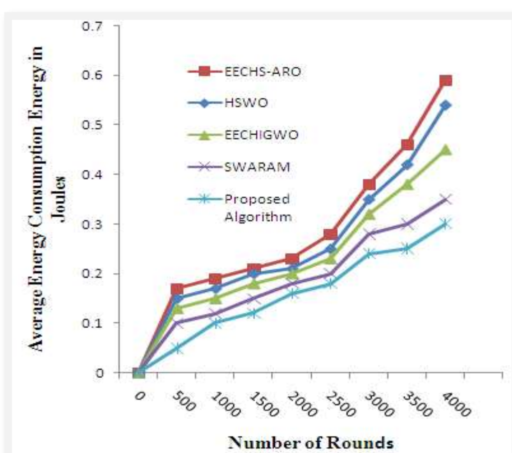

Fig.5 Analysis of nodes energy consumption in the network

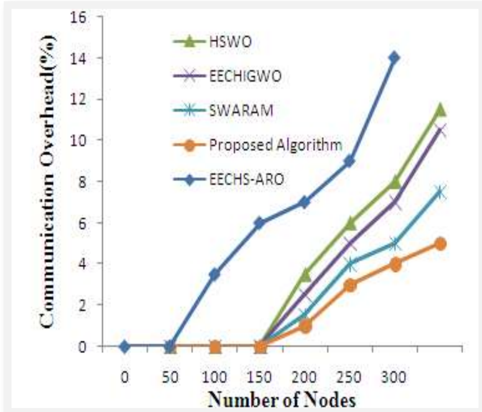

Fig.6. Analysis of communication overhead

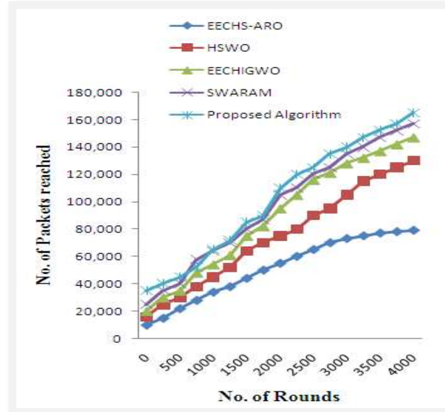

Fig.7. Analysis of packet reached to the destination

VI. Conclusion

An Adaptive Weather Resilient System using the FBODCHS algorithm provides a robust solution for IoT networks in weather-sensitive applications. By optimizing cluster head selection with fuzzy logic and considering environmental factors, the system enhances energy efficiency, network longevity and data reliability. This makes it well-suited for challenging operational environments. This study explores the development and implementation of this adaptive system, leveraging the FBODCHS algorithm to maintain optimal performance under varying and adverse weather conditions. Applications range from transportation and logistics to agriculture and disaster management. The results demonstrate that the FBODCHS algorithm significantly enhances resilience to weather-related disruptions. By incorporating fuzzy logic with dynamic optimization techniques, the algorithm adapts effectively to changing weather patterns and environmental conditions. This adaptability is achieved through a robust decision-making framework that adjusts system parameters in real time, ensuring continuous operational efficiency and reliability. The FBODCHS algorithm represents a significant advancement in adaptive systems, offering a promising solution for maintaining operational integrity and efficiency despite challenging weather conditions.

Future Enhancement

Future work should focus to refine the algorithm to improve its predictive accuracy and explore its integration with emerging technologies like IoT and machine learning for increased adaptability. Moreover, conducting real-world tests in various geographic and climatic conditions will be crucial to validate the system's performance and robustness

References

[1] R. Abraham and M. Vadivel, "An Energy Efficient Wireless Sensor Network with Flamingo Search Algorithm Based Cluster Head Selection,", Wireless Personal Communications, vol. 130, pp. 1503–1525, 2023.

[2] S. Ambareesh, H. C. Kantharaju, and M. Sakthivel, "A Novel Fuzzy TOPSIS Based Hybrid Jarratt Butterfly Optimization for Optimal Routing and Cluster Head Selection in WSN," Peer-to-Peer Netw. Appl., vol. 16, pp. 2512–2524, 2023.

[3] N. Arunachalam, G. Shanmugasundaram, and R. Arvind, "Squirrel Search Optimization-Based Cluster Head Selection Technique for Prolonging Lifetime in WSNs," Wireless Personal Communications, vol. 121, pp. 2681–2698, 2021.

[4] S. Chaurasia,S. Kumar and N. Kumar, "Mocraw: A Meta-Heuristic Optimized Cluster Head Selection Based Routing Algorithm for WSNs," Ad Hoc Netw., vol. 141, p. 103079, 2023.

[5] V. Cherappa, T. Thangarajan, S. S. Meenakshi Sundaram, F. Hajjej, A. K. Munusamy, and R. Shanmugam, "Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks," Sensors, vol. 23, p. 2788, 2023.

[6] E. F. A. Elsmany, M. A. Omar, T. C. Wan, and A. A. Altahir, "EESRA: Energy Efficient Scalable Routing Algorithm for Wireless Sensor Networks," IEEE Access, vol. 7, pp. 96974–96983, 2019.

[7] S. J. Pratha, V. Asanambigai, and S. R. Mugunthan, "Hybrid Mutualism Mechanism-Inspired Butterfly and Flower Pollination Optimization Algorithm for Lifetime Improving Energy-Efficient Cluster Head Selection in WSNs,"Wireless Personal Communications, vol. 128, pp. 1567–1601, 2023.

[8] R. Ramalingam, B. Saleena, S. Basheer, P. Balasubramanian, M. Rashid, and G. Jayaraman, "EECHS-ARO: Energy-Efficient Cluster Head Selection Mechanism for Livestock Industry Using Artificial Rabbits Optimization and Wireless Sensor Networks," Electron. Res. Arch., vol. 31, pp. 3123–3144, 2023.
[9] M. Reddy, M. L. Ravi Chandra, P. Venkatramana, and R. Dilli, "Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm," Computers, vol. 12, p. 35, 2023.
[10] S. Sankar, S. Ramasubbareddy, A. K. Luhach, W. S. Alnumay, and P. Chatterjee, "NCCLA: New Caledonian Crow Learning Algorithm Based Cluster Head Selection for Internet of Things in Smart Cities," J. Ambient. Intell. Humaniz. Comput., vol. 13, pp. 4651–4661, 2022.
[11] D. Samiayya, S. Radhika, and A. Chandrasekar, "An Optimal Model for Enhancing Network Lifetime and Cluster Head Selection Using Hybrid Snake Whale Optimization," Peer-to-Peer Netw. Appl., vol. 16, pp. 1959–1974, 2023.
[12] A. Shahraki, A. Taherkordi, and F. Eliassen, "Clustering Objectives in Wireless Sensor Networks: A Survey and Research Direction Analysis," Comput. Netw., vol. 180, p. 107376, 2020.
[13] M. Sindhuja, S. Vidhya, B. S. Jayasri, and F. H. Shajin, "Multi-Objective Cluster Head Using Self-Attention Based Progressive Generative Adversarial Network for Secured Data Aggregation," Ad Hoc Netw., vol. 140, p. 103037, 2023.