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Tuna-Osprey Optimization for Energy Efficient Cluster-based Routing: Modified Deep Learning for Node's Energy Prediction

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Abstract: The main consideration of WSN design is maximization of the network lifetime. It is proven that the effective balancing of network energy consumption along with the maximization of network lifetime can be performed by clustering and routing approaches. Accordingly, a new Tuna Osprey Optimization algorithm for energy-efficient cluster-based routing has been developed in this work. This approach includes 2 working phases: clustering and routing process. Initially, a modified DL model named M-LSTM is proposed for predicting the node's energy. Subsequently clustering process is carried out by the TOO algorithm, which considers the energy, link lifetime, distance, trust, and delay as constraints for the selection of optimal CH. Finally, with the same TOO algorithm, the routing process is conducted, which considers the link quality as the constraint to provide optimal routing. Results proved that the proposed TOO for energy-efficient cluster-based routing can reduce energy utilization while attaining maximum network lifetime.

Keywords: *Network lifetime maximization, Tuna Osprey Optimization (TOO), Modified DL, M-LSTM, Link lifetime, optimal CHS*

1. Introduction

In WSN, numerous autonomous sensor devices are included to monitor ecological or physical phenomena [9][14]. To transfer its readings to a gateway or sink, this leverages the multi-hop wireless communication technologies. Recently, due to the swift progress in the integrated sensor field [9][21][24], microcontroller units and low-powered wireless transceivers have increased the availability of inexpensive multi-functional miniature sensing platforms. Most importantly, WSNs were utilized for data transferring as well as gathering. For numerous applications, this can be utilized because of its simple communication and inexpensive nature. WSN includes numerous sensors along with BS [10][11][12]. Sensors are deployed arbitrarily all over the sensing region because they are battery-powered. Depending on WSN, multiple application areas are created, due to the discovery of inexpensive, self-organizing, efficient, and consistent sensor technology. This can be applied to multiple areas like virtual reality, AI, healthcare services, ML, smart monitoring, military systems, smart homes as well as intelligent transportation systems, etc. Despite the multiple benefits of WSN, there are numerous issues such as connectivity loss, security susceptibility, deteriorated QoS, existence of congestion that affects its operation. It's accepted that the WSN's most crucial vulnerability is their SN's limited lifetime[13][14][15][16]. In any network, the process of path selection can be named routing. Generally, in a computer network, many machines are included that are called nodes, and these are connected by paths or links. In an interconnected network, communication among two nodes can occur in multiple dissimilar paths. This process is carried out by the network layer. Commonly, there are three kinds of routing, which are static, default, and dynamic routing. In WSN, the routing task should be managed carefully [17][18][19][20]. Consequently, multiple research efforts are made to conserve energy in the protocol stack's network layer by developing an energy-efficient routing. In WSN, a routing protocol's primary aim is to preserve the SN's energy to make it work for a long time and retain the network connectivity [21][22][23][24]. For developing a routing protocol, clustering is also very important. In each cluster, a CH is available, which is responsible for all cluster members. From cluster members, CH gathers the data and transfers it to the MS node [19][20]. This MS node can function as a BS. To ensure the WSN's energy consumption balance, clustering is crucial. In WSN, clustering algorithms like K-means clustering, CSOBCA, FLA, and RSA cryptography algorithms have been extensively utilized. Considering these optimization's contributions in multiple applications we have also developed an optimization-based approach named Tuna-Osprey Optimization for energy efficient Cluster-based Routing. Its contributions are Proposing a hybrid optimization named Tuna-Osprey optimization (TOO) for CH selection by considering the node energy (predicted) energy, link lifetime, trust, distance as well and delay. Proposing a modified DL (M-LSTM) model for predicting the node's energy during clustering to ensure the energy efficiency. Proposing an effective routing strategy using Tuna-Osprey optimization (TOO) with the consideration of link quality as the constraint.

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2. LITERATURE SURVEY

A few publications that were related to CHS as well as routing were discussed here Xiaoling Guo, Yongfei Ye, Ling Li, Renjie Wu, and Xinghua Sun developed a model named CRACSCA-LM. In this model, the CH count was evaluated dynamically by the CHS process depending on alive nodes, fitness function as well as node's current energy. For the current round, the SCA and LM have the least fitness function value leveraged for the ultimate election. To forward the data, to avoid the longer distance broadcast, the relay node was modeled in the phase of data transmission. Indra Kumar Shah, Tanmoy Maity et. al proposed ADMICICEMA for multi-hop WSN. This approach presented the intra-cluster communication and allotment of a dynamic duty cycle depending on the distance from the CH node to child nodes for lowering energy utilization. For forwarding the packets to BS, the route that utilizes lower energy was presented in the inter-cluster communication. With extant techniques, ADMICICEMA was contrasted over two situations count of rounds and node count. A hybrid clustering technique named EEHCT for IoT-dependent multiple-level HWSN was proposed by Sandip K. Chaurasiya, Santu Mondal, Arindam Biswas, Anand Nayyar, Mohd Asif Shah, Rajib Banerjee. During the formation of the cluster, energy utilization was diminished by EEHCT and the network load was evenly decentralized. Load-balanced clusters were developed by dynamic as well as static approaches. In regards to throughput, stability, and network lifetime, the EEHCT outperforms other methods. Tanvi Sood and Kanika Sharma proposed a LUET-dependent clustering protocol for HWSN. It was designed for multiple applications. LUET was designed for three-tier HWSN's energy efficiency coverage. Along with that, a rotation epoch-dependent LUET variant was proposed to beat the quick node death. In performance comparison, a LUET-dependent clustering protocol for the HWSN model showed superior power efficiency, network lifetime, and throughput. Yadong Gong, Junbo Wanga, and Guoming Lai suggested an Energy-efficient QDC protocol for WSN on 5G communication. In WSN, the energy efficiency was enhanced by this QDC protocol. This model includes 4 parts which were a) a size-balanced network partitioning approach, b) an estimation-dependent mechanism for energy usage reduction in the maintenance of centralized sub-network c) distributed QDC for global clustering, d) a load-balanced as well as energy-efficient inter-cluster routing scheme for each sub-network's inter-cluster routing. For the clustering node, the global energy consumption was reduced by this approach. NTM-LEACH-RSA was proposed by S. Anitha, S. Saravanan, and A. Chandrasekar for network lifetime extension as well as diminishing energy usage. For CHS, constraints like distance, threshold function value, density, as well as trust value were utilized by the proposed NTMLEACH technique. To ensure data integrity and data transmission protection, the RSA cryptography technique was employed in the 2nd phase. Sercan Yalçın, and Ebubekir Erdem proposed TEO-MCRP having a mobile sink for HWSNs. This is a mobile clustering routing protocol. Two algorithms were utilized in this TEO-MCRP for CHS and detection of MS path with objective functions like independent fitness parameters. For every node round, the TEO algorithm was utilized to evaluate the effectiveness of CHS as well as MS trajectory. From all CHs, data are gathered by the MS node and that is transmitted to BS. Shaha Al-Otaibi, Amal Al-Rasheed et. al proposed an HMCBR for WSN. A BSO-LD-dependent clustering makes use of the fitness function including parameters like distance to neighbors, energy, distance to BS as well and network load. Furthermore, a routing process based on WWO-HC was conducted to choose the optimal route. To ensure the HMBCR technique's network lifetime as well as energy efficiency performance, experiment analysis was conducted.

3. Research Methodology

Due to their great abilities and growing applications, WSNs are considered the most promising technology. However, WSN's lifetime has been restricted because of their SN's delimited energy capacity. This is the reason for considering energy conservation as the WSN's most crucial research concern. In WSN, the utmost energy is consumed by radio communication. Thus, increases the energy efficient routing requirements like energy conservation and enlarging the network lifetime. For this reason, a novel TOO for energy efficient Cluster based Routing has been proposed with 2 working phases which were Optimal CHS as well as routing. The initial process is selecting the CH via the TOO algorithm. The proposed TOO is the mixture of the Osprey Tuna Swarm optimization algorithm. Here, the selection process will be done considering Energy (predicted energy), Link Lifetime, trust, distance, and delay constraints as well. Here, a modified Deep learning algorithm that is M-LSTM is used for predicting the node energy. The routing can be conducted with the same TOO algorithm with the consideration of link quality. The detailed process is given below:

3.1 Node energy prediction utilizing the M-LSTM model

Generally, a sensor network includes SNs associated together utilizing wireless communication protocol. Numerous kinds of SNs having multiple capabilities are included in a sensor network. In this work, two kinds of nodes Normal node (N) and Advanced node (A) are considered, and depending on the kinds of nodes, energy will get changed. During the network initialization, node energy is predicted using the modified DL model. By considering the better handling of long-term dependencies, we have utilized modified LSTM in our work. The node's locations as well as the kinds of nodes (N and A) are subjected as the input to the modified LSTM. If the node type is N, then the target will be . Here is symbolized by initial energy. The predicted energy value will be between 0.5-1. An LSTM network's core elements are the sequence input layer as well as an LSTM layer. For inputting the time series or input sequence data into the NN, a sequence input layer has been utilized. Long-term dependencies among the sequence data's time steps are learned by an LSTM layer. Our work uses the regression process, where NN starts with a sequence input layer following that an LSTM layer is used [25]. Afterward, following the fully connected layer, a regression output layer is utilized which is displayed in Fig.1.

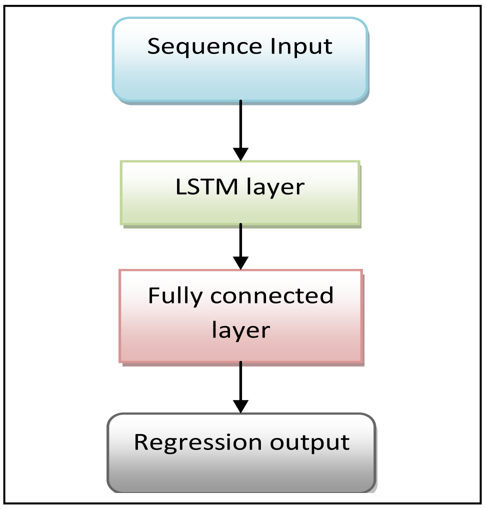

Fig 1: Architecture of LSTM

Modified LSTM utilizes the 3 stacked LSTM layers instead of single LSTM layers. Input sequence's more informative representations can be learned by these stacked LSTM layers, which enhances its capability to generalize and create more precise predictions. The architecture of the modified LSTM is shown in Fig. 2.

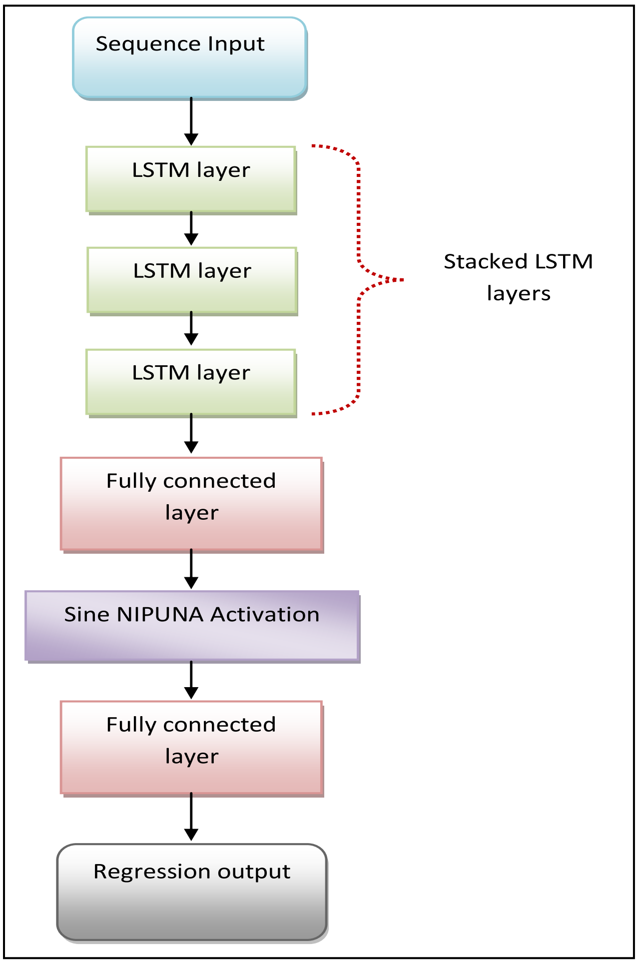

Fig 2: Architecture of M-LSTM

Furthermore, in our M-LSTM, a custom activation layer named Sine NIPUNA Activation layer is introduced with adjustable parameters alpha and beta. The NIPUNA allows the model to capture small negative inputs. This activation is the hybrid of the sine-based element from Comb-H-Sine as well as the sigmoid-dependent element from NIPUNA. By utilizing this modified LSTM, we can reduce the risk of vanishing gradient and get smooth as well as monotonic activation.

3.2. Optimal CHS via Tuna-Osprey Optimization

For increasing the network lifetime, clustering is the main approach in WSN. Here, clusters are formed by grouping the SNs, and CHs are chosen for each other. This work proposes a Tuna-Osprey Optimization for optimal CHS with the consideration of consideration of energy (predicted), link lifetime, trust, distance, and delay constraints that are briefed below.

a) Energy (Predicted)

The mean of the CH node's remaining energy is referred to as energy that is numerically expressed in Eq. (1).

$$Energy = mean(E_{CHmode}) \quad (1)$$

Here E_{CHmode} symbolizes the CH node's remaining energy (predicted).

b) Link Lifetime

A network's link lifetime can be referred to as the length of time from network deployment till the initial relay node runs out of energy, which has been expressed in Eq. (2) [27].

$$LLT = E_0/E_{total} \quad (2)$$

Where, E_0 indicates the sensor node's initial energy and E_{total} implies the total energy spent in the data transmission.

(c) Trust

By aggregating direct as well as direct trust ratings, the final trust is evaluated as given in Eq. (3) [28].

$$Trust_{(AN-BN)} = wt * DT_{(AN-BN)} + (1-wt) * IDT_{(AN-BN)}$$

, Here $wt = 0.5$ (3)

In Eq. (3), the weights connected with direct as well as indirect trusts were symbolized as wt and $Trust_{(AN-BN)}$ imply the final trust of node AN on BN.

- **Direct Trust**: Depending on the node's interaction, direct trust is evaluated. From Eq. (4), considered trust metrics were energy and distance.

$$DT_{(AN-BN)} = \frac{E_{remain}}{d_{(nodeAN,nodeBN)}} \quad (4)$$

Where, node B's remaining energy is symbolized as E_{remain}, Direct trust value evaluated by *AN* for *BN* is $DT_{(A-B)}$ and $d_{(nodeAN,nodeBN)}$ is the various distances of node AN and BN.

- **Indirect Trust:** Based on the node's recommendations, indirect trust is evaluated. The sum of trust ratings, evaluated using other nodes was referred to as indirect trust which is shown in Eq. (5).

$$IDT_{(AN-BN)} = \sum DT_{(AN-CN)} * DT_{(CN-BN)} \quad (5)$$

Direct trust value evaluated by AN for CN is $DT_{(AN-CN)}$ and direct trust value evaluated by CN for BN is $DT_{(CN-BN)}$ and also $IDT_{(AN-BN)}$ implies the indirect trust value evaluated by AN for BN, regarding suggestion from *CN; CN AN*.

(e) Distance

Distance among two nodes has been evaluated by Euclidean distance which is given in Eq. (6).

$$D_{no.FG} = \sqrt{(F_2 - F_1)^2 + (G_2 - G_1)^2} \quad (6)$$

Here, F_1, G_1 were the CH node's coordinates and F_2, G_2 were the sink node's coordinates.

(f) Delay

The delay rating is obtained by dividing the rating of distance by speed which is given in Eq. (15).

$$Delay = \frac{Distance}{Speed} \quad (7)$$

Here, $Speed = 2.1 \times 10^{8}\ m/\sec$

3.2.1 CHS using Tuna-Osprey Optimization

To choose the CH optimally, this work proposed a Tuna-Osprey Optimization which is the hybridization of Osprey [29] and Tuna Swarm optimization algorithms. A meta-heuristic algorithm that mimics the osprey's behavior in nature is named OOA. Motivated by the tuna swarm's cooperative foraging behavior, TSO was created. TSO [30] imitates the tuna swarm's two foraging behaviors including spiral as well as parabolic foraging. In our work, all the modifications are done in TSO. The proposed Tuna-Osprey Optimization's mathematical model has been detailed below and its architecture is given in Fig 3.

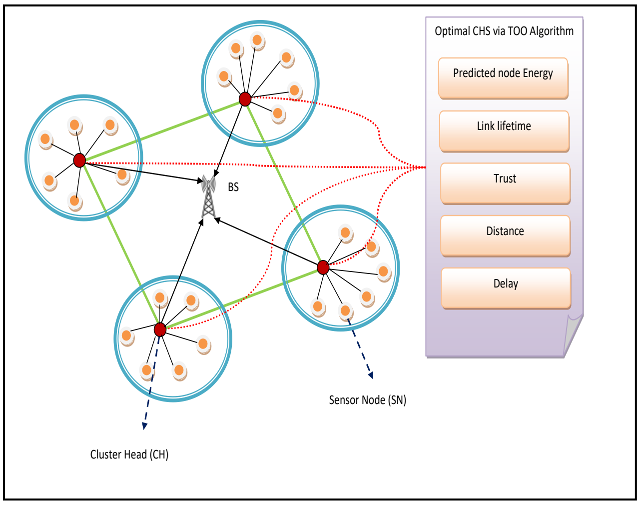

Fig 3: CHS using TOO algorithm

3.2.2 Spiral Foraging: To stop the predators from locking a target, a dense formation was created by the whole school of fish by constantly altering its swimming direction. At that time, the prey was chased by the tuna group by creating a tight spiral formation. Even though several fishes have a sense of direction when a tiny fish group swims in a particular direction and that are followed by the nearby fishes, that makes a group have a similar goal and start the hunt. Additionally, the information is also exchanged between each tuna.

3.2.3 Parabolic Foraging.

Here, considering food as a reference point, tuna creates a parabolic formation. By searching around themselves also they hunt for food. Simultaneously, two approaches were performed, which assume both have a 50% selection probability. An arbitrary number is TF which has the value of 1 or -1. Tuna-Osprey Optimization uses the scaling factor to provide faster convergence. To control the scaling degree, a scaling factor has been utilized. This also enhances the population diversity. By two foraging behaviors, tuna hunt to find their prey. In the search space, the population is first arbitrarily created for the TSO's optimization. From the two foraging strategies, one is chosen by each individual to execute. Till met the end condition, TSO's all the individuals were continuously updated. Afterwards, the optimal individual along with the respective fitness value was returned. Finally, using the Tuna-Osprey Optimization, the CH is selected and afterward, routing is conducted using this same optimization with the consideration of link quality which is briefly described below.

3.3. Routing via TOO algorithm

A process, that chooses the proper way to transfer data from source to destination, is named routing. While choosing the route, it faces more difficulties which depend on the channel characteristics, kind of network, and the performance metrics. We have utilized the same Tuna-Osprey Optimization explained above to choose the optimal route, which considers link quality as a constraint during the routing process that is displayed in Fig. 4

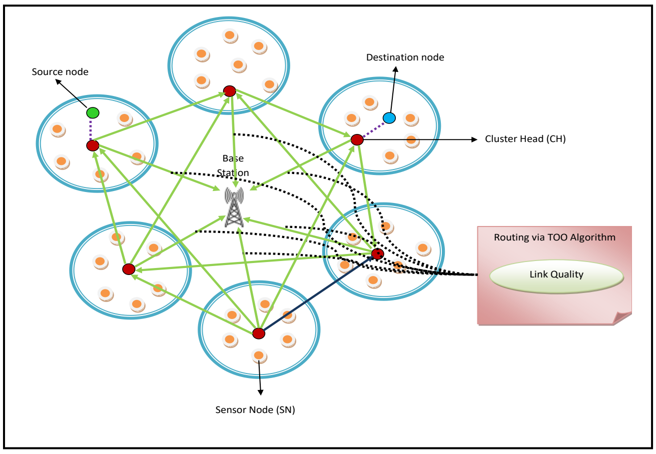

Fig 4: Routing via TOO Algorithm

3.3.1. Link Quality

For the best possible route, link quality is one of the typical restrictions. Effective link quality estimation can guarantee the transmission of data, as well as improve the throughput rate, and hence, extend the life of the entire network that is expressed in Eq. (8).

$$LQT = \left(Wt_1 * RSSI_{norm}\right) + \left(Wt_2 * PDR\right) \quad (8)$$

Here, $RSSI_{norm}$ indicates the normalized revised signal strength indicator, Wt_1 and Wt_2 are weights and PDR indicate the Packet Delivery Ratio.

PDR ratio can be defined as the %of successfully delivered packets over the total count of packets sent that is given in Eq. (9)

$$PDR = \frac{No.of\ successfully\ delivered\ packets}{Total\ no.of\ packets\ sent} \times 100 \quad (9)$$

4. Result & Discussion

4.1 Simulation Procedure

The TOO model for energy-efficient Cluster-based Routing was implemented in an i5 CPU with 16GB RAM using MATLAB 2021A, and the results were confirmed. The efficacy of the TOO approach was compared to several conventional optimization algorithms, including COA, SCA, OOA, TSO, BWO, JS, and

AVOA model, in relation to the following metrics: trust, link quality, delay, energy efficiency, distance, and link life time. The suggested model, which employs MLSTM for energy prediction in routing, was contrasted with other techniques such as CNN, LSTM, NB, and RF. In this instance, testing was conducted across a range of 0 to 2000 rounds. The 100 m×100 m network has a distributed number of sensor nodes thanks to a centralized base station. In the field, 100 and 200 nodes are taken into consideration. A node's optimal election probability is fixed at 0.1. The model's initial energy is 0.5J. 5n J/bits/signal is the data aggregation energy, denoted by the symbol E D. Ten clusters in total were present. Figures 5 depict the simulation configuration of the TOO model, which displays 10 clusters for nodes 100 respectively. Setup consists of 10 cluster with 10 cluster head, cluster head was represented by big circle and neighbor nodes are in small circles. Sink node is shown in black color flower like structure and the source node is represented by red color small circle.

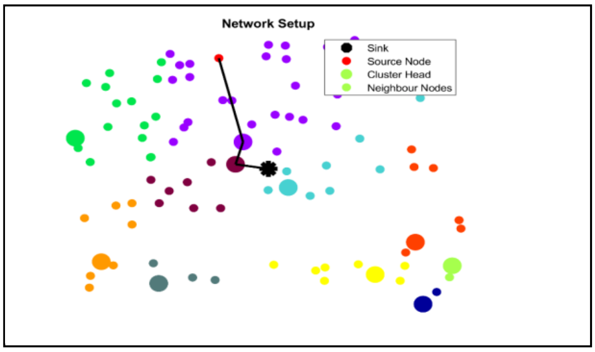

Fig 5. The TOO model's simulation setup for node 100

4.2 Analysis on Energy prediction for node 100

Energy prediction of the MLSTM model is evaluated for node 100 by contrasting the MLSTM to conventional classifiers such as CNN, LSTM, NB, RF. For the MLSTM model MLSTM is used as the classifier for energy prediction and it is compared based on error measures like MSE, MAE, RMSE, MARE, MSRE, RMSRE, MAPE, MSPE, RMPSE. Table 1 represents the energy prediction analysis for node 100. For node 100, the MLSTM model performs well for predicting the energy as it has very less error occurrence chance as shown in table 1. MARE of the MLSTM is 0.004, where other techniques has error chance above 0.03. RF has the higher chance of error as its MARE is 0.1. MSE of the MLSTM model for node 100 is 9.73E-06, which is the least error chance compared to conventional classifiers. For MLSTM for node 100, MAE is 0.002, RMSE is 0.003, MARE is 0.004, MSRE is 3.15E-05, RMSRE is 0.005, MAPE is 0.28, MSPE is 0.17, RMPSE is 0.34. All the metrices results shows that the MLSTM performs better than other existing techniques. The MLSTM outperforms other current methods, according to all of the metrics data for both the node 100 and node 200.

4.3 Analysis on Delay for node 100

The delay of the TOO model is examined by contrasting it with conventional methods as COA, SCA, OOA, TSO, BWO, JS, and AVOA. The TOO model's delay is examined in terms of simulation rounds. As the number of rounds grows to 500, 1000, 1500, and 2000 the TOO model's delay also increases. The TOO model for node 100 achieves almost 2 x 10-7 at the final round of 2000; all other nodes are above 3 x 10-7, indicating that the TOO model's delay is less than the conventional methos. All of the traditional methods reach their maximum delay around round 1500, however the suggested model performs better and has a lower delay. The brown color bar in Figure 6 indicates the TOO model, which is plainly lower in all rounds. As a result, it can be shown from the delay study that the TOO model guarantees a quicker connection establishment in routing, whereas the highest delay rate for node 100 indicates that the conventional approaches perform poorly.

Table 1. Analysis on Energy prediction for node 100

	MSE	MAE	RMSE	MARE	MSRE	RMSRE	MAPE	MSPE	RMSPE
CNN	0.000303	0.016848	0.017419	0.030484	0.001048	0.032369	0.72106	0.99284	0.7686
LSTM	0.017429	0.094555	0.13202	0.14833	0.036517	0.19109	0.39247	0.20682	0.53618
NB	0.045	0.09	0.21213	0.09	0.045	0.21213	0.82476	0.65016	0.39663
RF	0.05	0.1	0.22361	0.1	0.05	0.22361	0.4081	0.64584	0.64315
MLSTM	9.73E-06	0.002478	0.00312	0.004511	3.15E-05	0.005611	0.28596	0.17252	0.34476

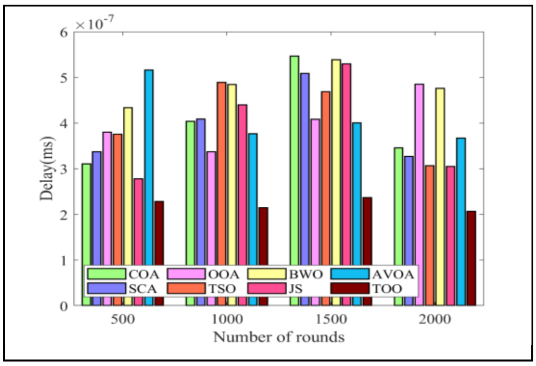

Fig 6. The TOO model's Delay analysis for node 100

4.4 Analysis on Distance for node 100

The graphical results of the TOO technique's distance analysis in comparison to traditional methods for nodes 100 and 200 are shown in Figure 7. In contrast to the TOO approach, the typical approaches are COA, SCA, OOA, TSO, BWO, JS, and AVOA. The TOO model's distance is less than that of other traditional methods, as Figure 7 illustrates for Node 100. The TOO model reaches its minimum in different rounds. Meters are used to calculate distance. TOO model achieves the goal in several rounds of 500, 100, 1500, and 2000, respectively, in 47, 44, 50, and 43 meters. To reach the destination, all other conventional ways require a greater travel distance. The COA in 1500 rounds reaches a maximum distance of about 117 m, while the TOO model achieved 50 m in the same round. As a result, the TOO model produced the shortest distance when compared to traditional methods based on the examination of distance. This demonstrates how well the TOO work on ideal cluster-based routing performs

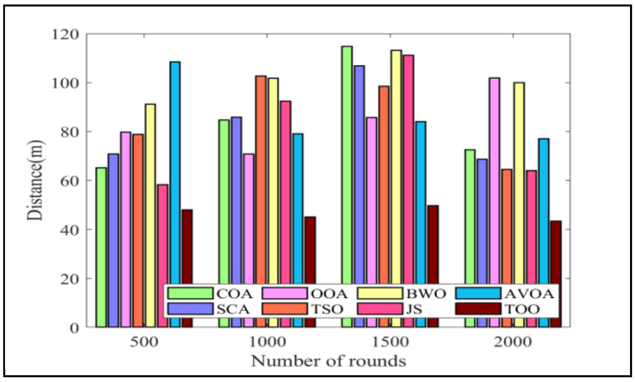

Fig. 7. The TOO model's Distance analysis for node 100

4.5 Analysis on Link Quality for node 100 & node 200

Link quality is an indication of the quality of the data packets received by the receiver. Here the analysis on link quality of the TOO model for node 100 and node 200 are contrasted to traditional approaches such as COA, SCA, OOA, TSO, BWO, JS, and AVOA.

Link quality of the TOO model for node 100 is higher than all other techniques, which was shown in figure 8. TOO model is represented by brown color bar. X-axis represents the number of rounds, 500, 1000, 1500, 2000. Y-axis represents the Link quality percentage of various approaches. In all rounds for node 100 the TOO model has 85% above link quality. At 2000 rounds the TOO model achieved nearly 90% of link quality, which is the maximum of all other techniques. Minimum link quality is achieved by COA at 1000 rounds at the same time TOO approach attained nearly 90% of link quality.

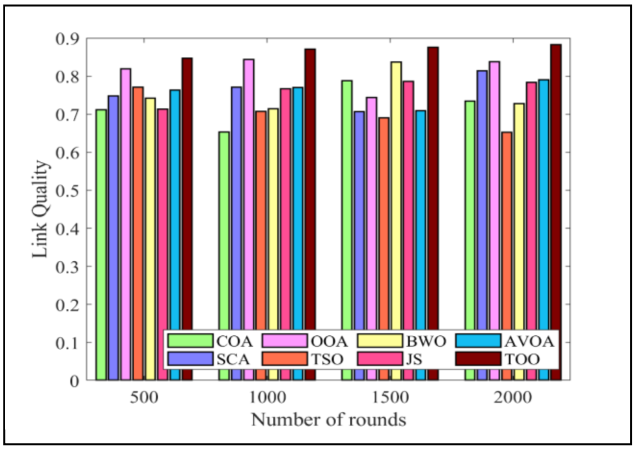

Fig 8. The TOO model's Link Quality analysis for node 100

4.6 Analysis on Link Life Time for node 100

Link Lifetime analysis in routing refers to the examination of the duration for which a link remains operational within a network. It involves assessing factors such as reliability, maintenance, and failure rates to predict and optimize the longevity of communication paths in a routing infrastructure. TOO model has higher efficient life time as it uses Osprey optimization and Tuna swarm optimization algorithm. Analysis for node 100 and node 200 are shown in figure 9. TOO model is compared to conventional techniques, COA, SCA, OOA, TSO, BWO, JS, and AVOA. From figure 13, it shows that the bar represents the TOO model is higher than all other techniques at all rounds. At round 2000, TOO approach attained nearly 1200, where other techniques were below 1150. SCA and TOO approach looks like nearly same at round 500 even though the TOO model overcome the SCA algorithm. From the analysis it is proven that the TOO model has higher link lifetime than other approaches.

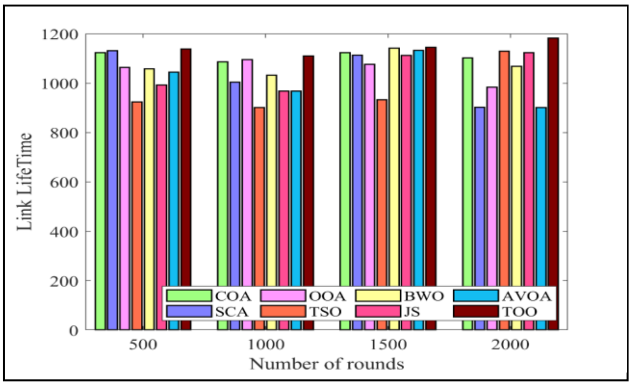

Fig 9. The TOO model's Link Life Time analysis for node 100

4.7 Analysis on Trust for node 100 & node 200

Figures 10 illustrate the trust factor of the TOO model for nodes 100 and 200 in comparison to traditional methods. There are several rounds for evaluating trust value: 500, 1000, 1500, and 2000. As seen in figure 15, the TOO model achieved a 90% trust value for node 100 in the 500th round, while other previous methods only managed to achieve trust values of 87% or below. In every round—500, 1000, 1500, and 2000—the trust value is almost the same (90%) whereas the trust value of conventional techniques is lower than that of the proposal. The TOO model has the highest trust value across all rounds. As a result, we can guarantee that the model's output is reliable in comparison to traditional methods like COA, SCA, OOA, TSO, BWO, JS, and AVOA

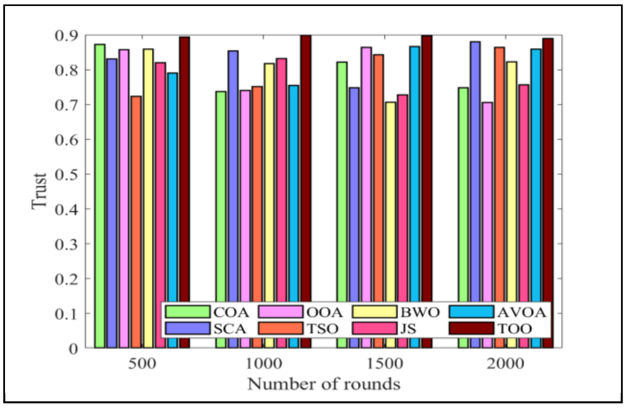

Fig 10. The TOO model's Trust analysis for node 100

4.8 Analysis on Remaining Energy for node 100 & node 200

The analysis for nodes 100 and 200 compares the residual energy of the TOO model with traditional approaches after the final process. Figures 11 provide a graphic representation of the analysis on remaining energy. The standard methodologies for comparison include COA, SCA, OOA, TSO, BWO, JS, and AVOA. Based on the analysis, the graph indicates that the TOO model has 0.6 J at the 0th round and the energy decreased to 0.28

J in round 2000 for node 100. The TOO model has a high residual energy, which indicates that it uses less energy than other standard methods. The residual energy of the other traditional model is less than 0.25 J, indicating a larger energy consumption of the conventional method. Nonetheless, the analysis demonstrated that, for node 100, the TOO model used less energy

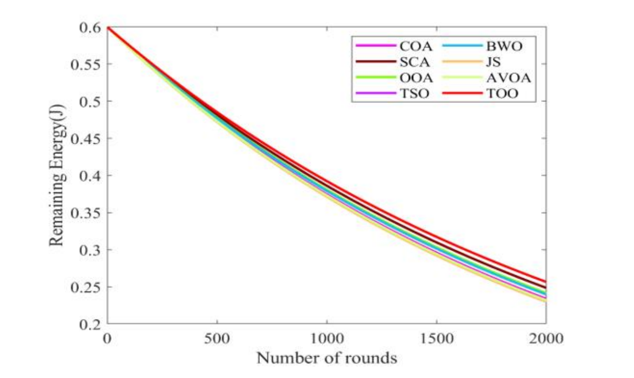

Fig 11. The TOO model's Remaining Energy analysis for node 100

4.9 Analysis on Convergence for node 100

The TOO model is iterated by changing the number of iterations to 0, 5, 10, 15, 20, 25. The TOO model's performance and cost value are assessed for node 100. Figure 19 illustrates how the TOO model produces extremely low cost value when compared to other earlier techniques as COA, SCA, OOA, TSO, BWO, JS, and AVOA. The cost value of the TOO strategy starts off roughly at 0.243 at the beginning and at 3rd iteration the value drops at 0.239 then stays stable till 9th iteration and then drops in 10th iteration to 0.2339 at which point it abruptly lowers to the lowest cost value. In the 25th iteration, the TOO technique produces a cost value of around 0.2339 at the end of the iteration. For node 200, at 0th iteration TOO model starts at 0.241 and drops to 0.237 at 6nd iteration from 5th iteration, then it been stable till 15th iteration and drops to 0.2339 till 20th iteration. However, with a least cost value of roughly 0.2339 for node 100 the TOO model achieves low-cost value and superior performance than conventional techniques. It has been demonstrated that the TOO model produces the best convergence at the lowest cost.

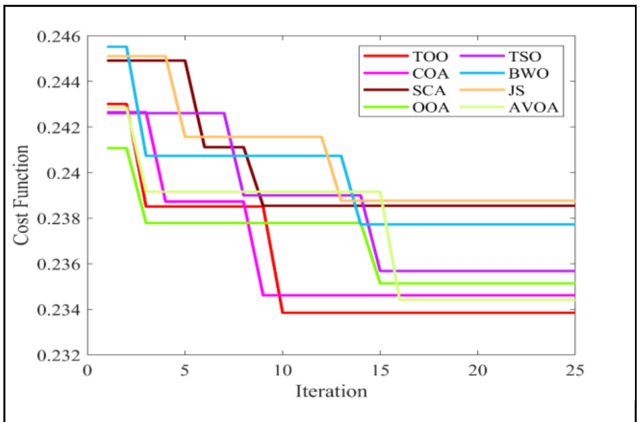

Fig 12. The TOO model's Convergence analysis for node 100

4.10 Analysis on Network Lifetime for node 100

TOO model is evaluated under the network lifetime for node 100 and 200, it was contrasted to conventional techniques such as COA, SCA, OOA, TSO, BWO, JS, and AVOA. TOO model stays for longer lifetime for node 100 as it ran for 2782 rounds, where other techniques ran at the maximum of 2617 by COA algorithm. Least lifetime was achieved by BWO as it ran for 2503 rounds. For node 200, TOO model ran at the max of 3584, which indicates that the TOO model has longer lifetime than any other techniques. TOO model nearly run 100 rounds longer than other techniques. From the study (Table 2), the TOO model proves that it performs well based on network lifetime on cluster-based routing for node 100 and node 200.

Table 2. Analysis on Network Life time for node 100

TOO	*2782*
COA	2617
SCA	2524
OOA	2580
TSO	2552
BWO	2503
JS	2555
AVOA	2587

5. CONCLUSION

For developing the routing algorithms in WSN, clustering was indeed an effective strategy that enlarges the network’s lifetime along with the scalability. During data transmission, CH plays a crucial role in a clustered WSN. Considering that a novel TOO algorithm for energy-efficient cluster-based routing was proposed in this work. This approach includes 2 working phases clustering as well as routing process. Initially, a modified DL model named M-LSTM was proposed for the prediction of node energy. Following that clustering process was carried out using the TOO algorithm, which utilized the energy, link lifetime, distance, trust as well as delay matrices as constraints during the optimal CHS. Finally routing process was conducted with the same TOO algorithm, which utilizes link quality as a constraint to offer optimal routing. Results indicate that the proposed TOO-based routing protocol can provide network lifetime maximization and reduce energy utilization.

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