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Research Paper

Depth-Regulated and Energy-Balanced Routing for UWSNs Using Chaotic Search and Rescue Optimization

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ABSTRACT

Underwater wireless sensor networks (UWSNs) employ numerous inexpensive sensor nodes deployed in deep ocean environments. These nodes, characterized by their limited transmission power, resources, and energy, serve various purposes including disaster management, underwater navigation, and environmental monitoring. In these networks it is very challenging to update their location or add new devices, and it is very important to enhance the energy performance and lifetime of the underwater wireless sensor network. Multi-hop communication can expand the range of communication in these networks and increase its connections. The use of clustering-based routing is effective for increasing energy efficiency in these networks, with the difference that, unlike conventional wireless sensor networks, they have limitations such as low bandwidth, extended persistence, underwater pressure, and higher error probability. An energy balance routing protocol with multi-hop data transmission based on search and rescue (EBMH_CSR) is proposed, which balances by adjusting the depth of less energy nodes and replacing them with more energy nodes, and by combining chaotic concepts in the search and rescue optimization algorithm and with Considering residual energy, distance and degree of sensor nodes, fitness function is calculated. Simulation results show that the EBMH_CSR algorithm has improved the packet delivery rate (PDR) in different number of nodes by 23.6 percent, the packet reception rate (NPR) in different number of loads by 26.7 percent, the energy consumption in different number of rounds by 31.2 percent, the end-to-end delay by 31.7 percent, and the network lifetime in different number of nodes by 36 percent compared to the compared algorithms.

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I. Introduction

Recently, underwater wireless sensor networks (UWSN) have been widely used for detecting and tracking various targets and underwater exploration using high-resolution audio signals due to their ease and cost-effectiveness [1]. These networks differ from terrestrial wireless sensor networks (TWSNs) in terms of communication and data transmission. (TWSNs use radio signal and UWSNs use underwater audio channels to transmit data. Also, replacing nodes in UWSNs is cumbersome due to the type of environment and cost [2].

UWSNs face significant obstacles, including excessive energy usage from audio signal processing, constrained battery capacity and bandwidth, extended propagation times, and elevated bit error rates. Despite these challenges, they offer numerous applications, such as monitoring the environment, exploring the ocean depths, preventing disasters, aiding navigation, conducting distributed tactical surveillance, and detecting mines [3].

As illustrated in Figure 1, underwater wireless sensor networks comprise numerous sensor nodes, base stations, and sink nodes. These components gather environmental data like temperature from beneath the water's surface and transmit it to the sink node through one or multiple hops.

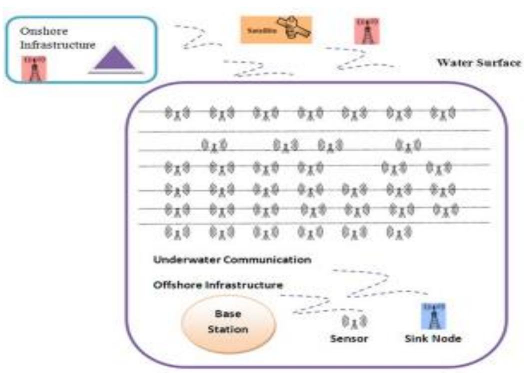

Fig 1. Underwater wireless sensor networks consist of a large number of sensor nodes, base stations, and sink nodes [4]

Routing in underwater wireless sensor networks is done using three methods, direct, hop-to-hop and clustering-based routing. In hop-to-hop routing, unlike direct routing where each of the sensor nodes directly sends information to the sink, each node selects the nearest neighbor and sends the information to the sink through it, which reduces the performance and lifespan of the network [4]. In the routing method based on clustering, each node sends the collected data to its cluster head (CHs) and after accumulating the data, it is sent to the base station. This method reduces bandwidth usage and increases network performance.

The routing technique based on depth data reduces the delay and energy consumption in which the sender sends the data to another node that has less depth than the sender and also covers its neighbors. Also, a multi-hop algorithm based on chaotic search and rescue is used to optimize energy efficiency and lifetime, which includes a weighted clustering approach (WCA) to select cluster heads (CHs) and cluster construction. In this research, a combined depth-controlled and energy-balanced routing protocol (EEP) is proposed to increase lifetime, improve transmission efficiency, reduce packet loss ratio (PLR) and minimize energy consumption during data transmission in the network based on multiple algorithms. The HOP based chaotic search and rescue was proposed and the simulation results were evaluated in several aspects.

II. Related works

One of the main factors for maintaining underwater wireless sensor networks is cooperation and connectivity between sensor nodes. Various issues related to the connectivity of omni-directional underwater wireless sensor networks have been discussed by the authors in [5] and various evaluation models have been proposed. The coverage problem of heterogeneous and homogeneous underwater wireless sensor networks has been investigated by the authors in [6].

Water as the mode of interaction in underwater wireless sensor networks is compared to conventional sensor networks, so the use of terrestrial sensor network communication systems in deep water is useless.

In underwater wireless sensor networks, transmitters use the sea surface to exchange information over short distances. The problem of these networks is that during radio signals at very low frequencies for long distances, to solve this problem, huge antennas and very high network throughput must be used, which reduces the network's lifespan. Therefore, many routing algorithms in terrestrial wireless sensor networks cannot be used in underwater wireless sensor networks. Recently, scientists have proposed many researches to optimize energy consumption and increase lifespan.

Gola and Gupta in [7] proposed an underwater cluster-based approach based on electromagnetics for underwater wireless sensor networks, where Voronoi diagram is used to create clusters and jellyfish breathing method to classify cluster heads, which results in saving Energy consumption and network efficiency improvement.

Goyal et al. in [8] proposed a new underwater cluster-based routing approach based on an adaptive routing mechanism, which uses a combination of route optimization and power control method and significantly improves the network model. In [9], an approach to data collection and fusion of portable sensor collection centers was proposed by Nazareth and Chandavarkar which reduces energy consumption and increases the lifespan of the network. In [10], Goyal et al. proposed a new vector-based routing approach where all sensors are aware of their location and send information packets with detailed details of sender address, sensor location, destination address, and transmission range. Choudhary and Goyal in [11] proposed a more advanced method based on vector-based transmission protocol, which helps to increase the packet delivery rate and reduce energy consumption.

The first spatial routing technique with a depth-based controlled routing (DCR) approach was proposed by Al-Bukhari and Bouabdullah in [12], where it changes the network topology as soon as the route discovery fails. This approach predicts and selects the next sender based on depth data. However, it has high consumption and high latency. Durrani et al. in [13] presented a routing approach for smart ocean underwater sensor networks (SOSNET) that uses a butterfly flame optimizer (MFO) to calculate the optimal number of effective clusters in routing.

Due to water variations, including the Doppler effect that is formed due to the movement of sensor nodes and sea level changes, such as temperature and salinity, and geometric expansion, NR et al. in [14] to reduce the delay and packet loss during transmission in networks. They proposed an underwater wireless sensor and valve optimization algorithm. In [15], researchers employed a bio-inspired technique known as the Penguin Swarm Optimization Protocol to identify the optimal route in underwater wireless sensor networks. This approach enhances network longevity and effectiveness by equalizing energy distribution and preventing the formation of empty zones.

The study presented in [16] introduced a novel improved energy balanced routing (IEBR) method for underwater wireless sensor networks, comprising two stages: data dissemination and routing establishment. This technique reduces the number of hops in depth-threshold-based connections and resolves the data communication loop issue. It achieves this by precisely calculating transmission distances to determine optimally positioned neighbors, establishing network connections, and selecting relays based on neighbor depth.

Rajeswari et al. proposed a Cooperative Beam Optimization (CoROA) approach in [17] to reduce losses and delays caused by geometric propagation and Doppler environment in underwater acoustic networks. This approach improves throughput, battery life, and network lifetime. In [18], Fei et al. proposed an FCM and MFO based hybrid clustering approach (FCMMFO) to improve system performance. In this approach, FCM is used to create energy-efficient clusters and MFO is used to select the optimal cluster head for each cluster. Jiang Jin et al. proposed a congestion avoidance routing protocol for underwater wireless sensor networks based on reinforcement learning in [19]. This approach can be used to find the optimal way to relieve congestion and save energy.

In [20], Yugan Chen et al. proposed a novel approach for sensor load balancing in multi-hop wireless underwater sensor networks, which reduces energy consumption and improves network throughput and durability by grouping packets based on the importance of the data they contain.

Table 1 shows the comparison of different routing protocols using clustering and multi-hop routing in underwater wireless sensor networks. Table 1. Comparison of different routing protocols using clustering and multi-hop routing in underwater wireless sensor networks

Ref No	year of publication	Suggested approach	Disadvantages	Advantages
[21]	2022	Quality of Service Routing Protocol	It consumes more electricity	Higher package delivery ratio
[22]	2020	Depth-based routing	In a distributed network, it performs poorly	Increase package delivery ratio
[23]	2022	Adaptive node clustering	Network lifetime	The throughput and reliability in the clustering process are high
[24]	2021	LOCAN method	Packet loss	energy consumption
[25]	2019	Sensor Web distributed routing protocol	It consumes more energy in deep water connections	Provides better performance
[26]	2022	Bee algorithm	Not suitable for deep UWSNs	Reliable transmission
[27]	2022	Hydroxt routing protocol	Poor performance in sparse network	Use less energy
[28]	2022	Gray wolf optimization algorithm	Sensor failure	Reduce packet loss and traffic systems
[29]	2022	Threshold partition and energy level	Maximize energy resources	Reduced latency and high throughput
[30]	2021	Route selection strategy	delay	High throughput
[31]	2020	C fuzzy method and	Time delay and packet loss	Reducing energy

		propeller-flame optimization method		consumption
[32]	2022	Vector based transport protocol	Sometimes it may encounter additional node problems	Improved data transmission
[33]	2022	Optimized depth-based routing	It consumes more energy in E2ED connection	It consumes less energy
[34]	2021	Routing protocol based on fuzzy logic vectors	Encountering packet loss issues in long distance communications	Higher PDR and throughput
[35]	2021	New efficient transport protocol	In a distributed network, it performs poorly	It consumes less energy
[36]	2022	Adaptive distributed tree-based multicast routing protocol	More packet loss when the destination is unreachable	It has better output power and less delay

In [38], a new model for clustering sensor nodes based on the Shahin-Harris optimization algorithm is proposed, in which the intra-cluster distance, extra-cluster distance, and residual energy of sensor nodes are considered. And the distance of non-cluster nodes to the cluster head node is evaluated and the closest nodes to the cluster head are selected. The evaluation results indicate a higher number of live nodes, a longer lifespan, and increased efficiency compared to other algorithms. In [39], a hybrid method of deep neural networks for intrusion prevention is presented, which has the ability to detect and extract more complex features, and by combining different results and features, the accuracy and performance of the model are improved.

III. Suggested approach

In this paper, a new approach is proposed for the optimal selection of depth-controlled and energy-balancing paths for data transmission in an underwater wireless sensor network. which can minimize the energy consumption by using the clustering strategy with minimum cost. This strategy consists of the parameters, the amount of energy consumed by the nodes during the transfer to the cluster head, the amount of remaining energy of the cluster head node, and the distance between the cluster head node and the base station, which by calculating the amount of energy of the sensors and the weight-based clustering technique, the cluster head nodes and neighboring nodes have A less specific energy and multi-step data transmission process based on chaotic search and rescue optimization is initiated. Then, by examining the intra-cluster communication, a localization method is proposed to track the position of the sensors with the aim of depth-controlled and energy-balancing routing. Finally, the EBMH_CSR is measured and evaluated with the parameters of packet loss rate, energy consumption, delay, packet delivery rate, number of live nodes, number of received

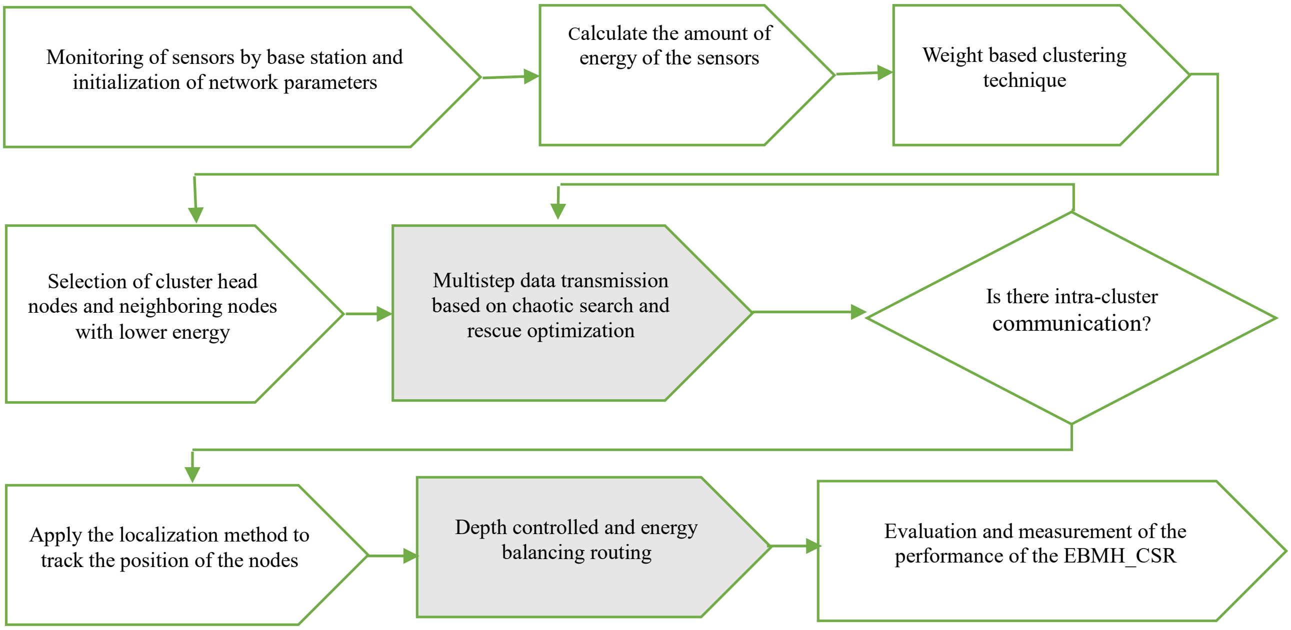

Fig 2. The overall process of the EBMH_SCR

packets, and network lifetime. Figure 2 shows the overall process of the EBMH_CSR.

In this network, a number of sensor nodes are scattered in the underwater environment with flow, pressure and temperature parameters, which have the ability to communicate with each other through radio frequency and voice modem, as well as collect underwater information. In these networks, the underwater sensors are moved at about 1-3 meters per second due to the water flow and the topology of the network is constantly changing. Since unnecessary energy consumption causes the death of the sensor node and the reduction of the network's lifespan, therefore, energy consumption can be saved by integrating information by cluster heads. The following relationship shows the energy required by each sensor node to transmit k bits of data in an underwater wireless sensor network:

$$E_{Tx}(k,d) = k * E_{elec} + {}^{k}/_{R}\, P_{tx}$$

Where E_{elec} is routing power and P_{tx} is transmission power.

In weighted clustering, cluster structure and cluster head are calculated using the three main criteria of degree, residual energy, and definition distance, and the weight of each node is calculated from the relationship $Pi = w_1 * Eng + w_2 * Deg + w_3 * Dis$, where $w_1 + w_2 + w_3 = 1$ is

To calculate the distance between one-step neighboring nodes from the relation $Dis = {\sum_1^{NB_i} Dist\ (i, nb_j)}\big/{NB_i}$ and the degree of the neighboring nodes that have the sending radius, From the relation $Deg = \left|\left\{\frac{n_y}{dist(x,y)} < trans_{range}\right\} x \neq y\right|$ It is used where $dist(x,y)$ is the distance between two nodes n_x and n_y and $trans_{range}$ is the range of moving nodes.

The chaotic search and rescue optimization algorithm is one of the meta-search algorithms inspired by human search behavior in the entire search and rescue process. In it, the missing person situation is posed before the solution of the optimization problem, and the importance of the index obtained in this situation shows the suitability of this solution. This optimal solution represents a route of great importance and vice versa [37]. During the search process, members of the information group will collect clues and leave clues to find other important clues and use this information to optimize the search process. The figure below shows the index matrix, which contains the locations of the found indices and has two matrices M and X. These two matrices are the memory matrix that stores the locations of the left indices and the X matrix that stores the locations of the humans, respectively. These matrices are of equal size, with the Y dimension representing the problem and the Z dimension representing the number of group members. The chaotic search and rescue optimization algorithm consists of two main phases, individual and social, both of which are generated based on the main matrix and updated at every stage of the human search.

$$C = \begin{bmatrix} X \\ M \end{bmatrix} = \begin{bmatrix} X_{1,1} & \cdots & X_{1,d} \\ \vdots & \ddots & \vdots \\ X_{n,l} & \cdots & X_{n,d} \\ M_{1,1} & \cdots & M_{1,d} \\ \vdots & \ddots & \vdots \\ M_{n,l} & \cdots & M_{n,d} \end{bmatrix}$$

In the social phase, the search direction is obtained by considering a random clue among the found clues, according to the following relationship.

$$SZ_i = (X_i - C_k)\ , k \neq i$$

Where SZ_i is the search direction of the ith human, X_i is the position of the ith human, C_k is the position of the ith lead and k is a random integer in the range of 1 to 2n.

In order to avoid repeated search of the position, the movement of the group members towards each other should be limited during the search. If the importance of the clue of the current position is less than the considered clue, the area around the direction of $SZ_i$and around the clue position is searched. Otherwise, the search will continue around the current position along the SZ_idirection. The jth new position is obtained by the ith person according to the following relationship.

$$\acute{X}_{i,j} = \begin{cases} C_{k,j} + r_1 * (X_{i,j} - C_{k,j}) if f(C_k) > f(X_i) \\ X_{i,j} + r_2 * (X_{i,j} - C_{k,j}) if\ r_2 < sp_i \\ X_i \quad otherwise \end{cases}$$

where $\acute{X}_{i,j}$ is the new position of the ith human, $C_{k,j}$ is the new position of the kth lead, $f(X_i)$ and $f(C_k)$ are the objective function values from the solutions X_i and C_k, r_1 is a random number in the range [-1, 1] and r_2 is a random number in the range [0, 1].

In the individual phase, human searches around the current position individually and different clues are connected according to the social phase, and the new position of the ith human is calculated from the following relationship.

$$\acute{X}_i = X_i + r_3 * (C_k - C_m)$$

Where r_3 is a random number in the range 0 and 1 and the integers k and m are randomly selected in the range 1 to 2N such that $i \neq k \neq m$ to avoid moving along other leads.

The solutions adopted by the individual and social phases in the chaotic search and rescue optimization algorithm must be located in the solution space, otherwise the new position of the ith human must be modified according to the following relationship.

$$\dot{X}_{ij} = \begin{cases} \dfrac{(X_{i,j} + X_j^{max})}{2} & if\ \dot{X}_{i,j} > X_j^{max} \\ \dfrac{(X_{i,j} + X_j^{min})}{2} & if\ \dot{X}_{i,j} < X_j^{min} \end{cases}$$

where $X_j^{min}$and X_j^{max} represent the minimum and maximum thresholds for parameter j, respectively.

If the value of the objective function exceeds the previous value, that position is updated and stored in the memory matrix and described as a new position. Otherwise, the memory will not be updated.

$$M_n = \begin{cases} X_j & if\ f(\dot{X}_i) > f(X_i) \\ M_n & otherwise \end{cases}$$

$$X_i = \begin{cases} \dot{X}_i & if\ f(\dot{X}_i) > f(X_i) \\ X_i & otherwise \end{cases}$$

M_n indicates the position of the nth clue kept in the memory matrix and n is an integer in the range of 1 and N. In chaotic search and rescue processes, time is an essential factor because delaying search and rescue teams may result in death and loss. Therefore, the maximum space should be searched in the shortest possible time. Therefore, if the important clues are not found after several searches around the current position, the current position should be left and the search process should continue in the new position.

To overcome the energy consumption problem in underwater wireless sensor networks and ensure continuous energy utilization, in this paper, a depth-controlled and energy-balanced routing is proposed, in which the depth of low-energy endpoints is adjusted and swapped with higher-energy nodes. At this stage, a cryptographic-based diffusion neural network is used for data fusion operations. By analyzing the residual energy and direction of participating nodes, it reduces the number of iterations and data transmissions, and improves energy consumption and efficiency. The energy balancing protocol is based on mixed packet transmission and divides the limited energy of each network node according to the following relationship.

$$E(distance, fc) = EnergyTH(distance, fa)$$

E is the distance between the transmitter and receiver nodes, i is the frequency of the node and Fa is the minimum energy consumption by the node for data transmission, which is calculated from the following equation.

$$Fa = 10^{Fa(Fc)/_{10}}$$

$$Fa(Fc) = 0.11 * \left((Fc)^2 * \left({}^1/_{(1+Fc)}{}^2\right)\right) + 0.22 * \left((Fc)^2 * \left({}^1/_{(1+Fc)}{}^2\right)\right) \ldots + n * \left((Fc)^2 * \left({}^1/_{(1+Fc)}{}^2\right)\right)$$

Also, the cumulative number of participants (NP) is calculated from the following equation, where NR is the radial distance, ND is the density of nodes, RW is the width of each circle segment or the maximum number of loop regions, and MaxHop is the maximum hop value.

$$NP = \sum_{i=0}^{n} NR * ND * MaxHop * RW^2$$

In order to find the optimal multi-step routes between the cluster heads, distributed neural networks based on cryptography are used, which by finding the best routes for data transmission, reduce the rate of packet loss, reduce energy consumption, increase the lifetime and performance of the network.

IV. Simulation results and discussion

Energy consumption, packet delivery rate, packet drop rate, number of live nodes, network lifetime and throughput are important parameters used to evaluate the efficiency and performance of routing protocol in underwater wireless sensor networks. In this paper, the EBMH_CSR is simulated using MATLAB simulator. The simulation parameters of the EBMH_CSR are shown in the table below.

TABLE 2. The simulation parameters of the EBMH_CSR

Parameters	Amounts
The number of nodes	250,500,1000
Package size	1 byte
Data transfer rate	2 bytes per second
Frequency	15 kHz
Energy consumption at the level of data composition	70 joules
Simulation environment	750*750
Primary energy	10 joules
Number of sink nodes	5

Energy Consumption

The total amount of energy used to transmit, receive and collect data in the network is called energy consumption. The table 3 shows the amount of energy consumption in the number of rounds for the EBMH_CSR and DBR, EEDBR, FCMMFO and LEACH-ERE protocols.

TABLE 3. Energy consumption for the compared protocols in different number of rounds

Number of rounds	DBR	EEDBR	FCMMFO	LEACH-ERE	EBMH_CSR
20	12	11	14	15	8
40	17	16	18	19	15
60	16	14	19	19	12
80	24	22	25	26	21
100	24	22	25	26	19
120	27	23	28	29	25
140	33	30	34	35	29
160	30	28	32	33	22
180	29	28	30	31	18
200	29	25	30	31	16

The figure 3 shows the energy consumption diagram of the compared protocols in different number of iterations. As shown in the figure, the simulation results show the improvement of energy consumption in the EBMH_CSR compared to other protocols.

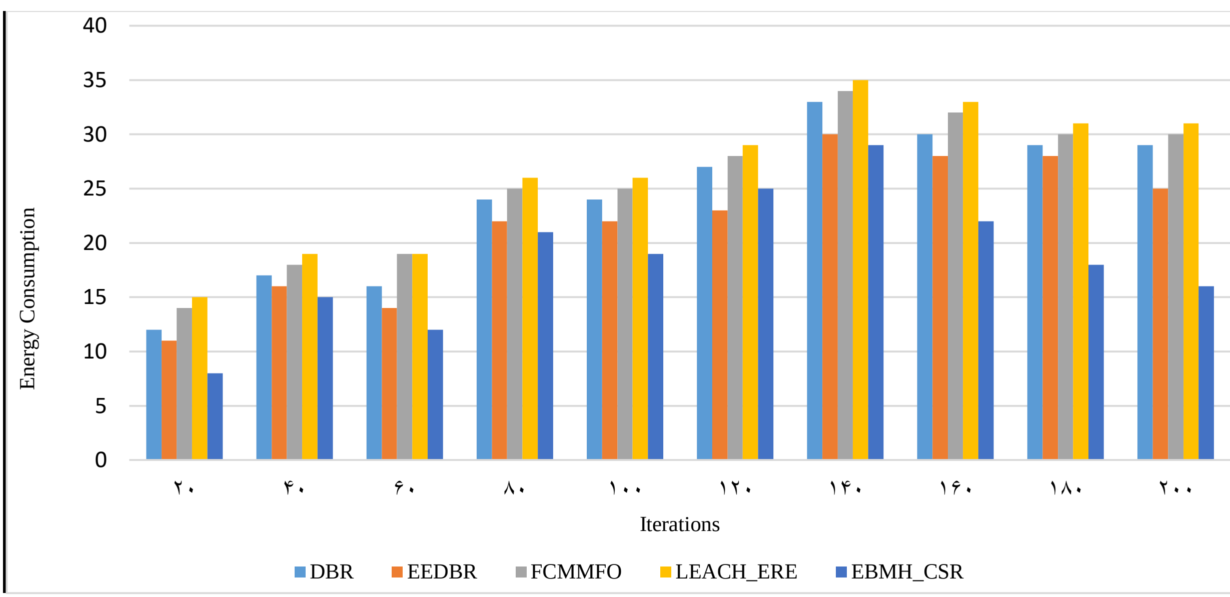

Fig 3. The energy consumption diagram of the compared protocols in different number of iterations

Package Delivery Rate

The ratio of total packets sent to total packets received is called packet delivery rate (PDR). The table 4 shows the packet delivery rate in different number of nodes for the EBMH_CSR and DBR, EEDBR, FCMMFO and LEACH-ERE protocols.

TABLE 4. Packet delivery rate for the compared protocols at different number of nodes

The number of nodes	DBR	EEDBR	FCMMFO	LEACH-ERE	EBMH_CSR
100	96	94	88	90	97
200	90	92	88	88	95
300	90	92	86	88	95
400	89	91	85	87	94
500	88	90	85	87	93
600	88	90	85	85	92
700	86	89	84	83	92
800	87	89	85	83	91
900	86	88	85	82	91
1000	83	86	82	82	89

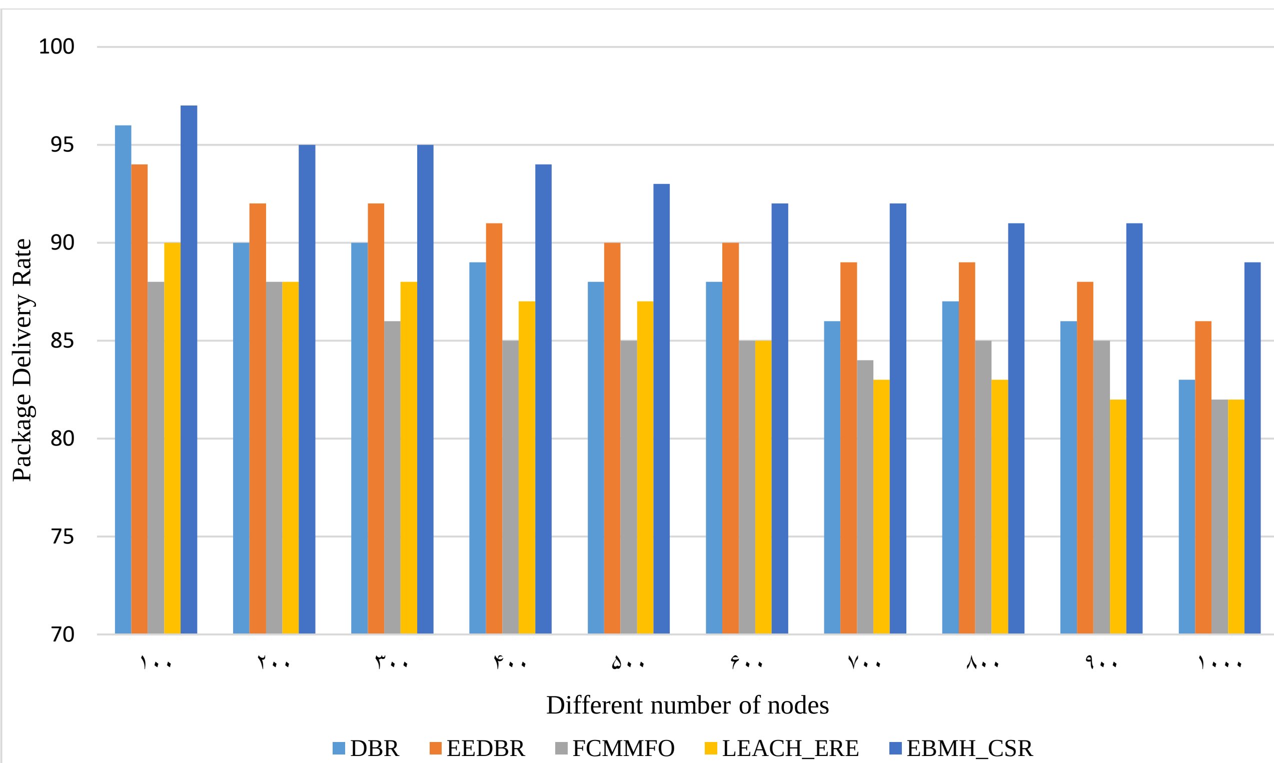

Fig 4. Packet delivery rate for compared protocols at different number of nodes

As shown in the figure 4, the packet delivery rate of the EBMH_CSR provides better results in different number of nodes compared to other parameters. These results show that the FCMMFO protocol had the worst performance.

Packet Drop Rate

Packages sent from the origin may not reach the destination for any reason. The ratio of unreached or lost packets to the total number of sent packets is called packet loss rate. The table 5 shows the simulation results in the packet drop rate parameter of the EBMH_CSR along with other routing protocols at different network loads (packets/min).

TABLE 5. Packet drop rates for the compared protocols at different network loads

network loads	DBR	EEDBR	FCMMFO	LEACH-ERE	EBMH_CSR
0	0	0	0	0	0
10	12	11	15	13	9
20	12	14	17	15	14
30	13	15	17	14	13
40	15	16	18	15	14
50	17	17	19	17	16
60	18	17	21	19	16
70	19	18	23	21	16
80	22	21	25	24	19
90	23	23	25	24	19
100	25	24	27	25	20

The figure 5 shows the packet drop rate graph for the compared protocols at different network loads. According to the figure, the EBMH_CSR performs better than other routing protocols in different network loads from 10 to 100 packets per minute.

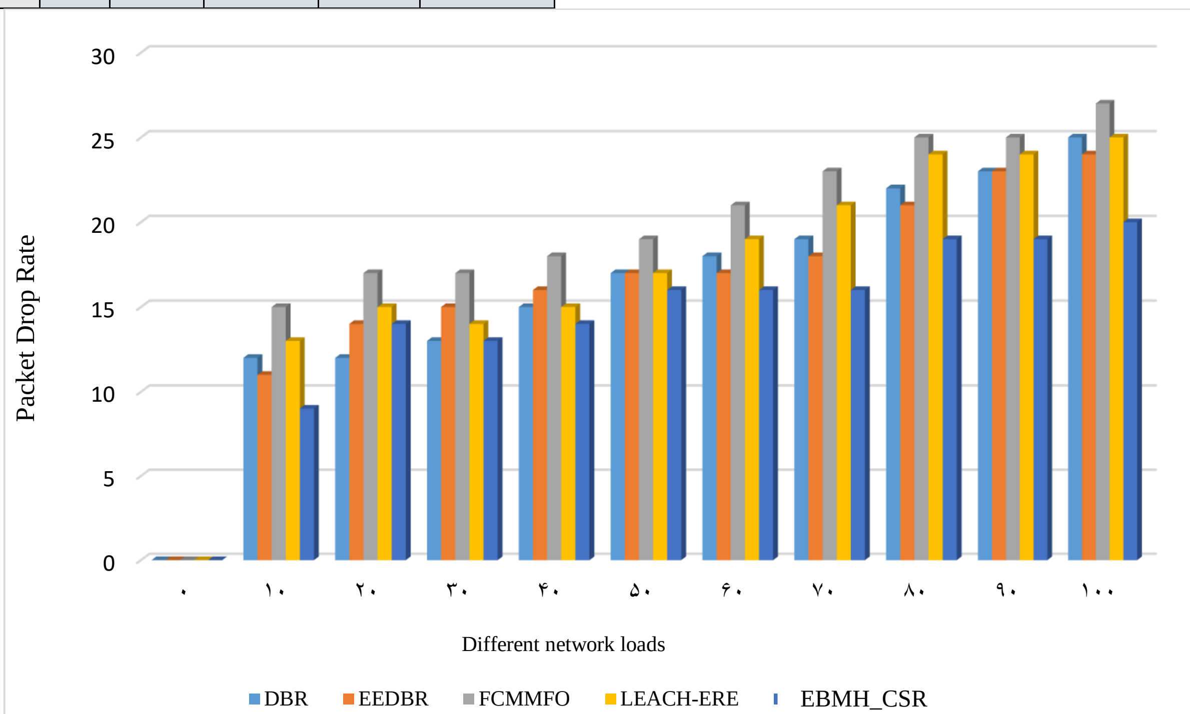

Fig 5. The packet drops rate diagram for the compared protocols at different network loads

Network Lifetime

The time it takes for the first sensor to fail is called the network lifetime. It depends on factors such as the frequency of nodes, connectivity, and distribution. Figure 6 shows the network lifetime for different number of nodes and a radius of 10 km.

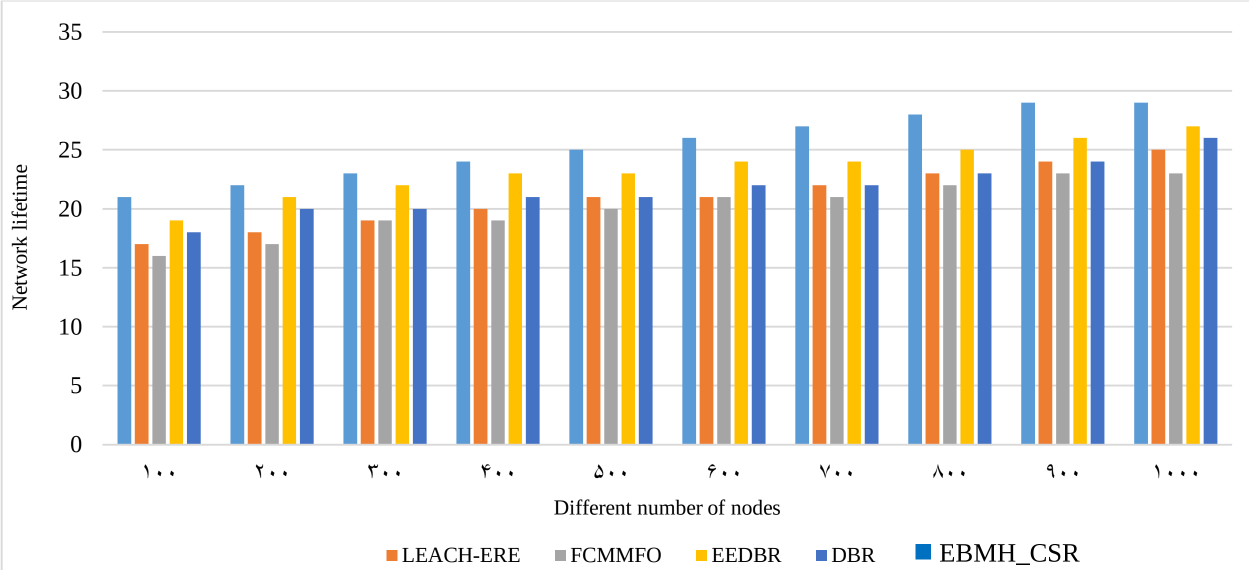

Fig 6. Network lifetime for compared protocols at different number of nodes

The figure 7 shows the graph of the number of live nodes in different rounds. As it is clear in the diagram, with the increase in the number of rounds, the number of live nodes also decreases for all protocols. But the intensity of live node reduction in the EBMH_CSR is less than other protocols and it performs better.

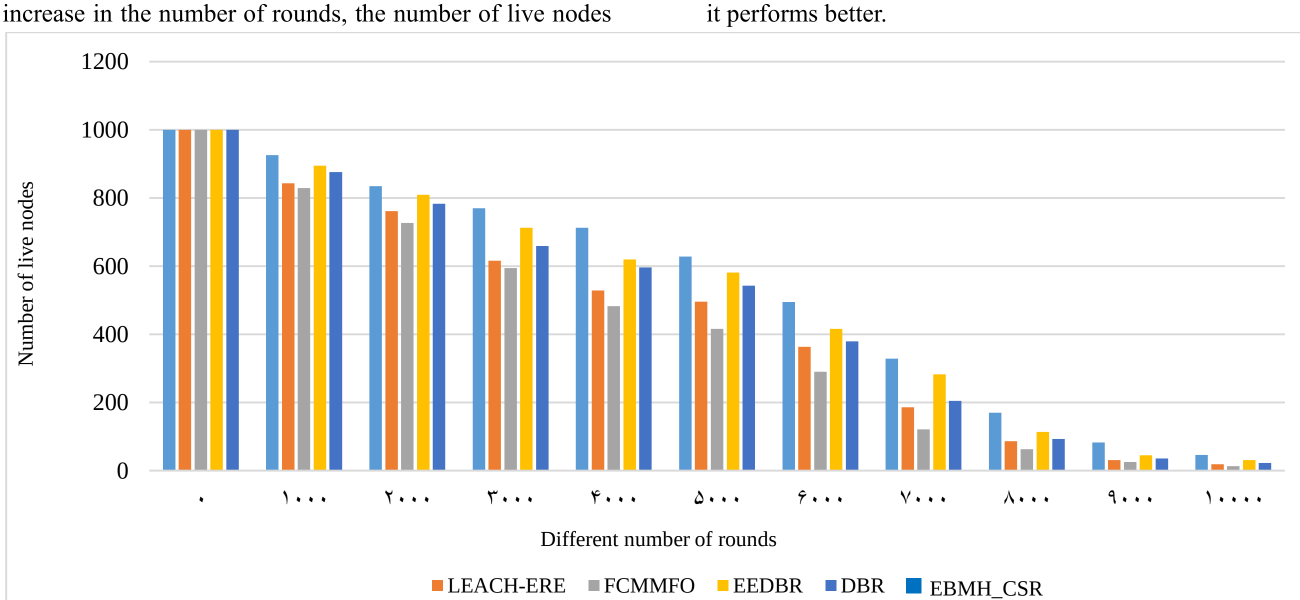

Fig 7. Number of live nodes for the compared protocols in different number of rounds

V. Conclusions

In this paper, a novel method is proposed to optimally select depth-controlled and energy-balanced paths for data transmission in underwater wireless sensor networks (EBMH_CSR). The energy consumption can be reduced by using a cluster strategy with minimum cost. The strategy includes parameters, the amount of energy consumed by nodes during transmission to the cluster head, the remaining energy of the cluster head, and the distance between the cluster head and the base station, through calculating the energy amount of the sensor energy and the weight-based distribution technique, the cluster head nodes and the neighboring nodes have less specific energy, and the multi-stage data transmission process based on chaotic search and rescue optimization is initiated. Then, by examining the intra-cluster communication, a positioning method is proposed to track the location of the sensors for the purpose of depth-controlled and energy-balanced routing. To evaluate the results of the EBMH_CSR, an extensive experimental test was conducted and the results were evaluated from several aspects. Comparative analysis shows that the EBMH_CSR gives better performance than other existing methods. The time complexity of the EBMH_CSR is (O (n2)), which will allow us to attempt to reduce and improve the performance of underwater wireless sensor networks using delay-sensitive data aggregation schemes.

REFERENCES

[1] Harinder Singh, D.; Ramya, R. Saravanakumar, Nayani Sateesh, Rohit Anand, Swarnjit Singh Artificial intelligence-based quality of transmission predictive model for cognitive optical networks. Optik 2022, 257, 168789. [CrossRef]

[2] Chen, Y.; Tang, Y. PB-ACR: Node Payload Balanced Ant Colony Optimal Cooperative Routing for Multi-Hop Under Water Acoustic Sensor Networks. IEEE Access 2021, 9, 57165–57178. [CrossRef]

[3] Chen, Y.; Zhu, J.; Wan, L.; Huang, S.; Zhang, X.; Xu, X. ACOA-AFSA Fusion Dynamic Coded Cooperation Routing for Different Scale Multi- Hop Underwater Acoustic Sensor Networks. IEEE Access 2020, 8, 186773–186788. [CrossRef]

[4] Lilhore, U. K., Khalaf, O. I., Simaiya, S., Tavera Romero, C. A., Abdulsahib, G. M., & Kumar, D. (2022). A depth-controlled and energy-efficient routing protocol for underwater wireless sensor networks. *International Journal of Distributed Sensor Networks*, *18*(9), 15501329221117118.

[5] Bhargava, S.; Mohan, K.; Robert, N.R.; Upadhye, S. Optimal Stacked Sparse Autoencoder Based Traffic Flow Prediction in Intelligent Transportation Systems. Innov. Vis. Appl. Stud. Syst. Decis. Control. 2022, 412, 111–127. [CrossRef]

[6] Jayapradha, J.; Prakash, M.; Alotaibi, Y.; Khalaf, O.I.; Alghamdi, S. Heap Bucketization Anonymity- An Efficient Privacy-Preserving Data Publishing Model for Multiple Sensitive Attributes. IEEE Access 2022, 10, 28773–28791. [CrossRef]

[7] Rawat, S.S.; Alghamdi, S.; Kumar, G.; Alotaibi, Y.; Khalaf, O.I.; Verma, L.P. Infrared Small Target Detection Based on Partial Sum Minimization and Total Variation. Mathematics 2022, 10, 671. [CrossRef]

[8] Gola, Gupta, et al. Networks of underwater sensor wireless systems: latest problems and threats. Int J Wirel Netw Broadband Technol 2021; 10(1): 59–69.

[9] Goyal, Guo R, Qin D, Zhao M, et al. Mobile target localization based on iterative tracing for underwater wireless sensor networks. Int J Distrib Sens Netw 2020; 16(7): 1550147720940634.

[10] Nazareth, Chandavarkar, Alotaibi, Y.; Khalaf, O.I.; Alghamdi, S. Authentication and Resource Allocation Strategies during Handoff for 5G IoVs Using Deep Learning. Energies 2022, 15, 2006. [CrossRef]

[11] Goyal, Alotaibi, Y. A New Meta-Heuristics Data Clustering Algorithm Based on Tabu Search and Adaptive Search Memory. Symmetry 2022, 14, 623. [CrossRef]

[12] Choudhary, Kavitha, T.; Mathai, P.P.; Karthikeyan, C.; Ashok, M.; Kohar, R.; Avanija, J.; Neelakandan, S. Deep Learning Based Capsule Neural Network Model for Breast Cancer Diagnosis Using Mammogram Images. Interdiscip. Sci. Comput. Life Sci. 2021, 14, 113–129. [CrossRef]

[13] Al-Bukhari, Bouabdullah Sunitha, G.; Geetha, K.; Neelakandan, S.; Pundir, A.K.; Hemalatha, S.; Kumar, V. Intelligent deep learning-based ethnicity recognition and classification using facial images. Image Vis. Comput. 2022, 121, 104404. [CrossRef]

[14] Durrani, Su, Y.; Wang, M.L. Optimal cooperative relaying and power control for IoUT networks with reinforcement learning. IEEE Internet Things J. 2021, 8, 791–801. [CrossRef]

[15] NR, Khater E, El-Fishawy N, Tolba M, et al. Buffering_Slotted_ALOHA protocol for underwater acoustic sensor networks based on the slot status. Wirel Netw 2021; 27(5): 3127–3145.

[16] Haque KF, Kabir KH and Abdelgawad A. Advancement of routing protocols and applications of underwater wireless sensor network (UWSN)-a survey. J Sens Actuator Netw 2020; 9(2): 19–31.

[17] Beulah, J.R.; Prathiba, L.; Murthy, G.L.N.; Fantin Irudaya Raj, E.; Arulkumar, N. Blockchain with deep learning-enabled secure healthcare data transmission and diagnostic model. Int. J. Modeling Simul. Sci. Computing. 2021, 15, 1–14. [CrossRef]

[18] Rajeswari, Venu, D.; Mayuri, A.V.R.; Murthy, G.L.N.; Arulkumar, N.; Shelke, N. An efficient low complexity compression based optimal homomorphic encryption for secure fiber optic communication. Optik 2022, 252, 168545. [CrossRef]

[19] Jiang Jin, Reshma, G.; Al-Atroshi, C.; Nassa, V.K.; Geetha, B. Deep Learning-Based Skin Lesion Diagnosis Model Using Dermoscopic Images. Intell. Autom. Soft Comput. 2022, 31, 621–634. [CrossRef]

[20] Yugan Chen, Arun, A.; Bhukya, R.R.; Hardas, B.M.; Anil Kumar, C.T.; Ashok, M. An Automated Word Embedding with Parameter Tuned Model for Web Crawling. Intell. Autom. Soft Comput. 2022, 32, 1617–1632.

[21] Asha, P.; Natrayan, L.; Geetha, B.T.; Beulah, J.R.; Sumathy, R.; Varalakshmi, G. IoT enabled environmental toxicology for air pollution monitoring using AI techniques. Environ. Res. 2022, 205, 112574. [CrossRef] [PubMed]

[22] Paulraj, D. A gradient boosted decision tree-based sentiment classification of twitter data. Int. J. Wavelets. Multiresolut. Inf. Processing 2020, 18, 205027. [CrossRef]

[23] Houssein, E.H.; Saber, E.; Ali, A.A.; Wazery, Y.M. Centroid mutation-based Search and Rescue optimization algorithm for feature selection and classification. Expert Syst. Appl. 2022, 191, 116235. [CrossRef]

[24] Choudhary M and Goyal N. Node deployment strategies in underwater wireless sensor network. In: 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India,4-5 March 2021, pp. 2212–2231. New York: IEEE.

[25] Satpathy, S.; Debbarma, S.; Sengupta Aditya, S.C.; Bhattacaryya Bidyut, K.D. Design a FPGA, fuzzy based, insolent method for prediction of multi-diseases in rural area. J. Intell. Fuzzy Syst. 2019, 37, 7039–7046. [CrossRef]

[26] Li, M.; Xu, G.; Lai, Q.; Chen, J. A chaotic strategy-based quadratic Opposition-Based Learning adaptive variable-speed whale optimization algorithm. Math. Comput. Simul. 2022, 193, 71–99. [CrossRef]

[27] V. K. Kamboj, C. L. Kumari, S. K. Bath, D. Prashar, M. Rashid, S. S. Alshamrani, and A. S. AlGhamdi,

''A cost-effective solution for nonconvex economic load dispatch problems in power systems using slime mould algorithm,'' Sustainability, vol. 14, no. 5, p. 2586, Feb. 2022.

[28] A. Srivastava and D. K. Das, ''An adaptive chaotic class topper optimization technique to solve economic load dispatch and emission economic dispatch problem in power system,'' Soft Comput., vol. 2022, pp. 1–22, Jan. 2022

[29] Subramani, N.; Mohan, P.; Alotaibi, Y.; Alghamdi, S.; Khalaf, O.I. An Efficient Metaheuristic-Based Clustering with Routing Protocol for Underwater Wireless Sensor Networks. Sensors 2022, 22, 415. [CrossRef] [PubMed]

[30] Simaiya S. EEPSA: energy efficiency priority scheduling algorithm for cloud computing. In: 2021 2nd international conference on smart electronics and communication (ICOSEC), Trichy, India, 7–9 October 2021. New York: IEEE.

[31] Guleria K, Prasad D, Lilhore UK, et al. Asynchronous media access control protocols and cross-layer optimizations for wireless sensor networks: an energy-efficient perspective. J Comput Theor Nanosci 2020; 17(6): 2531–2538.

[32] Srilakshmi, U.; Alghamdi, S.; Ankalu, V.V.; Veeraiah, N.; Alotaibi, Y. A secure optimization routing algorithm for mobile ad hoc networks. IEEE Access 2022, 10, 14260–14269. [CrossRef]

[33] Choudhary, M.; Goyal, N. A rendezvous point-based data gathering in underwater wireless sensor networks for monitoring applications. Int. J. Commun. Syst. 2022, 14, e5078. [CrossRef]

[34] Alotaibi, Y.; Subahi, A.F. New goal-oriented requirements extraction framework for e-health services: A case study of diagnostic testing during the COVID-19 outbreak. Bus. Process Manag. J. 2021, 38, 1–19. [CrossRef]

[35] Suryanarayana, G.; Chandran, K.; Khalaf, O.I.; Alotaibi, Y.; Alsufyani, A.; Alghamdi, S.A. Accurate Magnetic Resonance Image Super-Resolution Using Deep Networks and Gaussian Filtering in the Stationary Wavelet Domain. IEEE Access 2021, 9, 71406–71417. [CrossRef]

[36] Mohan, P.; Subramani, N.; Alotaibi, Y.; Alghamdi, S.; Khalaf, O.I.; Ulaganathan, S. Improved Metaheuristics-Based Clustering with Multihop Routing Protocol for Underwater Wireless Sensor Networks. Sensors 2022, 22, 1618. [CrossRef] [PubMed]

[37] Chithambaramani, R.; Prakash, M. An Efficient Applications Cloud Interoperability Framework UsingI-Anfis. Symmetry 2021, 13, 268.

[38] Bayat, J.; Karimi, S. A novel method for improving energy efficiency in wireless visual sensor networks. Journal of Intelligent Multimedia Processing and Communication Systems 2023, *5*(1), 27-36. [CrossRef]

[39] Roknoddini, M.; Noroozi, E. A hybrid deep neural network approach for intrusion prevention in computer networks. Journal of Intelligent Multimedia Processing and Communication Systems 2022, *4*(4), 57-65. [CrossRef]