DEEP NEURAL NETWORK WITH META-HEURISTIC BASED TRUST AWARE CLUSTER HEAD SELECTION IN WSN

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Abstract

The advanced progressions in Wireless Sensor Network (WSN) made this network an effective one in a huge range of applications. Though, the WSN environment suffers from security and energy complexities. WSN has several benefits and still, it has a few challenges. These complexities help the attackers for analyzing the network security and then, they may destroy entire networks. Hence, this work addresses the energy and security issue and adopts the deep learning and meta-heuristic-based trust-aware cluster head selection protocol in WSN. Here, Whale Optimization Algorithm (WOA) is used to select the optimal cluster head using the multi-objective function using constraints like the distance, energy, delay, and trust of nodes. Here, the security management in terms of node trust is determined by the artificial intelligent model termed Deep Neural Network (DNN) for maintaining the security in routing. Through the performance analysis, the performance evaluation has shown that the designed architecture offers reliable and feasible performance in WSN.

***Keywords*: Wireless Sensor Network; Cluster Head Selection; Whale Optimization Algorithm; Deep Neural Network; Multi-objective function; Energy; Distance; Delay; Trust of Nodes.**

1. Introduction

Owing to the advanced progressions of WSNs, it has been utilized in several areas [1], like hospitals, military tracking, fire monitoring, etc as it influences the short-range sensors, which are utilized in environments like monitoring [12]. The implementation of sensor nodes is done through several constraints like storage capacities, energy factors, limited computation and so, the measurement can be performed by the collaboration of the sensors among them [11]. In general, the operation of WSNs with the sensor nodes is practically based on battery, and hence, WSN considers the major constraint as energy since the network lifetime is mainly performed with the help of battery-operated sensors [12]. Clustering is one of the eminent techniques in WSNs, which is used for forming the cluster of nodes with the factor of energy consumption of the sensor nodes that are known as cluster [16]. Here, each cluster has one cluster controller termed cluster head while the remaining nodes are taken as the cluster members [13].

In WSN, each sensor node is allocated to a cluster and is responsible for relaying the accumulated data to its cluster head [8], which is further forwarded via single- or multi-hop communication to a base station [14]. One of the major constraints in WSN is security, where the design of a secured communication among nodes of a sensor network is more complicated and thus, there is a need of establishing trust among nodes [13]. Thus, in a sensor network, nodes should carry out their functionalities at reliable manner. Though, sometimes, not all the sensor nodes behave reliably at all times because of the risk of physical attacks, deployment in inhospitable physical frameworks, and their limited capabilities [9]. Due to resource limits and network dynamics, maintaining trust in a wireless sensor network is a tough challenge. While building a network, the major factor is to create trust among nodes, which must also perform efficiently even deleting or adding sensor nodes in the network [7]. Generally, trust establishment in WSN has several benefits, which are secure communication via the trusted cluster heads and trusted cluster members to sink node, selection of trustworthy routing nodes in multi-hop clustering, detection of malicious or faulty nodes in the cluster through trust factor, guarantees reliable routing paths without faulty, selfish or malicious nodes, and handling of access control through the quality of nodes and their services [6]. Thus, this paper suggests a new trust-aware cluster head selection in WSN for secure communication.

The performance of WSN is also decided based on the selection of routing protocols through taking the requirements of the application and network resources. Thus, the deployment of routing protocols is specifically carried out for prolonging the network lifetime. But, it is also a challenging task owing to the limited energy in the sensor nodes, limited communication, and limited availability of the resources [21]. By considering all these factors, routing is executed for solving the complications correlated with communication overhead and routing. In recent studies, various clustering algorithms have been suggested for routing, which is constrained "coverage algorithm, Low Energy Adaptive Clustering Hierarchy (LEACH)", virtual force algorithm, etc. however, the conventional clustering algorithms suffer from problems like lower lifetime of networks, death of sensor nodes, lifetime imbalance in sensor nodes, increased energy consumption, poor residual energy, delay, and bad stability [4]. These challenges have been solved through some meta-heuristic and nature-inspired algorithms. However, they also have some merits and demerits during the routing and clustering process in selecting the cluster heads [15]. Thus, this paper adopts deep learning for suggesting a new cluster head selection scheme with trust among nodes.

The main contribution from the proposed model is to design a trust-aware cluster head selection in WSN through a heuristic-assisted deep learning algorithm. Here, the cluster head selection is carried out through a WOA with the help of solving the multi-objective function regarding energy, distance, delay, and trust of nodes. Further, the training and testing of node details with trust are ensured by DNN-based deep learning model. Further, the performance analysis with the help of different performance measures by comparing over conventional approaches is carried out.

The remaining sections of this work are arranged as follows. The existing works are analyzed in section number 2. The enhanced cluster head selection model using deep learning and WOA is discussed in section number 3. The WOA-based trust aware cluster head selection in WSN is depicted in section number 4. The results and findings are discussed in section number 5. The conclusion is presented in the 6th section.

2. Literature Survey

2.1. *Related works*

In 2021, Ali et al. [1] have suggested a new cluster head selection strategy for maximizing the network lifetime through ARSH-FATI that has minimized the energy consumption among nodes communication. They have focused on dynamically switched among the exploitation and exploration of the processes for achieving the superior performance trade-off. This model has considered the constraints like workload during selection of cluster heads, communication distance factors, and residual energy. They have maximized the network lifetime.

In 2020, Lata et al. [12] have implemented a new LEACH with Fuzzy Clustering (FC) protocol for forming the clusters and selecting cluster heads for maximizing the network lifetime. A centralized architecture was followed to achieve it. The major contribution of their designed model is to choose a vice cluster head, which was carried out through fuzzy logic technique. They have efficiently balanced the energy load at every node to maximize the WSN reliability. Finally, the designed model has reduced the energy consumption and improved the network lifetime.

In 2019, Kumar and Gangwar [11] have selected Bitmap-Assisted Efficient Scalable-Time-Division Multiple Access-based on "Media Access Control (BEST-MAC)" protocol to maximize the throughput and energy efficiency of WSN for maximizing the lifetime by selecting the cluster heads. In this paper, the cluster head selection was done through several constraints like number of neighboring nodes in cluster, residual energy, etc. This model has overcome the control overheads and maximized the energy efficiency while comparing to the conventional techniques. In 2020, Arunachalam et al. [2] have implemented a new cluster head selection technique by SSO algorithm to prolong the network lifetime through a gliding factor with the procedure of data dissemination and aggregation. The fitness value of each sensor node was estimated and then, they have arranged in ascending order, where the cluster member was selected through identifying the node with lower fitness value. Then, the cluster head selection was done by nodes with higher fitness value. They have verified the performance regarding the minimum energy consumption, enhanced the network lifetime, and improved throughput.

In 2019, Mahesh and Vijayachitra [16] have suggested a "Dolphin Echolocation-based Crow Search Algorithm (DECSA)" for assuring the selection of cluster heads to maximize the convergence rate with multi-constraints regarding link lifetime, mobility, delay, and distance among two cluster heads within the cluster and improved the energy efficiently. The transmission in the network was initiated with base station. Finally, the measurement phase has updated the remaining energy in the nodes.

2.2. *Problem statement*

The existing clustering approaches are discussed in Table 1. ARSH-FATI [1] has improved the network lifetime and has increased the performance in terms of residual energy among the nodes. Though, the performance enhancement can be affected by the higher number of alive nodes.

LEACH-FC [12] have exhibited lower energy consumption and increased the lifespan, network scalability, and efficiency. Conversely, the optimal performance is affected by suggested method's FND correlation with the existing method. BEST-MAC [11] has avoided the collisions by reducing the control overheads in communication and has maximized the efficiency regarding delay, throughput, and energy efficiency. However, this model does not consider the factors like scalability and data aggregation. SSO [2] has minimized the normalized energy consumption and has reported improved network lifetime and superior throughput. On the other hand, it suffers from classifying the "nodes with worst fitness from the nodes with best fitness in the network". DECSA [16] provides a higher network lifetime when evaluated with other approaches and increases the throughput performance. The performance degradation is observed when the number of nodes increases. The challenges that existed in the traditional clustering approaches in WSN help the researchers to propose a new clustering strategy.

Author	Methodology	Features	Challenges
Ali et al. [1]	ARSH-FATI	• The network lifetime improved. • The performance in terms of residual energy among the nodes has increased.	• The performance enhancement can be "influenced by higher number of alive nodes".
Lata et al. [12]	LEACH-FC	• They have exhibited lower energy consumption. • It increases the lifespan, network scalability and efficiency.	• The optimal performance is affected by suggested method's FND correlation with existing method.
Kumar and Gangwar [11]	BEST-MAC	• It has avoided the collisions by reducing the control overheads in communication. • It has maximized the efficiency regarding delay, throughput and energy efficiency.	• This model does not consider the factors like scalability and data aggregation.
Arunachalam et al. [2]	SSO	• It has minimized the normalized energy consumption. • It has reported improved network lifetime and superior throughput.	• It suffers from classifying the "nodes with lowest fitness from the nodes with highest fitness in the network".
Mahesh and Vijayachitra [16]	DECSA	• It provides higher network lifetime when evaluated with other approaches. • It increases the throughput performance.	• The performance degradation is observed while increasing the number of nodes.

Table 1. Advantages and Challenges of Existing Clustering Techniques in WSN

3. Proposed Cluster Head Selection Architecture with New Approaches

3.1. *Trust aware cluster head selection*

The implementation of sustainable WSNs is a complicated task and also, there is a expectation on designing the energy-constrained sensor nodes, which has the major aim on extending the network lifetime. Moreover, replacement of the battery is mostly impossible and the sensor nodes may have limited power source that affects the performance of WSN. The existing research works suggest numerous energy efficient algorithms through clustering to operate WSNs. Clustering have confirmed their ability in efficient communication among "the base station and sensor nodes". Moreover, the significant constraint to design WSN protocol is to suggest WSNs with minimum energy expenditure. Thus, the proposed model considers the multi-objective function for ensuring secure communication in WSNs. The proposed trust-aware WSN is depicted in Figure. 1.

A new trust-aware cluster head selection protocol is implemented in WSN to address the energy and security issue. Here, WOA is used to select the optimal cluster head in each cluster using the multi-objective function using the constraints like energy, distance, delay, and trust of nodes. In addition, DNN is used for determining the security management in terms of node trust that gives security to the communication among nodes and base station. Finally, the performance analysis has offered a reliable and feasible performance in WSN.

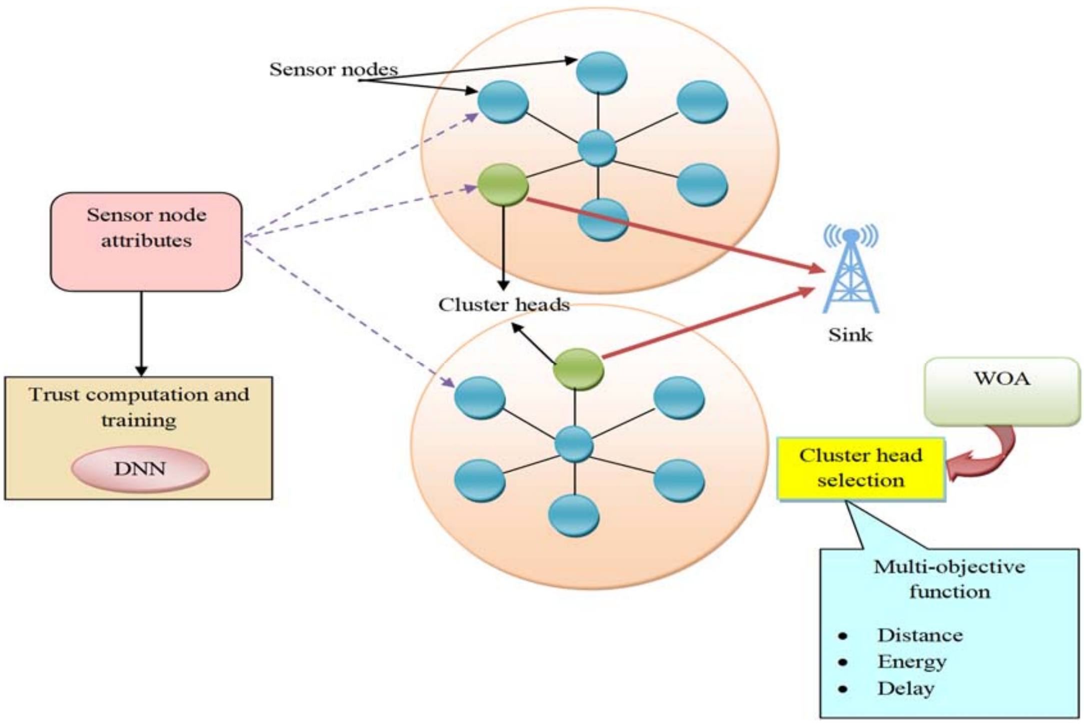


Fig. 1. Trust aware Cluster Head Selection in WSN with heuristic-based deep learning

3.2 *Training and testing of data for trust calculation*

As a new contribution to the designed trust-aware cluster head selection in WSN model, DNN [26] is used for training the data regarding nodes in cluster along with trust constraints of nodes. Initially, the node data is trained using DNN and then, new upcoming nodes will be evaluated by DNN for testing the trust among nodes. If trust is not attained by the nodes then, the penalty will be added or else the trusted nodes will be used for clustering. The node attributes like "limit of initial energy, the transmission energy, the energy required to accept the packets, the dissipation energy in channels, receiving energy, current energy of each node, distances threshold, distance between the two nodes, calculated residual energy, and primary energy" will be trained by DNN along with trust factor. It is a simpler feed-forward neural network and utilized a standard back propagation technique for training the designed model. DNN has consisted of mainly three types of layers like "a single input layer, zero or more hidden layers, and one output layer". The role of input layer is to consider the input as node attributes along with trust factor and gets the output as trained parameters for testing the trust of each node. The fundamental component of the layers is the neurons, which get the information from the previous layer and then, it is transmitted to the next layer after using a non-linear activation function. DNNs have the ability of solving the non-linear problems through considering the activation functions. Moreover, the DNNs have several features, which make it more suitable for this trust computation in designed model. The privacy and security problems are more significant owing to the majorly introduced deep learning models in several applications. DNN training is required for training the data with trust computation. It gets the large number of input data, and keeps a huge set of hidden units. Then, it initializes the weight for breaking the symmetry among several units. DNN uses sigmoid as activation function. Further, uniform distribution is chosen here for initializing the weights with even distribution. One of the major hyper parameter of DNN is learning rate; which has to be assigned after each epoch. Here, the stochastic gradient descent algorithm is used in DNN for training. At last, the final trained DNN is used for automatic trust computation to offer security in WSN.

The trust computation is carried out in training of node using DNN, where trust is defined as, "the combined characteristics model for providing the reliability, security, and privacy with respect to the mobility", as stated in Eq. (1).

$$Tr = \sum_{k=1}^{K}\left(\sum_{k=1}^{K} DTr_{N_k}(CHS_k)\right) + \sum_{k=1}^{K}\left(\sum_{k=1}^{K} ITr_{N_k}(CHS_k)\right) \quad (1)$$

In Eq. (1), the total trust of node is derived as Tr, the indirect trust of neighbor nodes N_k on CHS_k is shown by $ITr_{N_{ki}}(CHS_k)$, and the direct trust of neighbour nodes on CHS_k is formulated as $DTr_{N_k}(CHS_k)$. The trust value associated with a sensor node is calculated to determine whether it is malicious or benign.

Finally, the trusted nodes are selected for transferring the data during communication process. The proposed trust calculation using DNN is depicted in Figure 2.

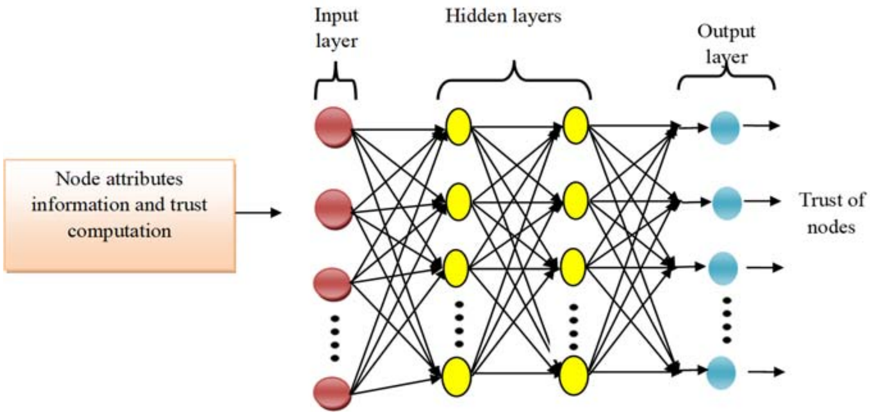


Fig. 2. Trust determination using DNN

4. Heuristic Algorithm For Trust Aware Cluster Head Selection In WSN

4.1. *Multi-objective function*

The proposed "trust-aware cluster head selection" in WSN model uses WOA for selecting the cluster heads. This cluster head selection is carried out by computing multi-objective function using the constraints like distance, delay, energy, and node trust. The major objective function is given in Eq. (2).

$$Fs = \arg\min_{\{\mathrm{CHS_k}\}}(Of_3) \qquad (2)$$

In Eq. (2), the selected cluster heads using WOA represents the total number of cluster heads in WSN. The range of selected cluster heads is formulated among [1, N] and N represents the total number of sensor nodes present in the WSN. The objective function regarding several constraints is formulated here.

$$Of_1 = (\alpha \times Dis) + (1-\alpha) \times \frac{1}{Eg} \qquad (3)$$

$$Of_2 = (\beta \times Of_1) + (1-\beta) \times Dy \qquad (4)$$

$$Of_3 = (\gamma \times Of_2) + (1-\gamma) \times Tr \qquad (5)$$

The multi-objective function regarding several constraints is explained here, where the values of α, β and γ are assigned as 0.2, respectively. The "distance between two sensor nodes either in same cluster or in different clusters" is calculated for offering the optimal routing, where the distance is termed as Dis. "Euclidean distance termed Dis is determined among two nodes" is specified as "the line segment length between the nodes" that is derived in Eq. (6).

$$Dis = \sqrt{\sum_{u=1}^{U}(m_u - n_u)^2} \qquad (6)$$

In Eq. (6), the cluster heads taken for communication is formulated as m and n and the "coordinates corresponding to these two nodes" are represented with the help of u.

The residual energy is derived as Eg and described as the "mean remaining energy of the engaged sensor nodes just at end of the each simulation experiment" as suggested in Eq. (7).

$$Eg = Eg_h - \left(eg_h^{cs} + eg_h^{sh}\right) \qquad (7)$$

In Eq. (7), the initial energy of any node N_h is termed as Eg_h, the "energy consumption by collecting the number of data" unit is given as eg_{h}^{cs} and the "energy consumption" by sending the number of data units is given as eg_{h}^{sh}. Delay termed Dy is computed based on the propagation delay and transmission delay during transmission of packets and derived in Eq. (8).

$$Dy = \frac{\max\sum_{k=1}^{K} CHS_k}{N} \qquad (8)$$

In Eq. (8), the "data transmission from cluster head to base station" is noted asmax$\sum_{k=1}^{K} CHS_k$and term N indicates "the number of nodes present in the sensor network".

4.2. *Whale optimization algorithm*

In this proposed trust-aware cluster head selection in WSN model, WOA technique is utilized for selecting the cluster heads that helps in effective transmission among nodes and base station. WOA [18] is suggested from the inspiration of hunting nature of humpback whales in sea. These whales have capability of identifying the prey and then, it is encircled. Initially, the population of humpback whales is initialized and then, the fitness of each individual in population is determined. The position updating in encircling phase is derived in Eq. (9).

$$\vec{B}(i+1) = \vec{B}^{*}(i) - \vec{S}.\vec{A} \tag{9}$$

$$\vec{A} = \left|\vec{C}.\vec{B}^{*}(i) - \vec{B}(i)\right| \tag{10}$$

In the aforementioned equations, the $\vec{B}^{*}$ represents the better result acquired by position vectors, " . " denotes the product of element-by-element, | | represents the absolute function, and the coefficient vectors are referred by $\vec{C}$ and S as derived here.

$$\vec{C} = 2.\vec{r} \tag{11}$$

$$\vec{S} = 2\vec{s}\,.\vec{r} - \vec{s} \tag{12}$$

In the aforementioned equations, the random vector is given as $\vec{r}$ in the range of [0, 1]. Next, the bubble-net method is used to update solutions, which has two basic mechanisms like spiral updating and shrinking encircling mechanisms. The working of shrinking encircling mechanism is to decrease the value of $\vec{s}$ and then, the spiral updating scheme is derived in Eq. (13), which is formulated among the location of the prey and location of the whale.

$$\vec{B}(i+1) = \vec{A}'.e^{pq}.cos(2\,\pi\,q) + \vec{B}^{*}(i) \tag{13}$$

In Eq. (13), a constant number to define the logarithmic spiral shape is mentioned as p and q denotes the random number in the bounding limit of -1 to 1 and the random number is denoted as q and the distance among the whale and prey is termed as $\vec{A}'$ and derived in $\vec{A}' = \left|\vec{B}^{*}(i) - \vec{B}(i)\right|$. Moreover, the mathematical model of choosing either the spiral model or shrinking encircling strategy is derived in Eq. (14) with the probability ρ that lies in the range of [-1, 1].

$$\vec{B}(i+1) = \begin{cases} \vec{B}^{*}(i) - \vec{S}.\vec{A} & if\ \rho < 0.5 \\ \vec{A}'.e^{pq}.cos(2\,\pi\,q) + \vec{B}^{*}(i) & if\ \rho \geq 0.5 \end{cases} \tag{14}$$

Further, the "solutions are updated based on" the exploration phase for performing the global search, which is done by varying the $\vec{S}$ as derived in Eq. (15).

$$\vec{B}(i+1) = \vec{B}_{rand} - \vec{S}.\vec{A} \tag{15}$$

$$\vec{A} = \left|\vec{C}.\vec{B}_{rand} - \vec{B}\right| \tag{16}$$

Here, $\vec{A}$ denotes the distance among the prey and whale with random search, $\vec{B}_{rand}$ denotes a random position vector, and the prey is searched using $\vec{S}$. Finally, the algorithm is terminated while reaching the stopping condition. The WOA algorithm pseudo code is given in Algorithm 1.

Algorithm 1: WOA [18]

```
Initialization of population and random parameters
Determine the fitness of every search individual
Choose the best search individual B*
while ( i < i_max)
    for every search agent
        if ρ < 0.5
            if |S − 1|
                Update the solutions using Eq. (9)
            else
                Update the random search agent B_rand
                Update the solutions using Eq. (15)
            end if
        else if ρ ≥ 0.5
            Update the solutions using Eq. (13)
        end if
    end for
Update and return best solutions
 i = i + 1
```

end while
Return $\vec{B}^{*}$

Thus, finally, the WOA chooses the optimal cluster heads in every cluster in WSN.

5. Results and Discussions

5.1. *Experimental setup*

The suggested "trust-aware cluster head selection in WSN" was implemented in MATLAB 2020a, and the performance analysis was conducted by comparing with existing models like "Grey Wolf Optimizer (GWO) [19], DHOA [5], Jaya Algorithm (JA) [20], HOA [17], Support Vector Machines (SVM) [25], Random Forest (RF) [10], Neural Network [24], Decision Trees (DT) [22] and K-nearest neighbour (KNN) [23]". The evaluation was conducted by considering the experimental simulation parameters given in Table 2.

Parameters	Description
The number of rounds	2000
The number of nodes	[50, 100, and 150]
Maximum number of iterations	10
Area	100×100m
Initial energy	0.5 J
Percentage of nodes that are advanced	0.1
Data aggregation energy	5×0.0000000001

Table 2. Simulation parameters of Trust-Aware Cluster Head Selection in WSN

5.2. *Convergence analysis*

The convergence analysis of the designed "trust-aware cluster head selection in WSN" is given by altering number of the sensor nodes as given in Figure 3.While considering the number of nodes as 50, the convergence of the designed WOA-DNN is 95%, 94%, 50% and 80% progressed than GWO-DNN, DHOA-DNN, JA-DNN, and HOA-DNN, respectively. Similarly, the optimal performance is evaluated while both increasing and decreasing number of the nodes.

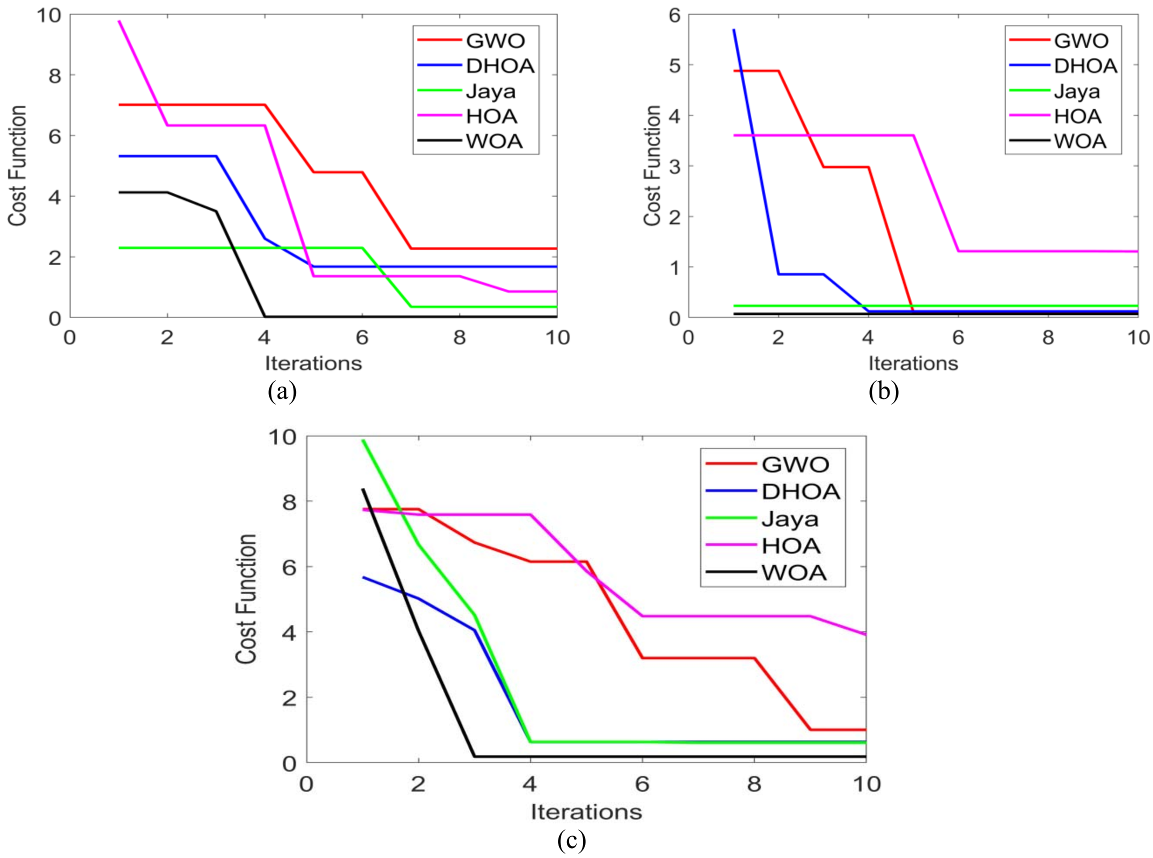


Fig. 3. Convergence analysis on the designed trust aware "cluster head selection in WSN" by varying number of sensor nodes as (a) 50, (b) 100 and (c) 150

5.3. *Analysis on number of alive nodes*

The designed model performance analysis is carried out on number of alive nodes by adjusting the number of rounds as depicted in Figure 4. It is demonstrated that the WOA-DNN gets higher number of alive nodes and proves the maximum performance while comparing with other existing approaches. The slight variation in the designed model has explored the performance of various algorithms.

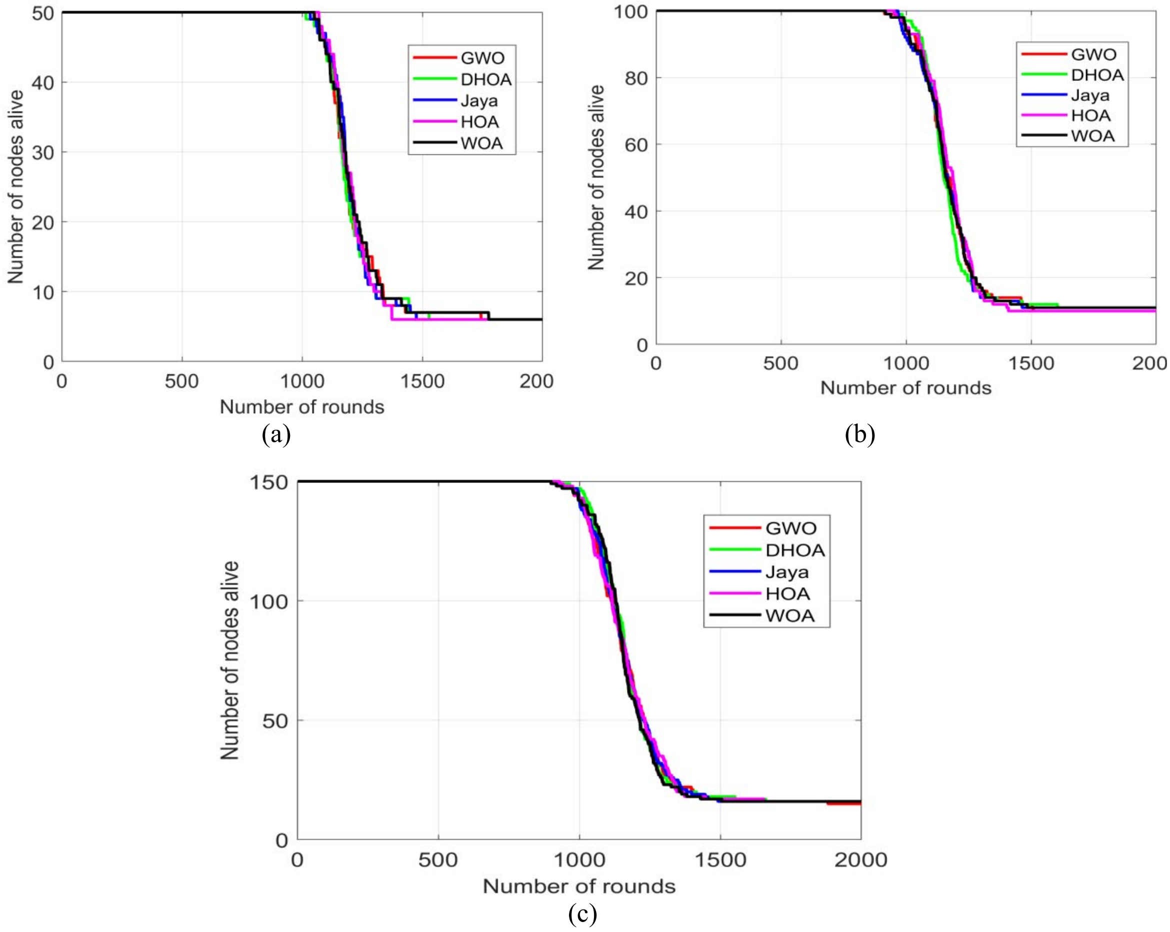
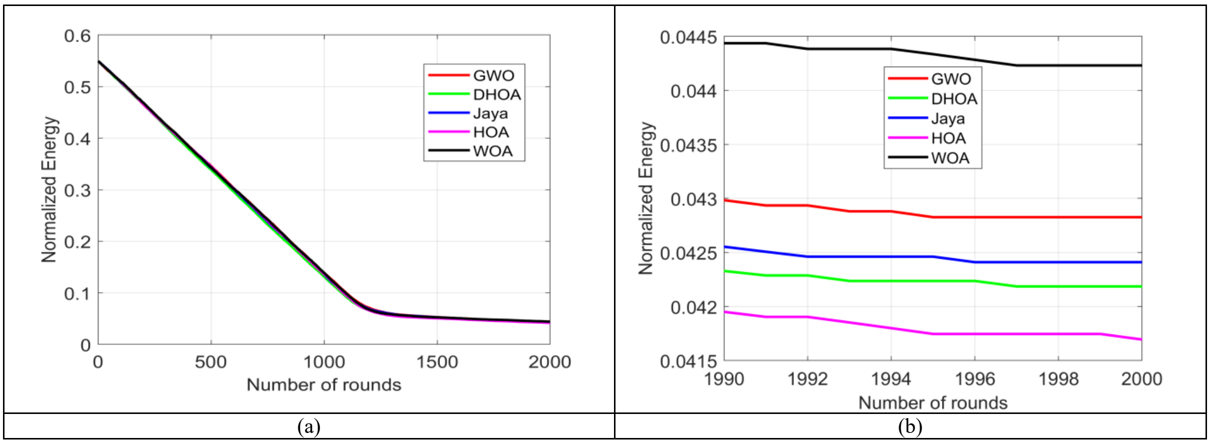


Fig. 4. Analysis on the designed trust aware "cluster head selection in WSN in terms of number of the alive nodes by altering the total number of the sensor nodes" as (a) 50, (b) 100 and (c) 150

5.4. *Analysis on normalized energy*

The efficiency of the proposed "trust-aware cluster head selection in WSN" is given by varying number of the sensor nodes as presented in Figure 5, where the zoomed images exhibit the detailed responses of the suggested model using different heuristic algorithms. It is noticed that the superior efficiency is attained using WOA-DNN when comparing with other existing algorithms.



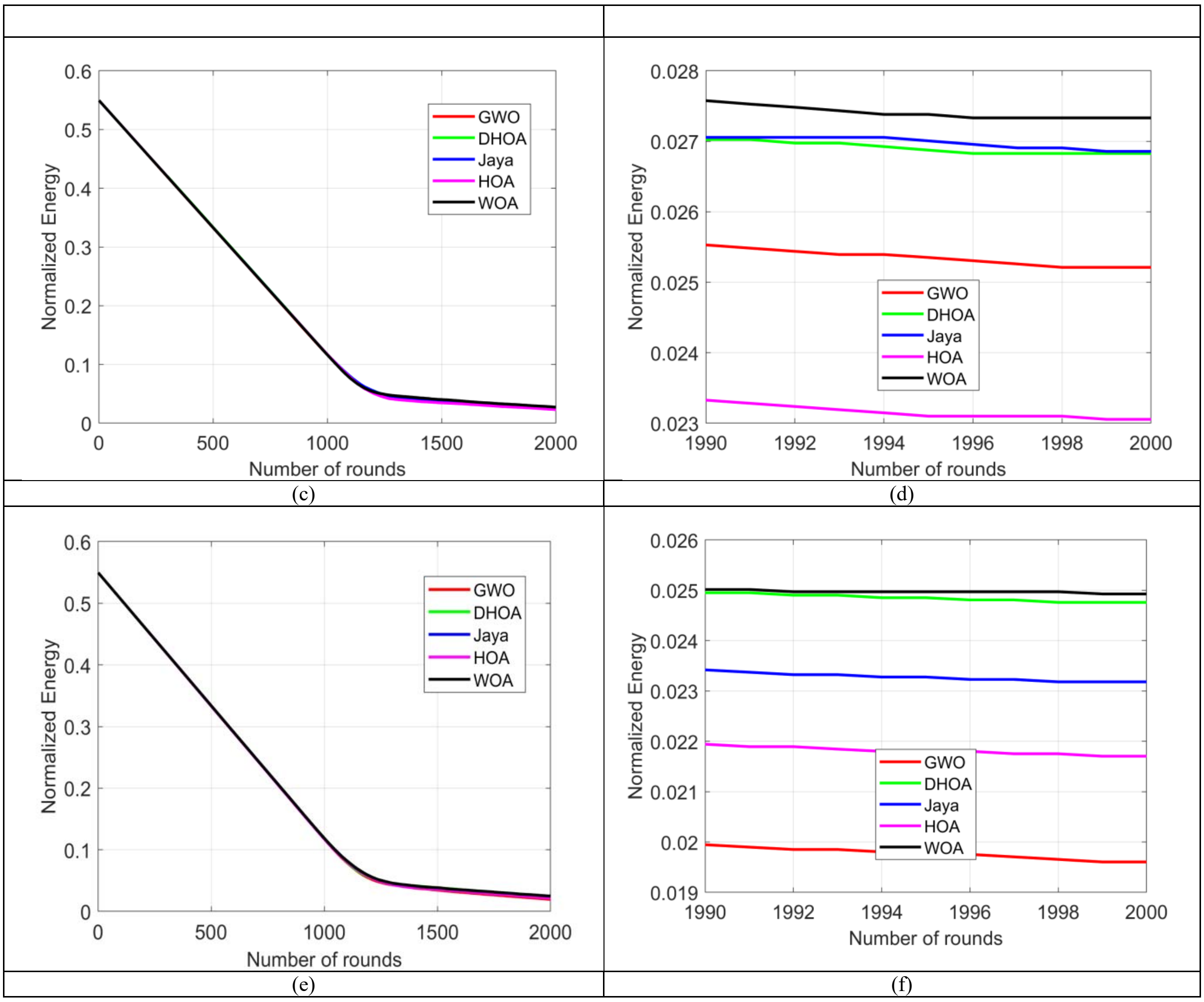


Fig. 5. Analysis on the designed trust aware cluster head selection in WSN in terms of normalized energy by varying the number of sensor nodes as (a) 50, (b) Zoom in of (a), (c) 100 (d) Zoom in of (c), (e) 150, and (f) Zoom in of (e)

5.5. *Trust computation analysis*

The performance of the designed "trust-aware cluster head selection in WSN" is evaluated in terms of trust computation through DNN over other classifiers as given in Table 3. The accuracy of the DNN is 2.7%, 2.5%, 1.3%, and 2.7% superior to SVM, RF, NN, and DT, respectively. Similarly, the optimal performance is accomplished by DNN while comparing with existing techniques over different measures.

METRIC	SVM [25]	RF [10]	NN [24]	DT [22]	KNN [23]	DNN
"Accuracy"	0.952	0.954	0.965	0.952	0.953	0.978
"Specificity"	0.94815	0.94568	0.96049	0.94444	0.94506	0.97407
"Sensitivity"	0.96842	0.98947	0.98421	0.98421	0.98684	0.99474
"Precision"	0.81416	0.81034	0.85388	0.80603	0.80819	0.9
"FNR"	0.031579	0.010526	0.015789	0.015789	0.013158	0.005263
"FPR"	0.051852	0.054321	0.039506	0.055556	0.054938	0.025926
"FDR"	0.18584	0.18966	0.14612	0.19397	0.19181	0.1
"NPV"	0.94815	0.94568	0.96049	0.94444	0.94506	0.97407
"F1-Score"	0.88462	0.891	0.91443	0.88626	0.88863	0.945
"MCC"	0.85973	0.86911	0.89612	0.86308	0.8661	0.93311

Table 3. Trust computation analysis of the designed trust-aware cluster head selection in WSN over other classifiers

5.6. *Analysis on overhead*

The performance evaluation is carried out on the basis of overhead for the designed "trust-aware cluster head selection in WSN" as given in Figure 6. From the analysis, the designed WOA-DNN gets lesser overhead while comparing with other heuristic algorithms.

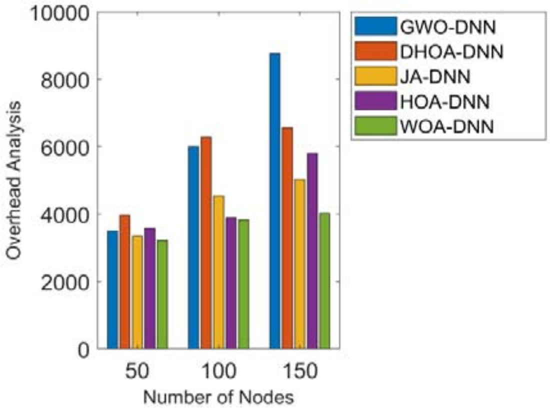


Fig. 6. Analysis on the designed trust aware "cluster head selection in WSN" in terms of overhead

6. Conclusion and Future work

This paper has implemented a new "trust-aware cluster head selection in WSN" through a heuristic-assisted deep learning approach. The multi-objective derived cluster head selection was performed through WOA. Further, the training of node characteristics and trust computation was done through DNN, which has ensured secured communication among nodes. This cluster head selection strategy has maximized the performance while comparing with the existing measures in terms of several performance measures. Network lifespan is critical aspect in the Wireless Sensor Networks because of scarcity of sources. Therefore, the future scope in terms of network lifetime with trust-aware cluster head selection will be conducted.

Acknowledgment

None.

Conflicts of interest

The authors have no conflicts of interest to declare.

Author's contribution statement

The paper conceptualizations, methodology, software, validation, formal analysis, investigation, resources, writing original draft preparation have been done by Chada Sampath Reddy. The supervision and project administration have been done by Dr. G.Narsimha.

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