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DEQLFER — A Deep Extreme Q-Learning Firefly Energy Efficient and high performance routing protocol for underwater communication

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ABSTRACT

With an advent of Underwater sensor networks, underwater communication has reached its new dimension of research. These networks are characterized by the elongated end to end delay, high energy utility and most importantly dynamic network topologies. By incorporating these characteristics, numerous automated routing algorithms has been proposed to achieve the energy efficient and low latency data transmission. But still, short-comings still exists due to the above mentioned characteristics and the most comprehensive routing algorithms are badly desired. In this article, a novel routing scheme based on Q-learning framework and Deep Extreme Learning Machines aided with Adaptive Firefly Routing algorithm to address the above mentioned research constraints including energy efficiency and network unsteadiness in underwater communication , that practices the hybrid combination of reward function and adaptive fireflies to determine the optimal routing mechanism. In this algorithm, traditional q-learning mechanism has been replaced by the powerful q-deep extreme learning mechanism which uses the adaptive reward function for the varying underwater environment and to boost the packet-delivery ratio (PDR) and throughputs. Also the paper uses the powerful firefly aided routing mechanism to achieve the energy efficient data transmission and to avoid the void dilemma problems. The extensive experimentations has been conducted on the proposed algorithm and compared with other state of art schemes such as Q deep q-Learning energy aware routing protocol (DQLER), DELR Protocols and VBF protocols in which the proposed algorithm has outperformed than the compared existing algorithms in terms of complexity, energy consumption , packet delivery ratio and end to end delay.

1. Introduction

Underwater wireless sensor networks (UWSNs) have gained more interest due to the rapid scientific development and advancements in defense needs in underwater environment [1]. Not like terrestrial wireless sensor networks, UWSN stands for Underwater Wireless Sensor Network which gathers the data from sensor nodes deployed in the underwater environments. There are multiple applications of UWSN systems in various fields including military, technology and other industrial needs. The UWSN mainly concerns with communication established in acoustic nature. Acoustic signals are affected generally by noise in the underwater environment, path loss in communication and other delay in networks. Also the terrestrial protocol of WSNs turn irrelevant in certain cases as they are deployed in underwater environments. This is because of the properties exhibited by the signals. Usually the terrestrial WSNs are built to transmit radio or optical signals and such signal behavior are entirely different from acoustic signals [2–5].

Additionally, uncertain factors in underwater environments has huge impact in the communication which leads to the drastic changes in the network topology and also affects the link connectivity [6]. Moreover, factors such as larger area implementation, high power consumption, complex replacement also plays the important role in affecting the underwater networks. [7,8].

To overcome these above drawbacks, many researchers has been concentrated on designing intelligent protocol suitable for underwater communication. Traditional routing algorithms fit to most of the distance oriented algorithms to generate best path, in turn reduces energy consumption and the end-to-end latency. Still few frequently used can hinder the performance resulting in limited network lifetime. The algorithms such as directional flooding-based routing protocol [9], vector based directional protocols [10], depth based protocols [11] provides the good routing mechanism but still proves to have poor packet delivery ratio.

For improvising the lifetime of network and to increase the performance, considerable number of algorithms have been developed so far. These routing algorithms estimate the path based on the residual energy of nodes. The subsequent nodes with higher residual energy is queued for the next hop. These routing schemes mainly concentrate on

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energy utility and these models often compromise the latency and life expectancy of network.

The interaction of messages within the network consume considerable amount of energy in path estimation. Few algorithms mainly concentrate only on distance related path estimation and does not concentrate on dynamic nature of nodes. To add brighter light in research challenge, Q-learning based Ant-Colony Optimization routing algorithm was proposed by Zhengru Fang et al. [12]. This intelligent learning algorithm provides the good network performance such as packet delivery ratio, low energy consumption and so on. Although the QACOL algorithm provides the good performances such as packet delivery ratio and low energy consumption, convergence time complexity of ant-colonies and lack of depth knowledge leads to the degradation in underwater routing mechanism.

To overcome this aforementioned problems, this paper proposes the new kind of Deep Extreme Q-learning and Adaptive Fire fly algorithms which comprehensively considers all the parameters which are mentioned above to prolong the life time of network. The Contribution of the paper is as follows

1. The Deep Extreme Q-learning aided Adaptive Firefly is designed for underwater sensor network, which includes both the reward function and fireflies nature to arrive at a global optimal routing selection. According to the adaptive reward function, the proposed routing algorithm holds good for the dynamic nature of sensor nodes with low energy consumption.
2. The proposed algorithm can extend the network lifetime by estimating the routes related to various parameters such as Energy Distance and depth under the premise of strictly limiting to low latencies.(End to End Delay).
3. For the sake of evaluating the proposed algorithm, extensive experimentations are carried out with the parameters such as network life time, energy utilization and delay of end to end nodes.

The reminder of this paper is as follows as: Section 2 discusses about the related works by more than one authors. The system model and preliminary views of the Deep Q-Learning, Extreme Learning machines and Firefly optimization algorithms are presented in Section 3. Section 4 discusses about the proposed Q-AFEEL techniques with its working mechanism. The experimentations, results along with comparative analysis are discussed in Section 5. Finally the paper is concluded in Section 6.

2. Related works

Syed Hassan Ahmed et al. (2017) proposed a routing model based on the Qos aware directional flooding based routing with and without threshold. These adaptive threshold scheme helps in fixing dynamic changes exhibited in the established network. This two schemes helps in improving the current directional flooding protocol by reducing the hold time for each established link. The limitation is no overhead over lost packets and this introduces additional delay in the network. Also redundancy in packet increases the holding time [13].

Zhengru Fang et al. (2020) introduced a new learning assisted routing protocol for underwater acoustic models. The optimization in finding the best routing path is established using a Q-learning based ant colony method. By inspiring the artificial ant path finding strategy, the reward for all possible routing paths are estimated. Based on the Q-learning scheme the best solution is fixed for efficient UWSNs. Energy consumption is moderate due to increased node points [14].

Bo-Min Seo et al. (2019) developed a CDMA based underwater signaling model which controls communication among node based on their individual requirement. The energy necessity is estimated by the corresponding sensor node depending on the distance of the neighbor node to which communication need to be established. The energy value is estimated by setting a threshold value to avoid wrong link establishment. As the communication in underwater sensor nodes are established in node level the congestion is high because of the one-to-one serving basis network [15].

Mohammad Faheen et al. (2017) proposed a routing protocol considering the QoS of underwater sensor network. As the quality of communication is limited with delays, excess noise, reduced bandwidth, environmental interference by considering the QoS desired, a routing protocol is proposed. Energy in the network is fluctuating creating void issues in transmission. The increase in distance between source node and the destination node leads to delay in the network. The model works based on shortest path selection protocol. If any node failure appear, the routing table will be updated with new shortest path [16].

Salmah Fattah et al. (2020) studied the behavior of underwater wireless sensor networks and their underlying challenges. The study is compiled based on the routing architectures in past five years in terms of providing secure and stable transmission. The study provides detailed investigation of platforms needed for UWSNs and the various taxonomy of routing policies. The research highlights the gaps in research including mobility of nodes, better coverage, energy consumption and the latency of network. The throughput for efficient UWSN models can be improved with redesigning in the architectures still open for improvement. Ocean environmental condition favored models are highly preferred with more renewable energy source impartment applications [17].

Shuxiang Cuo et al. (2009) designed a QPSK based CDMA model for UAVs. This is designed to establish communication between more than one underwater vehicles. The model uses spread spectrum effect, channel CDMA scheme and Rake receiver module for transmission of data between vehicles. In practical implementation a moderate bit error rate and SNR with -10 dB alone is acceptable for communication. The model cannot withstand increased bit rate data [18].

Yishan Su et al. (2018) developed a routing protocol with latency awareness and Q-based energy awareness model. The Q-values are updated based on the on-policy training mechanism to go for new routing paths. The network life expectancy is improved up to 36% in UWSNs. Due to increased path selection, packet collision can occur leading to failure in communication. This collision reduces the throughput of the network [19].

Aqeb Yahya et al. (2019) introduced a cooperative routing model for efficient energy management. The proposed routing protocol is introduced at the network layer of UWSNs. The region based link establishment is practiced in choosing the routing path. After a path selection, incrementing the node slots provides the upcoming paths for link establishment. The proposed routing algorithm provides nature of ocean environment often dislocates the node leading to failure in incrementally updating the routing paths [20].

3. Preliminary overview

This Section discusses about the System Model, Q-Learning techniques, Extreme Learning Machines and working of Adaptive Firefly algorithms.

3.1. System model

The UWSN schemes are modeled based on the sensors deployed in underwater environments. As the behavior of UWSN are different from the terrestrial WSN, the system model of UWSN are modeled as follows.

Fig. 1 illustrates the architecture of UWSN models. The topology illustrated in the model shows the existence of numerous sensor nodes. The autonomous underwater vehicles (AUV) collects information from the sensors deployed. The top layer in the UWSN topology is complex as it comprises both acoustic and radio signals. The acoustic signals are exchanged to communicate within water medium and the radio waves exchange information to on-shore systems.

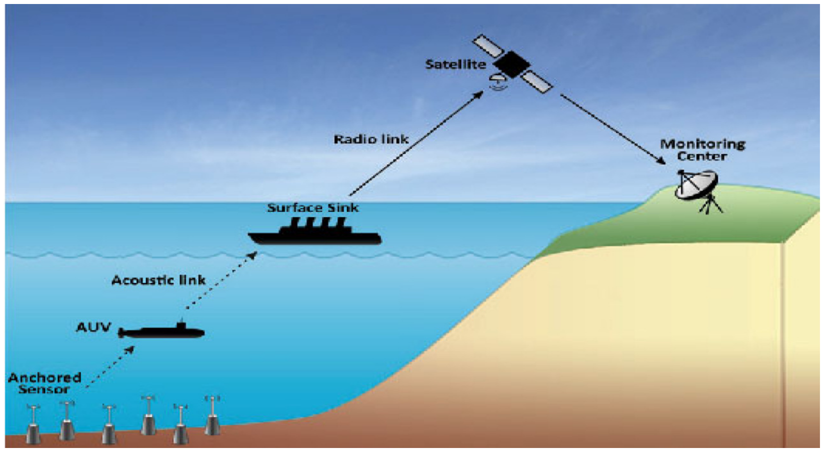

Fig. 1. Overview of underwater wireless sensor network.

3.2. Acoustic comuunication analysis

Consider the underwater acoustic system model developed in [21]. The acoustic signal is attenuated with respect to distance and frequency involved. The acoustic attenuation is expressed as

$$A(d,f) = A_0 d^l a(f)^d \tag{1}$$

where d is the distance of transmission, f is the frequency of acoustic signal, A_0 is the normalization factor, l be the spread function and $a(f)$ be the absorption coefficient. In terms of dB range of frequency, the above equation can be expressed as

$$10\log\frac{A(d,f)}{A_0} = l.10\log d + d.10\log a(f) \tag{2}$$

The r.h.s of the above expression holds both the propagation loss of the signal and the absorption loss. The term $l.10\log d$ corresponds to the propagation loss of signal. The term $d.10\log a(f)$ corresponds to the loss due to absorption.

The spread function l ranges to a maximum of 2 to 4 with $l = 2$ for spherical spread function, $l = 1$ for cylindrical spread function and $l = 1.5$ for other non-regular spread function. Considering the acoustic signal frequency in kHz range Eq. (2) is rewritten as

$$10\log a(f) = 0.11\frac{f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75\times10^{-4}f^2 + 0.003 \tag{3}$$

For low range acoustic signals expression (3) becomes

$$10\log a(f) = 0.002 + 0.11\frac{f^2}{1+f^2} + 0.011f^2 \tag{4}$$

In general, along with the attenuation factor, three noise functions coexist in acoustic communication. The noise due to turbulence, wave movement and thermal noise also exist in the channel given as

$$10\log N(f) = N_i - \eta\log f \tag{5}$$

The loss occurs due to directional gain are ignored and the SNR of the acoustic channel is confined as

$$SNR(d,f) = \frac{P/A(d,f)}{N(f)\Delta f} \tag{6}$$

where Δf corresponds to the noise at receiver end. P the transmitted signal power. The fading effect is modeled with Rayleigh fading effect and the bit error rate (BER) is evaluated for single bit transmission for particular distance as

$$P_e(d) = \frac{1}{2}\left(1-\sqrt{\frac{SNR(d,f)}{1+SNR(d,f)}}\right) \tag{7}$$

3.3. Q-learning process

The routing protocol is mainly built with the Q-learning mechanism. Due to the various limitations of existing routing algorithm, the Q-learning is chosen. The Q-learning model helps in learning features corresponding to dynamic environments. Thus Q-learning as a reinforcement learning strategy is currently derived as Markov Decision Process (MDP). This MDP sets the parameters such as states action, reward and the probability of its occurrence as (S, A, P, R) and $P^a_{zz'}$. Let z is current state and z' is the next state with action value a.

$$P^a_{zz'} = Prob\left\{z_{i+1} = z' | z_t = z, a_t = a\right\} \tag{8}$$

The reward function for state z and z' is given as $R^a_{z_t z_{t+1}}$.t. The overall reward function of current state is

$$R_t = \sum_{z_{t+1}\in Z} P^{a_t}_{s_t s_{t+1}} R^{a_t}_{z_t z_{t+1}|z_t=z,a_t=a} \tag{9}$$

Let $Q_\omega(z,a)$ be the utility function with a policy variable ω.

$$Q_\omega(z,a) = \left\{R_t + \gamma\sum_{z_{t+1}\epsilon Z} P^{a_t}_{zz_{t+1}} Q_\omega(z_t,a)\right\} \tag{10}$$

γ be the reduction factor ranging from [0,1] and practically γ values are mostly [0.5,0.99].

$$\begin{aligned} Q^*(z,a) &= max\left\{Q_\omega(z,a)\right\} \\ &= \left\{R_t + \gamma\sum_{z_{t+1}\epsilon Z} P^{a_t}_{z_t z_{t+1}} max\left\{Q_\omega(z_{t+1},a)\right\}\right\} | z_t = z, a_t = a \\ &= \left\{R_t + \gamma\sum_{z_{t+1}\epsilon Z} P^{a_t}_{z_t z_{t+1}} Q^*(z_{t+1},a)\right\} | z_t = z, a_t = a \end{aligned} \tag{11}$$

3.4. Extreme learning machines

The features of data are extracted and now the proposed BORN uses Extreme learning machines developed by G.B. Huang [22], which comprises of a hidden layer, speed, velocity and accuracy with great speculation/exactness, and universal function approximation abilities [23, 24].

According to this mechanism, the' L' neurons of the hidden layer are associated with an activation function which is consistent (for instance, the sigmoid function), even when the output layer is equated to be in line. It is not necessary to tune the hidden layer individually in ELMs. The weights of the hidden layer are fixed randomly (counting the bias loads).

Prior to consideration of training data the model is equated. For a single-hidden layer ELM, the system yield is given by Eq. (12)

$$f_L(x) = \sum_{i=1}^{L} \beta_i h_i(x) = h(x)\beta \tag{12}$$

where x → input

β → output weight vector which is expressed as

$$\beta = [\beta_1, \beta_2, \dots\dots\dots\dots.\beta_L]^T \tag{13}$$

H(x)→ hidden layer output defined as

$$h(x) = [h_1(x), h_2(x), \dots\dots\dots\dots..h_L(x)] \tag{14}$$

For estimation of Output vector O which is the target vector, and the hidden layers are defined by Eq. (15)

$$H = \begin{bmatrix} h(x_1) \\ h(x_2) \\ \vdots \\ h(x_N) \end{bmatrix} \tag{15}$$

The ELM are implemented based on the marginal non-linear feature of least square model and is expressed as

$$\beta' = H^{*}O = H^T(HH^T)^{-1}O \tag{16}$$

where H∗ → inverse of H known as Moore–Penrose generalized inverse.

Eq. (16) can be reformulated as

$$\beta' = H^T(\frac{1}{C}HH^T)^{-1}O \tag{17}$$

The output function is thus estimated as

$$f_L(x) = h(x)\beta = h(x)H^T(\frac{1}{C}HH^T)^{-1}O \tag{18}$$

ELM uses the kernel function to yield good accuracy for the better performance. The major advantages of the ELM are minimal training error and better approximation. Since ELM uses the auto-tuning of the weight biases and non-zero activation functions, ELM finds its applications in classification and prediction values. The detailed description of ELM 's equations can be found in [22,23] The pseudo code for the ELM is shown in Algorithm 1

Step 1: Training Sets of 'N' data with an Activation Function and n Hidden neurons
Step 2: Input weights are assigned and biases are assigned.
Step 3: Calculate the hidden matrix H
Step 4: Calculate the Output weight Matrix β
Step 5: Classify /Predict the values

3.5. Firefly algorithms

Yang [25] developed the Firefly algorithm which is considered to be the family of swarm intelligence algorithms. The lighting bugs called fireflies for the most part observed blazing their glittering lights in the sky of summer evenings. The essentialness of the blazing conduct of fireflies moreover draws the consideration of a mating accomplice or to get protected from the exploiters. Another significant attribute of fireflies is that not just the force of the light I get diminishes when the firefly is not presentable in front of another more brilliant one yet the air additionally influences the light power by retaining it when the separation increments. Therefore, the worth power of light is legitimately relating to the wellness esteem. Be that as it may, the difficulties of the common practices of fireflies persuade to create three presumptions for building up a working rule of the calculation. The speculations are as per the following:

(i) All fireflies thought to be unisex and fascination occurred among them paying little heed to their sex.
(ii) Engaging quality is moderately corresponding to the brilliance of fireflies and it decreases as the separation increments amongst them.
(iii) The splendor or the light force is registered by the doable arrangements of the goal work.

It is obvious from the assumptions that the force of light I(r) of fireflies is conversely identified with the separation r as it diminishes when separation increments and again light additionally gets ingested when goes over the air. The documentation y is utilized as a coefficient of light ingestion. Therefore, condition (4) shows the variety of power of light I(r) of fireflies regarding separation r

$$I(r) = I0e - yr2 \tag{19}$$

where I0 is the underlying estimation of power at the source end and the engaging quality parameter β can be characterized in two distinct manners as appeared in β

$$\beta(r) = \beta 0e - yr2 \tag{20}$$

At the underlying separation of zero, appealing parameters are meant as $\beta 0$. The social guideline for processing firefly positions are given in the condition underneath

$$xi + 1 = xi + \beta(r(i, j))(xj - xi) + AE \tag{21}$$

where An is the randomization factor and E is the arbitrary number vector and both the elements are gotten from the Gaussian dissemination. xI is the ith position of the firefly and xi+1 s term speaks to the estimation of fascination.

4. Proposed protocol

The detailed explanation of the proposed Deep Extreme Q-Learning aided hybrid firefly algorithm is elaborated in this section. We also particularized the significance of reward function in deep extreme Q-learning and fireflies to decide a global optimal routing selection. The proposed algorithm depends on the three phases of working such as initialization phase, training network models, firefly based route discovery and route maintenance strategy. The complete architecture of the proposed algorithm is given in Fig. 2.

4.1. Protocol overview

According to the proposed mechanism, the routing scheme applied in underwater communication is described as follows. In the underwater communication, each source nodes are positioned underwater to transmit the collected data packets to sink nodes on the shallow area with the help of relay nodes. Thus each packet includes featuring of network comprises an agent, and current data of the sensor nodes including residual energy, depth, distance and signal strength and forwarding to the neighboring nodes are considered as the action. In the proposed algorithm, all the nodes together gather information to compute the different Q-values over the broadcast communication with its nearby node circle, which makes the agent to uses the firefly algorithm to decide the optimum path selection to establish communication to send the packets, which ultimately conserves energy.

4.2. Initialization phase

As the first step, nodes status and the network topology are expected to be recognized, with the residual energy, depth rates, distance and the neighbors of noes with the similar information. At this stage, proposed algorithm uses the off-line training to train the deep extreme learning machines to make routing decisions and also no optimization is incorporated. These known nodes are positioned underwater based on the assumed states and its topology.

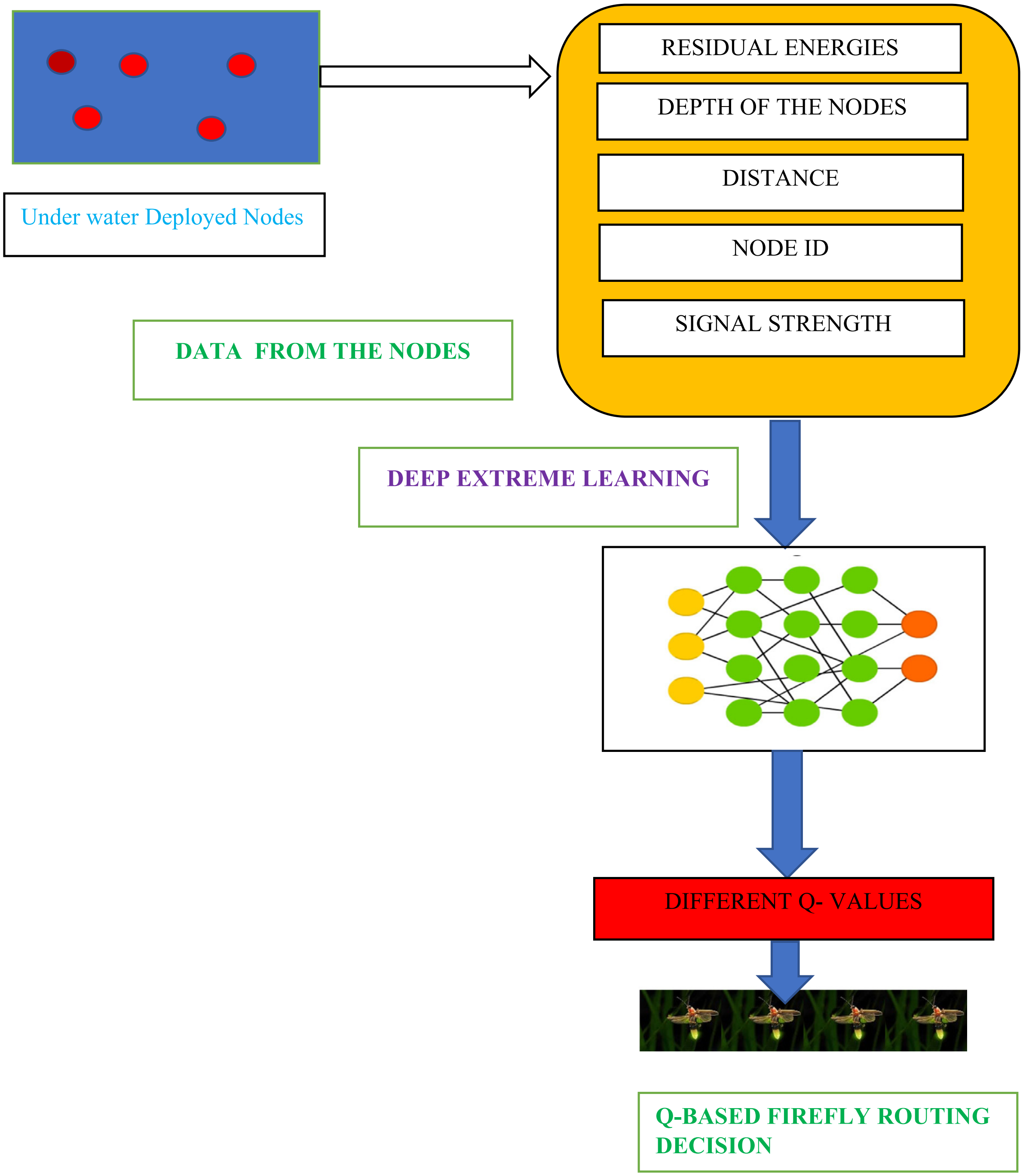

Fig. 2. Architecture for the proposed protocol.

4.3. Training the network

The proposed model has been incorporated in the sink and uses the unicast communication to collecting the data packets from the other nodes. Fig. 3 shows the data packets received from the different nodes.

These variable packet size are used for training the network in reinforcement manner. Fig. 4 shows the architecture of the proposed deep extreme Q-learning machines which are the trained by the dynamic data from the sensor nodes.

In this Model, input layer comprises of five nodes containing the residual energy, depth of the nodes, distance between the nodes, and nodes' signal strength respectively. The output layer is the Q-value. Table 1 illustrates the parameters used for the training the proposed model.

Table 1
Parameters used for the training the proposed model.

Sl.no	Parameters used in the networks	Specifications
01	No of input layers	05
02	No of output layers	n–Q values
03	No of hidden layers	05
04	No of hidden nodes in layers - 1	250
05	No of hidden nodes in layers - 2	100
06	No of hidden nodes in layers - 3	100
07	Bias weights	Auto-Tuned
08	Activations functions - layer1	RELU
09	Activations functions - layer2	Sigmoidal
10	Activations functions - layer3	Sigmoidal

Packet ID	Source Address	Residual Energy	Depth of the Nodes	Distance	Signal Strength	Destination Address

Fig. 3. Packet information used for the data transmission.

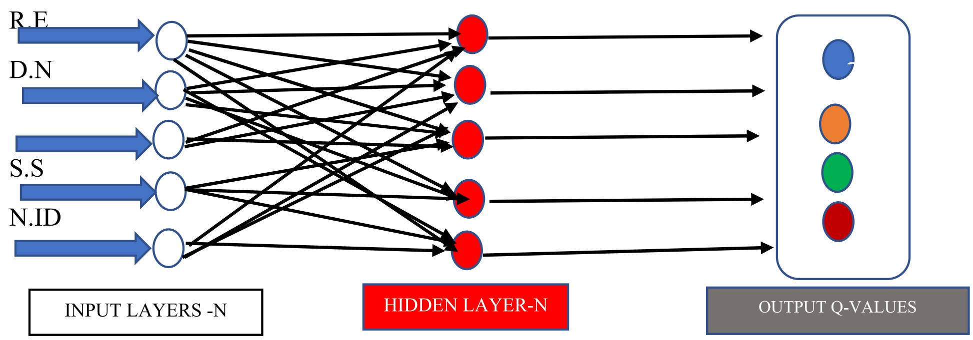

Fig. 4. Architecture diagram for the proposed model.

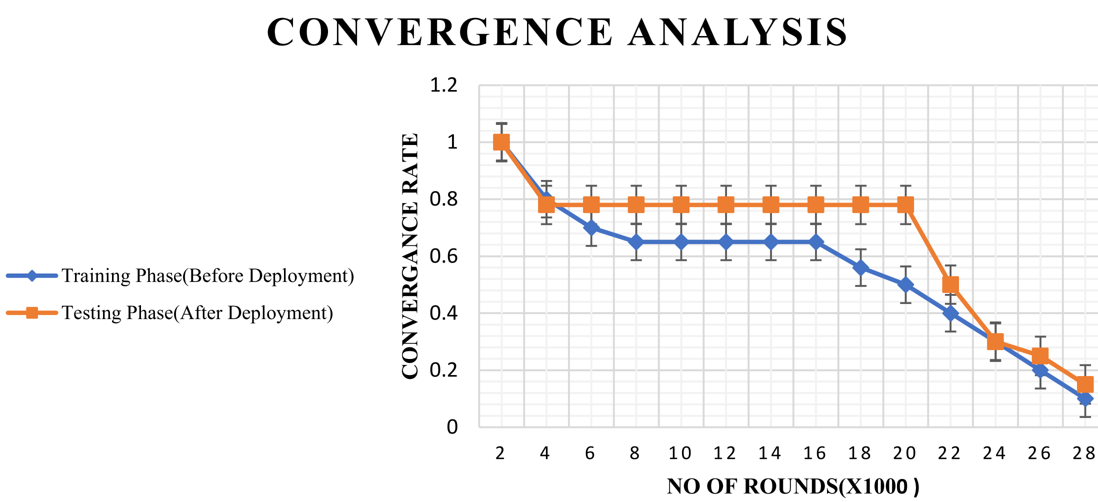

Fig. 5. Convergence analysis for the proposed deep learning algorithms during testing and training phases.

Since finding all the possible optimal paths consumes larger time and also leads to computational complexity of the networks, which may affect the networks' parameters. Hence the proposed algorithm incorporates the adaptive firefly algorithms to find the optimized routing mechanism of the nodes based on the different Q-values obtained from the neural networks.

4.4. Reward and loss function

The mathematical expression () represents the loss function of the proposed Extreme Learning machines. The reward function R(S_i, N_i) is generated at each set comprising of a state and an action. The reward function for the proposed network is given as follows as

$$R(S_i, N_i) = b + \alpha Re + \beta D(i) + \theta d(t) + \mu S \tag{22}$$

where α is the residual Energy, β is the Depth of the nodes, θ is the distance and μ is the signal strength between the nodes. B is the sum of α, β, θ and μ respectively. Then based on Eq. (22), the proposed deep extreme machines are iterated and convergences through the training to get the multiple Q-Values for each and every nodes. Initially reward of sink is set to 100 which is greater than those of the other nodes between 0 and B. The routing decision by the fireflies takes this reward function of the other nodes which are very close to the sink. Thus the detour rate is reduced in which the fireflies optimizes the path by selecting the nodes with increased residual energy, high depth and closer to the sink for every routing iteration.

4.5. Route discovery using fireflies

The different Q-values are obtained from deep extreme learning machines and based on the Q-values, adaptive firefly optimization is adopted for the best routing decision. The multi-objective fitness function are used for the selecting the energy efficient path among the nodes. The fitness function for the selecting the best routing decision is given by the working mechanism of the proposed algorithm is depicted in the algorithm-

5. Results and discussion

In our simulation environment, 100 sensor nodes are homogeneously deployed in the area of 500 × 400 × 450 cubic.meters with one sink being positioned on the middle of the water surface (250 × 200 × 250). Each node in the network itself replicate as source node for information generation which follows Poisson distribution to aid transmission of packets to the sink node. The other simulation parameter values are listed in Table 2.

5.1. Convergence analysis

Figs. 5 and 6 shows the convergence analysis as the amount of training rounds increases. Before deployment, proposed learning models takes approximately 12000 training rounds to make the loss value

Sl.no	/*Algorithm-1*/-Pseudo code for the proposed algorithms
01	Input Features from the Nodes-
02	Initialize the network parameters, rewards, and Q-values
03	Train the model with the network parameters : Loop
04	Find the different Q-values
05	Calculate the fitness function using the equation (23)
06	If fitness _function is equal to the threshold
07	Choose the best routing algorithm based on Q-Firefly using the Equation(20)
08	Broadcast the information to all participating nodes
09	End
10	If topology changes
11	From the current time update do
12	Receive the parameters from the Nodes
13	Go to Step 3
14	Go to Loop
15	End
16	End
17	End

Table 2
Specification of simulation parameters used in experimentation.

Sl.no	Experimentation parameters	Values
01	Transmission range	2000 m
02	Initial energy	10 000 J
03	Transmission power	10 W
04	Receiving power	1 W
05	Idle power	30 mwW
06	Transmission packet size	100 kbps
07	Number of iterations	100

converge since still in the learning rate to produce the different optimal Q-values. Once the sensor nodes are positioned under water, it takes around 478 training rounds to make the loss value convergence when the data updating assignment is accomplished through the broadcast. Thus the up-dation is related to the complete practice stored previously during the initial stage, which leads to the computational overhead of the sensor nodes. Fig. 7 shows the comparative analysis between the proposed learning with the existing deep Q-neural networks.

It has been found that, implementation of the extreme learning machines for constructing the deep Q-networks has taken the less time for training in which it reduces the computational complexity in the networks and also reduction of computational overhead of the sensor nodes when compared to the existing algorithm.

5.2. Performance analysis

In this section, we have analyzed the impact of $\alpha, \beta, \theta, \mu$ on the energy consumption, end to end delay, and packet delivery ratio using the proposed algorithms deployed over the underwater.

Fig. 8 shows the relationship between the variance of energy consumption and the residual energy α for delivering 1000 packets. It was observed from the Fig. 8, when α and no of rounds increases, variance of the energy consumption reduces slowly. It is because as the number of the rounds increases, proposed model will select the forwarder with ample energy instead of selecting the lower energy. Moreover, the algorithm has been adaptively selects the node with the highest energy which results in the nodes in the networks are used more uniformly which makes the variance of energy consumption decreased. Fig. 9 shows the relationship between the variance of energy consumption and the depth of the nodes β for delivering 1000 packets. Again the proposed model selects forwarder based on the highest energy at each and every rounds, which makes the variance of energy consumption decreases as the depth of the nodes decreases. The similar fashion has been observed in Fig. 10 and it clearly shows that variance of energy consumption decreases as the signal strength decreases and distance increases.

Fig. 11 shows the relationship between the network life time and the residual energy along with depth parameter at constant distance and signal strength. It can be observed from the Fig. 11, as the α increases and β decreases, the network lifetime increases. In the initial stage, network can send most of the 6000 packets. This is because, proposed model will select the next forwarded with the more energy and replace the forwarded nodes adaptively to an environment which maximize the network life time. Moreover it consumes only 20% of its maximum lifetime when sending the 2000 packets. The selection of adaptive shortest path by the proposed models which makes the topology based on the more energy nodes. Fig. 12 shows the relationship between the end to end delay analysis and the residual energy and depth parameters. It has been observed that the end to end delay varies some where between the 3.4 to 3.6 s because optimized algorithm shows only the high energy forwarders for transmitting the data in the network. In this case, highest reward function plays an important role for promoting the data packets in the networks. Hence the nodes with more energy will be participating as the forwarders and consumes the energy uniformly. This removes the nodes with low energy and makes the protocol more suitable to prolong the network life time and decrease in latency.

5.2.1. Comparative analysis

In this section, we have compared the performance of the proposed learning models with the other existing models such as VBF, QELR, and DQELR algorithms in which the different parameters such as packet delivery ratio, energy consumption, latency and network life time were compared. QELR integrates the Q-learning and DQELR uses the deep q-learning algorithm for routing mechanism.

Fig. 13 presents the energy consumption of different protocols for the 1600 round of iteration in which the both proposed and DQELR protocols consumes only 15% of energy after the 400 rounds where as other algorithms consumes 20%–30% of the total energy. The proposed protocol consumes 35% energy, DQELR consumes 45%, and other algorithms consumes 60% to 75% energy after 1600 rounds of iteration. Both the proposed protocol and DQELR consumes the energy consumption as equal to 20% to 30% after 1000 rounds but as the rounds increases, DQELR has shown degraded performance in energy consumption. The reason is adoption of firefly optimization over the different Q-values and integration of Extreme Learning machines in the proposed protocol has taken an edge over the DQELR

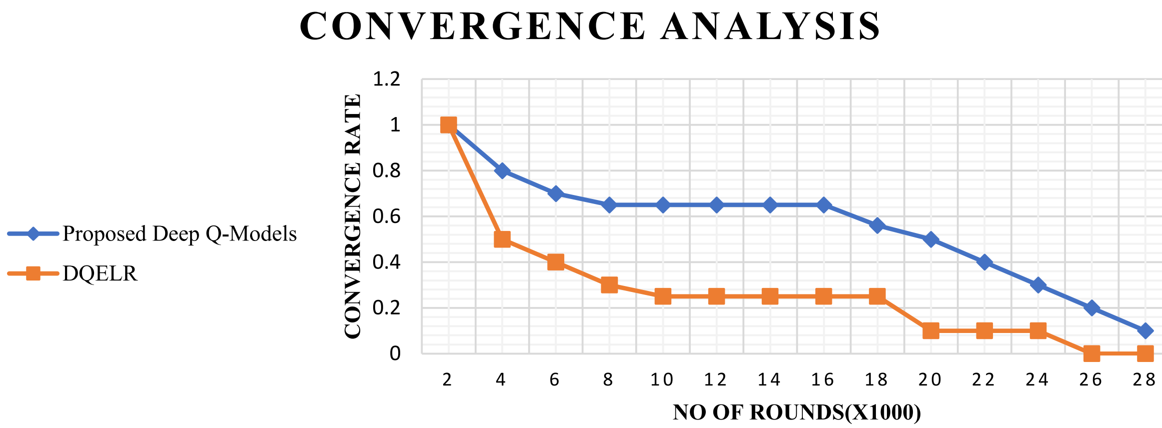

Fig. 6. Comparative analysis between the convergence analysis for the proposed deep learning algorithms and existing algorithms during the training phases.

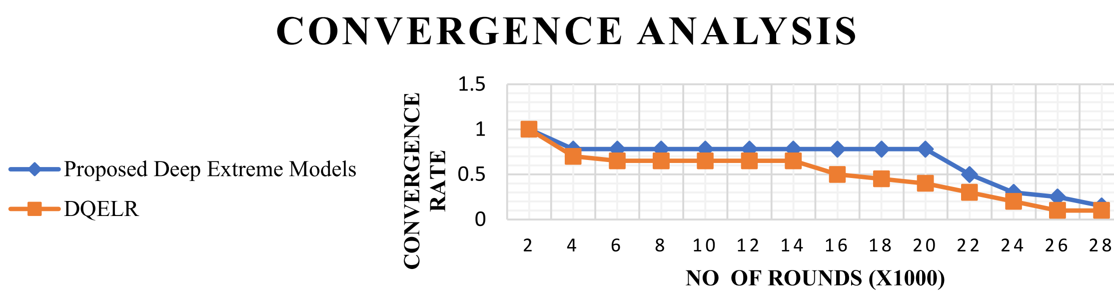

Fig. 7. Comparative analysis between the convergence analysis for the proposed deep learning algorithms and existing algorithms during the testing phases.

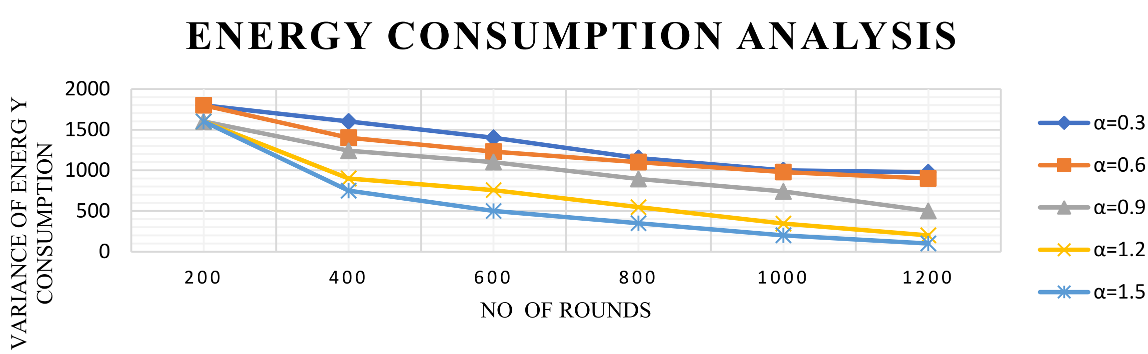

Fig. 8. Energy consumption analysis for the proposed models with the impact of different scenarios of residual energy.

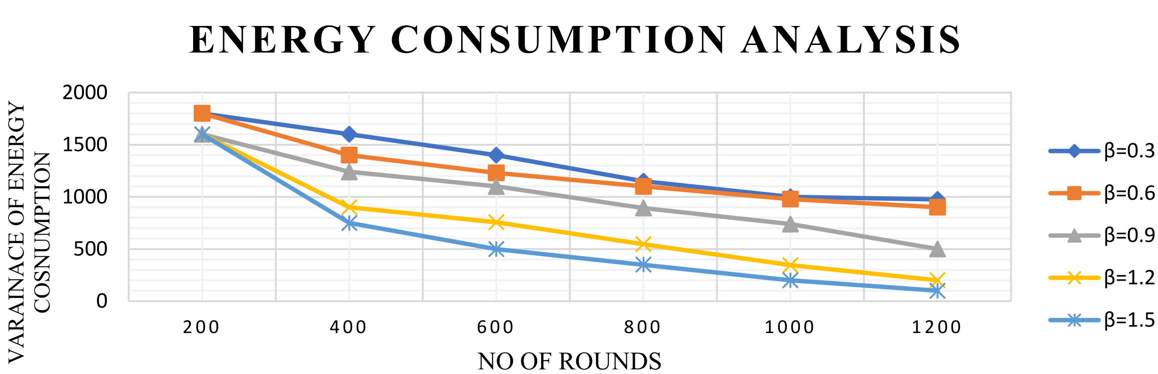

Fig. 9. Energy consumption analysis for the proposed models with the impact of different depth of the nodes.

which incorporates only the Deep Q-learning networks. Figs. 14 and 15 presents the network life time analysis and end to end delay analysis for the different algorithms. Both the network life time is maintained constantly at each and every rounds, DQELR comes second whereas the VBF as the least network life time. The adoption of selecting the best optimal path based on Q-firefly methods has shown 40%–45%

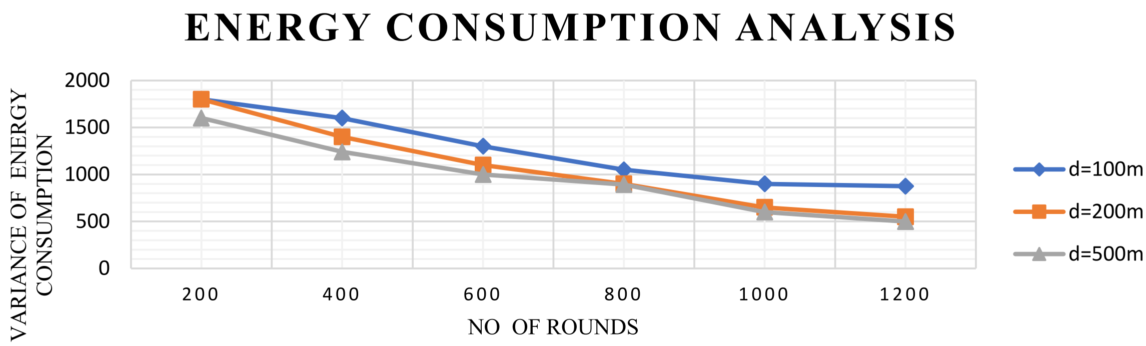

Fig. 10. Energy consumption analysis for the proposed models with the impact of different radius.

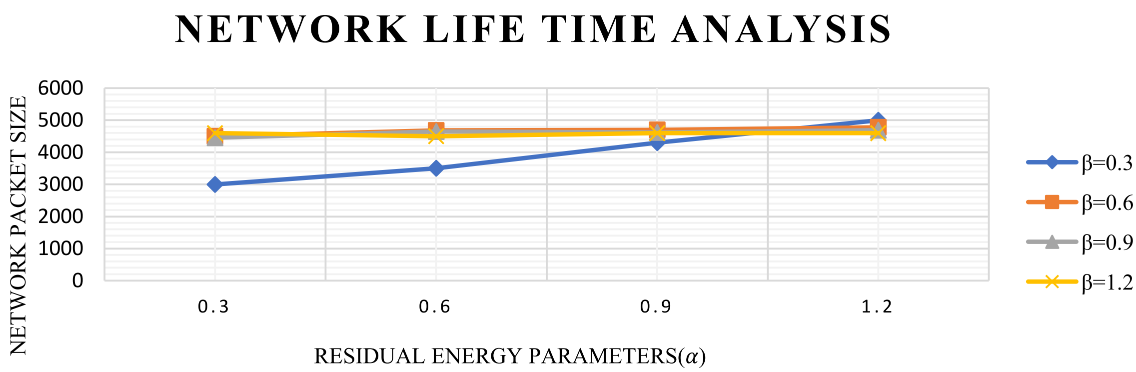

Fig. 11. Network life time analysis for the proposed model with the impact of residual energy and depth of the nodes.

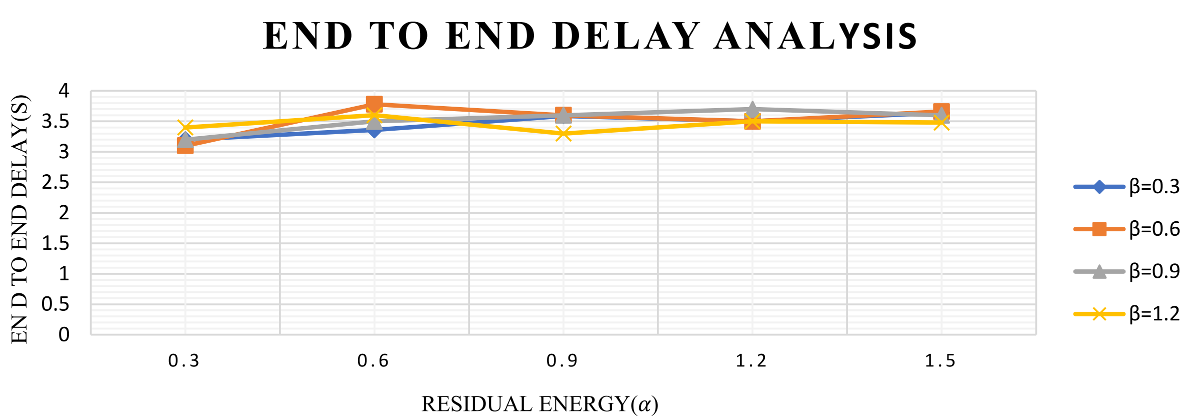

Fig. 12. End to end delay analysis for the proposed model with the impact of residual energy and depth of the nodes.

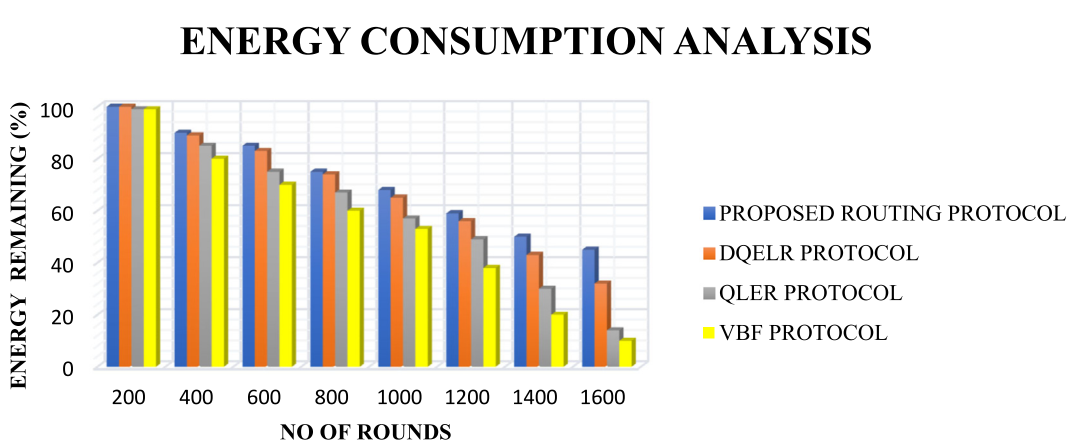

Fig. 13. Comparative analysis of the energy consumption between the different algorithms at radius = 100 m.

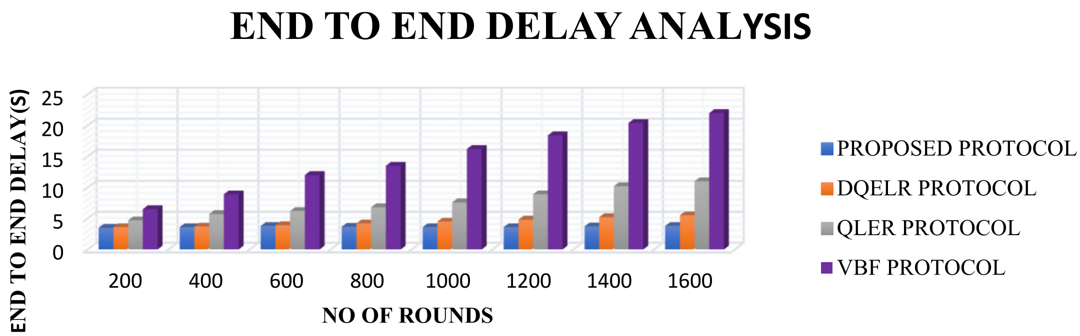

Fig. 14. Comparative analysis for the delay analysis between the different algorithms at radius = 100 m.

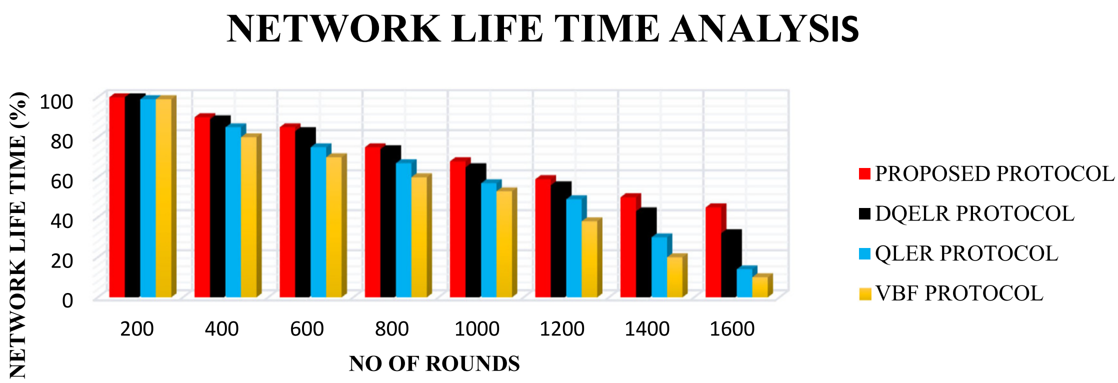

Fig. 15. Comparative analysis for network life time analysis between the different algorithms at radius = 100 m.

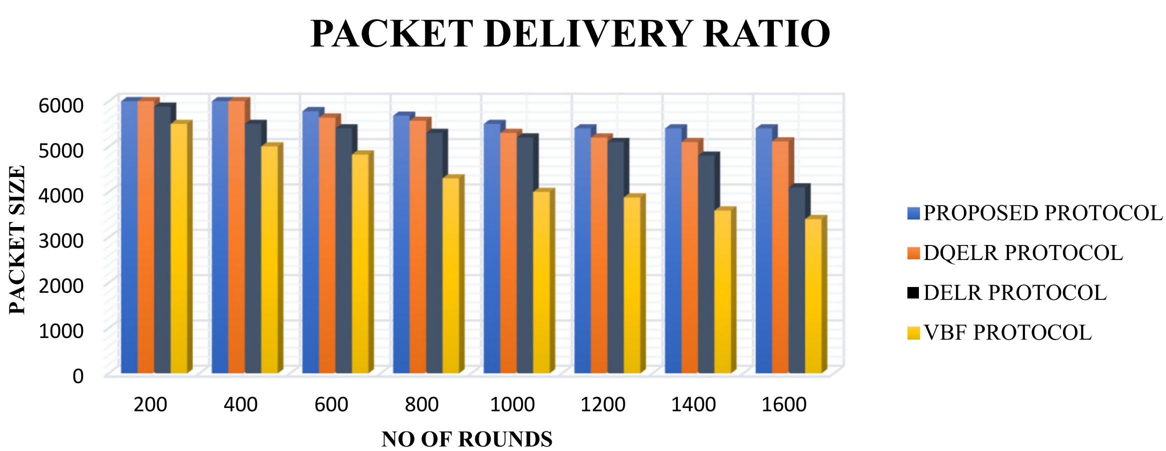

Fig. 16. Comparative analysis for packet delivery ratio between the different algorithms at radius = 100 m.

increased life time when compared to DQELR, 50% than DELR and 60% than VBF protocols. Yet, the QELR and the VBF adopt a broadcast communication method with increased energy consumption though the nodes are empty with null packets leading to energy wastage. The QELR also has no detour short comes while choosing forwarding nodes with high residual energy, and the energy of the nodes in the VBF can be drained quickly because of the repeated utility. Fig. 15 shows the similar fashion of performance as in Fig. 14 in which the proposed protocol has outperformed the other existing algorithm in achieving the less time for the data transmission. Fig. 16 shows the comparative analysis between the different algorithms in which the packets delivery ratio of the proposed algorithm has maintained constantly though there is an rapid change in the topologies and outperforms the other algorithms which makes it suitable for the underwater communication.

6. Conclusion

In this paper, energy aware, depth and distance aware deep extreme Q- Firefly Learning Routing protocol has been proposed. This algorithm adopts the deep extreme learning models along with Q-learned Fireflies are adopted to prolong the network lifetime and efficiency of the networks. In addition, the proposed algorithm incorporates the online training policy which can play an important role when the topology changes and also to make the best routing decisions with an adaptive topology. The extensive experimentations has been conducted to compared the performance of the proposed algorithm in terms of energy consumption, network life time, end to end delay and packet delivery ratio. Also the proposed protocol has consumed less of 40%–45% energy consumption than existing algorithms such as DQELR, 50% less than DELR and as high 60% than VBF protocols. Also the proposed protocol has better network life time, low end to end delay than the

DQELR, DELR and VBF protocols. In conclusion, the proposed protocol has achieved the better network life time and less latency which makes its more suitable for the underwater communication.

CRediT authorship contribution statement

D. Anitha: The paper background work, Conceptualization, Methodology, Dataset collection, Implementation, Result analysis and comparison, Preparing and editing draft, Visualization. **R.A. Karthika:** The supervision review of work, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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