Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. **70**, *2*, pp. 247–252, Bucarest, 2025

AQUILA AFRICAN VULTURE OPTIMIZED FUZZY DEEP BELIEF NETWORK FOR SECURE DATA TRANSMISSION IN WIRELESS SENSOR NETWORKS

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Keywords: Wireless sensor network; Aquila optimizer; African vulture optimization; Fuzzy deep belief network; Security; Aggregator.

A wireless sensor network (WSN) comprises several individual sensor nodes (SNs) that can perceive, analyze, and interact with data. Energy constraints and security are widely acknowledged as the two most challenging problems with WSNs. To overcome these drawbacks, a novel African aquila-optimized fuzzy deep belief network (AAVO-FDBN) framework is introduced in this paper. The AAVO model chooses the most reliable aggregator node based on ideal node selection criteria. After selecting the aggregator node, the cluster head (CH) data will be encrypted using the novel Crystal Kyber encryption (CKE) technique. An optimal routing path is established using a fuzzy deep belief network (Fuzzy-DBN), which considers the network lifespan, aggregate degree, aggregate coverage, and the distance between the aggregate and the sink. By using the NS2 simulator, we evaluate the suggested architecture based on parameters such as network lifetime (NL), energy consumption (EC), packet delivery ratio (PDR), and end-to-end delay (E2ED). According to experimental findings, AAVO-FDBN outperforms SEPC, REDAA, and SCDAP in terms of NL, with improvements of 22.80%, 12.50%, and 17.65%, respectively. The proposed AAVO-FDBN approach is more efficient and secure for real-time applications.

1. INTRODUCTION

WSNs are essential to the creation of smart systems, as they are composed of dispersed sensor nodes that collect and transmit data independently. These sensor nodes are outfitted with a transceiver, microprocessor, and power source, typically with a small battery. WSNs are becoming increasingly important due to the Internet of Things (IoT), which has enabled the deployment of interconnected devices on a large scale. However, these networks remain challenging to manage due to their limited resources.

EC is one of the most significant problems affecting WSNs, as SNs are often located in remote areas where it is not feasible to change the batteries. Data transmission (DT) without disruption rapidly depletes the battery, resulting in node failure and a shorter network lifespan. Due to the random dispersion of sensor nodes (SNs) throughout the network, conserving energy is a key concern for wireless sensor network (WSN) designs, which further complicates routing and management.

Clustering algorithms can help address these issues in WSNs. In networks with many clusters, cluster heads (CH) are in charge of gathering data from nearby SNs and transferring it to the base station or sink. WSNs, especially those installed in hostile or dynamic environments, may be vulnerable to security flaws that conventional routing protocols cannot address adequately. To overcome these drawbacks, a novel Aquila African vulture-optimized fuzzy deep belief network (AAVO-FDBN) approach is proposed in this paper. This model addresses the challenges of efficient data transmission, security, and energy conservation in WSNs. The significant contributions of the developed AAVO-FDBN technique are as follows.

- The proposed method uses the AAVO algorithm to elect the most reliable aggregator node based on optimal node selection criteria.
- After aggregator node selection, the data from the CH will be encrypted using the novel Crystal Kyber encryption algorithm to ensure security during transmission.
- The fuzzy deep belief network (Fuzzy-DBN) is utilized to establish an efficient routing path, further improving network efficacy.
- The efficacy of the proposed AAVO-FDBN technique has been evaluated in terms of specific parameters, including E2ED, EC, PDR, alive sensors (AS), and NL.

The structure of this paper is as follows: section 2 provides an in-depth literature review. Section 3 describes the preliminaries for the suggested AAVO-FDBN work and section 4 describes the AAVO-FDBN technique in detail. section 5 describes the results and discussions. Finally, Section 6 presents conclusions based on the study's findings.

2. LITERATURE REVIEW

Wireless sensor networks pose significant challenges in achieving energy efficiency and securing data. Many researchers have proposed cluster-based and trust-based strategies for WSNs to enhance energy efficiency. Among those, a few have been reviewed in this section.

In 2022, Robinson Y.H., et al. [23] introduced the secure energy-efficient and clustering (SEPC) method for sending data packets to the sink. Efficiency analysis indicates that the developed strategy outperforms competing methods in terms of throughput and energy consumption (EC). In 2023, Kingston Roberts, M, and Thangavel, J. [24] presented the residual-energy-based data availability approach (REDAA) to extend NL. Simulation findings show that compared to the MH-LEACH technique, the suggested REDAA approach may increase throughput by 37% respectively.

In 2023, Lavanya et al. [25] introduced a secure cluster-based data aggregation protocol (SCDAP) designed to enhance security. Through actual testing, the suggested system demonstrates that it can improve the packet delivery ratio while lowering high EC and E2ED. In 2024, Dinesh and Santhosh Kumar [26] proposed an energy-efficient cluster-based sparrow search optimization algorithm (NF-SSOA) to

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DOI: 10.59277/RRST-EE.2025.2.16

provide energy-efficient trust-aware cluster-based secure data transmission (DT) in WSNs. Comparing the suggested approach to other protocols already in use, the simulation results demonstrate improvements in EC analysis, throughput, E2ED, NL, and PDR.

In 2024, Rajaram et al. [27] introduced the enriched energy-optimized LEACH framework. Based on simulation findings, EE-OLEACH outperforms other current protocols in terms of energy efficiency by 30%, and throughput by 38%. In 2024, Osamy et al. [28] modified the sand cat swarm optimization method (SCSO) to create the secure and energy-aware clustering technique (SEACDSC) for WSNs. Based on the simulation findings, SEACDSC outperforms the existing approaches in terms of number of live nodes, energy efficiency, average trust value of CHs, and NL.

In 2024, Saravanaselvan, A., and Paramasivan, B., [29] proposed a feed forward back propagation neural network (FFBPNN) optimized with woodpecker mating algorithm, dynamic cluster-based secure routing in WSN (FFBPNN-WMA-ECHC-WSN). When comparing the FFBPNN-WMA-ECHC-WSN method's performance to other models, including EHCERA-SDT-WSN, DSA-ECC-PSO-SDT-WSN, IPECC-PDF-ABC-SDT-WSN, and IBFA-LDCSN-BSHHO-SDT-WSN, it shows lower latency of 99.01%, 98.34%, 95.23%, and 97.45%, and greater throughput of 97.25%, 90.12%, 89.39%, and 95.47%, respectively.

While the methods discussed significantly enhance energy efficiency, security, and overall network efficiency in WSNs, several drawbacks persist. Many of these protocols rely heavily on clustering, which, although it reduces energy consumption, can introduce computational overhead and complexity during the selection of cluster heads. To overcome these drawbacks, a novel AAVO-FDBN framework has been proposed in this work.

3. PRELIMINARIES

This section provides a brief description of the two AOA and AVA algorithms, which are essential building blocks for creating the combined AAVA algorithm.

3.1 AQUILA OPTIMIZATION ALGORITHM

Aquila algorithms typically use social behavior mimicking to ensnare their targets. The population of N agents is initialized at the beginning. The initial population P, which is made up of N solutions, is produced by using

$$P_x = ma + B \text{ and } (1, C) * (va - ma), \tag{1}$$

where the number of features is denoted by C. A random vector with C values is shown by B and (1, C). The bounds of the search space are va and ma. Then, use equation 2 to convert P_x to binary.

$$RP_{xy} = \begin{cases} 1 & if\ P_{xy} > 0.5, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Equation (2) has the effect of reducing the number of chosen features by ignoring the characteristics that are not important and correspond to zero values in $\frac{|RP_x|}{C}$ |. Next, the value of fitness is calculated as follows:

$$fitness = \beta * \gamma_x + (1 - \beta) * (\frac{|RP_x|}{C}), \tag{3}$$

where the weights used to balance the ratio of relevant characteristics $\frac{|RP_x|}{C}$ and classification error γ_x are indicated by $\beta \epsilon [0,1]$.

Algorithm 1 Aquila Optimizer (AO)

```
Set the initial value for the parameters
Initial population generation.
while (condition is false) do
Fitness values computation for each Px.
Find Pbest(s)
for (x=1,2…, m) do
if s≤ (23) *T then
Update Px
if Fit (P1(s + 1)) < Fit(P(s)) then
Pbest(s) = P1(s + 1)
end if
Update Px
if Fit (P2(s + 1)) < Fit(P(s)) then
Pbest(s) = P2(s + 1)
end if
else
Update Px
if Fit (X3(t + 1)) < Fit(X(t)) then
Xbest(t) = X3(t + 1)
end if
Update Xi
if Fitness (X4(t + 1)) < Fitness(X(t)) then
Xbest(t) = X4(t + 1)
end if
end if
end for
end while
return (Xbest).
```

3.2 AFRICAN VULTURE OPTIMIZATION

The AVA is motivated by its hunt for food. The procedure is as follows: for the N amount of vulture population examining for food, vultures are divided into two groups, where every vulture determines the capability to facilitate, and the second finest result in either is swapped, as the crowds have numerous abilities for examining for food.

Initialization Stage

The inhabitant is feasting over the examine zone:

$$S = \text{rand}(m, 1) * (U_i - V_i) + V_i, \tag{4}$$

Where the solution parameter is represented as S. A random value is denoted as rand. The upper limit and lower limits are represented as U_i and V_i. The number of the vulture population is denoted as m.

Famine rate of eagles

Vultures frequently search for food while they are overfilled and have great vitality. However, in the instance of hunger, they didn't need sufficient energy to wing over elongated spaces to find food, unlike the robust eagle.

$$P' = (2\ \text{rand} + 1)x\left(1 - \frac{I}{I_{max}}\right) + t, \tag{5}$$

where fulfilled position of eagles is represented as P'. Current and maximum iterations are denoted as $I\ and\ I_{max}$. A random amount in the range (-1, 1) is denoted by x.

Exploration stage

In the African vulture optimization algorithm, there is parameter P1 which works to choose one of the two plans in this stage, the value of P1 is between 0 and 1, and the plan is designated using the following formulation:

$$S(t+1) = \begin{cases} C(i) - |Z - C(i) - S(i)| \times P \times S1 \geq \text{rand}_{s1}, \\ C(i) - P + \text{rand}_2 - \left((U_i - V_i) \times \text{rand}_3 + V_i\right)S1 \\ \quad < \text{rand}_{s1}, \end{cases} \tag{6}$$

where one of the best eagles is denoted as $C(i)$. The space that the eagle changes to guard the food from others is represented as Z.

Exploitation stage

In this algorithm, exploitation is the last stage. It has two plans and everyone is designated based on two parameters.The first phase in the exploitation stage is measured when the value of f is in the middle of 0.5 and 1, and then two revolving expeditions and a restriction flight are led. In this phase, the eagles require enough energy to hunt food.

$$S(t+1) = \begin{cases} |Z - C(i) - S(i)|(P + \mathrm{rand}_4) - \\ \big(C(i) - S(i)\big)S2 \geq \mathrm{rand}_{s2} \\ C(i) - C(i) \times \left(\frac{S(i)}{2\pi}\right)\mathrm{rand}_5 \times \cos\big(S(i)\big) + \\ \mathrm{rand}_6 \times \sin\big(S(i)\big)S2 < \mathrm{rand}_{s2} \end{cases} \quad (7)$$

$$S(t+1) = \begin{cases} 0.5\left(C_1(i) + C_2(i) - \left(\frac{C_1(i)\times S(i)}{C_1(i)-S(i)^2} + \frac{C_2(i)\times C(i)}{C_2(i)-C(i)^2}\right) \times P\right) \\ S3 \geq \mathrm{rand}_{s3} \\ C(i) - |C(i) - S(i)| \times P - V(C(i) - \\ S(i))S3 < \mathrm{rand}_{s3} \end{cases} \quad 8)$$

In eq. (15), the second phase in the exploitation stage is shown. At this stage, the actions of two eagles appeal to numerous vultures based on their needs, and a passionate battle for food restriction ensues.

4. AQUILA AFRICAN VULTURE OPTIMIZED FUZZY DEEP BELIEF NETWORK MODEL

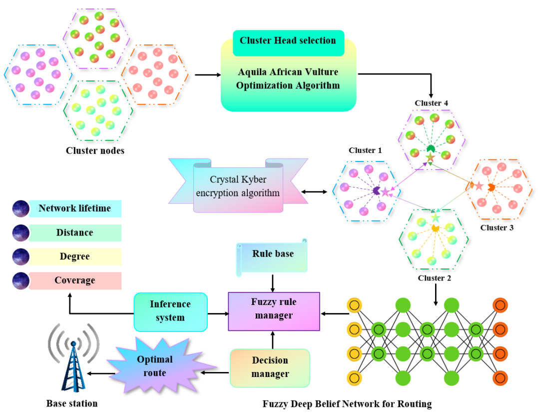


Fig. 1 – AAVO-FDBN framework.

This section presents a novel approach called the AAVO-FDBN. The developed method employs the AOA algorithm to elect the most reliable aggregator node based on optimal node selection criteria. After aggregator node selection, the data from the CH will be encrypted using the novel Kyber encryption algorithm to ensure security during transmission. To create an ideal routing path and increase network efficiency, the fuzzy deep belief network (fuzzy-DBN) is employed. The central block diagram of the suggested model is depicted in Fig. 1.

4.1 CH SELECTION USING AQUILA AFRICAN VULTURE OPTIMIZATION ALGORITHM

This section details how the AOA and AVA algorithms are combined to carry out CH selection. Figure 2 depicts the flow diagram of the suggested AAVA model for CH selection in a WSN context.

Equation (2) yields the objective function, which is then used to generate the fitness function. The best solution is determined as the one with the lowest energy value. The competition between AOA and AVA operators is used to update the solutions—consequently, eq. (9) is used to update the answer Pi. The solutions are updated until the halting condition is satisfied.

$$B_x = \frac{fit_x}{\sum_{x=1}^{M} fit_x} \ . \quad (9)$$

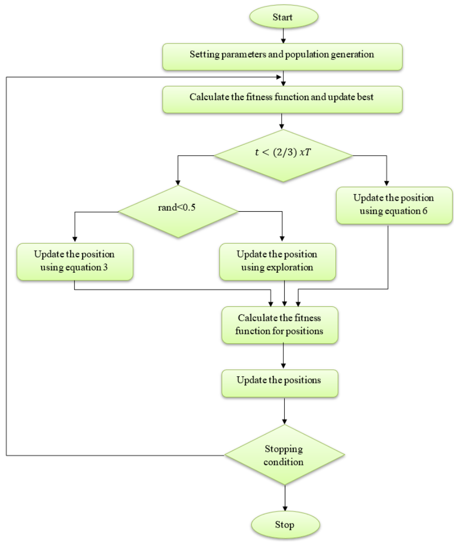


Fig. 2 – Flow diagram of the AAVA model.

Therefore, the solution ps_x is updated using the following equation:

$$ps_x = \begin{cases} \text{operators of } AOA & B_x > th, \\ \text{operators of } AVA & \text{otherwise.} \end{cases} \quad (10)$$

Updating the solutions continues until the stopping condition is reached. Afterwards, the optimal fit aggregator node has been determined.

4.2 ENCRYPTION USING CRYSTAL KYBER

Data from the aggregator node will be encrypted with the Crystal Kyber encryption algorithm before being transmitted to the sink node. Let n = 256 and the parameters p, s_t, s_u, s_v be positive integers. Let $A = \{0,1\}^{256}$ represent the message space, where each message $m \in A$ may be thought of as a polynomial in L with coefficients in $\{0,1\}$. Cipher text is of the form of $(b, a) \in \{0,1\}^{256 \cdot ps_v} \times \{0,1\}^{256 \cdot ps_u}$.

Algorithm :1 Kyber: Key generation

1. $\boldsymbol{\delta, \mu \leftarrow \{0, 1\}^{256}}$
2. $\boldsymbol{B \sim S_l^{p\times p} \coloneqq \mathrm{msg}(\delta)}$
3. (r, E) $\sim \boldsymbol{\alpha_m^p \times \alpha_m^p : \mathrm{msg}(\mu)}$
4. $\boldsymbol{c \coloneqq \mathrm{compress}_k\ (B_r + E, s_t)}$
5. $\boldsymbol{\mathrm{return}\ (Pub_p \coloneqq (t, s), Lr_p \coloneqq L_p}$

Algorithm :2 Kyber. Enc ($\boldsymbol{Pub_P = (c, \delta), m \in A}$): **encryption**

1. $\boldsymbol{p \leftarrow \{0, 1\}^{256}}$
2. $\boldsymbol{c \coloneqq decompress_k(c, s_t)}$
3. $\boldsymbol{B \sim L_l^{p\times p} \coloneqq msg(\delta)}$
4. $\boldsymbol{(p, E_1, E_2) \sim \alpha_m^p \times \alpha_m^p \times \alpha_m \coloneqq \mathrm{msg}(p)}$
5. $\boldsymbol{b \coloneqq \mathrm{compress}_l(B^T p + E_1, s_v)}$
6. $\boldsymbol{a \coloneqq \mathrm{compress}_l(t^T p\ + E_2 + \left\lceil \frac{L}{2} \right\rfloor \cdot m, s_u}$
7. $\boldsymbol{\mathrm{return}\ c \coloneqq (b, a)}$

Algorithm :3 Kyber ($\boldsymbol{Lr_p} = \boldsymbol{L_p}$, c= (b, a)): decryption

1. $\boldsymbol{b \coloneqq \mathrm{Decompress}_l(b, s_v)}$
2. $\boldsymbol{a \coloneqq \mathrm{Decompress}_l(a, d_u)}$
3. $\boldsymbol{\mathrm{return\ compress}_l(a - r^T a, 1)}$

Let $J: \{0,1\}^* \rightarrow \{0,1\}^{2\times 256}$ and $L: \{0,1\}^* \rightarrow \{0,1\}^{256}$ be hash function. The data packets from the aggregator node have been securely encrypted using the Crystal Kyber algorithm, and the encrypted data is then transmitted to the sink node.

4.3 OPTIMAL ROUTE SELECTION USING FUZZY-DBN

Using fuzzy-DBN rules, the proposed method determines the shortest route from the nodes to the aggregators and finally to the sink nodes. Equation 11 illustrates how to compute, using this model, the energy needed to send an m-bit message over the WSN for a distance called D:

$$EG_M(m,D) = \begin{cases} mEG_{ee} + mE_{fs}D^2 \; for \; D < D_{0,} \\ mEG_{ee} + mE_{mp}D^4 \; for \; D \geq D_{0.} \end{cases} \quad (11)$$

A threshold distance D_0 determines the energy level in this case. To receive a message of size m bits, the energy $EG_R(m)$ required is as follows:

$$EG_R(m) = mEG_{ee}. \quad (12)$$

Fuzzification

For Fuzzification in eq. (13) of this model, the Mamdani inference rules in conjunction with trapezoidal membership functions are employed. R indicates the value of trust for the user in this equation.

$$f(w,x,y,z,\mu) = \begin{cases} 0 \text{ when } R < w \text{ and } R > z, \\ \frac{(w-R)\mu}{w-x} \text{ when } w \leq R \leq x, \\ \mu \text{ when } x \leq R \leq y, \\ \frac{(z-R)\mu}{z-y} \text{ when } y \leq R \leq z. \end{cases} \quad (13)$$

The inputs and outputs are not exact; instead, they are imprecise estimations that establish broad categories as opposed to inflexible, defined sets. The output calculated in this study was created by using seven levels: weak (W), less weak (LW), less medium (LM), medium (M), very medium (VM), less strong (LS), and strong (S).

Table 1

Fuzzy rules.

Network lifetime	Aggregator degree	Distance between aggregator and sink	Aggregator coverage	Output calculated
Less	High	Distant	High	W
Less	Average	Distant	Average	LW
Less	Low	Distant	Low	M
Medium	High	Medium Distant	High	LM
Medium	Average	Medium Distant	Average	M
Medium	Low	Medium Distant	Low	HM
High	High	Distant	High	M
High	Average	Distant	Average	LS
High	Low	Distant	Low	S

Defuzzification is the final step in fuzzy rule-based inference. The method of analysis used in this study is a weighted average. Using the weighted average method, the result of the sum of the weighting functions μ_g is divided by the maximum value of the membership value, $\bar{g}$, to calculate the crisp output value g^*. This idea is presented in:

$$g^* = \frac{\sum|\mu_g(\bar{g}) \times \bar{g}|}{\sum \mu_g(\bar{g})}. \quad (14)$$

The phases in this routing method are given in the following:

Step 1: Evaluate the energy and position (e_x l_x) of the sensor nodes N_x, where $x = \{1,2\ldots, m\}$.

Step 2: Discover the route by calculating the shortest path through the aggregator nodes from each node to the sink.

Step 3: Use the shortest path and fuzzy rules found in step 2 to transfer the data collected by nodes through the aggregators.

Step 4: Obtain data from the sink.

Step 5: If nodes lose at least 50% of their energy, STOP.

This method transfers the data gathered by the SNs to the sink nodes on a regular basis.

5. RESULTS AND DISCUSSION

Simulations of the suggested technique were conducted in the NS2 simulator. Furthermore, an extensive range of nodes was tested, beginning with 100 and extending up to 500, in each of the trials. The list of parameters used in this proposal is found in Table 2.

Table 2

Parameters for simulation.

Number of sensors	100
Simulation area	200m×200m
Initial energy	2J
BS coordinate	(80,120)
Number of clusters	25
Efs	10PJ/bit/m2
Emp	0.0013PJ/bit/m4
EGee	50nJ/bit

5.1 PERFORMANCE ANALYSIS

The suggested model has been assessed, and the experimental results are presented in this section. For creating the inference system, four input variables were used: network lifetime, aggregate degree, aggregate coverage, and distance between aggregate and sink.

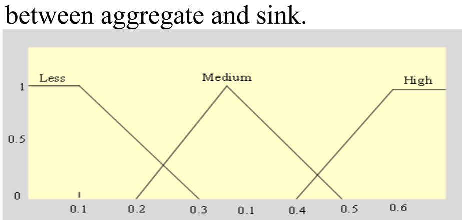


Fig. 3 – Fuzzy output for network lifetime

Figure 3 illustrates the semantic variable, NL, and its values. The sink was located at (50,50). The values low, medium, and high are used in this fuzzy set. Using the trapezoidal membership function yields the low and high values, while using the triangular membership function yields the medium value.

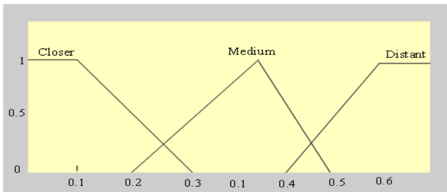


Fig. 4 – Fuzzy output for the distance between the aggregator and the sink.

As can be seen in Fig. 4, the semantic variable represents the distance between the aggregator and the shows. Additionally, low, average, and high values are used in this simulation. A triangular and a trapezoidal function indicate low and high values, respectively.

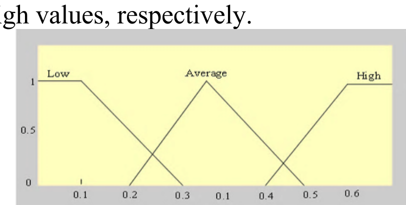


Fig. 5 – Fuzzy output for aggregator degree.

Fig. 5 shows the degree of the fourth semantic variable of the aggregator. A set of low, average, and high values is included in this set. As before, the triangle function is applied to other values and the trapezoidal function is used to low and high values.

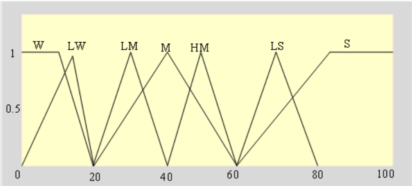


Fig. 6 – Fuzzy output for member choice.

The fuzzy output variable of member selection is shown in Figure 6. It consists of nine values, namely W, LW, M, LM, HM, LS, and S. The triangle function is used for all other values of the semantic variable's output. In contrast, the trapezoidal function is employed for its boundary values.

5.2 COMPARATIVE ANALYSIS

The developed AO-FDBN framework is compared with existing methods, such as SEPC [23], REDAA [24], and SCDAP [25], in terms of specific parameters, including EC, E2ED, PDR, AS, and NL.

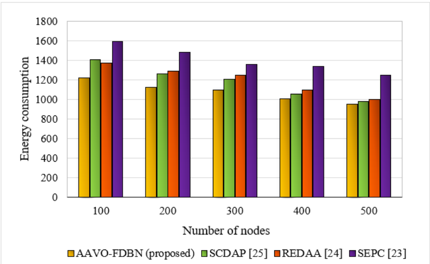
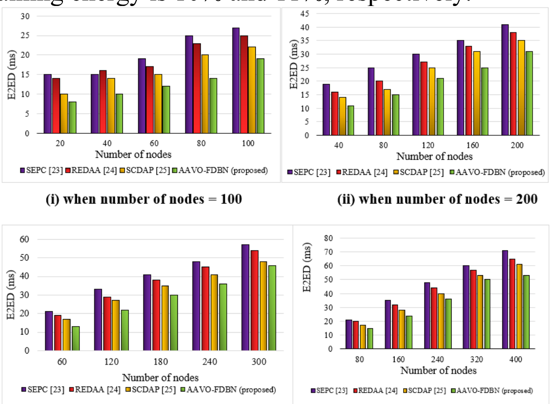


Fig. 7– Energy consumption

Figure 7 illustrates that the proposed AAVO-FDBN system uses less energy than SEPC, REDAA, and SCDAP systems. A SEPC network runs for approximately 280 rounds before there is only 7% residual energy remaining. After 1000 rounds of SCDAP and AAVO-FDBN, the remaining energy is 10% and 11%, respectively.

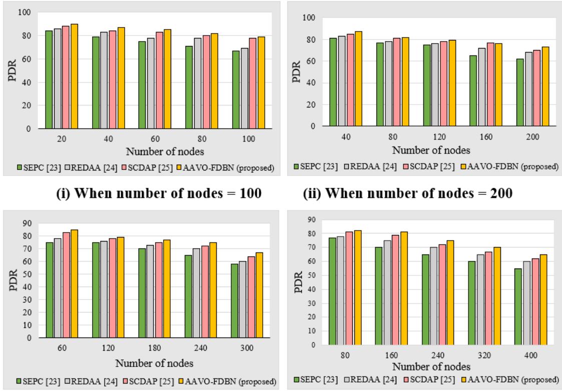


(i) when number of nodes = 100 (ii) when number of nodes = 200

(iii) when number of nodes = 300 (iv) when number of nodes = 400

Fig. 8 – Comparison of average end-to-end delay.

The E2ED with a range of nodes is shown in Fig. 8. The delays shown in Fig. 8. a, 8.b, 8.c, and 8.d indicate the number of nodes at 100, 200, 300, and 400, respectively, and indicate the corresponding delays. Figure 8 compares the packet delivery ratio (PDR) of the proposed AAVO-FDN model with existing techniques, including SEPC, REDAA, and SCDAP. Figure 9,a shows the PDR when there are 100 nodes, Fig. 9,b shows the PDR when there are 200 nodes, Figure 9.c shows the PDR when there are 300 nodes, and Figure 9.d shows the PDR when there are 400 nodes. The proposed approach achieves a higher packet delivery ratio than current methods.



(i) When number of nodes = 100 (ii) When number of nodes = 200

(iii) When number of nodes = 300 (iv) When number of nodes = 400

Fig. 9 – PDR comparison.

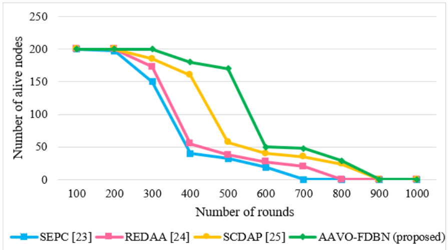


Fig. 10 – Alive sensors comparison

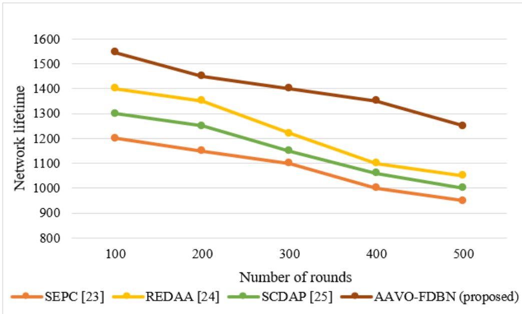


Fig. 11– Network lifetime.

Figure 10 describes the number of alive nodes after the simulation is complete. A comparison is made between the four protocols. Due to increased energy consumption, SEPC, REDAA, and SCDAP have fewer alive nodes. However, in the proposed AO-FDBN protocol, there are many active nodes. The network lifetime of the suggested AAVO-FDBN system is compared with the existing models, such as SEPC, REDAA, and SCDAP, as shown in Fig. 11. The proposed AAVO-FDBN method has better performance of 22.80%, 12.50%, and 17.65% than SEPC, REDAA, and SCDAP methods.

6. **CONCLUSION**

In this paper, a novel Aquila African Vulture Optimised Fuzzy DBN (AAVO-FDBN) model has been suggested to address the issues of EC and security in WSN. The recommended approach has been tested using NS2 simulator, where variables like aggregator degree, aggregator energy, aggregator coverage, distance and network lifetime between sink and aggregator were employed as fuzzy variables in fuzzy-DBN. The experimental findings show that the developed protocol outperforms in terms of PDR, EC, E2ED, and NL than the existing techniques, such as SCDAP, REDAA, and SEPC.

The proposed AAVO-FDBN method achieves better network lifetime of 22.80%, 12.50% and 17.65% than SEPC, REDAA and SCDAP methods. In the future, this method will be used to analyse more deep learning enabled robust routing protocols and to help develop a new protocol that will be more resilient to denial-of-service attacks.

ACKNOWLEDGMENT

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

CREDIT AUTHORSHIP CONTRIBUTION

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