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Performance Analysis of Deep Learning-Based Routing Protocol for an Efficient Data Transmission in 5G WSN Communication

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ABSTRACT For the past few years, huge interest and dramatic development have been shown for the Internet of Things (IoT) based constrained Wireless sensor network (WSN) to achieve efficient resource utilization and better service delivery. IoT requires a better communication network for data transmission between heterogeneous devices and an optimally deployed energy-efficient WSN. The clustering technique applied for WSN node deployment needs to be efficient; therefore, the entire architecture can obtain a better network lifetime. While clustering, the entire network is partitioned into various clusters. Moreover, the cluster head (CH) selection process also needs proper attention for achieving efficient data communication towards the sink node via selected CH and also for increasing the node reachability within the cluster. In this proposed framework, an energy efficient deep belief network (DBN) based routing protocol is developed, which achieves better data transmission through the selected path. Due to this the packet delivery ratio (PDR) gets improved. In this framework, initially, the nodes in the whole network is grouped as clusters using a reinforcement learning (RL) algorithm, which assigns a reward for the nodes that belong to the particular cluster. Then, the CH required for efficient data communication is selected using a Mantaray Foraging Optimization (MRFO) algorithm. The data is transmitted to the sink node via the selected CH using an efficient deep learning approach. At last, the performance of proposed deep network based routing protocol is evaluated using different evaluation metrics they are network lifetime, energy consumption, number of alive nodes, and packet delivery rate. Finally, the evaluated results are compared with few existing algorithms. Among all these algorithms, the proposed DBN routing protocol has achieved better network lifetime.

INDEX TERMS WSN, cluster head (CH), mantaray foraging optimization (MRFO), reinforcement learning (RL), deep belief network (DBN).

NOMENCLATURE

d	Distance between transmitter and receiver.
P_s	Energy consumption model.
P_{ec}	Energy for SNs electronic circuit stimulation.
r	Return value.
y	Discount factor.
α	Learning rate.
N_l^H	l^{th} CH.
P_{dr}	Packet drop.
B_{ut}	Buffer utilization.
C_l	Channel load.
B_{size},	Buffer size.
B_{space}	Buffer shape.
D_p	Dropped packets.
P_x	Transmitted packets.
β	Weight coefficient.
$T_{\max}$	Maximum iteration.
Ub^d	Upper boundary in dimension d.
Lb^d	Lower boundary in dimension d.
$w_{nn'}^2$	Weight coefficient of RBM 2.
f	Nodes life.
M	Coverage matrix.
E_T	Overall energy consumed by the network.
CH_E	Energy utilized by the CH in network.
S_E	Energy consumption of the member node.

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I. INTRODUCTION

With 2G (2nd generation) networks, the user needs like voice and data transmissions are fulfilled by wireless communication. Smart phones utilize 3G technology for the use of multimedia and video transmissions with limited bandwidth. But, the increased bandwidth was provided by the revolutionary change in 4G communication. Moreover, billions of users across the world adopt the smart phones for their daily use [1]. It is said that the usage of smart phone is higher than the population in the world. But, the heavy traffic is generated by the smart phones, which utilizes the 3G and 4G communication for their data as well as video transmission. Also, other issues like congestion and quality of service (QoS) problems are created by this overdue usage of smart phones [2], [3]. At this juncture, the advancement of technology (5G) is needed and Device-to-device (D2D) communications came into existence. For cellular networks, 5G technology is standard in which the cellular companies around the world is started to deploy the 5G telecommunications worldwide in 2019 [4]. But most of the current cell phones utilize the 4G networks for their data as well as video transmission. Service area of 5G networks are separated into small geographical areas named as cells which is like a previous network [5]. In each cell, the 5G wireless devices are connected via local antenna to telephone network and internet using radio waves. Benefit of this 5G network is that it has higher download speeds up to 10 gigabits per second (Gbit/s) and provides greater bandwidth [6].

IoT is one of the fastest-growing technologies for 5G communication, and it may be used in many aspects of our lives. Large densities of sensing devices, such as WSN, are used in IoT systems to monitor the surrounding environment. In recent decades, WSN places its vital role in the communication domain due to their unique characteristics like ease of connection and mobility. This characteristics makes them a major carrier of data across networks [7]. So, the communication revolution holds several standard wireless networks simultaneously in the communication side. In telecommunication side, mobile communication is considered as one of the most prevalent technique than any other wireless networks due to their higher bandwidth. So, the data packet transmission in wireless communication is done with the help of 5G communication protocols [8].

With specific routing technique, the protocol which is defined as the set of rules utilized to forward the data packet from source to destination. Protocols are already written with routing rules. To execute the protocols and to transfer information from one layer to other layers, the wireless communications are constructed with different layers [9]. In mobile wireless communication, data transfer is done based on the transport layer and it launches a particular protocol for data transmission. To confirm a good network resource allocation, the congestion control mechanism is utilized by the transport layer protocol. In addition to that, congestion control in wireless network is considered as the most critical event of the transport layer. In case, if the congestion control is applied in any of the mobile wireless communication (i.e. 5G communication) then the performance of entire wireless network will get collapsed. So, in order to avoid this problem, routing protocols are developed [10], [11].

For sensor network, the routing protocol is considered as a basic requirement to discover the route from sender node to destination sink node. To alleviate the delay, routing protocols are developed and they identify exact routes for data forwarding to accomplish energy efficiency in WSN [12]. Reliable routes are generated by inherit the benefits of both energy conservation as well as route discovery methods. For data-intensive sensor networks, it is adaptive to the traffic patterns as well as network density [13]. To adjust scalability and flexibility of the network, neighbour adoption, routing decision and power conservation are considered as the functions of routing protocols. Particular routing protocols concentrates on the network lifetime maximization, delay and hop-count rather than energy efficiency. So, these metrics are selected to enhance the design features of routing protocol [14].

To obtain a better network outcome as well as to solve a complex decision making problem, machine learning algorithms are considered as prominent solution [15]. In routing and energy management, the strong machine learning algorithms are combined with WSN assisted IoT to moderate and examine the complex decision making issue. To generate the optimal routing paths, learning based algorithms create correct solutions to the problem [16]. In the routing process, machine learning techniques analyse the constraints and automatically learns the dynamic of networks specifically congestion points, quality of links, topology changes as well as new flow arrivals to enhance the service quality. Each sensor nodes (SNs) make decision on the basis of observation state and decision making, which may result in intelligent behaviours. Further, the iterations of learning and decision-making are repeated till determining the optimal solution [17]. The proposed routing architecture mainly aims:

- ➢ To perform a SN grouping based on clustering algorithm.
- ➢ To present a recent optimization algorithm for CH selection
- ➢ To propose a machine learning based algorithm for efficient routing.
- ➢ To estimate the proposed performance and it is compared with recent developed methods.

The Main Contribution of the Proposed Architecture Is: Initially, the cluster formation is achieved using RL algorithm. The RL algorithm checks the entire nodes in the network and assign a reward to the nodes that belongs to the particular network. Then, an optimization based CH selection is carried out which performs an effective selection than the existing optimization algorithms. The selection algorithm considered in this work is MRFO which optimally selects the best CH that satisfies the multi-objective functions. The multi-objective functions considered for CH selection are energy, delay, traffic density, and distance. However, a number of protocols are developed recently for efficient routing but none had attained a better and efficient routing. Recently, the artificial intelligence (AI) techniques have introduced its pathway in routing problem. In our proposed approach, we have also used the deep learning approach to achieve efficient routing. The routing results of proposed DBN architecture is found effective than the other existing architectures.

The Remaining Sections Are Organized as: Few recent works related to clustering and routing is discussed in section II. The problem definition and motivation are discussed in section III. Then, the detailed description for each technique in proposed framework and the details about the multi-objective functions are discussed in section IV. Then, the results obtained using the proposed routing protocol and its corresponding results are deliberated in section V. At last, the whole proposed architecture is summarized in section VI.

II. LITERATURE REVIEW

A. FEW RECENT WORKS RELATED TO OUR PROPOSAL IS GIVEN BELOW

To improve the performance of 5G wireless communication, many studies have been conducted. Routing protocols proposed for wireless communication receives a great attention because of major improvements in 5G technology. Here, a brief overview about the existing research on routing protocols were discussed.

Thangaramya *et al.* [18] developed Neuro-Fuzzy based routing technique for WSNs in IoT. Data sensing, data collection and data transfer from one to another one was done with the help of WSNs in IoT. The network's QoS was enhanced by using the intelligent routing in IoT assisted WSN. Plenty of researches were conducted for energy efficient routing in previous years. So as to improve the existing technique, this paper developed Neuro-Fuzzy Rule for Cluster generation in IoT based WSNs. Conversely, the technique must be improved to ensemble WSN within the IoT environment. Finally, it was analysed that this routing algorithm provides efficient performance in terms of various parameters like delay, energy utilization, network lifetime, and PDR.

For dynamic cluster-based routing, Sujanthi and Kalyani [19] proposed a QoS-aware secure deep learning method in WSN assisted IoT. Because of the open and resource constrained nature of WSN-assisted IoT, security and energy efficiency of IoT was considered as a challenging issue. So, this paper the dynamic cluster based hybrid WSN-IoT network was developed using Secure Deep Learning (SecDL) approach. Moreover, the network was designed to be Bi-Centric Hexagons together with mobile sink technology for energy efficiency enhancement. To handle the data aggregation in each and every cluster, a Two-way Data Elimination and Reduction outline was enabled. For aggregated data, high level security was accomplished by a One Time-PRESENT (OT-PRESENT) cryptography algorithm. The ciphertext was transformed to mobile sink through selected route to confirm high QoS. To perform optimal route identification, Crossover based Fitted Deep Neural Network (Co-FitDNN) was developed. Subsequently, this work concentrates over user-security because, Iot users were used to access the sensory data.

Huang *et al.* [20] established a deep learning link reliability prediction for routing in WSN. Resilient routing algorithm was developed in this paper for better routing process in WSN. A deep-learning model referred as Weisfeiler-Lehman kernel and Dual Convolutional Neural Network (WL-DCNN) method was proposed in this process for lightweight subgraph extraction and labelling. It was influenced to improve self-learning capacity with strong generality. For WSN, the WL-DCNN model was designed to perform resilient routing. The design of resilient routing was applied in WSN for estimating the target links reliability in which it captures topological features under the routing table attack that shows varied degrees of damage to local link community.

A blockchain-based deep trusted routing framework was developed by Ibrahim El-Moghith and Darwish [21] for WSNs. The basic operations of WSN were easily destroyed by the routing attacks in which it significantly damage the whole network. To guarantee the efficiency of WSN and protection of routing, it requires a trustworthy routing scheme. The dependability among the routing protocols were enhanced with the trust protection, centralized decisions, or Cryptographic schemes. So, in this a trusted routing with Markov Decision Processes (MDPs) and deep-chain was proposed to improve the routing efficiency and security. To authenticate the process of delivering information, the suggested architecture uses a proof of authority mechanism within the blockchain network. A deep learning technique was developed to absorb the properties of several nodes. MDPs were used to choose the finest neighbouring hop as a forwarding node to transfer the messages quickly and safely.

Composite fuzzy method was proposed by Raghavendra and Mahadevaswamy [22] for an energy efficient routing in WSN. In WSN, energy consumption optimization in SN battery plays a major role. Due to transmission and sampling rate, the energy in WSN's battery got depleted. The energy consumption technique was modelled for important parameters which affects the longevity of WSN network. In this work, Fuzzy membership functions were considered as the parameters to enhance the network lifetime. The parameters were optimized with the help of Fuzzy logic at multiple levels. In [32], a hybrid metaheuristic cluster based routing (HMBCR) approach was introduced which performs efficient clustering and routing process. Levy distribution based brainstorm optimization (BSO-LD) was introduced for efficient clustering. Then, a hill climbing based water wave optimization (WWO-HC) approach was introduced which performs optimal route selection process.

CH selection using an efficient algorithm by including some critical parameters was performed in [33]. Routing via the selected CH will be efficient for performance enhancement. By considering in this process, a hybrid optimization algorithm was introduced for CH selection and routing which was named as GA-PSO (genetic based particle swarm optimization algorithm). Optimal route for sink mobility was identified using PSO. Distributed Autonomous Fashion integrated with Fuzzy If-then Rules (IDAF-FIT) algorithm was introduced in [34] for efficient clustering. During clustering the CH was also selected using the if-then rule. Then, an Adaptive Source Location Privacy Preservation Technique using Randomized Routes (ASLPP-RR) was used in this method for optimal route selection. Finally, the security analysis process was introduced to enhance the data confidentiality. Along with cluster based routing, the rate control concept was also included in [35], which further enhances the lifetime for high simulation time. For lifetime enhancement, initially the nodes were clustered using hybrid K-means and Greedy best first search algorithm. Then, the firefly (FF) optimization was introduced for rate control. Finally, the Ant Colony Optimization (ACO) was introduced which selects optimal path for data transmission. African buffalo optimization (ABO) based routing was introduced in [36]. Based on African buffalos behavior, the optimal route selection process was performed. ABO acts as main controller, and all the nodes were managed in correspondence with BS. It effectively transfers the packets from source to sink with high network lifetime.

Most efficient approach for decision making was multi-criteria decision making (MCDM) approach. To further improve the MCDM, the fuzzy logic was introduced which overcome the issues shown by MCDM. In [37], a fuzzy based MCDM for CH selection and a hybrid model for routing was introduced. Then, optimal CH selection was achieved using generalized intuitionistic fuzzy soft set (GIFSS) method and a hybrid shark smell optimization (SSO), and a genetic algorithm (GA) was used to achieve efficient routing. Finally, few performance metrics were evaluated which shows the effectiveness of GIFSS-SSO approach.

WSN utilizes number of nodes to gather data from surrounding environment. However, during such process energy conservation was considered as major objective. It mainly relies on clustering and routing strategies. Therefore, in [38] an Energy Aware Distance-based Cluster Head selection and Routing (EADCR) protocol was developed which enhances the lifetime and energy efficiency of the nodes in WSN. A modified form of fitness function was introduced during CH selection which aims to reduce the energy consumption. Then, a shortest path identification approach was introduced for routing process. This approach utilizes Euclidean distance to reduce the consumed energy. This combined approach had enhances the overall network energy and lifetime.

WSN utilized large number of SNs to achieve complex communication. However, nowadays the amount of SNs has reduced, further the communication and sensing capabilities also gets reduced. It automatically reduces the routing QoS performance. To overcome this, a Fuzzy based Relay Node Selection and Energy Efficient Routing (FRNSEER) was introduced in [39] which makes the routing more efficient and effective. In this, the fuzzy rules was utilized to select the sink node. During data transmission, a better utility factor and energy can be achieved by introducing the active selection of relay nodes. To achieve better communication, a sensor hub with less energy expenditure was scheduled in between the sink and relay node.

In [40], a two-tier distributed fuzzy logic based protocol (TTDFP) was introduced for efficiency enhancement in multi-hop WSN. Clustering is used to meet the needs of efficient aggregation in terms of used energy. Gathered data were transferred to CHs, while CHs relay received packets to the base station in a clustered network. Hotspots and/or energy-hole issues may emerge as a result of using a multi-hop topology. This was reduced by TTDFP approach which is an adaptive, distributed protocol which effectively scales and execute for WSN applications. Moreover, it utilizes optimization technique to tune the fuzzy parameters. It achieved high network lifetime and energy efficiency.

Clustering was identified as the effective communication platform in WSN. Recently, fuzzy were considered as an efficient approaches for clustering, as they have provided a crisp output. However, optimal solution identification may take large time. Therefore, a clonal selection with rule based fuzzy clustering was introduced in [41] which overcomes the issues shown by fuzzy algorithm. While comparing with other fuzzy based approaches this CLONALG-M has shown better achievement. It depends on the principle of clonal selection which integrates adaptive immune process as its basic principle. The output that were approximately deployed on the basis of membership function was determined using immune system principle to increase the overall performance. Experimental analysis have shown that this approach had outperformed other techniques.

Clustering increases the network's energy efficiency, scalability, and communication capacity. Static and dynamic clustering, as well as equal and unequal clustering, are the two types of clustering. Hotspots need a large overhead and are prone to connection issues in wireless sensor networks, which can only be achieved by uneven clustering. To avoid such hotspot issue, a zonal division based fuzzy logic approach was introduced in [42]. In this, the clustering was performed by fuzzy logic, which minimize the energy consumption rate. It shows better performance by achieving reduced energy consumption, enlarging network lifetime and load balancing.

Normally, all the existing approaches has introduced optimization based techniques or some other techniques for clustering and routing. But, none of the works were concentrated on AI and optimization approach. In our work, we have used RL and DBN approaches for cluster formation and routing. This approaches have further improved the overall network lifetime therefore the system can withstand for longer time period.

III. PROBLEM IDENTIFICATION AND MOTIVATION

Routing in WSN assisted IoT is considered as the significant task which should be controlled very carefully. Routing is to establish a data transmission communication between the SNs as well as base station (BS). Data routing process differentiates the WSNs from remaining wireless ad hoc networks as well as modern communication strategies in terms of several challenging characteristics like energy consumption and low network lifetime. There are three main problems are considered in the WSN routing process. First of all, for the deployment of more number of SNs, there is no possible way to develop a global addressing process. So, traditional IP-based protocols are not essential for sensor networks. Secondly, the applications of all the sensor network wants a stream of sensed data from multiple sources to a specific sink node or BS in which it conflicts the typical communication networks. Thirdly, similar data generation is achieved using multiple sensors within the phenomenon data vicinity in which it leads to the heavy redundancy traffic in whole network. Moreover, this kind of redundancy leads to more energy consumption as well as more bandwidth utilization. Also leads too many other issues, such as delay, packet loss, and bandwidth degradation. So, this motivate us to develop an efficient routing process based on machine learning concept in which it learns from the previous interactions to efficiently select its action in the future.

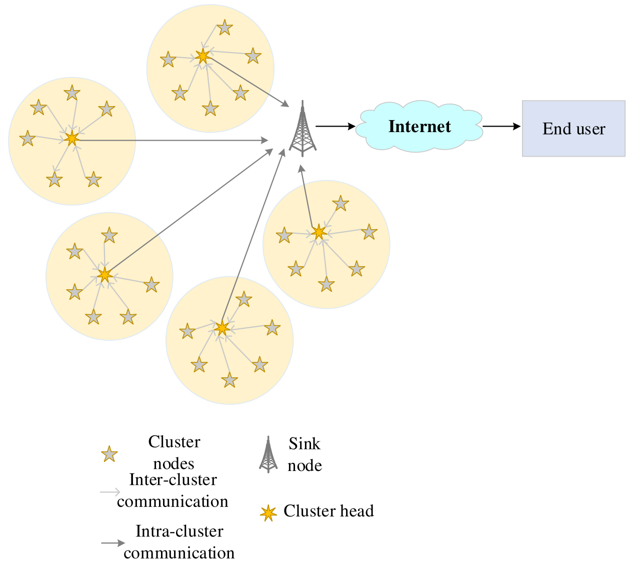

FIGURE 1. Cluster-based single-hop communication in WSN assisted IoT.

IV. METHODOLOGY

This section describes the RL based routing protocol in detail. Then the energy consumption model is introduced. In addition, some definitions, terminology, and assumptions are presented to aid understanding.

A. NETWORK MODEL

The assumptions that are considered while developing the WSNs network model is discussed below:

- The source and SNs are static in nature.
- Data collection from the CH is done using one sink.
- Based on heterogeneous nature, the SNs are classified as advanced, intermediate and normal nodes.
- Sink should be a super node, which needs to kept update regarding the details about all the SNs.
- CH aggregate data from SNs and transfer the gathered information to sink node.
- Inter-data communication technique is selected in this approach to perform the data communication via CH.
- The node that reaches zero battery level is considered as the dead node.

The model for Cluster based single-hop communication in WSN assisted IoT is shown in Fig. 1. This work focuses on the development of optimal path routing in a 5G wireless communication network (WSN assisted IoT) based on machine learning (deep neural network) concept. Before performing the routing process, it is very essential to cluster the sensors into a group of nodes. Because clustering technique is very essential to perform the energy efficient transmission which extends the networks survival rate and also consumes the minimum energy. So, in this work, clustering is performed based on the RL algorithm. This algorithm is a centralized technique in which the BS or sink node performs the clustering process and assigns each SN into a specific cluster based on the information of their location. After the allocation of SNs in a cluster, CH selection is done by using the optimization algorithm. However, the overloading of data aggregation and data receiving from their member SN of each CH consumes more energy in a hierarchical clustering based WSN. So, it is very essential to select the CH in a proper way to achieve extended network lifetime. In order to achieve this, Multi-Objective MRFO algorithm is introduced here to elect the CH from a cluster. This algorithm is recently developed to bio-inspired optimization algorithm to address real-world engineering problems. The process flow for proposed approach is shown in Fig. 2.

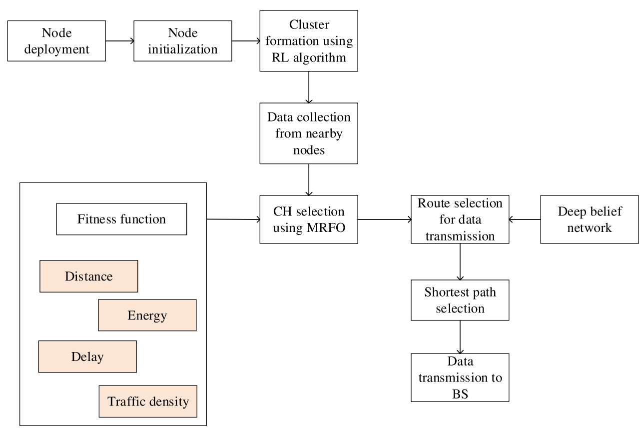

FIGURE 2. Process flow for proposed approach.

The multi-constraints like delay, energy, traffic density, and distance, are considered as some parameters to finalize the CH from each cluster. Most important tasks in sensor networks for enhancing WSN performance in terms of data integrity, throughput, energy efficiency, and latency in dynamically unreliable, asymmetric and changing, unreliable, and varying wireless channels is the right selection of optimal route. After the selection of CH, the efficient data transmission is done by proposing a Deep Belief Neural Network (DBN) based routing protocol. In order to achieve this routing process, the neural network considers some factors like residual energy, distance from CH, number of neighbour nodes and link distance. In this way, the proposed routing deeply learn about the nodes behaviour in terms of communication so that an energy efficient routing can be achieved.

B. ENERGY MODEL

The radio energy dissipation model considered in this work is obtained from [23]. In this, the energy to the radio electronics is served by receiver whereas the transmitter provides the energy to power amplifiers and radio electronics. The fading model used in this process is multi-path. The distance d exist between transmitter and receiver is found higher than the defined threshold. The energy dissipation encountered in free space is represented as d^2. Then, the energy dissipation corresponding to multi-path fading is represented as d^4. The energy consumption model P_s during the k^{th} bit packet transmission is represented in (1),

$$P_s = \begin{cases} k * \left(P_{ec} + P_{frs} * dis^2\right); & dis < d_o \\ k * \left(P_{ec} + P_{mpf} * dis^4\right) & dis \geq d_o \end{cases} \tag{1}$$

Then, the distance between the tolerant bit error rate (BER) and sender and receiver is identified to evaluate the multi-path or free space fading model, $P_{frs} * dis^2$ or $P_{mpf} * dis^4$. d represents the distance between the sender and receiver. The requisite energy for transmitting the bit to the free-space via the multi-path fading channel is represented as P_{frs} and P_{mpf} respectively. The threshold distance figured out using (2) is denoted as d_0.

$$d_0 = \sqrt{\frac{P_{frs}}{P_{mpf}}} \tag{2}$$

The energy consumed while receiving a k bits of data packets is represented in (3),

$$P_{rec} = k * P_{ec} \tag{3}$$

During data aggregation, the energy consumed by CH is represented in (4),

$$P_{agg} = P_{Eagg} * k * n \tag{4}$$

where, n- number of messages, k - bits number in the data packet, and the total energy that is consumed while aggregating a single bit is represented as P_{Eagg}.

C. CLUSTER GENERATION USING REINFORCEMENT LEARNING

RL is a process which performs learning process and provide a reward value to the favourable actions. RL process includes few essential components they are agent, action, state, reward, policy, value function, and environment model. Based on Markov decision process (MDP), the RL performs its process, which integrates ε-greedy selection and temporal difference approaches as a selection and mathematical modelling process [24], [25]. In this work, the SNs are clustered using a RL algorithm. For RL based clustering, the nodes in WSN acts as the learning agent. Based on particular policies the learning agents analyse the energy level of each adjacent neighbours for clustering. Before forming the clusters, the MDP for each node is evaluated. State, action, policy, and reward are integrated within the MDP. The temporal difference procedure is used by the learning agents to obtain the action policy regarding the network environment.

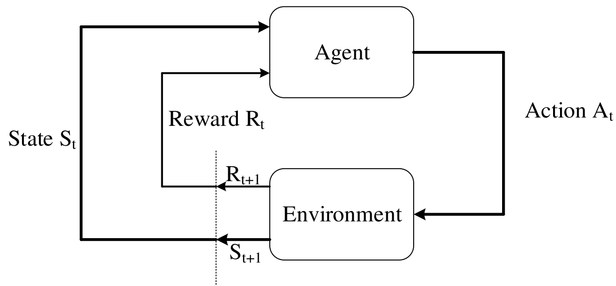

FIGURE 3. Reinforcement learning.

The model RL is shown in Fig. 3. Each SN integrates the RL concept for clustering which initially evaluate the route cost and provide that information to CH on the basis of updated Q-value. The link cost exhibit between the present node and next-hop node is illustrated by reward parameter [24]. Basic rule followed by MDP is [S- set of states, T – transition function, A – set of actions, and R – reward function]. All states S which exhibit action A is selected by learning agent and then with these selected action the energy consumption is estimated for each cluster. Finally, a proper decision is made by evaluating the reward R parameter obtained from the estimated energy consumption. Then, the current state and action are incremented to 1 which is represented as S to Si+1 (state) and A to Ai+1 (action). The optimal policy Q which increments the reward parameter is developed by the learning agent from the learning experience. This optimal policy is used for optimal CH selection.

The reward R and state transition T of MDP are interconnected with present action and state. The major goal of learning agent is policy development, π:

$S \rightarrow A$: The learning agent determines the action A_i based on the current state S_i (i.e. $\pi\ (S_i) = A_i$), Then, the initial state S_i is analysed to determine the cumulative value function $V^{\pi}\ (S_i)$ which is defined in (5),

$$\begin{aligned} V^{\pi}\ (S_i) &= r_i + yr_{i+1} + y^2 r_{i+2} + \ldots = r_i + y + V^{\pi} \cdot (S_{i+1}) \\ &= \sum_{i=1}^{\infty} y^i r_{i+1} \end{aligned} \tag{5}$$

The learning agent aims to improve the intelligent strategy by making the $V^{\pi}\ (S_i)$ value high. This process is referred as policy and it is represented in (6),

$$V^{\#} = \arg\max_{\pi} V^{\pi}\left(S_i\right) V_s \tag{6}$$

Finally, the Q-value is updated using (7),

$$\begin{aligned} Q_{t+1}\left(S_t, \alpha_t\right) &= (1-\alpha) Q_t\left(S_t, \alpha_t\right) \\ &+ \alpha\left[r^{t+1} + y \max Q_t\left(S_{t+1}, \alpha'\right) - Q_t\left(S, \alpha_t\right)\right] \end{aligned} \tag{7}$$

Using (7), it constantly updates the Q-table. The largest Q-value and return value are represented as $\max Q_t\left(S_{t+1}, \alpha'\right)$ and r_t. The action performed by each learning agent is represented as α'. An algorithm for RL based cluster generation is shown below in Algorithm 1.

Algorithm 1 Algorithm for RL Based Cluster Generation

For each
State and action pair (S, α)
Initialize
Assign 0 to the table entry $Q(S, \alpha)$
Do loop
Execute the selected action
Assign immediate reward R to the executed action.
Observe new state S'
Using equation (7), update the table entry $Q(S, \alpha)$ which is defined as follows,
$Q_{t+1}\left(S_t, \alpha_t\right) = (1-\alpha) Q_t\left(S_t, \alpha_t\right) + \alpha\left[r^{t+1} + y \max Q_t\left(S_{t+1}, \alpha'\right) - Q_t\left(S, \alpha_t\right)\right]$
$S = S'$
Select action
$\pi\left(S_i\right) = \arg\max \alpha Q(S, \alpha)$
Exploration
$\frac{P(\alpha i|S) = kQ(S,\alpha)}{\sum kQ(S,\alpha)}$
End loop

D. CLUSTER HEAD SELECTION USING MRFO ALGORITHM

The probabilistic process is used along with CH selection, which selects the appropriate node from the cluster as CH. It analyse multiple objectives such as traffic density, energy, delay, and distance for CH selection. Excess energy is consumed by nodes during data gathering, forwarding and receiving. While comparing to the other nodes, the CH node will get enormous energy as they are highly responsible for forwarding and receiving data from different SNs, further it also aggregate the collected data. Therefore, it is essential to select the nodes that sustains more energy while performing all these tasks. Such nodes needs to be selected as CH which is identified by analysing the multi-objectives which are discussed below,

1) MULTI-OBJECTIVES FOR CH SELECTION

The node having high energy, coverage with lowest cost and closest to the user will be chosen as CH. All CHs which are selected from each clusters perform data aggregation and packet forwarding to BS, either directly or via additional hop [26]. After picking the CH from each cluster, the route for transferring the aggregated data to BS will be determined. Distance, energy, latency, and traffic density are the multi-constraints utilized to attain energy-aware routing. The relevance related to energy-aware restriction in WSN routing is discussed in this section.

a: DISTANCE

In WSN, the requirement for the distance metric in data transmission is explained by the distance measure. When a SN is converted into a CH, the distance between cluster members is computed so that it kept to a minimum. The shortest distance between the SN and the CH is taken into account, and the SN closest to the CH is chosen for data transmission. In (8), the formula for distance has explained. The distance occupied by data from CH to sink and the data packet travelling distance from the sink to cluster node is taken as the numerator term in the distance formula. The distance should be in the range of 0 to 1. As a result, the normalization is completed.

The denominator $\sum_{k=1}^{m}\sum_{l=1}^{m}\left\|N_k^n - N_l^H\right\|$ is used to normalize the distance metric. The distance parameter gets a significant value for the distance which exist between the CH and normal node is large.

$$F_i^d = \frac{\sum_{k=1}^{m}\sum_{\substack{l=1 \\ l\in k}}^{h}\left\|N_k^n - N_l^H\right\| + \left\|N_l^H - N^S\right\|}{\sum_{k=1}^{m}\sum_{l=1}^{m}\left\|N_k^n - N_l^H\right\|} \tag{8}$$

where, h indicates total CHs, and m denotes the total nodes in the network. The sink node, normal node, and CH node are represented as N^S, N^n, and N^H respectively.

b: ENERGY

The energy parameter for the network node should be set to maximum, indicating that the node's energy is adequate to carry on data forwarding over the network, however the energy encountered for data forwarding in WSNs is set at minimum. By removing the cumulative energies from one, the maximising issue is turned into a minimization problem, as indicated in (9). Most essential metric is energy which can be estimated by determining the remaining energy in each node. The remaining energy is obtained by identifying the cumulative cluster energy and sum of energy from all clusters. The energy metric is modelled and it is shown in (9),

$$F_i^{\varepsilon} = \frac{\sum_{l=1}^{h} N_c^{\varepsilon}(l)}{h \times \underset{l=1}{\overset{h}{Max}}\left[\varepsilon\left(N_l^n\right)\right] \times \underset{l=1}{\overset{h}{Max}}\left[\varepsilon\left(N_l^H\right)\right]} \tag{9}$$

$$N_c^{\varepsilon}(l) = \sum_{\substack{k=1 \\ k\in l}}^{m}\left[1 - \varepsilon\left(N_k^n\right) * \varepsilon\left(N_l^H\right)\right]; \quad (1 \le l \le h) \tag{10}$$

The node which shows maximum energy will be considered as optimal CH. The cumulative energy related to CH is represented as $\sum_{l=1}^{h} N_c^{\varepsilon}(l)$. The product of overall CHs and highest energy shown by CH and other nodes (i.e. the nodes involved in data transmission) is represented as $h \times \underset{l=1}{\overset{h}{Max}}\left[\varepsilon\left(N_l^n\right)\right] \times \underset{l=1}{\overset{h}{Max}}\left[\varepsilon\left(N_l^H\right)\right]$. Maximum value shown by denominator is 1.

c: DELAY

For the ideal cluster head, the network latency [27] must be reduced, and its result is found and it directly related to total members in that particular cluster. The latency grows in proportion to the number of cluster members, indicating that the number of cluster members aggregated under the ideal cluster should be kept to a minimum. In other words, the transmission delay is determined by the number of cluster members. As a result, the cluster with the smallest number of members starts transferring data packets.

The network delay needs to be reduced while selecting the optimal CH and it is directly related to all the cluster members. If the cluster member increased, then the delay in the network also gets increased.

$$F_i^{\delta} = \frac{\underset{l=1}{\overset{h}{Max}}\left(C_{m,l}^{H}\right)}{m} \tag{11}$$

The l^{th} CH in the network is represented as $C_{m,l}^{H}$. The delay value may varied from 0 to 1.

d: TRAFFIC DENSITY

To maintain an effective network, the traffic density needs to be maintained minimum. Traffic density mainly depends on dropping packet, channel load, and buffer utilization. The average obtained by these three parameters will provide the traffic density.

$$F_i^{t} = \frac{1}{3}\left[B_{ut} + P_{dr} + C_l\right] \tag{12}$$

The ratio between the buffer space and buffer size are evaluated to determine the buffer utilization which is defined in (13),

$$B_{ut} = \frac{B_{space}}{B_{size}} \tag{13}$$

$$P_{dr} = \frac{D_p}{P_x} \tag{14}$$

During data transmission, the ratio between the transmitted packets and dropped packets are evaluated to determine the packet drop ratio. The channel load is defined in (15),

$$C_l = \frac{C_{busy}}{R} \tag{15}$$

where, the channel that are in busy state is represented as C_{busy}, and the total rounds that are specified during the simulation time is represented as R. The channel load is obtained by considering the number of rounds and channel state of the simulation time.

2) MANTARAY FORAGING OPTIMIZATION (MRFO) ALGORITHM

Manta ray is a marine creature which contains two pectoral fins and flat body [28]. The MRFO algorithm is used in this proposed architecture which analyse the multi-objective function for CH selection. The mathematical modelling for the MRFO algorithm is discussed below:

a: MATHEMATICAL MODEL OF MRFO

The mathematical model for the foraging behaviour of MRFO contains three different strategies they are chain foraging, cyclone foraging, and somersault foraging.

b: CHAIN FORAGING

Initially, mantaray search the entire solution space for plankton (the node that satisfies the objective function), after determining the plankton position they swim towards the optimal solution. The node that contains high energy, less distance to sink node, less traffic density, and less delay are considered as best CH. Each mantaray move towards the best plankton by following the preceding mantarays. Based on identified best solution, each individuals update its current position. The charging foraging model is represented in (16),

$$x_i^d(t+1) = \begin{cases} x_i^d(t) + r\cdot\left(x_{best}^d(t) - x_i^d(t)\right) \\ \quad +\alpha\cdot\left(x_{best}^d(t) - x_i^d(t)\right) & i=1 \\ x_i^d(t) + r\cdot\left(x_{i-1}^d(t) - x_i^d(t)\right) \\ \quad +\alpha\cdot\left(x_{best}^d(t) - x_i^d(t)\right) & i=2,..,N \end{cases} \tag{16}$$

where, $\alpha = 2\cdot r\cdot\sqrt{|\log(r)|}$, d and t represents the dimension and iteration number respectively. The position of i^{th} individual is represented as $x_i^d(t)$, and the random vector whose value ranges from [0, 1] is represented as r. α indicates weight coefficient. The area which is having higher plankton concentration is represented as $x_{best}^d(t)$. The updated position of i^{th} individual is represented as $x_{i-1}^d(t)$.

c: CYCLONE FORAGING

All solutions follow its preceding solutions to reach the best position of plankton. Then, the individuals perform a spiral-path and it is modelled in (17),

$$\begin{cases} X_i(t+1) = X_{best} + r\cdot\left(X_{i-1}(t) - X_i(t)\right) + e^{b\omega} \\ \quad\cdot\cos(2\pi\omega)\cdot\left(X_{best} - X_i(t)\right) \\ Y_i(t+1) = Y_{best} + r\cdot\left(Y_{i-1}(t) - Y_i(t)\right) + e^{b\omega} \\ \quad\cdot\sin(2\pi\omega)\cdot\left(Y_{best} - Y_i(t)\right) \end{cases} \tag{17}$$

where, the random number in (17) is represented as ω whose value may range from [0, 1]. The mathematical expression for cyclone foraging in n-D dimension is defined in (18),

$$x_i^d(t+1) = \begin{cases} x_{best}^d + r \cdot \left(x_{best}^d - x_i^d(t)\right) \\ \quad + \beta \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i=1 \\ x_{best}^d + r \cdot \left(x_{i-1}^d(t) - x_i^d(t)\right) \\ \quad + \beta \cdot \left(x_{best}^d(t) - x_i^d(t)\right) & i=2,..,N \end{cases} \tag{18}$$

$$\beta = 2e^{r_1 \frac{T\max - t + 1}{T}} \cdot \sin(2\pi r_1) \tag{19}$$

where, r_1 represents the random number whose value ranges from 0 to 1. Each individuals perform random search based on the reference position (i.e. plankton). The cyclone foraging attains good exploitation and also improves the exploration capability. To reach the optimal solution each individual needs to update its position instead of staying in the current position. To achieve such position update a new reference position is allocated for each individuals. This stage is represented in (20),

$$x_{rand}^d = Lb^d + r \cdot \left(Ub^d - Lb^d\right) \tag{20}$$

$$x_i^d(t+1) = \begin{cases} x_{rand}^d + r \cdot \left(x_{rand}^d - x_i^d(t)\right) \\ \quad + \beta \cdot \left(x_{rand}^d(t) - x_i^d(t)\right) & i=1 \\ x_{rand}^d + r \cdot \left(x_{i-1}^d(t) - x_i^d(t)\right) \\ \quad + \beta \cdot \left(x_{rand}^d(t) - x_i^d(t)\right) & i=2,..,N \end{cases} \tag{21}$$

where, the randomly initialized solutions are represented as x_{rand}^d. The flowchart for MRFO algorithm is shown in Fig. 4.

d: SOMERSAULT FORAGING

Each individual makes a random movement around the plankton and perform the somersault to reach new position. The somersault foraging performed by mantaray is described in (22),

$$x_i^d(t+1) = x_i^d(t) + S \cdot \left(r_2 \cdot x_{best}^d - r_3 \cdot x_i^d(t)\right), \quad i = 1,..,N \tag{22}$$

where, S indicates the somersault factor (i.e. $S = 2$), r_2 and r_3 represents the random number whose values ranges from 0 to 1. The individuals in the entire search space may update its new position between the current and best position. The solution present at its current position experience disturbance which may get reduced while moving close to the best solution. The three strategies shown by this MRFO algorithm improves the efficiency of CH selection process. Almost all the nodes will reach near to the optimal solution, but the node that perfectly satisfies the fitness function is selected as the best CH.

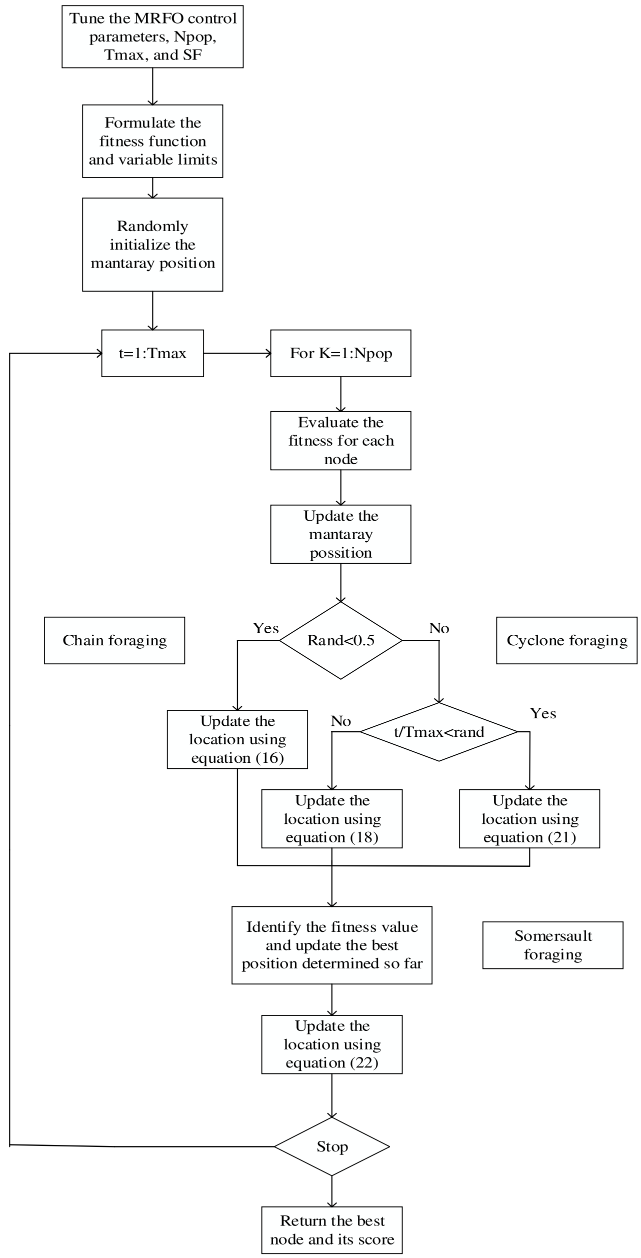

FIGURE 4. Flowchart for MRFO algorithm.

E. DEEP BELIEF NETWORK BASED ROUTING

DBN is most efficient deep learning network which is otherwise represented as probabilistic generative networks (PGN). It contains multiple layers whereas each layer contains number of hidden and visible neurons. DBN layers include restricted Boltzmann machine (RBM) and a multilayer perception (MLP) layers [29], [30]. Two of these layer contain input and hidden layers and the MLP additionally contains output layer. In DBN, the two different layers, such as hidden, and input layers are connected with tuneable weights which considered as the major significance of DBN architecture.

The input given to the neural network is discussed below,

Sink: It is considered as the destination nodes which gathers the aggregated data.

Action history: Before aggregating current data, the data communication for the previously aggregated k data is performed which is considered as the action.

Future node: Total number of 'C' aggregated data which waits behind the present aggregated data is represented as future node

Max-distance node: The maximum possible distance exhibited by the node from all the nearby nodes is considered as max-distance node.

The hidden layer present at first contains a combination of 4 hidden neuron subsets. There are 28 neurons found in each subset which are meshed with its respective input neurons. Additionally, two hidden layers having 128 neurons are also considered in this DBN architecture.

Two RBM layers are present they are RBM 1 and RBM 2, which contains input and hidden layers. The mathematical model for RBM 1 is represented in (23),

$$N^1 = \left\{N_1^1, N_2^1, \ldots, N_g^1, .., N_r^1\right\} \tag{23}$$

$$G^1 = \left\{G_1^1, G_2^1, \ldots, G_g^1, \ldots, G_r^1\right\} \tag{24}$$

where, N_m^1 indicates the j^{th} input neuron and the hidden neuron g of RBM 1 is represented as G_n^1. The bias is provided to both the hidden and visible layers. In RBM 1, the total neurons in the hidden and input layers are represented as r and v respectively. The weight coefficient of RBM 1 is represented as w_{mn}^1 $(1 \leq m \leq v)$ and, $(1 \leq n \leq r)$. The RBM 1 output is defined in (25),

$$G_n^1 = \aleph\left[\varpi_n^1 + \sum_m N_m^1 \times w_{mn}^1\right] \tag{25}$$

where, the bias provided to the n^{th} hidden layer of RBM 1 is represented as ϖ_n^1 and the weight corresponding to the hidden neuron n and input neuron m is represented as w_{mn}^1. Based on the input features of DBN classifier the RBM 1 provides the output. Then, the obtained output is provided as an input to RBM 2, which is defined in (26),

$$N^2 = \left\{N_1^2, N_2^2, \ldots, N_g^2, .., N_r^2\right\} \tag{26}$$

$$G^2 = \left\{G_1^2, G_2^2, \ldots, G_z^2, \ldots, g_h^2\right\} \tag{27}$$

where, A and G represents the input and hidden neurons corresponding to RBM 1 and RBM 2 layers. In RBM 2, the weight value obtained from the successive layers are represented as

$$w^2 = \left\{w_{gg}^2\right\} \tag{28}$$

$w_{nn'}^2$ combines the hidden neuron n with the visible neuron n' of RBM 2. The output obtained from RBM 2 is represented as

$$G_n^2 = \omega\left[\varpi_n^2 + \sum_m N_m^2 \times w_{nn'}^2\right] \forall N_m^2 \approx G_n^1 \tag{29}$$

The output obtained from RBM 2 is then fed as an input to MLP layer, and the input neurons in the input layer of MLP is represented in (30),

$$D = \left\{D_1, D_2, .., D_g, \ldots, D_r\right\} = G_n^2 \tag{30}$$

where, the total neurons present at the input of MLP is represented as r. The hidden neurons of MLP layer is represented as,

$$G = \left\{G_1, G_2, \ldots G_x, \ldots, G_y\right\}; \quad (1 \leq x \leq y) \tag{31}$$

where, the total hidden layer neurons of MLP layer is represented as y. The output of MLP layer is defined in (32),

$$P = \{P_1, P_2, \ldots, P_z, .., P_h\} \tag{32}$$

where, the total neurons present at the output of MLP is represented as h. The output of MLP is represented as

$$P_z = \sum_{x=1}^{y} w_{xz}^G * G_x \; (1 \leq x \leq y) \; ; \; (1 \leq z \leq h) \tag{33}$$

where, the weight corresponding to the hidden neuron x and output neuron z of MLP layer is represented as w_{xz}^G. The output provided by the hidden layer is represented as G_x.

$$G_v = \left[\sum_{n=1}^{r} w_{nx} * K_n\right] B_x \forall D_n = G_z^2; \quad (1 \leq x \leq y)\,; \quad (1 \leq n \leq r) \tag{34}$$

where, the bias corresponding to the output of MLP is represented as K_n. Then, the weight that links the input neuron n with the hidden neuron x is represented as w_{nx}. Algorithm for DBN routing is presented in Algorithm 2.

Algorithm 2

Initialize, sink, action history, future node, and max-distance node as initial parameters
Define RBM 1,
RBM 1 input is defined using equation (23)
Then, apply weight coefficient w_{mn}^1 $(1 \leq m \leq v)$ and, $(1 \leq n \leq r)$
Output from RBM 1 is obtained using equation (25)
Step 1: Train RBM 1 and RBM 2 layers
Input, the RBM 1 output as input to RBM 2
RBM 2 input is defined using equation (26)
Then, apply weight coefficient $w^2 = \left\{w_{nn'}^2\right\}$
Output from RBM 1 is obtained using equation (29)
Step 2: Train MLP layers
Input, the RBM 2 output as input to MLP layer, and MLP weights
MLP output is represented as G_x and P_z.
Determine, the network error
$E = \frac{1}{\chi} \times \sum_{v=1}^{\chi} \left(P_z^v - P_{nr}^v\right)\; ; \; (1 \leq z \leq h)$
end

1) TRAINING PHASE OF DBN CLASSIFIER

The DBN classifier needs to be trained well to obtain the weights and biases rather than identifying the finest data transmission route. The training procedure mainly intends to tune the MLP and RBM layers, which highly depends on the weights obtained from the each learning phase.

Step 1: Train RBM 1 and RBM 2 layers: Initially, provide the input features to RBM 1 and identify the probability distribution for each data. Then, encode the weight to each input to obtain the output from RBM 1 and the obtained output is provided as an input to RBM 2. The similar process is carried out in RBM 2 to obtain the input in the vector format for the MLP layer.

Step 2: Training phase of MLP layer: Following steps are processed by MLP layer and the input for this MLP layer is obtained from the RBM 2 layer.

Initialization: at first the MLP weights are initialized and then the random initialization process gets progressed. The weight of hidden and visible layers are represented as w_{xz}^{H} and w_{gx} respectively. Let, the input of MLP is represented as H_g^2.

Identify output from MLP layer: The MLP layers output is represented as H_x and O_z.

Network error determination: Based on average MSE (mean square error), the error is obtained which is defined in (35),

$$E = \frac{1}{\chi} \times \sum_{v=1}^{\chi} \left(O_z^v - O_{gr}^v \right); \quad (1 \leq z \leq h) \tag{35}$$

where, χ represents the training samples, O_{gr}^v and O_z^v represents ground value and network output. The network error needs to be less, therefore best solution can be achieved. Finally, through the selected path the data transmission is carried out successfully with less energy consumption.

V. RESULTS AND DISCUSSIONS

The performance of proposed deep learning based routing protocol is analysed through simulating the proposed architecture in Matlab platform. To conduct such experiment, the nodes number may varied from 200 to 1000 nodes. These nodes are deployed in (1000 × 1000) m^2 area. The performance of proposed DBN-RP is compared with five existing algorithms they are Genetic based energy efficient clustering (GEEC) protocol, TTDFP, EADCR, CLONALG-M, and Deep neural network (DNN). The simulated parameters used in this work are listed in Table 1.

TABLE 1. Simulation parameters.

Parameter	Value(s)
Sensor field	1000, 1000
Initial energy	0.25 nJ
Number of SNs	200 to 1000
Transmission energy	50 nJ/bit
Data packet size	4000 bits
Free space	10 nJ/bit/m^2
Multipath (amplification)	0.0013 pJ/bit/m^4
Effective data aggregation	5 nJ/bit/signal
Absolute remaining energy	0.2
Threshold distance	87 m
CH selection probability	0.1

A. EVALUATION METRICS

1) NETWORK LIFETIME

The total rounds or time taken by network to perform the operation is identified by network lifetime metric. It also provides the information regarding the time in which the node dies while performing the data transmission task [31]. The equation used to evaluate the network lifetime is represented in (36),

$$Network\ lifetime = \frac{\sum_{a=1}^{p} M_{ab} * f_a}{q_b} \tag{36}$$

If coverage is k, then assign $q_b = k \quad b = 1, 2, \ldots..n.\ q$, indicates total nodes.

2) THROUGHPUT

The ratio of total packets received with respect to time is defined using the throughput. The equation used to evaluate the throughput is defined in (37),

$$Throughput = \frac{Number\ of\ packets\ received}{Time} \tag{37}$$

3) NUMBER OF ALIVE NODES

The total nodes that contains considerable amount of energy to forward and receive the packet is provided. With this factor, the network lifetime can also be evaluated.

4) ENERGY CONSUMPTION

The total energy consumed by the CHs and the member nodes are known as Network Energy Utilization of the network.

$$E_T = \sum_{n=1}^{l} \left[CH_E(n) + \sum_{m=1}^{kn} S_E\ (mn) \right] \tag{38}$$

where, the energy utilized by the CH in network is indicated as $CH_E,\ and\ S_E$ is the energy consumption of the member node.

B. PERFORMANCE ANALYSIS

In this section, the performance analysis for CH selection and routing is carried out using different network parameters they are network lifetime, throughput, number of alive nodes, and packet transmitted to CH. The results obtained by this different metrics are illustrated and discussed in below paragraphs. The overall performance obtained by proposed and existing routing protocols are illustrated in Table 2.

TABLE 2. Performance comparison of proposed and different existing techniques.

Methods	Total number of nodes	Energy consumption	Network lifetime	Throughput
Proposed	200	0.4	32320	0.954
	400	0.416	32240	0.864
	600	0.55	32000	0.936
	800	0.6	31600	0.882
	1000	0.656	31200	0.918
CLONALG-M	200	0.87	30970	0.71
	400	0.92	30590	0.78
	600	0.81	31750	0.77
	800	0.77	30200	0.71
	1000	0.82	30050	0.73
EADCR	200	0.89	29420	0.68
	400	1.46	29220	0.73
	600	1.08	30640	0.68
	800	0.98	30130	0.69
	1000	0.92	30780	0.69
DNN	200	0.95	28270	0.59
	400	1.73	29860	0.68
	600	1.33	29350	0.71
	800	1.03	29700	0.7
	1000	1.05	30970	0.65
TTDFP	200	0.52	27940	0.56
	400	1.7	28820	0.58
	600	1.27	28900	0.73
	800	0.98	29000	0.63
	1000	1.44	29580	0.58
GEEC	200	1.74	27480	0.53
	400	1.41	28800	0.56
	600	1.79	28540	0.61
	800	1.12	28800	0.53
	1000	1.79	29630	0.53

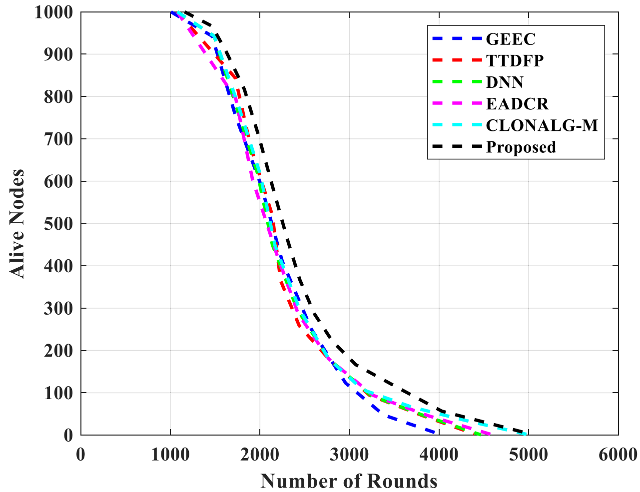

FIGURE 5. Alive nodes vs number of rounds.

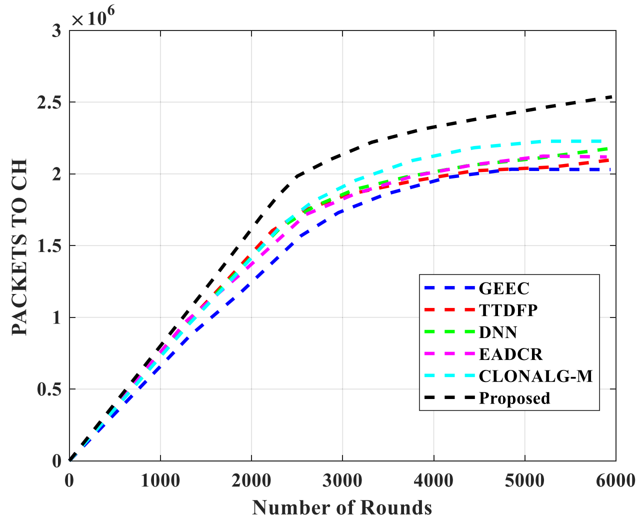

FIGURE 6. Packets send to CH vs number of rounds.

The total number of alive nodes that are obtained for different rounds is illustrated in Fig. 5. The total number of alive nodes available in the overall area with increase in number of rounds is found better for proposed approach than other existing algorithms. The major objective shown by energy-aware clustering protocol is network lifetime enhancement. It is useful to evaluate the time in which the last SN becomes lifeless. The number of alive nodes achieved by GEEC for various rounds is found much less than the proposed routing protocol. However, the alive nodes obtained by DNN is almost similar to the proposed protocol. It illustrates that the introduction of deep learning in WSN routing has attained better network lifetime by identifying the best path for data transmission without causing much reduction in energy efficiency.

The total packets that are successfully transmitted to CH for different rounds is shown in Fig. 6. The packets are successfully transmitted to sink node via CH by the proposed architecture which is found better than other algorithms. This is because the proposed architecture has integrates the most efficient and simple optimization algorithm for CH selection. The multi-objective fitness function is considered by proposed MRFO algorithm for CH selection. The four different objective functions are energy, delay, traffic density, and distance. The node that satisfies these multi-objective conditions are selected as the CH. Then, the remaining nodes in the cluster transfer the gathered data to CH.

The energy maintained by each node in the network for various iterations is shown in Fig. 7. The energy rate attained by proposed technique is found higher than the other existing algorithm. The proposed approach has conserved more energy than existing techniques. This is because the optimal selection of CH has improved the energy conservation efficiency of proposed architecture. While reaching the 5000 rounds the energy in the network gets drained.

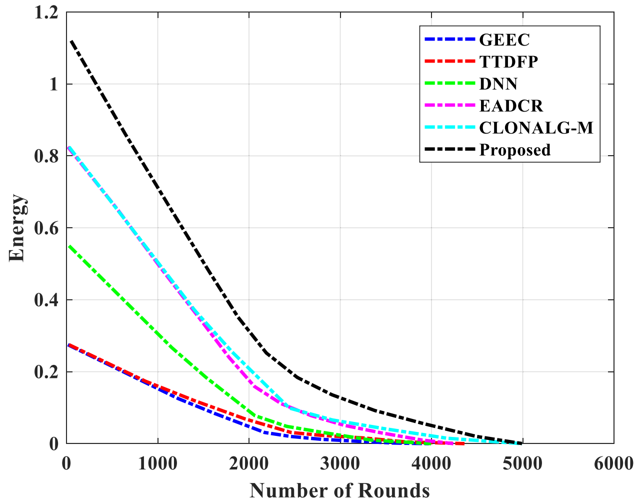

FIGURE 7. Energy vs number of rounds comparison.

The existing DNN architecture has conserved 1.0348% energy which is found better than the GEEC, TTDFP, DNN, EADCR, and CLONALG-M techniques. The energy efficient network can be widely demanded by various applications. The total energy rate maintained by proposed routing protocol is found better therefore the lifetime of entire network is also gets enhanced.

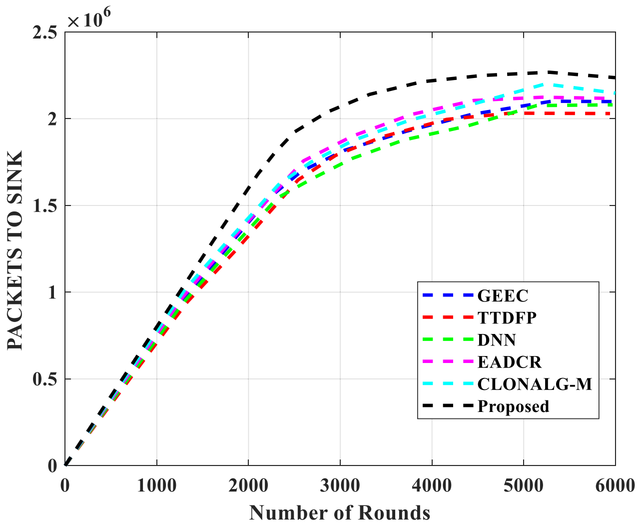

FIGURE 8. Packets transmitted to sink vs number of rounds.

The average improvement shown by proposed method while transmitting the data packets to sink is shown in Fig. 8. The overall improvement shown by DNN while transferring the data to the sink is 3.0852% which is found larger than other existing algorithms. But still it shows little degrade in network performance which is overcome by the proposed DBN based routing protocol. The other existing algorithms like GEEC, TTDFP, DNN, EADCR, and CLONALG-M have shown less improvement in data packet transmission. However, the effective clustering done by RL algorithm has shown an effective result in data transmission. Moreover, the proposed protocol has performed the packet transmission in better rate without causing any loss in transmitted data.

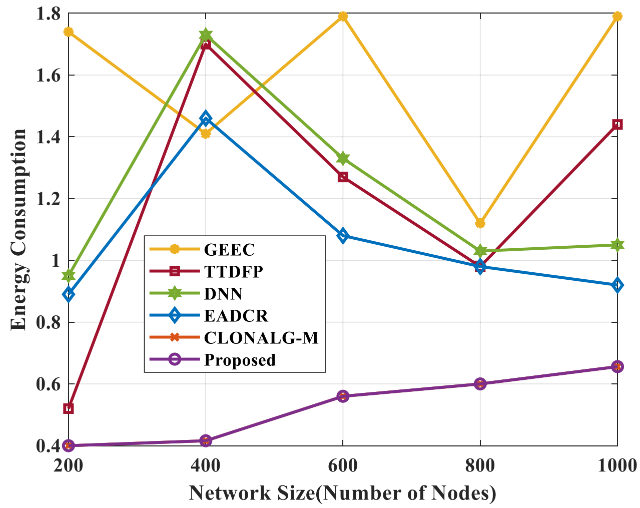

FIGURE 9. Energy consumption vs network size.

The energy consumed by proposed protocol is compared with existing protocols and the comparison results are shown in Fig. 9. The energy consumption needs to be less therefore better network lifetime can be achieved. The entire nodes in the network is deployed randomly, therefore a particular threshold needs to be define during CH selection. Further, different route selection needs to be define to achieve efficient routing process. The energy consumed by proposed architecture is found less than other existing protocols. Increase in network size increases the energy consumption which needs to be reduced to achieve effective performance. To achieve such objective, the entire network is initially clustered using an efficient RL algorithm.

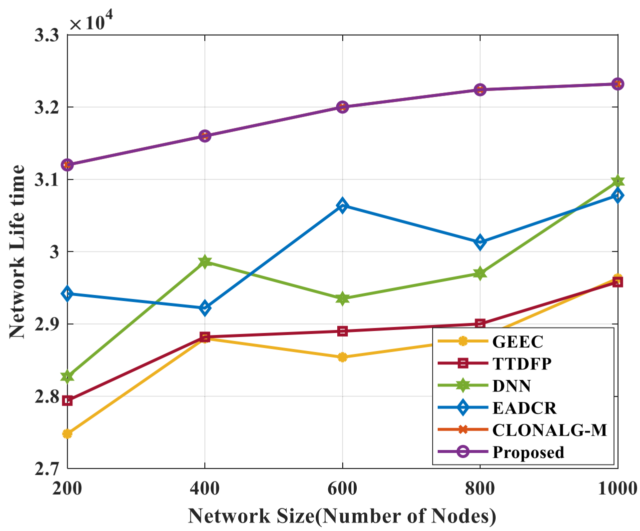

FIGURE 10. Network lifetime vs network size.

The network lifetime achieved by proposed algorithm against the five different existing algorithms is determined and the comparison results are illustrated in Fig. 10. The CH selected using the MRFO has achieved better lifetime which is found higher than the other existing algorithms. The existing algorithms have shown a large changes in network lifetime but the proposed architecture depicts only a little variation. This is because the proposed DBN architecture has analysed the network repeatedly by assigning a different weight parameters for each path. Due to this, the proposed architecture has attained better network lifetime.

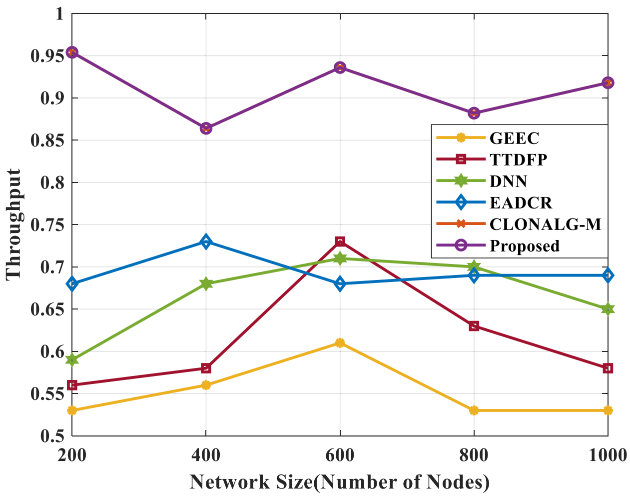

FIGURE 11. Throughput vs network size.

The data that are sensed by each node in the entire network is then transferred to CH, which then transmit the gathered data to sink node. The data is transmitted in the form of packet. The CH that transmits large amount of data is considered as the most efficient one. The throughput is obtained based on the transmitted packets. The throughput obtained by proposed algorithm is compared with existing algorithms and the comparison outcomes are shown in Fig. 11. The throughput is found higher for proposed protocol than the other existing algorithms. Recently developed CLONALG-M also obtained almost similar performance however it fails to attain an effective result on energy consumption due to this the network lifetime is also gets reduced. To avoid such defect, the DBN based routing protocol is introduced in this proposed work which automatically maximize the effectiveness of entire network.

C. ANOVA ANALYSIS

Most efficient and well-known statistical analysis approach is analysis of variance (ANOVA). It is performed to prove the accuracy and reliability of proposed framework. It is used to determine the variation that occurs between 2 or more means. ANOVA determines the F-value (test statistic), using F-value the p-value is determined. The p-value is used to identify the data that makes assumption regarding the null hypothesis. Based on mathematical notation H0 is: $n1 = n2 = n3 = n4$. To frame an alternate hypothesis, let us assume that at least one of the obtained mean needs to be different. In this, the ANOVA is performed for 1000 SNs, the number of simulation instances is 20, and the critical significant level is set as 0.05. The ANOVA result concludes whether the mean obtained by the algorithms are found similar (accept H0 (null hypothesis)/ reject alternative hypothesis (H1)) or not (reject H0). ANOVA outputs the F-statistic value, using that the p-value is estimated. In ANOVA two conditions are checked for rejecting the null hypothesis they are: (i) If the value shown by p-value is found minimum than significant level, and (ii) if f-statistic greater than f-critical value.

TABLE 3. ANOVA analysis for proposed and existing approaches in-terms of energy consumption.

Source of variation	Sum of Square	df	Mean Square	F-statics	P-value
Between groups	218.156	3	72.7187	3.33	0.463
Within groups	349.662	16	21.8538		
Total	567.818	19			

TABLE 4. ANOVA analysis for proposed and existing approaches in-terms of network lifetime.

Source of variation	Sum of Square	df	Mean Square	F-statics	P-value
Between groups	310356	3	103452020	17628.57	2.33718e-28
Within groups	938948.8	16	58684.3		
Total	310449	19			

TABLE 5. ANOVA analysis for proposed and existing approaches in-terms of throughput.

Source of variation	Sum of Square	df	Mean Square	F-statics	P-value
Between groups	0.36895	3	0.12298	50.86	2.10459e-08
Within groups	0.03869	16	0.00242		
Total	0.40765	19			

The tables 3, 4, and 5 has shown the ANOVA results achieved by proposed and existing techniques in-terms of energy consumption, network lifetime, and throughput. Here, degree of freedom is represented as df. Let, n1, n2, n3, n4 represents the total samples in SSO, GA, GIFSS-SSOGA, and proposed DBN. 30 samples (n1 = n2 = n3 = n4 = 30) from each method are utilised by the ANOVA test with the similar network settings having significant level = 0.05.

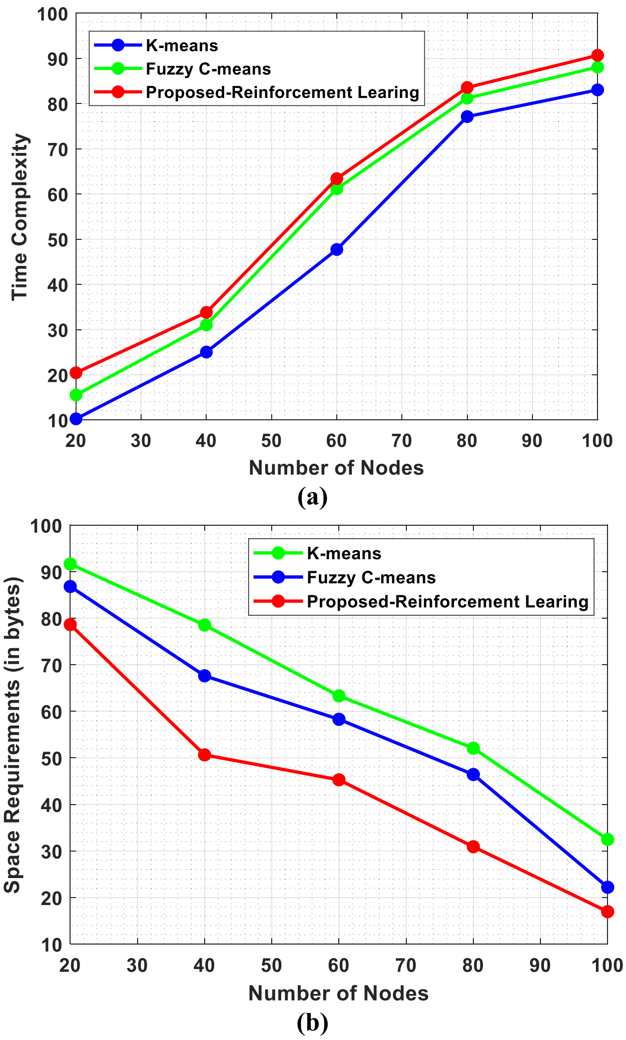

FIGURE 12. Time and space complexity analysis for clustering process.

D. COMPLEXITY ANALYSIS

1) SPACE AND TIME COMPLEXITY ANALYSIS FOR CLUSTERING

The time and space complexity related to clustering algorithm is depicted in figure 12 (a, & b). In this proposed framework, the RL algorithm is introduced for clustering. The time complexity of proposed RL is compared with existing k-means, and fuzzy c-means clustering techniques. While comparing with these two clustering approaches, the learning algorithm used in this proposed work has attained better time complexity. Increase in nodes number may automatically increases the time complexity. However, the proposed has taken less time than other existing techniques for clustering. The space complexity is found inverse of time complexity, i.e. increase in node number reduces the total space complexity. For that, the proposed has shown better result than existing technique. The learning strategy exhibited by RL clustering algorithm has improved the total clustering performance which is found better than traditional unsupervised clustering algorithms.

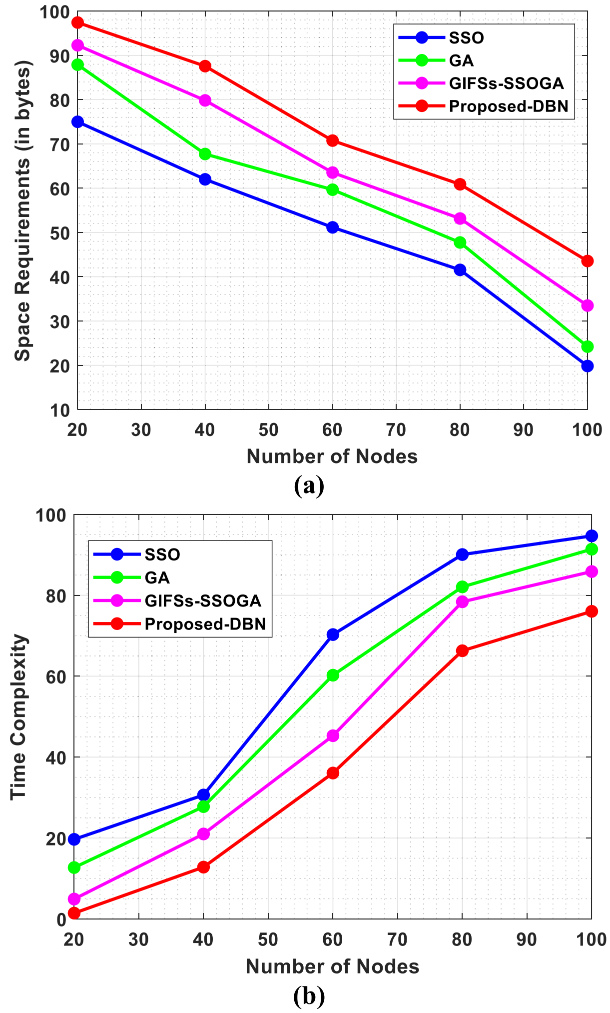

FIGURE 13. The space and time complexity analysis related to routing process is shown in figure 13 (a, & b). The complexity of proposed DBN routing is compared with three existing routing techniques they are, GIFSS-SSOGA, SSO, and GA algorithms. The computational complexity of proposed approach is, $(n^0 + 2)n^1 \cdot O(n(m + mD + 1))$, where n is input size, m represents number of iterations and D represents the dimension.

2) SPACE AND TIME COMPLEXITY ANALYSIS FOR ROUTING

The comparative analysis for time and space complexity indicates that the proposed has attained efficient result than the techniques taken for comparison. The proposed framework highly intends to obtain an efficient routing. For that, a learning based clustering and optimized CH selection process are introduced. These two approaches have enhanced the overall performance of DBN based routing process. In the next section, the overall proposed framework is summarized and conclusion is provided. In conclusion, the improvements and achievements of proposed architecture are discussed.

VI. CONCLUSION

In this work, a DBN based routing protocol is developed for IoT based WSN which includes the RL algorithm for node clustering. With this routing protocol, the energy balanced clustering and routing is achieved. The learning algorithm integrated within the proposed architecture has improved the network lifetime of entire architecture. Then, the CH from each cluster needs to be selected to perform an effective data transmission. The selection of CH is identified as the major consideration in WSN therefore, to achieve such objective an efficient MRFO algorithm is introduced in this proposed architecture. It considers four different objectives to select the best CH for transmitting the data to the sink node. The objectives that are considered for CH selection are distance, delay, traffic density, and energy. Through these selected CH, the data is transmitted to sink node without causing any loss to transmitted packets. Then, the shortest path that is needed for data transmission is selected using a deep learning based routing algorithm. Basically, the routing protocols developed at the existing architectures does not attained a satisfied result. To avoid such issue, a DBN architecture is introduced in this proposed methodology for shortest path identification. Through the identified path the data transmission can be achieved in an effective manner. The performance shown by the proposed DBN is found better than the existing techniques. The selection of shortest path for data transmission has attained better network lifetime and energy efficiency. Finally, the complexity analysis and statistical analysis are also evaluated to show the effectiveness of proposed architecture.

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