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Implementation of deep belief neural network on energy efficient Routing Algorithm in WSN

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***Abstract*—WSNs (Wireless sensor networks) have lately gained popularity such as remote tracking, a wide range of applications where information transfer through nodes to base stations necessitates a substantial amount of power. As a consequence, efficient routing methods for forwarding data to the base station should be used to decrease energy utilization and thus prolong the network's life span. Thus, Deterministic energy efficient protocol enhanced with deep learning model is proposed to obtain optimal routing that indirectly improves the life span of WSN. Ant Colony (AC) Environment is considered for system optimization with the goal of picking the proper conceivable clusters in the shortest amount of duration in a feasible cluster. Furthermore, in routing optimization to increase the effectiveness of service, a Newly Designed Enhanced Ant Colony has been suggested, where premier operators were used to increase speed of iteration and choose the shortest path. Ultimately, a Deep Convolution Classifier is used to discover the optimal path. Consequently, compared to other existing methods, our suggested model enhances QoS, reduces energy consumption, and provides superior routing to the sensor nodes, all of which mobile nodes increase their lifespan.**

***Keywords*—Wireless Sensor Network (WSNs); Ant Colony (AC); Deep belief Neural Network; Cluster head; Sink**

I. INTRODUCTION

WSNs were primarily made up of low-energy sensor nodes (SNs). To gather different kinds of air exposures and send data to the base station, WSNs were sporadically positioned throughout the region to facilitate activity detection and tracking [1]. Typically, sensor nodes are equipped with a variety of sensor kinds, such as acoustic energy, motion, weather, pressure, and heat sensors etc. WSNs have a wide range of applications, ranging from security, agriculture, and even human daily life.

Despite its wide range of applications, WSN suffers from many critical barriers, such as limited sources of energy, computing power, transmission bandwidth and memory; as a result, sensor network efficacy in terms network lifespan are compromised [2-5]. Furthermore, it is widely stated that the most notable limitations of WSNs appears to be a way smaller span of its sensor network due to the rigorous energy defects. Given that sensor nodes are usually situated in challenging environments, it's probable that the batteries that continuously supply energy to sensor networks are challenging to maintain or replenish. The primary cause of sensor node procedure and, consequently, it appears that WSNs' low power sufficiency is the cause of their diminishing lifespan. Therefore, achieving energy efficiency is crucial for the correct functioning of WSNs [6]. In actuality, a sensor node uses very little of its total energy for sensor readings and detection and spends most of its energy on wireless communications [7]. Consequently, a great deal of research is being done at the network layer of the protocol stack to provide dependable data transfer and an energy-efficient path layout between the sensor network and the BS. Acknowledging the necessity of managing resource constraints, preventing congestion between access points [8], and extending the lifetime of the topology as much as practical [9-10] is a critical issue in WSNs, especially there are a limited number of access points.WSN designers must address data compilation, clustering, tracking, locating, defect diagnosis, multitasking, and event monitoring, among other issues, Consequently, many research interactions have been developed to provide energy-efficient path construction and precise data transport from the sensor network and BS to minimize energy at the system network’s stack level. Scientists should prioritize optimal battery energy utilization while developing hardware and methodologies for supernovae. To increase a sensor network's energy efficiency, other routing strategies have also been created. Reducing sensor node [11-14] energy consumption is the main objective of WSN routing algorithms. The sensor programmer has to examine the problems of the consumption of energy of all the sensor nodes to maintain the network system's functionality for a longer duration. These processes seem to be highly energy-intensive and substantially dependent on certain numerical combinations. Novel strategies are therefore needed to overcome these obstacles [15]. Several models are taken into consideration to extend the network's lifespan. Individual nodes' energy requirements can be reduced by using a grouped setup with wireless sensor nodes. In this clustered architecture, clusters can be formed by adjacent nodes. To serve as the cluster head one node with an enormous amount of energy is selected by each cluster. Overloaded cluster heads quickly exhaust their energy stores, causing the cluster to collapse. These hotspots could cause permanent data loss because of the remote placement of the sensor nodes. To overcome the shortcomings of the conventional energy-efficient forwarding in WSNs, machine learning-related procedures have recently been used [16], giving complicated problems that nearly match the requirements for creating efficient routing approaches within WSNs a flexible and varied environment for engaging with information and computation. To extend the network lifetime and decide the best energy-saving route and hence, we integrate clustered design with the profound learning concept in this study. The following

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contains a summary of the DEC [17] with enhanced Ant Colony (AC) Optimization utilizing the Deep Learning Model contribution:

- The cluster head with the most neighboring nodes, intra-cluster distance, inter-cluster variety, and shortest way from the base station is determined using the Deterministic energy efficient protocol.
- A New enhanced (AC) optimization has been proposed to improve the lifespan of WSN, in which the sequential adaptable operator and the finest operator are used to boost iterative process pace and the signals built as evolution time increases.
- Finally, an intense belief neural network determines the best route based on the calculated energy.

II. Literature Survey

A number of investigations have been carried out to lower the energy needed to start wireless sensor networks (WSNs). Grey Wolf Algorithm-Based Clustering Technique [18] provides efficient scheduling in a selected network. This proposed approach reduces energy utilization even further the clustering is adequate by passing the cluster construction process in cycles. Relay selection was shown to optimize energy utilization while attempting to balance energy consumption between CHs and relays, preventing remote nodes from BS from experiencing rapid energy degradation. Because although the protocol has a fault tolerance mechanism, failure-critical applications should not use it.

a cluster head selection mechanism based solely on Taylor kernel fuzzy C-means was created to obtain maximum throughput [19]

sand cat swarm optimization[20] based on stochastic variation, a straightforward and energy-efficient routing technique, assists in determining the critical phases in routing evolution. The hybrid optimization that is offered to the CHs determines the optimal paths based on energy limitations like energy, delay, cross-distance, connection durability, and distance. The CHs engage in multi-hop routing. Their quality of service (QoS) has not yet been assessed, though.

The considered DEC [17][21-23] algorithm works in two phases i.e. setup phase and steady phase. In setup phase cluster formation and distribution of duties towards clusters nodes as cluster member and cluster head. The algorithm is purely based on residual energy rather than initial energy.

Further improved the algorithm in terms on improving the lifespan of the network by adding few working parameters and techniques like sleep/awake, multihop, and change in deployment schemes [21-27].

We can conclude from the above-mentioned works that previous systems have some boundaries that can still be improved. Compared to other existing systems, a new strategy that considers all performance parameters provides better routing to the sensor nodes and lower energy consumption. In the proposed work, for cluster head selection, DEC protocol has been taken and for route selection with best path Enhanced Ant Colony Optimization is proposed and Deep Learning Model is applied in the process for efficient utility of energy.

III. Deterministic Energy Efficient

DEC protocol WSNs seem to be connected to networks of sensor nodes to communicate wirelessly. The advancement of a reliable, limited routing technique for Wireless Sensor Networks (WSNs) has become critical at this stage. Unfortunately, current energy-efficient developing patterns are concerned solely with the energy basis, which ignores the QoS requirements and speed of execution in same work, as well as the computational burden of the algorithms used.

As a result, our study employs the Deterministic energy efficient clustering protocol as a constraint in trying to ascertain the cluster head nodes with remaining energy, the inter-cluster actual distance, the total maximum count of neighbor nodes, and the limiting distance from the base station

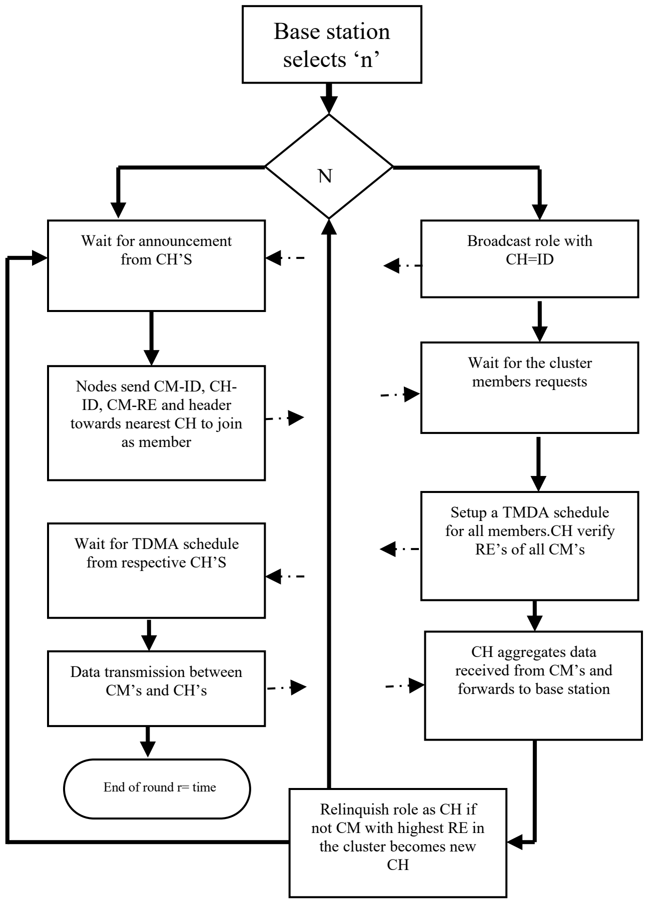

Fig. 1.Working flowchart of DEC

DEC protocol desirable:

1) Every node's RE is used to determine the CH election locally. Additionally, every round stands alone from the one after it.

2) Every node has an election chance according to DEC as long as its RE is greater than that of its neighbors.

3) DEC guarantees the selection of a fixed N_{opt} cluster-head .

4) By focusing the CH search on cluster Ni at round m, DEC drastically lowers the computational overhead associated with this search in the current protocols.

5) Until at least the network's lifespan is reached, DEC ensures that each CH has adequate energy to carry out its function.

A. *Deep Learning Model for Improved Ant Colony Optimization*

Creating a steady, reduced power routing scheme using (WSNs) is an enormous task Wireless sensor networks (WSN) have advanced, however, optimal energy usage is still required to extend the network lifespan. A unique ACO Nature employing Deep Learning Model is proposed to address this. Briefly, the Deterministic energy efficient protocol was used to choose the cluster head, taking into account surplus energy, the greatest number of neighbor nodes, the separation between clusters, and the distance inside clusters.

Furthermore, to enhance the lifespan of the network, a Novel improved ACO was developed, wherein the sequential adaptable operator, as well as the key operator, was used to increase loop pace and choose the smallest path in Wireless sensor networks (WSNs). Consequently, there are more and more ants taking this route. With enough accurate data, all ants will finally focus on the optimal path, where the neural network estimates energy using a deep belief network. As a result, the best route has been determined. Figure 1 depicts the flow chart of deterministic energy-efficient protocol

Enhanced ACO is provided to address the QoS routing difficulty for WSNs.Every ant has a fitness rating and a way of choosing a path. As a result, the fitness function significantly affects how well the algorithm performs. When the delay, link bandwidth, packet drop, and vibration latency requirements of the several constrained QoS optimization technique are satisfied, the performance index may be determined using equation (1);

$$fitness = min\{LSp(v_1, v_m)\} \quad (1)$$

As a result, LS stands for the energy consumed during data transport between nearby nodes. Each data transfer route is denoted by $p(v_1, v_m) and$ is mostly used in restricted Qos optimization concerns

Every ant in the population uses actual routing energy as a result so that data transfer may be estimated. The ideal path is the one that consumes the minimal energy. Thus, each ant's path is evaluated based on its energy use. The route that consumes the least energy would be the most ideal one.

The following characteristics of each N ant in the colony: they all select a node according to the pheromone content and the energy cost of the path.

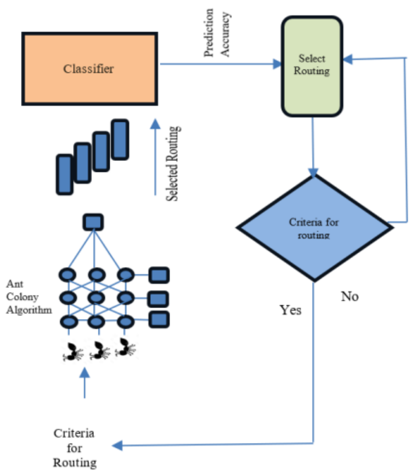

Fig.2. Process of routing using Ant Colony Algorithm

B. *Deep belief neural network (DBN) Evaluation of the optimum route*

DBN [28] is an amazing deep model that functions similarly to an RBM stack. Figure 3 shows k hidden levels and its layer-by-layer pre-training method of DBN structure.

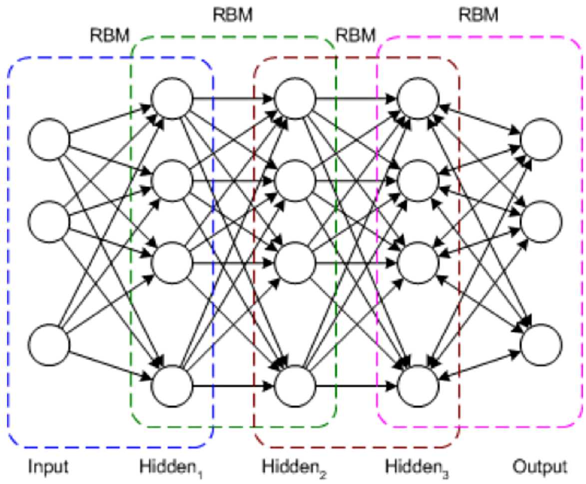

Fig. 3. Architecture of Deep Belief Network

With input sample x, the efficacy activation of a kth hidden layer could be calculated as follows:

$$C_k(y) = \sigma(b_k + w_k\sigma(\ldots. + w_2\sigma(b_1 w_1 y))) \quad (2)$$

where $\boldsymbol{w_k}$ as well as $\boldsymbol{b_k}$ (k = 1,2,...,n) are, in fact, the weighting matrices with hidden bias vectors for the nth nth RBM respectively. Additionally, it appears that $\boldsymbol{\sigma}$ is the logistic sigmoid function $\boldsymbol{\sigma}$ (y) = $1/(1+e^{-y})$. With the help of layer-wise pre-training and deep architecture, its DBN optimizes the weighing matrix between layers to improve feature representations. In the end, if favorable input is received Since the neural network uses a deep learning model to estimate energy, all ants will focus on the optimal path, which has been identified. First, let's assume that we might have gathered sample data for M days in a row, obtaining T data points per day. As demonstrated below, it is possible to express each chosen period series of energy use data as a set of one-dimensional vectors with great ease.

$$Y = \{Y_1, Y_2 \ldots., Y_M\} \quad (3)$$

$$Y_1 = [y_1(1), y_1(2) \ldots\ldots, y_1(T)] \quad (4)$$

$$Y_M = [y_m(1), y_m(2) \ldots\ldots, y_m(T)] \quad (5)$$

T stands for the same number of samples each day.

The following describes the design strategy for the deep belief network:

Step 1: First, identify the energy-usage pattern from the training data that most closely matches the periodic concept.

Step 2: To collect residual data, first remove the energy-usage patterns in the training data.

Step 3: Build this DBN model using this residual data.

Step 4: To create the finalized predictive performance for such a hybrid technique, combine the results of the same DBN system using periodic knowledge.

As a result, compared to other existing techniques, our improved ACO environment optimization employing deep learning method in DEC gives excellent routing to the sensor nodes also improves lifespan of the network.

IV. Result and Discussion

The usefulness of our suggested methodology is demonstrated in the final part, along with implementation results. Additionally, comparison results from previous efforts are displayed.

Tool	: MATLAB R2023a
Operation System	: Windows 10 (64 bit)
Processor	: Intel Premium
RAM	: 8GB RAM

A. Evaluation Metrics Performance

Although a number of factors are used to evaluate the effectiveness of the novel approach, this section outlines our recommended method.

1) Count of Dead Nodes

When a node reaches zero energy, it is considered dead. According to Fig. 4, for every data transmission cycle, an expected total number of dead nodes is shown.

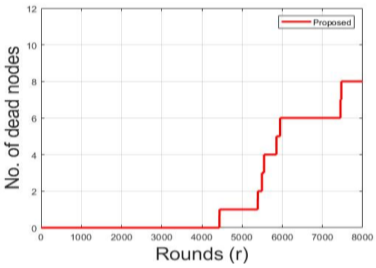

Fig. 4. Count of dead nodes

Dead nodes in our protocol WSNs are shown in Fig. 4. Additionally, it shows that the first node in our suggested protocol expires during round 6000 and is maintained for up to 7,500 rounds. In addition, the final node expires during round 7500, continuing for up to 8000 rounds, and this is true for the entire network. As the number of rounds increases, a proportion of nodes that appears to be alive increases. The proposed optimization method keeps connected nodes for 8000 cycles.

2) Packets sent to sink

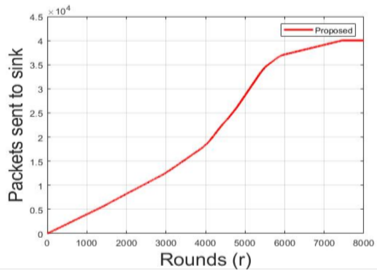

Fig. 5. Packets sent to sink

The proposed paradigm, as shown in Fig. 5, sends very few packages to the sink. The given DEC protocol uses very few cluster heads in terms of routers. As the number of packets increases, heads of clusters became noticeably more involved during data transport and reception. One method is to send only packets that are inside the coverage regions of the nodes to the sink. The amount of copied information is reduced as a result of this approach.

3) Packets dropped

The quantity of packets dropped during transmission is evaluated by demonstration metric. This result, in the packet loss caused by our suggested method is minimal. Fig. 6 shows the related graph.

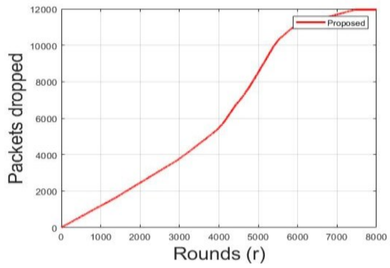

Fig. 6. Packets dropped

The patterns of total packet loss at various transmit power levels are shown in Fig. 6. Transmit power reduction greatly enhances packet delivery performance. These simulation results show that the method considerably improves data network transmission services. The experiment's findings demonstrate that our recommended DEC combined with the enhanced ACO optimization algorithm enhances network traffic stability, lowers packet loss rates, and raises data arrival rates.

4) Packets Received to sink

The overall number of packets that are collected at the sink is shown in Fig.7. The nodes that acquire the most packages at the sink have a different transmission range and a different package holding time.

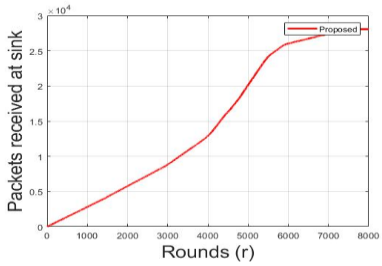

Fig. 7. Packets received to sink

Enhanced ACO optimization sender nodes expand their broadcast distance to include one or even more routing nodes when they are unable to identify a neighbor. This increases the likelihood that packets will reach the sink. Additionally, it assures that data loss is kept to a minimum, which enhances the data transmission capabilities of our suggested protocol.

5) Residual Energy

By quantifying and hierarchically aggregating the remaining energy of such unnecessary nodes, the methodology enables the cluster head to proactively choose unnecessary nodes for relays that complete information transfer and update those redundant nodes. The remaining energy of either cluster heads, as shown in Fig. 8, may also cause each sink node to recluster in a particular layer.

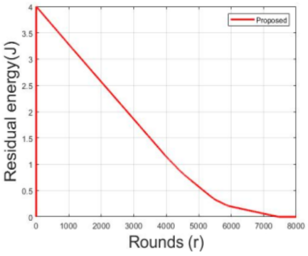

Fig. 8. Residual Energy

After 5000 cycles, the leftover energy of this established technology gradually decreases, demonstrating its dependability. The network’s lifespan is extended to more rounds because our designed algorithm’s energy progressively dissipates.

6) Path Loss

A graphical chart of total path loss versus rounds is shown in Fig. 9. Every time the graph is drawn, the same 1000 rounds have been used. This graph shows how overall route loss increases linearly till it reaches to a maximum. Following that, the total path loss steadily decreases before rising once more

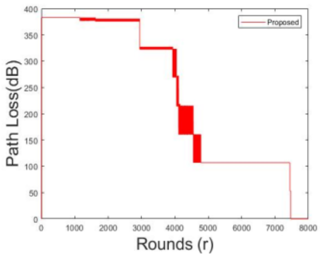

Fig. 9. Path Loss

Fig.9 shows that several round increases at the same time path loss get decreases. Because of route loss, the signal's received power level is many orders of magnitude lesser than the broadcast power level. Therefore, our suggested model demonstrates that while path loss decreases, transmission power increases.

7) Delay Time

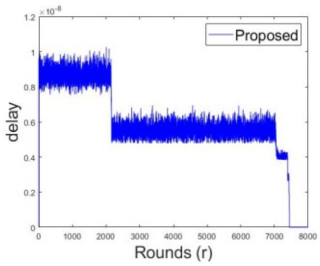

Fig.10. Delay Time

When considering such a sensor network setting, Fig. 10 shows a graphical representation of delay vs the number of iterations that may be achieved. This graph was created with a deployment region of 1000 meters in mind. The quickest routes from either a source or a target can be found using this limited zone forwarder node selection. Overall end-to-end latency is decreased by our designed optimization strategy. At 1000 rounds, the biggest delay was 0.89×10^{-8}, while at 8000 rounds, the smallest delay was 0.012×10^{-8}. In general, there is some lag between 7500 and 8000 rounds.

8) Convergence Curve

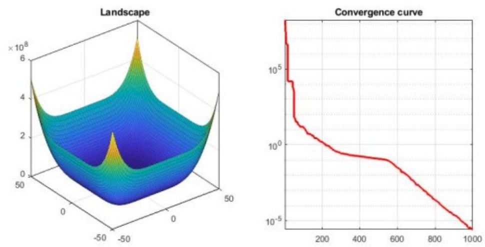

Fig. 11. (a) Landscape &Fig.11, (b) Convergence Curve

Fig.11 (a) shows the geography of the standard function. Fig.11 (b) shows the initial search agent's journey along the x-axis. The plots in that graph show how the search agents now experience significant variations in their position even in the early stages of the optimization approach before slowing down and convergent toward the optimal. It shows how the proposed strategy effectively raises efficiency to ultimately converge towards the ideal. It is shown that for unimodal functions, the convergence curve improves with time.

9) Enhanced ant colony optimization

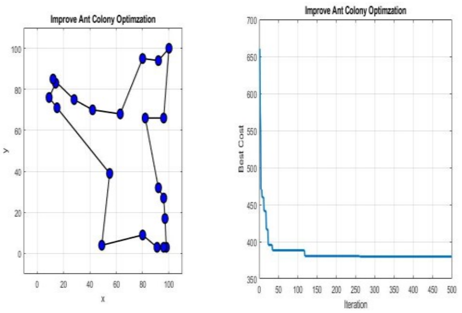

Fig. 12. Best cost Vs. Iteration

The curve relation of a revised ant colony algorithm is shown in Fig. 12 to fade more gradually than the regular ant colony technique and to show a constant falling trend as the number of iterations increases. This enhanced ant colony method now finds its optimal route after 150 iterations, outperforming the results of the original algorithm and eliminating the challenge of the original algorithm decreasing into a local optimum.

B. Comparison Results

The created technique's comparison findings are analyzed in this part. Our innovative approach is contrasted to standard approaches like the Genetic Algorithm (GA) [29], which provides solutions in a short time of computation but cannot guarantee an optimal solution, Particle Swarm Optimization (PSO) [30], which having fewer parameters to tune but shows poor quality results for complex and large data sets and Adaptive Elite Ant Colony Optimization (AEACO) [31] that provides good stability but limitations in the convergence speed and key accuracy when working with a big quantity of data.

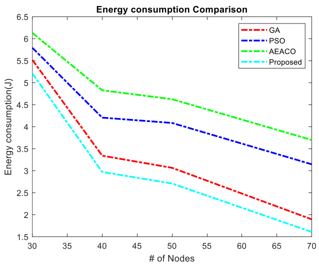

Fig. 13. Comparison of Energy Consumption

In contrast to the results from AEACO, PSO, and GA at various node scales is shown in Fig. 13. When the number of nodes approaches 70, our novel, improved Ant colony capability is still most apparent, and the energy consumption is close to 1.554 J between the iterations 30 and 70. The values of AEACO, PSO, and GA were, respectively, 3.7012 J, 3.1489 J, and 1.986 J. Fig. 13 shows that, for various node sizes, our devised technique exceeds AEACO, PSO, and GA.

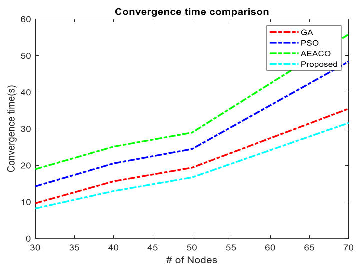

Fig. 14. Comparison on Convergence Time

The convergence times for AEACO, PSO, and GA at various node sizes are compared in Fig. 14. When there are 70 nodes, our proposed optimization strategy performs well, with convergence taking close to 19.4 seconds from 30 to 70 iterations. Fig. 14 demonstrates unequivocally that the suggested technique beats AEACO, PSO, and GA at various node dimensions. For AEACO, PSO, and GA, the corresponding timings are 21.9, 43.6, and 53.8 seconds, respectively.

Conclusion

The key to extending the life of the network is energy conservation. In effective scenarios, multi-level routing may choose a sloppy route, by reducing the output and increasing energy. The energy reserves may quickly deplete as a result, shortening the network's life. The Enhanced ACO with DEC protocol utilizing Deep Learning Model has also overcome routing issues to reach the final forecast results. The cluster head in this suggested system is chosen using the DEC protocols set up phase. This approach uses residual energy as a limitation when choosing cluster head nodes as part of the track being built. Traditional ant colony optimization's benefits, an malleable technique, and other factors have been included into an improved ant colony optimization to improve route choice. The optimal route has been determined since the neural network employs a network of deep beliefs to predict energy, and all ants will concentrate on it if good input is received. The results show that the hybrid algorithm that was developed has a rapid convergence period and can only find the quickest path by consuming a small quantity of energy. The effectiveness and supremacy of such a developed hybrid model have been evaluated through experimentation with comparison data.

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