Cognitive Fish Swarm Optimization for Multi-Objective Routing in IoT-based Wireless Sensor Networks utilized in Greenhouse Agriculture

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ABSTRACT

This research presents the working mechanism of Cognitive Fish Swarm Optimization (CFSO) for multi-objective routing and channel selection in Internet of Things (IoT)-based Wireless Sensor Networks (IWSNs). CFSO is inspired by the collective intelligence and cooperation observed in fish swarms. The model involves three main components: perception, cognition, and behavior. Each fish in the swarm perceives the network conditions by gathering information from its surrounding environment, including signal strength, channel availability, and network congestion. The fish then utilizes its cognitive abilities to evaluate different routing paths and channel options based on specific objectives, namely energy efficiency, packet delivery ratio, and delay. This evaluation process involves analyzing historical information and utilizing heuristics to create notified results. Each fish adapts its behavior by adjusting its movement pattern and selecting optimal routing paths and channels. This adaptive behavior is critical for achieving reliable and efficient data transmission in IWSNs. The fish swarm balances exploration and exploitation strategies to search for optimal solutions comprehensively. Exploration allows for discovering new paths and channels, while exploitation focuses on refining the best-known solutions. The efficiency of the CFSO method in enhancing data transmission efficiency in greenhouse agriculture applications was validated through extensive simulations in the NS-3 network simulation framework. The findings suggest that the CFSO method is a promising technique for addressing routing and channel selection challenges in IWSN by leveraging the collective intelligence of fish swarms. The CFSO model portrayed a superior throughput and Network Lifetime (NLT) values of 71.34% and 77.20%, respectively, significantly outpacing SSEER and CRP across overall node counts.

Keywords-CFSO; multi-objective routing; IoT; WSNs; greenhouse agriculture; optimization algorithms

I. INTRODUCTION

Greenhouse agriculture is a method that allows for the cultivation of plants in controlled environments, providing optimal conditions for their growth and productivity [1]. Unlike traditional open-field farming, greenhouse agriculture offers a range of benefits, such as protection from adverse weather conditions, pests, and diseases, which often pose significant challenges to crop cultivation [2]. The controlled environment within greenhouses also enables farmers to optimize resource utilization, such as water and fertilizers, resulting in improved sustainability and efficiency [3, 4]. In the past few years, there has been an increasing interest in integrating Internet of Thing (IoT) technology with greenhouse agriculture to further enhance efficiency and productivity [5]. IoT represents a network of interrelated gadgets and objects, which may gather and interchange data across the Internet. It enables seamless communication and data sharing, resulting in improved physical system automation, monitoring, and control [6, 7]. Within the context of greenhouse agriculture, IoT technologies can transform the way greenhouses are managed. By deploying IoT-enabled devices and sensors throughout the greenhouse, farmers can obtain real time data on different environmental factors. These conditions may include light intensity, temperature, soil moisture, humidity, CO_2 levels, and food concentrations. The data accumulated by this sensor are communicated through IoT connectivity to a cloud-based platform or central server for further investigation and decision-making [8]. Wireless Sensor Networks (WSNs) facilitate data collection within greenhouse environments. WSNs consist of smaller, lower-power devices named sensors distributed and deployed for monitoring and collecting data from the physical surroundings [9]. These sensors are strategically placed throughout the greenhouse, allowing for comprehensive coverage and data collection from various locations. WSNs enable remote data collection, transmission, and processing, and are essential for efficient and accurate monitoring of greenhouse conditions [10].

This study focuses on advancing and evaluating effectual routing methods and channel selection strategies for the utilization of IoT-based WSN (IWSN) in greenhouse agriculture. The study aims to develop optimized routing algorithms that prioritize energy efficiency, data reliability, network scalability, and resource utilization, intelligently choosing optimal paths for data transmission while considering performance and resource constraints. Furthermore, the research will explore the application of CFSO in improving routing and channel selection within greenhouse environments. Comprehensive analysis is performed through modeling and real-world investigations to evaluate the performance of the proposed strategies. The key contributions of the current paper are:

- The study comprises the development of optimized routing algorithms that prioritize energy efficiency and data reliability, improving the overall performance of IWSNs in greenhouse agriculture while effectually managing resources for enhanced crop productivity.
- A thorough analysis is made through both modeling and real-world tests, ensuring the efficiency of the proposed model in practical applications and giving details into their performance in diverse greenhouse scenarios.
- The study provides practical recommendations for deploying IWSNs that aim to improve crop productivity and optimize resource efficiency, presenting insights for practitioners in the field.
- The application of CFSO to improve routing and channel selection in greenhouse environments is explored, introducing innovative methods that utilize unique environmental factors to optimize data transmission and resource management.

II. LITERATURE REVIEW

Authors in [11] utilized clustering techniques to segment WSNs, while incorporating fault tolerance mechanisms to manage node failures. Authors in [12] presented the SplitPath methodology by utilizing multipath routing and dual-radio capabilities. Authors in [13] proposed the hybrid Chimp Optimization and Hunger Games Search (ChOA-HGS) approach. Authors in [14] presented the Trust Aware Oppositional Sine Cosine-based Multihop Routing (TAOSC-MHR) technique. Authors in [15] introduced the ybrid tree-based and cluster-based routing protocol. Authors in [16] introduced a novel routing strategy in WSNs/IoT. Authors in [17] employed the Exponentially-Ant Lion Whale Optimization (E-ALWO) approach, which integrates E-ALWO for choosing Cluster Heads (CHs) based on energy and delay. Authors in [18] introduced two UAWSN routing protocols. Authors in [19] presented the Energy Efficient Hybrid Clustering and Hierarchical Routing (EEHCHR) methodology. Authors in [20] proposed the Seagull Optimization Algorithm based Energy Aware Cluster Routing Protocol (SOA-EACR) model. Authors in [21] introduced a segmented sector network by using heterogeneity among Sensor Nodes (SNs). Normal nodes use direct diffusion for data transmission. Authors in [22] proposed the C-EEUC protocol utilizing residual energy and communication cost. Authors in [23] proposed the Optimized Machine Learning (ML)-based Efficiency Algorithm (OMLEA). Authors in [24] presented a multi-objective clustering approach by using the Election-based Aquila Optimizer (EAO) model. An Optimized CNN (O-CNN) method was also utilized. Authors in [25] utilized the Multi-Objective Moth-Flame Optimization (MOMFO) approach. Authors in [26] proposed a Deep Reinforcement Learning (DRL)-based routing technique for IoT-enabled WSNs. Authors in [27] introduced an effectual data aggregation methodology by using Blockchain (BC) and the "CH sleep schedule". Authors in [28] presented the energy-aware load-balancing methodology by using an artificial chemical reaction optimization model. Authors in [29] presented an IoT-based hydration system using the Cuckoo search-based Levy Adolescent Identity Search (CLAIS) algorithm with a CLAIS-DQN classifier for optimal feature selection. Authors in [30] proposed the utilization of distributed multi-task learning.

The existing approaches for WSNs and IoT enhance energy efficiency and fault tolerance but encounter issues like enhanced hardware complexity, trust measurement threats, and adaptability to dynamic conditions. Optimization techniques also struggle with convergence and scalability in real-world applications. Existing research often neglects adaptive mechanisms and comprehensive studies on the trade-offs between energy efficiency, routing complexity, and real-time performance in diverse environments.

III. CFSO MODEL FOR IWSN

A. *Energy Consumption Model*

Information transmission within an IWSN primarily relies on the distance between components, which follows a non-linear pattern. Signal propagation in free space and multi-channel systems is non-linear and exponential, impacting signal strength in an IWSN as distance increases. The user end collects data from sensors, the data center analyzes it, and the Base Station (BS) optimizes communication between them. Energy Consumption (EC) during data transmission is expressed in (1):

$$H_{F_p}(U,y) = H_{F_{p-elcc}}(U) + H_{F_{p-amp}}(U,y) = \begin{cases} U^* H_{F_{elec}} + U^* \varrho_{ge} * y^2, & y < y_0 \\ U^* H_{F_{elec}} + U^* \varrho_{cm} * y^4, & y \geq y_0 \end{cases} \quad (1)$$

The threshold distance y_0 is given by:

$$y_0 = \sqrt{\varrho_{ge}/\varrho_{cm}} \quad (2)$$

The energy consumed by the CH can be expressed as:

$$\mathrm{ECH} = \text{Computation Energy} + \text{Transmission Energy} \quad (3)$$

with:

$$\text{Computation Energy} = \frac{t}{a} * Eelec \quad (4)$$

The CH's uplink Energy Consumption (EC) is represented by:

$$H_{UL} = UH_{elec}\left(\frac{t}{a} - 1\right) + UH_{YD}\frac{t}{a} + UH_{elec} \quad (5)$$

This underscores the CH's high energy needs for computation and transmission, while unallocated energy space improves data transfer efficiency in a cluster-based system. The EC of a node within a cluster is stated by:

$$H_{st} = UH_{elec} + U\varrho_{ge}y^2 \quad (6)$$

where UH_{elec} represents the energy required for computation or processing tasks at the node, $U\varrho_{ge}$ denotes the EC per unit distance (ϱ_{ge}) for transmitting data within the cluster, and y represents the typical spacing between cluster members and the cluster center, as defined by:

$$y = \sqrt{1/2 * \frac{c^2}{a}} \quad (7)$$

where c depicts the number of sides of the area for SN deployment, while a denotes the number of clusters in the region. The total EC of each cluster is considered using (8):

$$yH_{uzo} = H_{UL} + \left(\frac{t}{a} - 1\right)H_{st} \quad (8)$$

where H_{UL} represents the EC of the CH for uplink (UL) transmission, *t*/*a* indicates the average number of SNs within each cluster, *t*/*a* - 1 denotes the energy used in the CH for computation and processing tasks of the other SNs within the cluster, and H_{st} denotes the EC of a cluster node.

B. Cluster Generation

The clustering process generates clusters with the K-means technique to minimize the within-cluster variance. The initial cluster region is based on the BS's location and proximity to the cluster center, using A-means and K-means to finalize clustering. The K-means method iteratively updates cluster centers based on node distances, with convergence criteria such as reaching maximum iterations, minimal changes in cluster center variation, and stable Sum of Squared Errors (SSE) indicating that clustering is complete. These criteria assist in determining when the model has efficiently stabilized, confirming reliable clustering outcomes. The K-means model assigns nodes to the nearest cluster depending on their distances to the cluster centers. Nodes are reallocated to the nearest cluster based on distance metrics after each iteration, and clustering is complete when the membership function stabilizes. A minimum cluster size may also be required for effective data processing and communication.

C. Cluster Formation

The K-means clustering model is utilized for IWSN nodes to facilitate clustering. This research accentuates using distance to select CHs, utilizing scoring formulas to detect robust nodes and improve system effectiveness through residual energy and location intensity. Once a CH is selected, it relays data while unselected nodes continue to contribute data, maintaining stability until the next selection cycle.

$$J_{EUL} = 0.2Z_v + 0.8Z_u \quad (9)$$

D. CFSO-based Routing

Inspired by the coordinated behavior of fish schools, FSO employs an initial population of artificial fish to explore potential solutions, iteratively updating their positions based on attraction to good solutions and collective communication. The optimization process continues until a termination condition is met, assessing each fish's fitness. An object-oriented model depicts each fish in an *f*-dimensional space, iterating with parameters like step size to find the optimal solution. The artificial fish food concentration is calculated with:

$$Q = g(p) \quad (10)$$

and the distance among fish is assessed using (11):

$$y_{s,w} = \|p_s - p_w\| \quad (11)$$

Each fish's state represents a potential solution evaluated for efficiency, simulating fish school foraging behavior in IWSN to mimic their collective food-locating abilities through spatial cues. The school of fish, depicted by P_s, moves toward areas with higher food concentrations, adapting to environmental changes by evaluating resource availability. If advantageous locations are found, the school repositions to maximize resource access. The movement process is ruled by various equations. For instance, (12) directs movement toward higher concentrations. If no suitable state is found, the fish takes a random step to explore new possibilities, represented by (13) and (14):

$$P_w = P_s + Visual^{*}\text{Rand}\,() \quad (12)$$

$$P_s^{f+1} = P_s^f + \frac{P_w - P_s^f}{\left\|P_w - P_s^f\right\|} {*Step}{*}\text{Rand}\,() \quad (13)$$

$$P_s^{f+1} = P_s^f + Visual^{*}\text{Rand}\,() \quad (14)$$

This model encourages exploration and avoids local optima. Fish schools form for protection and mutual learning, allowing them to gather resources and share knowledge collectively. The artificial fish swarm model simulates this interaction, preventing isolation. If an artificial fish is in state P_s, and perceives others within its visual range t_g, it evaluates the distance $y_{s,w}$. If this distance is less than the visual threshold and the condition $Q_u/t_g > \theta Q_s$ is satisfied, indicating a high food concentration, the fish moves toward the central position P_u. If not, it continues foraging locally. This movement is represented by:

$$P_s^{f+1} = P_s^f + \frac{P_u - Pf_s}{\|P_u - Pf\|} {*Step}{*}\text{Rand}\,() \quad (15)$$

This equation updates the fish's position, balancing directed movement toward P_u with randomness for exploration. Rear-end behavior in fish schools arises when multiple fish detect food, leading others to follow, akin to vehicles tailing, as they seek optimal paths to high food concentration P_{max}. The fish engages in foraging only if conditions $P_{max} > Q_s$ and $Q_{max}/t_g > \theta Q_s$ are satisfied. Movement towards P_{max} is governed by:

$$P_s^{f+1} = P_s^f + Step^{*}\text{Rand}\ ()^{*} \frac{P_{max}-P_s}{\|P_{max}-P_s\|} \quad (16)$$

This equation updates the fish position based on the highest food concentration, optimizing its foraging behavior and enhancing navigation within the school.

E. Chaotic Behavior

Fish exhibit a certain degree of unpredictability in their movements within the water, which aids the collective search for food. Similarly, artificial fish also incorporate an element of randomness in their behavior. They arbitrarily choose a condition within their perception range and then take a single stride in that chosen direction. This behavior is reminiscent of foraging strategies observed in nature, characterized by small-scale operations. By presenting this randomness, artificial fish emulate the natural exploration patterns of their biological counterparts, improving their capability to search for resources effectually. A bulletin board serves as a crucial component within the system, capturing and documenting the historical records of the optimal conditions seen by the artificial fish. The bulletin board centralizes resource concentrations found by the fish school, updating its records with higher values. It consolidates the collective knowledge and optimal conditions identified during the model's execution, guiding future decision-making processes.

IV. RESULTS AND DISCUSSION

This study utilizes NS-3 simulator, which is an open-source C++ network simulation tool widely used in research and education, giving features for protocol assessment, network topology maintenance, and analysis tools, alongside a Python interface for efficient simulation design. Its flexibility makes it valuable for evaluating technologies like Wi-Fi, 5G, and IoT. The suggested technique is simulated by employing Python 3.6.5 on a PC i5-8600k, 250 GB SSD, GeForce 1050Ti 4 GB, 16 GB RAM, with 1 TB HDD. The parameter settings are: learning rate: 0.01, activation: ReLU, epoch count: 50, dropout: 0.5, and batch size: 5.

Figure 1 provides the throughput outcome of CFSOR method with distinct nodes. The outcomes established that the CFSOR method has better performance. With 500 nodes, the CFSOR method attained greater throughput of 69.23%, whereas the SSEER and CRP techniques obtained lesser throughput of 30.59% and 43.81%, respectively. Likewise, with 1000 nodes, the CFSOR model attained higher throughput of 70.36%, while the SSEER and CRP techniques obtained lesser throughput of 31.03% and 44.35%, respectively. With 1500 nodes, the CFSOR model obtained advanced throughput of 71.34%, however the SSEER and CRP techniques acquired lesser throughput of 31.77% and 45.90%, correspondingly. The EC outcome of CFSOR method with varying number of nodes is indicated in Table I. The outcomes inferred that the CFSOR method attained enhanced performance. It can be seen that the CFSOR technique obtained lesser EC in every considered case. Table II provides the NLT comparison analysis of CFSOR method. NLT is the period a network operates before resource depletion or failure. The acquired values show that the CFSOR technique has improved performance and higher NLT in every considered case.

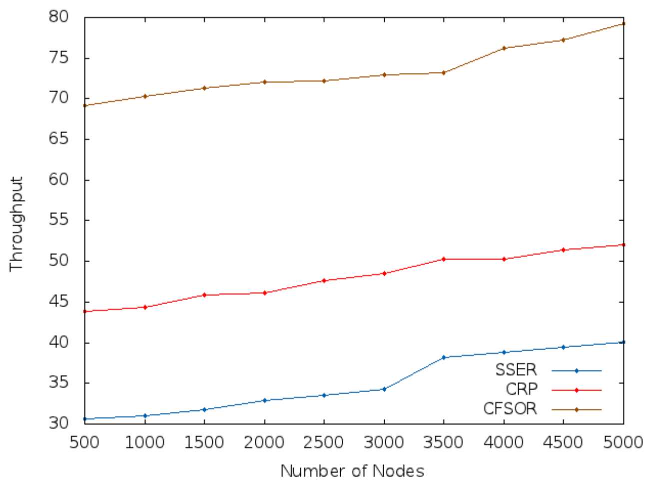

Fig. 1. Throughput outcome of CFSOR with varying number of nodes.

TABLE I. EC RESULT COMPARISON

EC (%)			
No. of Nodes	**SSEER**	**CRP**	**CFSOR**
500	77.47	59.35	29.64
1000	78.58	60.90	30.86
1500	80.86	63.32	34.45
2000	84.18	63.94	34.52
2500	85.24	64.48	34.56
3000	87.43	71.86	36.62
3500	89.60	72.47	37.76
4000	90.77	74.70	41.22
4500	91.72	76.92	41.93
5000	93.59	79.12	45.86

TABLE I. NLT RESULT COMPARISON

NLT (%)			
No. of Nodes	**SSEER**	**CRP**	**CFSOR**
500	22.36	48.08	77.20
1000	21.51	47.23	76.91
1500	18.68	43.79	71.88
2000	16.26	42.11	71.31
2500	15.18	35.04	70.79
3000	14.28	28.69	68.02
3500	10.98	27.27	67.09
4000	10.32	26.69	64.54
4500	9.77	25.41	64.28
5000	8.06	25.34	64.24

V. CONCLUSION

This research focused on multi-objective routing and channel selection in the IWSN using CFSO. The study aimed to address the challenges in routing within IWSN, particularly in the context of greenhouse agriculture. Through extensive literature review and analysis, it was identified that efficient routing algorithms are crucial for ensuring the reliable and energy-efficient transmission of data among WSNs deployed in greenhouses. The proposed approach of utilizing CFSO showed promising results in optimizing routing and channel selection in IWSN. The research objectives were successfully achieved by designing and implementing a simulation model using the NS-3 network framework. Various performance metrics, including throughput, EC, and NLT, were evaluated to assess the effectiveness of the proposed approach. The results demonstrated the CFSO's effectiveness in improving the routing and channel selection performance in IWSN. The CFSO model portrayed a superior throughput and NLT values, significantly outpacing SSEER and CRP across overall node counts. This research contributes to IWSN and greenhouse agriculture by offering insights for developing efficient routing mechanisms, aiding in advanced protocol design for better data transmission and greenhouse management. However, it is limited by potential scalability issues and the need for real-world testing. The study emphasizes the importance of multi-objective routing and channel selection in IWSN for greenhouse agriculture and introduces a promising approach using CFSO. Future research can enhance the proposed approach by incorporating additional factors to improve efficiency and sustainability in greenhouse agriculture while refining the CFSO method for practical applicability and scalability in real-world deployments.

REFERENCES

[1] V. S. Reddy, G. Ramya, and V. M. Reddy, "Greenhouse Environment Monitoring and Automation using Intel Galileo gen and IoT," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 7, pp. 554–559, 2019.

[2] A. Sariga and J. Uthayakumar, "Type 2 Fuzzy Logic based Unequal Clustering algorithm for multi-hop wireless sensor networks," *International Journal of Wireless and Ad Hoc Communication*, vol. 1, no. 1, pp. 33–46, Jan. 2020, https://doi.org/10.54216/IJWAC.010102.

[3] A. Ghalazman E. *et al.*, "Applications of robotic and solar energy in precision agriculture and smart farming," in *Solar Energy Advancements in Agriculture and Food Production Systems*, S. Gorjian and P. E. Campana, Eds. Cambridge, MA, USA: Academic Press, 2022, pp. 351–390.

[4] J. Hellin and E. Fisher, "The Achilles heel of climate-smart agriculture," *Nature Climate Change*, vol. 9, no. 7, pp. 493–494, Jul. 2019, https://doi.org/10.1038/s41558-019-0515-8.

[5] T. Bharath Kumar and D. Prashar, "Exploration of research on Internet of Things enabled smart agriculture," *Materials Today: Proceedings*, vol. 80, pp. 1936–1939, Jan. 2023, https://doi.org/10.1016/j.matpr.2021.05.652.

[6] A. T. Albu-slaih and H. A. Khudhair, "ASR-FANET: An adaptive SDN-based routing framework for FANET," *International Journal of Electrical and Computer Engineering*, vol. 11, no. 5, pp. 4403–4412, Oct. 2021, https://doi.org/10.11591/ijece.v11i5.pp4403-4412.

[7] C. R. Mehta, N. S. Chandel, and Y. Rajwade, "Smart Farm Mechanization for Sustainable Indian Agriculture," *Ama, Agricultural Mechanization in Asia, Africa & Latin America*, vol. 50, no. 4, pp. 99–105, Oct. 2024.

[8] R. Zaghdoud, O. B. Rhaiem, M. Amara, K. Mesghouni, and S. Galet, "A Hybrid Genetic Algorithm Approach based on Patient Classification to Optimize Home Health Care Scheduling and Routing," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 15099–15105, Aug. 2024, https://doi.org/10.48084/etasr.7649.

[9] K. B. Vikhyath and N. A. Prasad, "Combined Osprey-Chimp Optimization for Cluster Based Routing in Wireless Sensor Networks: Improved DeepMaxout for Node Energy Prediction," *Engineering, Technology & Applied Science Research*, vol. 13, no. 6, pp. 12314–12319, Dec. 2023, https://doi.org/10.48084/etasr.6542.

[10] M. Sirajuddin, C. Ravela, S. R. Krishna, S. K. Ahamed, S. K. Basha, and N. M. J. Basha, "A Secure Framework based On Hybrid Cryptographic Scheme and Trusted Routing to Enhance the QoS of a WSN," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 15711–15716, Aug. 2024, https://doi.org/10.48084/etasr.7633.

[11] R. F. Mansour *et al.*, "Energy aware fault tolerant clustering with routing protocol for improved survivability in wireless sensor networks," *Computer Networks*, vol. 212, Jul. 2022, Art. no. 109049, https://doi.org/10.1016/j.comnet.2022.109049.

[12] N. dos S. Ribeiro, M. A. M. Vieira, L. F. M. Vieira, and O. Gnawali, "SplitPath: High throughput using multipath routing in dual-radio Wireless Sensor Networks," *Computer Networks*, vol. 207, Apr. 2022, Art. no. 108832, https://doi.org/10.1016/j.comnet.2022.108832.

[13] Y. Yang, Y. Wu, H. Yuan, M. Khishe, and M. Mohammadi, "Nodes clustering and multi-hop routing protocol optimization using hybrid chimp optimization and hunger games search algorithms for sustainable energy efficient underwater wireless sensor networks," *Sustainable Computing: Informatics and Systems*, vol. 35, Sep. 2022, Art. no. 100731, https://doi.org/10.1016/j.suscom.2022.100731.

[14] A. M. Hilal *et al.*, "Trust aware oppositional sine cosine based multihop routing protocol for improving survivability of wireless sensor network," *Computer Networks*, vol. 213, Aug. 2022, Art. no. 109119, https://doi.org/10.1016/j.comnet.2022.109119.

[15] Y. Zhang, L. Liu, M. Wang, J. Wu, and H. Huang, "An improved routing protocol for raw data collection in multihop wireless sensor networks," *Computer Communications*, vol. 188, pp. 66–80, Apr. 2022, https://doi.org/10.1016/j.comcom.2022.02.016.

[16] M. Navarro, Y. Liang, and X. Zhong, "Energy-efficient and balanced routing in low-power wireless sensor networks for data collection," *Ad Hoc Networks*, vol. 127, Mar. 2022, Art. no. 102766, https://doi.org/10.1016/j.adhoc.2021.102766.

[17] K. SureshKumar and P. Vimala, "Energy efficient routing protocol using exponentially-ant lion whale optimization algorithm in wireless sensor networks," *Computer Networks*, vol. 197, Oct. 2021, Art. no. 108250, https://doi.org/10.1016/j.comnet.2021.108250.

[18] A. Khan, M. Imran, M. Shoaib, A. U. Rahman, and N. Sama, "Link and stability-aware adaptive cooperative routing with restricted packets transmission and void-avoidance for underwater acoustic wireless sensor networks," *Computer Communications*, vol. 181, pp. 428–437, Jan. 2022, https://doi.org/10.1016/j.comcom.2021.10.012.

[19] A. Panchal and R. K. Singh, "EEHCHR: Energy Efficient Hybrid Clustering and Hierarchical Routing for Wireless Sensor Networks," *Ad Hoc Networks*, vol. 123, Dec. 2021, Art. no. 102692, https://doi.org/10.1016/j.adhoc.2021.102692.

[20] S. Sankar, R. Somula, B. Parvathala, S. Kolli, S. Pulipati, and S. S. T. Aditya, "SOA-EACR: Seagull optimization algorithm based energy aware cluster routing protocol for wireless sensor networks in the livestock industry," *Sustainable Computing: Informatics and Systems*, vol. 33, Jan. 2022, Art. no. 100645, https://doi.org/10.1016/j.suscom.2021.100645.

[21] S. K. Gupta, S. Kumar, S. Tyagi, and S. Tanwar, "SSEER: Segmented sectors in energy efficient routing for wireless sensor network," *Multimedia Tools and Applications*, vol. 81, no. 24, pp. 34697–34715, Oct. 2022, https://doi.org/10.1007/s11042-021-11829-5.

[22] W. Chen, B. Zhang, X. Yang, W. Fang, W. Zhang, and X. Jiang, "C-EEUC: a Cluster Routing Protocol for Coal Mine Wireless Sensor Network Based on Fog Computing and 5G," *Mobile Networks and Applications*, vol. 27, no. 5, pp. 1853–1866, Oct. 2022, https://doi.org/10.1007/s11036-019-01401-9.

[23] H. B. Mahesh, A. Ahammed, and S. M. Usha, "Optimized Efficiency of IoT-Based Next Generation Smart Wireless Sensor Networks Using a Machine Learning Algorithm," *International Journal of Computing and Digital Systems*, vol. 17, no. 1, pp.1-13, 2024.

[24] V. Pandiyaraju, S. Ganapathy, N. Mohith, and A. Kannan, "An optimal energy utilization model for precision agriculture in WSNs using multi-objective clustering and deep learning," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 10, Dec. 2023, Art. no. 101803, https://doi.org/10.1016/j.jksuci.2023.101803.

[25] T. Salehnia *et al.*, "An optimal task scheduling method in IoT-Fog-Cloud network using multi-objective moth-flame algorithm," *Multimedia Tools and Applications*, vol. 83, no. 12, pp. 34351–34372, Apr. 2024, https://doi.org/10.1007/s11042-023-16971-w.

[26] T. Poongodi and R. K. Sharma, "Energy Optimized Route Selection in WSNs for Smart IoT Applications," in *International Conference on*

Distributed Computing and Electrical Circuits and Electronics, Ballar, India, Apr. 2023, pp. 1–6, https://doi.org/10.1109/ICDCECE57866.2023.10150824.

[27] A. Ahmed, I. Parveen, S. Abdullah, I. Ahmad, N. Alturki, and L. Jamel, "Optimized Data Fusion With Scheduled Rest Periods for Enhanced Smart Agriculture via Blockchain Integration," *IEEE Access*, vol. 12, pp. 15171–15193, Jan. 2024, https://doi.org/10.1109/ACCESS.2024.3357538.

[28] S. Tabaghchi Milan, M. Darbandi, N. Jafari Navimipour, and S. Yalcın, "An Energy-Aware Load Balancing Method for IoT-Based Smart Recycling Machines Using an Artificial Chemical Reaction Optimization Algorithm," *Algorithms*, vol. 16, no. 2, Feb. 2023, Art. no. 115, https://doi.org/10.3390/a16020115.

[29] C. Muruganandam and V. Maniraj, "A Self-driven dual reinforcement model with meta heuristic framework to conquer the iot based clustering to enhance agriculture production," *The Scientific Temper*, vol. 15, no. 2, pp. 2169–2180, Jun. 2024, https://doi.org/10.58414/SCIENTIFICTEMPER.2024.15.2.29.

[30] S. Hamdan, S. Almajali, M. Ayyash, H. Bany Salameh, and Y. Jararweh, "An intelligent edge-enabled distributed multi-task learning architecture for large-scale IoT-based cyber–physical systems," *Simulation Modelling Practice and Theory*, vol. 122, Jan. 2023, Art. no. 102685, https://doi.org/10.1016/j.simpat.2022.102685.