Hybrid Metaheuristic Aided Energy Efficient Cluster Head Selection in Wireless Sensor Network

Turki Ali Alghamdi
Department of Computer Science, College of Computer and Information Systems, Umm Al-Qura University, Makkah, Saudi Arabia

***Abstract*—Clustering is one of the significant techniques for expanding the lifetime of networks in wireless sensor networks (WSNs). It entails combining of sensor nodes (SNs) into clusters and electing cluster heads (CHs) for each and every cluster. CH collects the information from particular cluster nodes and passes the cumulative data to the base station (BS). However, the most important requirement in WSN is to choose a suitable CH with an increased network life span. This work introduces a new CHS model in WSN. The optimal CH is elected by a new hybridized model termed as "Lion Updated Dragonfly Algorithm (LU-DA) that hybrid the concepts of Dragonfly Algorithm (DA) and Lion Algorithm (LA)". Moreover, the optimal selection of CH is done depending upon constraints like "energy, delay, distance, security (risk) and trust (direct and indirect trust)". This optimal CH ensures the network lifetime enhancement. At last, the superiority of the developed approach is proved on varied measures like energy and alive node analysis. Accordingly, the proposed model has accomplished higher energy of 0.55 at 1st round, whereas at the 2000th round, the normalized energy value has been dropped to 0.1.**

Keywords*—*Cluster head; security; trust; dragonfly algorithm; LU-DA model

Nomenclature

Abbreviation	Description
ACO	Ant Colony Optimization
APTEEN	Adaptive Threshold sensitive Energy Efficient sensor Network
BS	Base Station
BOA	Butterfly Optimization Algorithm
CH	Cluster Head
CHS	Cluster Head Selection
DA	Dragonfly Algorithm
EE	Energy Efficiency
FF	Firefly
FCM	Fuzzy C-Means
FPU-DA	fire fly replaced position update in dragonfly
GECR	Genetic Algorithm-based Energy-Efficient Clustering and Routing
GWO	grey wolf optimizer
GA	Genetic Algorithm
HSO	Harmony Search Optimization
HML	Hierarchical Maximum Likelihood
KFCM	kernel fuzzy C-means
LEACH	Low-Energy Adaptive Clustering Hierarchy
LU-DA	Lion Updated Dragonfly Algorithm
LA	Lion Algorithm
MOFPL	Multi-objective fractional particle lion algorithm
NAN	Number of Alive Node
OWSN	Optical WSN
PSO	Particle Swarm optimization
PEGASIS	Power-Efficient Gathering in Sensor Information Systems
QoS	Quality of Services
QCM2R	QoS-aware cross-layered multichannel multisink routing
SNs	Sensor Nodes
TEEN	Threshold sensitive Energy Efficient sensor Network
WSN	Wireless Sensor Network

I. Introduction

WSN [1] [2] involves various sensors connected to the wireless medium. The sensed data from SNs is typically forward to BS, where the data is collected, analyzed and performed certain actions accordingly [3]. The WSN is deployed in various applications like weather monitoring [4], meteorological data collection [5], and field surveillance, transportation, and health-care] [6] [7]. However, the nodes in WSN don't have any storage devices and facilities of researchable batteries [8] [9]. Though, it should support any system with effective power consumption [10] [11].

Clustering is a renowned procedure for effective data transmission with respect to energy and power utilization. Clustering involves dividing of SNs into different clusters [12] [13] [14]. All clusters in networks have distinctive CHs [15] [16], which is responsible to transfer information to other SNs in its cluster. Moreover, the communication to BS is carried out only through this CH. In this scenario, key role is to opt the optimal CH by concerning on lesser delay and low consumption of energy [17] [18]. Thereby, creating a cluster with aggregation and data fusion models, there is energy in network based on the data transmitted to BS [19] [20].

Thereby, the cluster-oriented models also engaged in facilitating the extension of network lifetime [21]. The frequently deployed algorithms include APTEEN, TEEN, LEACH, PEGASIS, and FCM. Further, "LEACH is the cluster-based algorithm that operates in the distributed manner, which elects the CH depending on the predetermined probability" [22].

Various cluster-oriented models have been introduced so far, which is based on meta-heuristic algorithms. However, the algorithms possess some common challenges such as high convergence, local search issues in FF, and high cost. Moreover, there is a prerequisite of standard optimizations and need consideration on constraints, namely security and trust [23]. So in order to solve the above mentioned issues, this paper introduces a new CHS model in WSN.

The foremost contribution is listed here:

- The selection of optimal CH depends on certain constraints such as energy consumption, trust, security, delay and distance.
- Proposes a Lion Updated Dragonfly Algorithm for optimal CH selection, which integrates the concepts of DA as well as LA models.

The organization of the paper is as follows: Section II reviews CHS models. Section III elaborates the adopted energy aware clustering model in WSN. Section IV depicts the optimal CHS: objective model. Section V explains Lion Updated Dragonfly Algorithm for optimal CHS. The resultants and conclusions are briefed in Section VI and Section VII.

II. LITERATURE SURVEY

A. Related Work

In 2020, Turki et al. [24] suggested a new clustering model with optimal CHS that considered 4 most important criterions such as security, delay, energy, and distance. Furthermore, for electing the optimum CHs, this work proposed a novel algorithm named as FF-PUD. At last, the performances of developed scheme were performed by evaluating it over other schemes regarding risk, alive nodes, energy and delay.

In 2020, Prachi et al. [25] have employed BOA for choosing an optimal CH from nodes. Accordingly, the developed work aims on lessening the energy usage and for maximizing the life span of network. The path among the CH and BS was determined using ACO and it selected optimal routes depending on node degree, residual energy and distance. At the end, the supremacy of adopted work was proved regarding energy consumption, alive and dead nodes.

In 2019, Reeta and Dinesh [26] have designed a multi-objective model that dependents on distance, traffic rates, energy, cluster densities and delay. Here, energy based routing was carried out based on MOFPL scheme. The implemented model determined the optimum CH from several nodes in WSN. Consequently, the optimal routes were introduced depending on the adopted multi-objective function. Furthermore, effective CHS with high network energy was accomplished by the designed model.

In 2020, Augustine and Ananth [27] have presented an enhanced framework for CHS based on Taylor KFCM that was modified from the KFCM approach in the Taylor series. The introduced model has chosen the CH by means of "acceptability factor" that was evaluated by the trust, distance, and energy. Further, the advantage of the proposed system was proved in terms of highest energy and high trust.

In 2019, Goswami *et al.* [28] introduced a cluster-based model by deploying HML and FF model in OWSN for improving the EE and minimizing the costs. Here, the issues in FF model were prevailed over by integrating the theory of HML with it. Furthermore, the distribution of power in nodes was carried out precisely via maximum likelihood property of HML. Finally, the resultants have shown the betterment of presented scheme regarding EE and cost function.

In 2019, Jain and Toor [29] offered a new framework for diverse WSN by considering "MEACBM routing protocol". Accordingly, optimal election of CHs takes place; particularly, the SNs with higher energy were preferred as CH. This model has minimized the energy utilization of SNs while conveying data to BS. The analysis resultants have revealed the enhancement regarding the CH count, network lifetime, throughput and dead node count.

In 2019, Daneshvar et al. [30] have offered a new clustering scheme, which selected CHs by means of GWO. For selecting CHs, the solutions were optimized depending on remaining energy of every node and predicted energy utilization. In addition, for improving the EE, the presented model deployed the similar clustering in numerous successive rounds. This allowed the framework to accumulate the energy, which was necessary for reforming the clustering. Eventually, the outcomes demonstrated that the designed model has ensured effective network lifetime.

In 2018, Tianshu *et al.* [31] suggested a routing scheme depending upon GECR and GA for expanding the lifetime of networks and improving EE. In addition, while modelling the objective function, the "load balancing factor" was taken into account that balanced the energy usage among SNs. The simulated results have exposed the supremacy of the adopted method with lower variance and improved EE.

B. Problem Formulation

Table I makes a review of existing cluster-based energy-aware CHS models in WSN. Numerous methods have been focused on energy-aware CHS models in WSN. But still, the existing models like FF-PUD[24], BOA + ACO [25], MOFPL [26], Taylor KFCM model [27], FF [28] have some common problems like high convergence, local search issues in FF, high-cost efficiency, there is a need of standard optimizations and need consideration on constraints like security and trust.

C. Objectives

The main objectives of this paper are:

- To select an optimal CH depends on certain constraints such as energy consumption, trust, security, delay and distance.
- To propose an improved Algorithm for optimal CH selection for solving the optimization issues.
- And to improve the better convergence rate.

TABLE I. REVIEWS ON TRADITIONAL ENERGY AWARE CHS MODELS IN WSN

Authors	Techniques	Feature	Challenge
Turki *et al.* [24]	FF-PUD	❖ Minimal delay ❖ High network energy	❖ Coverage issues are not deliberated.
Prachi *et al.* [25]	BOA + ACO	❖ Higher count of alive nodes ❖ Minimal energy consumption	❖ Should consider fault tolerance.
Reeta and Dinesh [26]	MOFPL	❖ Less simulation time ❖ Offers high network energy	❖ Resource management is not taken into account in this work. ❖ Cost efficiency is not considered.
Augustine and Ananth [27]	Taylor KFCM model	❖ High throughput and energy. ❖ Minimal delay	❖ No consideration on real time experiments. ❖ Standard optimizations are required for enhancing the CHS performance.
Goswami *et al.* [28]	FF	❖ Minimal cost function. ❖ Improved EE	❖ FF suffers from local search issues.
Toor and Jain [29]	MEACBM	❖ Minimized the consumption of energy ❖ Raises throughput and lifetime	❖ Needs consideration on scalability of SNs
Daneshvar *et al.* [30]	GWO	❖ Balanced energy consumption ❖ Offers high life span for network	❖ Fault tolerance is not considered.
Tianshu *et al.* [31]	GECR	❖ Better life span ❖ Optimal energy utilization	❖ More appropriate metaheuristic algorithms should be used.

III. PROPOSED ENERGY AWARE CLUSTERING MODEL IN WSN

A. Network Model

Assume M_n sensor nodes that are randomly deployed in appliance area. Consequently, the clustering process is done by merging the SNs. During clustering, the nodes forms clusters, wherein a CH is elected and the total count of CH is delineated by CH_n. Thus, the distances amongst nodes and CHs have to be reduced.

The most important task of WSN is to transfer the information among nodes. Here, the identification of shorter paths is required to enhance the data transmission. Moreover, the energy consumption of node also acts as the most role while transmitting the data. Particularly, a node requires more energy for transmitting massive data. In the clustering based strategy, the CH is responsible for transmitting more data with less energy consumption. However, the security is more crucial for minimizing the overhead and attacks. The architectural depiction of adopted model with varied SNs is illustrated in Fig. 1.

B. Distance Model

In the network, a CH is chosen only if the distance between CH and nodes is minimal. If distance among CH and nodes are higher than distances amid node and BS, the data are transmitted directly to BS by node. By deploying distance matrix $Di(g*w)$, the SNs gets clustered with selected CH as exposed in Eq. (1), wherein, $e_{M_{CH}}$ signifies Euclidean distance amid M_{CH} and normal node position, and $z_1, z_2, \ldots z_n$ signifies SNs. Assume 2 SNs q and d, and positions be x and y. The Euclidean distances amongst 2 nodes are revealed in Eq. (2). In Eq. (1), element e_{M_{CH2},z_1} occupies initial column matrix with minimal distance [24].

$$Di(g*w) = \begin{bmatrix} e_{M_{CH1},z_1} e_{M_{CH1},z_2} \ldots\ldots\ldots e_{M_{CH1},z_n} \\ e_{M_{CH2},z_1} e_{M_{CH2},z_2} \ldots\ldots\ldots e_{M_{CH2},z_n} \\ : \\ : \\ e_{M_{CHm},z_1} e_{M_{CHm},z_2} \ldots\ldots\ldots e_{M_{CHm},z_n} \end{bmatrix} \quad (1)$$

$$e_{q,d} = \sqrt{(q_x - d_x)^2 + (q_y - d_y)^2} \quad (2)$$

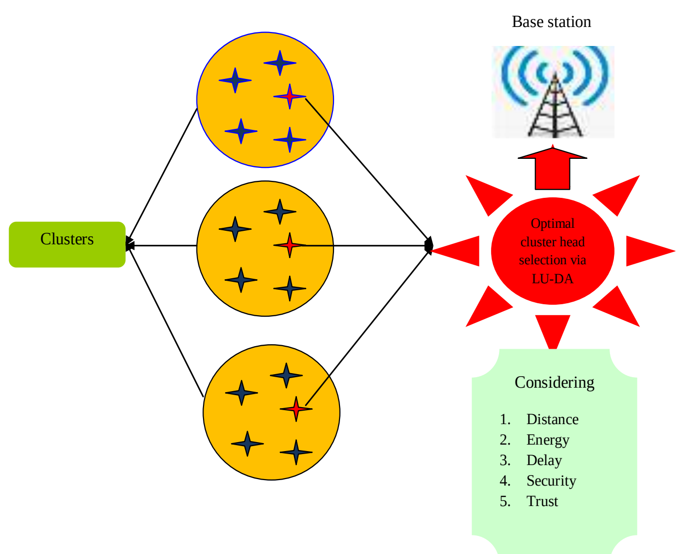


Fig. 1. Architecture of Proposed CHS Model.

Further, the time slots are assigned by M_{CH} to every node during data transmission. Here, M_{CH} collects data from all SNs in clusters. After data gathering, M_{CH} passes the specified data to BS.

C. Energy Model

Energy utilization is a foremost characteristic in WSNs. Actually, additional energy is crucial for conveying data to BS from every SNs. Thereby, the energy model for transmitting data is exposed in Eq. (3), wherein, "E_{ete} symbolizes the electronic energy as given in Eq. (4), wherein E_{agg} refers to the energy utilization during data collection and $E_{TX}(M:e)$ signifies the energy necessary for transferring M bytes of packets at distance e". Eq. (5) shows the essential energy for passing M bytes of packets. Eq. (6) shows the "amplification energy and E_{pr} refers to power amplifier energy and E_{fr} refers to energy required for deploying free space technique" [24].

$$E_{TX}(M:e) = \begin{cases} E_{ete} * M + E_{fr} * M * e^2, if \ e < e_0 \\ E_{ete} * M + E_{pr} * M * e^2, if \ e \geq e_0 \end{cases} \tag{3}$$

$$E_{ete} = E_{TX} + E_{agg} \tag{4}$$

$$E_{RX}(M:e) = E_{ete} M \tag{5}$$

$$E_{agg} = E_{fr} e^2 \tag{6}$$

$$e_0 = \sqrt{\frac{E_{fr}}{E_{pr}}} \tag{7}$$

The whole energy of network is given in Eq. (8), wherein E_1 symbolizes the energy at idle state and E_{ST} symbolizes energy at sensing time.

$$E_{total} = E_{ST} + E_1 + E_{RX} + E_{TX} \tag{8}$$

D. Security Model

The risky mode, γ-risky mode and security mode are the factors in security model that are explained below.

"Risky mode: This mode selects an existing CH for facilitating an optimal CHS, for which it takes all the risks. Thus, this mode is considered as an insistent mode while choosing CH [24].

γ-risky mode: The CH which could tolerate the utmost γ-risk are elected based upon γ-risky mode. Accordingly, γ signify the probability measure with values, $\gamma = 0$ and $\gamma = 1$ (i.e., 100%) similar to security and risky mode.

Security mode: This mode prefers the CH that fulfills the needs of security. In Eq. (1), s_r and s_d denotes the security rank and security needs associated with CHS. If $s_d \leq s_r$, the node are considered as CH".

The probability of security constraints is shown in Eq. (9). Further, "if the chosen CH achieves the state $s_d > s_r$ the risk should be less than 50%. If the condition is $0 < s_d - s_r \leq 1$, the selection process would be implemented, and if the state is $1 < s_d - s_r \leq 2$, there will be a delay in the selection process. Still, the CHS process could not be completed, and the corresponding function should be continued for the state $2 < s_d - s_r \leq 5$".

$$g_{risk} = \begin{cases} 0 & if \quad s_d - s_r \leq 0 \\ 1 - e^{\frac{(s_d - s_r)}{2}} & if \quad 0 < s_d - s_r \leq 1 \\ 1 - e^{\frac{3(s_d - s_r)}{2}} & if \quad 1 < s_d - s_r \leq 2 \\ 1 & if \quad 2 < s_d - s_r \leq 5 \end{cases} \tag{9}$$

E. Trust

"Trust is the degree of reliability about other node for performing certain action by keeping track of all past transaction or interactions with nodes by direct or indirect observation. Trust can also be defined as the level of confidence that one node about other node to get assigned work done within some time". Trust includes direct as well as indirect trust. The final trust is computed by combining both indirect and direct trust values [32].

Direct trust: It is computed depending upon interaction of nodes. The distance and energy are regarded as trust measures and is evaluated as per Eq. (10), where $DT_{(A-G)}$ denotes the value of direct trust computed by A and G, Er denotes residual energy of node G, $d(node\,A, node\,G)$ refers to differentiation distance of node A and G.

$$DT_{(A-G)} = \frac{Er}{d(node\,A, node\,G)} \tag{10}$$

Indirect trust: It is computed depending upon recommendation of nodes. It is the summation of trust values computed by other nodes and specified as in Eq. (11), wherein, $IDT_{(A-G)}$ refers to value of direct trust computed by A and G, $DT(A-P)$ and $DT(P-G)$ refers to value of direct trust computed by A, P as well as P and G in that order.

$$IDT_{(A-G)} = \sum DT(A-P) \times DT(P-G) \tag{11}$$

Further, the final trust is computed as in Eq. (12), wherein, $T_{(A-G)}$ refers to final trust A on G and w refers to weight related with indirect and direct trusts.

$$T_{(A-G)} = wDT_{(A-G)} + (1-w)IDT_{(A-G)} \tag{12}$$

IV. Optimal Cluster Head Selection: Objective Model

This work aims to diminish the distance amid the chosen CH and SN and it aims to lessen the delay and risk while transferring the information. On the other hand, the energy, and trust have to be high for better transmission of data. The objective of developed model is delineated in Eq. (13), in which η relies amid $0<\eta<1$, o_m and o_n are calculated as revealed in Eq. (14) and Eq. (15), respectively. The delay, energy, distance, security and trust are explained by ϖ_1, ϖ_2, ϖ_3, ϖ_4 ,ϖ_5 and are represented as $\varpi_1+\varpi_2+\varpi_3+\varpi_4+\varpi_5=1$. In Eq. (15), Z_z-A_s depicts distance amid normal node and sink.

$$K_n=\eta o_n+(1-\eta)o_m \tag{13}$$

$$o_m=\varpi_1 * o_i^{del}+\varpi_2 * o_i^{ene}+\varpi_3 * o_i^{dis}+\varpi_4 * o_i^{Sec}+\varpi_5 * o_i^{T} \tag{14}$$

$$o_n=\frac{1}{b}\sum_{z=1}^{b}\left\|Z_z-A_s\right\| \tag{15}$$

The fitness function for distance is specified by Eq. (16), wherein, $o_{(m)}^{dis}$ signify packets passed between SN to CH and between CH to BS. o_i^{dis} lies amongst [0, 1].

$$o_i^{dis}=\frac{o_{(m)}^{dis}}{o_{(n)}^{dis}} \tag{16}$$

$$o_{(m)}^{dis}=\sum_{z=1}^{M_z}\left[\left\|CH_z-A_s\right\|+\sum_{x=1}^{M_x}\left\|CH_z-Z_z\right\|\right] \tag{17}$$

$$o_{(n)}^{dis}=\sum_{z=1}^{M_z}\sum_{x=1}^{M_x}\left\|Z_s-Z_x\right\| \tag{18}$$

$o_{(m)}^{dis}$ and $o_{(n)}^{dis}$ are modelled as in Eq. (17) and (18), here Z_z symbolizes SN in z^{th} cluster, CH_z symbolizes CH of z^{th} cluster, the distance amid BS and CH is indicated as CH_z-A_s, CH_z-Z_z symbolizes distance among CH and SN and Z_z-Z_x symbolizes distance among 2 SNs, M_z and M_x symbolizes node count devoid of considering x^{th} and z^{th} clusters.

The fitness function for energy $\left(o_i^{ene}\right)$ is revealed in Eq. (19), here, $o_{(m)}^{ene}$ and $o_{(n)}^{ene}$ symbolizes high value of energy and larger CH count.

$$o_i^{ene}=\frac{o_{(m)}^{ene}}{o_{(n)}^{ene}} \tag{19}$$

The fitness function for delay $\left(o_i^{del}\right)$ is revealed in Eq. (20) and it is measured for every SN in cluster. Thus, delay gets lessened if the count of SN in CH is minimal. In Eq. (20), M_n symbolizes total node count, and numerator depicts the higher CH count.

$$o_i^{del}=\frac{\max\left(\left\|CH_z-Z_z\right\|\right)_{z=1}^{M_{CH}}}{M_n} \tag{20}$$

V. Proposed Lion Updated Dragonfly Algorithm for Optimal Cluster Head Selection

A. Solution Encoding

The proposed work focuses on introducing an efficient CHS in WSN. In WSN, the optimum selection of CH is a versatile task and it is performed based upon criteria like, trust, security energy, delay and distance. The input provided to LU-DA algorithm is shown by Fig. 2.

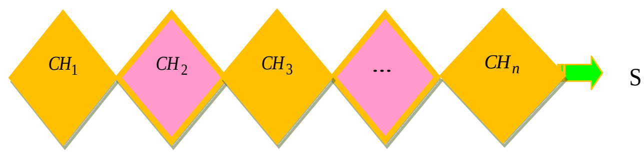


Fig. 2. Solution Encoding.

B. Proposed LU-DA Algorithm

Although the conventional DA [33] model encompasses a variety of enhancements; it suffers from specific limitations like, complexity in solving binary problems etc. Therefore, the theory of LA [34] is mingled with it to introduce a new model named as LU-DA. Hybridized optimization schemes are said to be more appropriate for specific search issues [23] [35] [36] [37]. The steps followed in the proposed LU-DA are as follows.

LU-DA model involve two stages such as: "(i) Exploration and (ii) Exploitation". The separation formula is modelled as exposed in Eq. (21), where, S_l signifies l^{th} closer individual's position, S and U symbolizes current position of individual and nearby individual's count.

$$C_i=-\sum_{l=1}^{U}\left(S-S_l\right) \tag{21}$$

Consequently, the alignment is evaluated as specified in Eq. (22), wherein, Q_l denotes velocity of l^{th} closer individual. The cohesion is modelled as in Eq. (23) and attraction to food is evaluated as in Eq. (24), wherein S^+ symbolizes position of food source and S symbolizes present individual position.

$$B_i=\frac{\sum_{l=1}^{U}Q_l}{U} \tag{22}$$

$$O_i = \frac{\sum_{l=1}^{U_b} S_l}{U_b} - S \tag{23}$$

$$F_i = S^+ - S \tag{24}$$

Distraction to enemies is indicated by Eq. (25), wherein, the enemy position is denoted as S^-.

$$En_i = S^- + S \tag{25}$$

Eq. (26) shows the modelling of step vector (ΔS), wherein, "v signifies separation weight, C_i denotes the separation of i^{th} individual, O denotes the i^{th} individual cohesion, c points out cohesion weight, B_i and F_i refers to the alignment and food resources of i^{th} individual, a signifies the alignment weight, f corresponds to food factor, b symbolizes enemy factor, h signifies the inertia weight, En_i refers to enemy's position of i^{th} individual and it points out iteration counter".

$$\Delta S(it+1) = (vC_i + aB_i + cO_i + fF_i + bEn_i) + h\Delta S(it) \tag{26}$$

As per LU-DA model, if random integer $ra \le \Delta S_{t+1}$ and if $\Delta S_{t+1} \le 0$, the position vector (S) is computed as in Eq. (27), wherein, it signifies current iteration.

$$S(it+1) = S(it) + \Delta S(it+1) \tag{27}$$

On the other hand, if $ra \le \Delta S_{t+1}$ and if $\Delta S_{t+1} > 0$,the position gets updated based on proposed female lion update as shown in Eq. (28), where, ∇_d is evaluated as in Eq. (29), $levy(\beta)$ denotes levy flight. S_d^{fem+} signifies k^{th} vector elements of S^{fem+}, ∇ refers to update function of female, k denotes arbitrary integer and $\breve{r}_2, \breve{r}_1$ signifies arbitrary integer among [0, 1].

$$S_d^{fem+} = \min[S_d^{\max}, \max(S_d^{\min}, \nabla_d)] + levy(\beta) \tag{28}$$

$$\nabla_d = \left[S_d^{fem} + (0.1\breve{r}_2 - 0.05)\left(S_d^{mal} - \breve{r}_1 S_d^{fem}\right)\right] \tag{29}$$

Else if, $ra > \Delta S_{t+1}$, the position gets updated as in Eq. (30).

$$S_{t+1} = S_t \tag{30}$$

Algorithm 1 shows the pseudo code of presented LU-DA scheme.

Algorithm 1 : Proposed LU-DA algorithm

```
Initializing population
    While end condition is not attained
    Evaluate objective as in Eq. (14)
    Update h, v, a, c, f and b
    Compute C B, O, En and F as in Eq. (21-25)
    Update close by radius
        If random integer ra ≤ ΔS_{t+1} and if ΔS_{t+1} ≤ 0
            Update position as in Eq. (27)
        else if ra ≤ ΔS_{t+1} and if ΔS_{t+1} > 0
            Update position based on proposed female lion update as
            shown in Eq. (28)
        else if ra > ΔS_{t+1}
            Update position as in Eq. (30)
        end If
end while
    New positions are verified on the basis of variable boundaries
end While
```

VI. Result and Discussion

A. Simulation Setup

The adopted LU-DA based CHS in WSN was simulated in MATLAB. The analysis was held by evaluating the alive node count for varied number of round that ranges from 0 t0 2000. Further, log of alive node count was analysed for varied distance that range from 0, 20, 40, 60 and 80. In addition, cost analysis was done for varied iterations that range from 0, 2, 4, 6, 8 and 10. Also, the proposed model was computed over extant approaches such as FF [8], GWO [9], LA [34], DA [23] and FPU-DA [24] and the outcomes were examined in terms of statistical analysis. The simulation parameters in this work are summarized in Table II.

TABLE II. Simulation Parameters

Parameters	Values
"Initial nodal energy	0.5J
Fraction of super nodes amidst advanced nodes	0.6
Network area	100×100
Energy factor of super node	3
Fraction of advanced sensor nodes amidst normal nodes	0.4
Total node count	100
Energy dispersed per bit	100nJ/bit
Data packet aggregation energy	5nJ/bit/message"

B. Analysis on Alive Nodes

The Analysis on NAN of suggested LU-DA scheme over FF, GWO, LA, DA and FPU-DA models is specified in Fig. 3(a), whereas, the log of NAN analysis is shown in Fig. 3(b). The Analysis on NAN is done for 2000 rounds, while, log of NAN is performed for varied distance that range from 0, 20, 40, 60 and 80. In fact, the transmission of data and clustering operations continues for several rounds up to the death of every node. Thereby, the NAN in cluster gets reduced in every cluster. Thus, the NAN reduces with raise in rounds. Till 700th round, the NAN for conventional and proposed models is 100, and it is gradually reduced as the round gets improved. Nevertheless, at 2000th round, the adopted scheme reveals higher NAN than extant models, thus guarantying the enhanced performance of adopted scheme. Particularly, within 75% variation in rounds (i.e. from 500th round to 2000th round), the NAN using presented technique has dropped from 100 to 40. On the other hand, for similar variation (75%) in rounds, the NAN using conventional GWO has dropped from 100 to 19. Thus, the analysis established the enhanced efficacy of LU-DA method with the subsistence of more NAN.

C. Analysis on Normalized Energy

Fig. 4 describes the examination on normalized energy attained using suggested LU-DA model over traditional models for varied number of rounds that ranges from 0 to 2000. The normalized energy is portrayed depending upon the residual network energy and it have to be high for better system performance. In Fig. 4, the network energy seems to be higher at initial rounds; however, with increase in rounds, the energy starts lessening steadily for both adopted as well as compared extant schemes. Especially, from Fig. 4, the presented model has attained higher energy of 0.55 at 1st round, while at 2000th round; the normalized energy value has been dropped to 0.1. However, the adopted model has accomplished a higher energy even at 2000th round, when distinguished over FF, GWO, LA, DA and FPU-DA models. Thus, the capable performance of developed model is confirmed.

D. Convergence Analysis

Fig. 5 describes the convergence analysis of the adopted model over conventional approaches regarding cost. Here, Analysis is performed for a varied number of iterations that ranges from 0, 2, 4, 6, 8 and 10. On noticing the analysis resultants, the developed LU-DA has a negligible cost for all iterations over conventional approaches. Predominantly, on noticing cost values from Fig. 5, the adopted scheme has attained reduced cost value (0.06) from iteration 3 to 10. At the initial iterations (from 1 to 3), the cost of developed model has accomplished a comparatively higher value, while at further iterations; the developed model has converged to a minimal cost value. Especially, at iteration 2, the adopted model is only 60% enhanced than extant FF model, while at iteration 10, the adopted model is 62.5% enhanced than FF model. Thus, the overall assessment shows the impact of the developed LU-DA on better convergence results with increase in iterations.

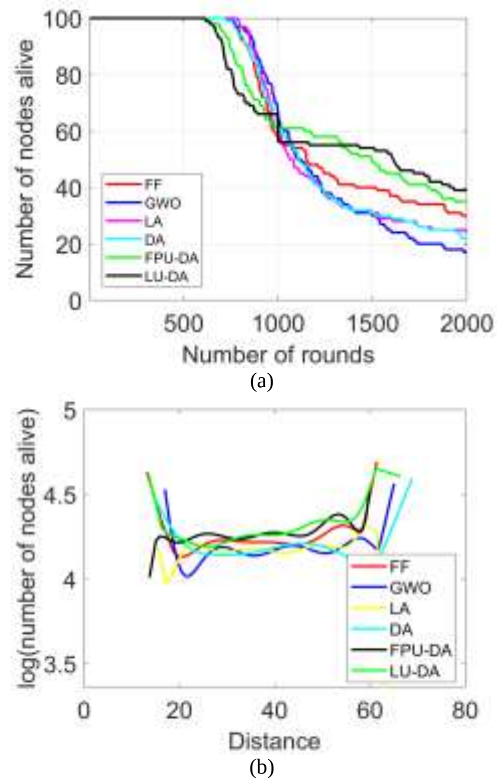


Fig. 3. NAN Analysis and Log of NAN Analysis for Adopted Scheme Over Extant Schemes in Terms of (a) Count of Rounds and (b) Distance.

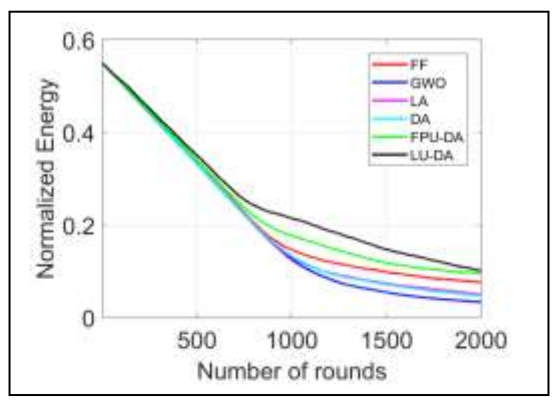


Fig. 4. Analysis on Normalized Energy Attained using Presented Work Over Existing Works.

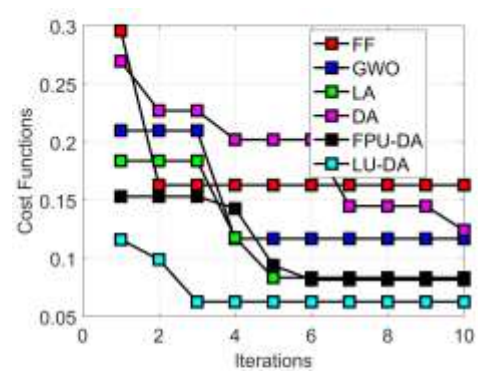


Fig. 5. Convergence Analysis of Developed Scheme Over Traditional Models in Terms of Cost.

E. Statistical Analysis

Table III describes the statistical analysis of the presented LU-DA model over prevailing approaches regarding alive nodes, energy, cost and time. “As meta-heuristic schemes are stochastic in nature, every algorithm is executed for the number of times to attain the statistic of objective function”. On noticing the resultants, the adopted LU-DA model has obtained high NAN and energy values and minimal cost and time values for all scenarios, when compared over the existing schemes. Especially, on noticing the NAN from Table III, the best case scenario using proposed LU-DA model has attained superior values over distinguished schemes. Moreover, the cost and time values of conventional schemes is superior to the presented model. Nevertheless, at specific scenarios, the conventional schemes have exposed its enhanced performance regarding time. Though, the entire evaluation of objectives reveals the impact of improving the adopted scheme, thus ensuring a secured transmission.

F. Analysis on Delay, Security and Trust

The analysis on delay, security and trust attained using implemented model over existing models is tabulated in Table IV. Here, examination is done by altering rounds from 0 to 2000. On analysing the delay, the presented LU-DA model has obtained high values for trust and minimal values for delay and security (risk) for all rounds. Initially, at round 1, the delay of adopted scheme seems to be 0.98, while, as the number of rounds increases, the developed method has acquired a minimal delay value of 0.89 at 2000th iteration. Simultaneously, while analysing the security (risk), the developed approach at 1st round has accomplished a minimal risk value of 0.06, whereas, at 2000th iteration, a comparatively higher risk value of 0.094 has been acquired by adopted model. However, for all rounds, the developed approach has acquired fine outcomes than the compared models as per the desired objectives. Also, while examining the trust values, the adopted method has accomplished a higher trust value of 0.32 at 2000th round, whereas, the compared models like FF, GWO, LA, DA and FPU-DA has acquired relatively minimal values of 0.24443, 0.21992, 0.17411, 0.23624 and 0.23446. Therefore, the improvement of LU-DA scheme is confirmed from the outcomes.

TABLE III. STATISTICAL ANALYSIS OF DEVELOPED SCHEME OVER TRADITIONAL SCHEMES REGARDING VARIED METRICS

Alive nodes						
Measures	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
Mean	67.887	64.314	64.819	64.82	70.774	70.693
Best	30	17	24	22	35	39
Median	58	65	61	62	61	56
Worst	100	100	100	100	100	100
STD	28.791	34.082	32.67	32.304	24.449	23
Normalized energy						
	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
Mean	0.21887	0.19672	0.20528	0.20481	0.23513	0.25519
Best	0.076316	0.033484	0.049668	0.046585	0.095484	0.10092
Median	0.14681	0.12504	0.13032	0.13293	0.17645	0.21429
Worst	0.54958	0.54958	0.54958	0.54958	0.54958	0.54958
STD	0.14569	0.1624	0.15523	0.15647	0.13754	0.12921
Cost Function						
	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
Median	0	0.14251	0.13267	0.12611	0.11535	0.017313
Worst	0.38671	0.25673	0.21372	0.23847	0.19976	0.15659
Best	0.023504	0.017313	0.029904	0.017313	0.023528	0
Mean	0	0.14035	0.1317	0.12599	0.11456	0.023129
STD	0	0.032131	0.028361	0.031633	0.027952	0.016704
Time						
	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
Mean	1.7643	1.5862	1.4678	1.6114	4.549	2.0993
Best	1.4428	1.4751	1.4255	1.4872	2.6577	1.1549
Median	1.5791	1.575	1.4588	1.5999	4.4943	1.6068
Worst	6.16	2.0474	2.2782	6.2107	6.888	8.0005
STD	0.58403	0.060094	0.036912	0.12653	0.36098	1.1177

TABLE IV. ANALYSIS ON DELAY, SECURITY AND TRUST: DEVELOPED SCHEME OVER TRADITIONAL SCHEMES

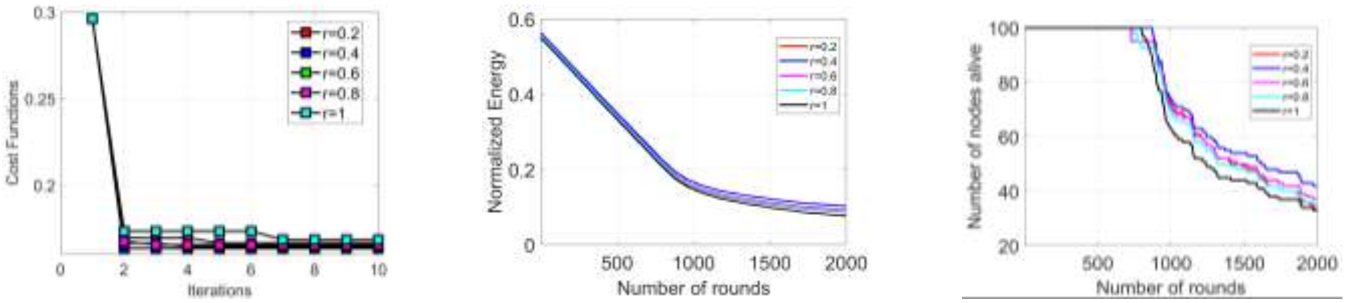
Delay						
Rounds	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
0	0.96697	0.93975	1.0545	1.0547	0.84699	0.98305
100	1.0892	1.1839	1.1871	0.96307	1.1825	0.92846
225	1.1839	0.97482	0.94676	1.1367	1.1019	0.92955
500	1.0665	1.015	1.02	1.015	1.0442	0.93306
725	0.94676	0.89849	1.1963	0.94247	1.0012	0.89247
1000	1.1112	1.0665	0.99593	1.0291	0.98194	1.1112
1225	0.89849	1.0218	1.0545	1.0044	0.81323	1.2899
1500	0.89658	0.93068	0.9879	1.1963	0.72301	0.94676
1726	1.0119	1.015	1.02	0.97447	0.81323	1.0218
2000	0.94767	1.1644	1.0116	1.0044	0.90933	0.893
Security (risk)						
	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
0	0.14793	0.11718	0.2206	0.10757	0.077825	0.065633
100	0.1713	0.18119	0.26347	0.071713	0.12692	0.097313
225	0.16429	0.15659	0.19628	0.1246	0.10803	0.086563
500	0.11718	0.10757	0.34161	0.13545	0.090417	0.085969
725	0.053169	0.15371	0.34767	0.063057	0.018887	0.018656
1000	0.089979	0.13928	0.3868	0.14793	0.072902	0.06253
1225	0.089979	0.12584	0.22542	0.13477	0.067928	0.065784
1500	0.19505	0.13449	0.46562	0.10825	0.077875	0.077313
1726	0.090257	0.11595	0.12679	0.14698	0.14311	0.1272
2000	0.1441	0.14451	0.19878	0.11628	0.11925	0.094513
Trust						
	FF	GWO	LA	DA	FPU-DA [24]	LU-DA
0	0.25457	0.32173	0.17335	0.34906	0.21982	0.25919
100	0.28324	0.2001	0.13852	0.25616	0.22706	0.39341
225	0.21758	0.23228	0.18336	0.21304	0.22499	0.24245
500	0.32646	0.20875	0.48212	0.33051	0.35113	0.3607
725	0.21877	0.25422	0.23838	0.25893	0.31657	0.46922
1000	0.24332	0.25835	0.19616	0.21464	0.30112	0.4071
1225	0.31622	0.20314	0.30029	0.23106	0.24709	0.17652
1500	0.26154	0.14357	0.13765	0.38285	0.25689	0.2413
1726	0.17468	0.16548	0.29837	0.26808	0.2644	0.51033
2000	0.24443	0.21992	0.17411	0.23624	0.23446	0.3193

G. *Parametric Analysis*

Fig. 6 shows the parametric analysis of normalized energy, convergence, and alive nodes. In the LU-DA scheme algorithm, there is a random number that varies from 0-1. Here, the analysis has been done by varying the random variable r=0.2, r=0.4, r=0.6, r=0.8, and r=1. On observing the results, it can be noticed that when r=0.4, the proposed LU-DA attains the best results. By setting the random variable r=0.4, the above analysis like normalized energy, convergence, and alive nodes has been portrayed by comparing with other existing models.

H. *Discussion*

This paper presents a new LU-DA model for optimal CHS. Here, the optimal CH selection is carried out by considering the constraints like “energy, delay, distance, security and trust. Here the analysis is performed for alive nodes, normalized energy, convergence analysis, analysis based on delay, security and trust. The betterment of the proposed LU-DA model is proved on various measures like energy and alive node analysis. From the above analysis, it is evident that the proposed model attains better results when compared with the existing models like FF, GWO, LA, DA and FPU-DA. Thereby attaining improved the network lifetime.



(a) (b) (c)

Fig. 6. Parametric Analysis on (a) Convergence Analysis (b) Normalized Energy (c) Alive Nodes.

VII. CONCLUSION

This paper introduced a new LU-DA model for optimal CHS. For optimization, a novel approach termed as LU-DA was developed. Eventually, the primacy of offered method was confirmed over conventional models. The presented model has attained higher energy of 0.55 at 1st round, while at the 2000th round; the normalized energy value has been dropped to 0.1. However, the adopted model has accomplished higher energy even at the 2000th round, when distinguished over FF, GWO, LA, DA and FPU-DA models. At the initial iterations (from 1 to 3), the cost of the developed model has accomplished a comparatively higher value, while at further iterations, the developed model has converged to a minimal cost value. Especially, at iteration 2, the adopted model was only 60% enhanced than the extant FF model, while at iteration 10, the adopted model was 62.5% enhanced than FF model. Therefore, the development of the suggested LU-DA scheme was authenticated over other techniques.

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