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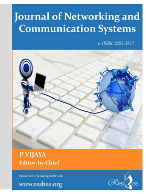

Hybrid Metaheuristic Algorithm for Cluster Head Selection in WSN

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Abstract: During routing, a crucial requirement in the Wireless Sensor Network (WSN) is to achieve energy efficiency since the sensor nodes have minimal energy resources. In WSN, mobility of node causes major problem in designing an energy-efficient routing protocol. Clustering helps to attain this by reducing the network overheads and complexities. Hence, this paper aims to explore the optimal cluster head (CH) for energy efficient routing in WSN. The key contribution relies on optimal CH selection, in which an algorithm named Lion based Firefly algorithm (L-FF) is used. Accordingly, a new multi-objective model is developed with respect to the various constraints such as distance, delay, and energy. Finally, in terms of throughput, network lifetime, mean residual energy and Standard deviation with the improvement of the presented method is established over existing models.

Keywords: Wireless Sensor Network; Cluster Head Selection; Energy Efficiency; Throughput: Network lifetime.

Nomenclature

Abbreviation	Description
WSN	Wireless Sensor Network
BS	Base Station
CHS	Cluster Head Selection
CH	Cluster Head
GA	Genetic Algorithm
DA	DragonFly Algorithm
FF	FireFly Algorithm
L-FF	Lion based Firefly algorithm
ACO	Ant Colony Optimization
PSO	Particle Swarm Optimization
GGWSO	Grouped Grey Wolf Search Optimization
SCBRP	Secure Cluster-Based Routing protocol
HABC-MBOA	Hybrid Artificial Bee Colony and Monarchy Butterfly Optimization Algorithm

1. Introduction

Recent technological advancements in WSN further lead to the development of incredibly lightweight and cost-effective sensor devices for encoding, data collection, connectivity and computing [6][7]. WSN has productive investment coverage owing to their flexibility in solving challenges throughout different domains and their capability to change our lives in a variety of ways. The earliest productions of the WSN were motivated through military requirements including such field surveillance, threat tracking, etc [8]. WSNs are quite effective monitoring methodologies often used in sectors such as greenhouse, agriculture, environmental control of air-water hazardous sludge, forestry, systemic control, , health monitoring, etc The advantages of wireless technology include computing capability, low power, low installation costs, energy, higher mobility and smart sensors compared to the wired network[9]. In fact, the data can be gathered from each sensor and the position can be identified. The continuous analog signal could be identified by means of a digital sensor utilizing an analog to digital converter as well as

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further analysis can also be worked out along with the controllers. WSN's application involves monitoring, controlling and tracking [10].

Clustering is one of the main important techniques for expanding the life of WSN. The cluster seems to have a header in the hierarchical network architectures known to as CH and executes different tasks including many common sensor nodes as leaders, aggregation and fusion [11]. The sensor nodes involved in the clustering protocol will detect the data and then transfer the appropriate data to the corresponding CH. The obtained data from CH shall have been sent to BS in the sensor nodes. The CH would then work harder as it will die quickly when compared to the sensor nodes [12]. The cluster production process eventually leads to a two-level hierarchy as cluster-member nodes sometimes seem at a lower level and CH nodes occur at a higher level [13]. Consequently, energy-efficient clustering is defined as an optimization problem that could be frequently estimated to extend the lifespan of WSNs with multiple cluster categories.

Clustering protocol is one of the most energy-efficient approaches to save resources and increase the lifespan of the network [14]. The network output can be influenced by the wrong selection in the CHS [15]. Therefore, the correct selection in CH plays an important function in clustering. To addition to solve the issue posed by the clustering strategy in WSN further optimization approaches were implemented more specifically PSO, ACO and so on, however it has several disadvantages. Convergence rate and speed are still limited by the traditional algorithm that must be developed by new models to increase the duration of the network.

This paper deals with the following sections: Section II shows the reviews on CHS. Optimal cluster head selection: defined objective model are presented in Section III. Section IV depicts the determination of proposed cluster based routing model. Moreover, Section V elaborates L-FF: a hybrid optimization algorithm for optimal cluster head selection. Section VI portrays the results and their discussions and Section VI shows the conclusion of this paper.

2. Literature Review

2.1 Related work

In 2019, Pavani et al. [1] have implemented a SCBRP comprising adaptive PSO and optimized firefly algorithms in WSN throughout transmission of data. The most significant task in the suggested approach might be to improved the duration of the network with reduced energy usage. The security testing, security routing, and energy-efficient clustering method were produced based on the framework of the hexagonal sensor network. Energy consumption, packet drop, decryption time, encryption time and network life rate are compared to the conventional techniques and therefore the experimental results indicated better results.

In 2019, Quoc et al. [2] have developed a routing approach in WSN focused on optimizing distance routing and energy routing in a Gaussian network clustering protocol. The four different directions between neighbouring nodes and node-symmetric was grouped into several virtual square grids in Gaussian network system. Each single square grid with in Gaussian network establishes routing techniques of protocol clustering and simplest routing protocol route. Compared with conventional WSN clustering routing, the simulation performance showed the better routing efficiency.

In 2019, Rambabu et al. [3] have presented a HABC-MBOA by using Cluster Head Selection approach to choose the CH only with clustering mechanism in such a significant way. The HABC-MBOA ignored the possibility of CH being crowded by other sensor nodes and thus offered sudden loss in sensor nodes mostly during consumption of incapable CH screening process; it eliminates the deficiency on ABC algorithms mostly during capacity of global search. At last, the simulation outcomes indicated as 18.92% superior to the other conventional methods.

In 2019, Shankar et al. [4] have introduced a hybrid GGWSO to achieved the higher CH selection efficiency in WSN as it increased the lifespan of the network. The important constraints used to check the proposed method performance to the conventional method seem to be security, distance, energy, and delay. Also for system of security awareness, three techniques, including such risky mode, γ-risky mode and security mode were already taken into consideration. Conversely, the experimental findings obtained a superior result using a hybrid system.

In 2019, Zhao et al. [5] have established a routing protocol with such a sustainable energy-optimization for dynamic hierarchical clustering that focuses on 3D WSN. To solve many challenges, both the original system of energy consumption and the current model of 3D spherical network configuration establish a structure for controlling the overall energy consumption. The optimal cluster-head could select the CH within each cluster in every round, and it has been developed depends entirely on the residual energy and node position. The experimental results were compared with different protocols with improved significance in applications for controlling 3D environment and more robustness.

3. Optimal Cluster Head Selection: Defined Objective Function

3.1 Objective Model

The major objective of the research work mentioned on CHS is always to find the shortest route between the selected CH and the node and reduce the delay in sending data from one node to another. Conversely, the network efficiency must be significant, i.e. only a small amount of energy should be consumed throughout data processing. The primary role of the adopted CH model could be demonstrated in Eq. (1), in which the value of γ will rely on $0 < \gamma < 1$. In Eq. (2) and Eq. (3) the R_l and R_m indicates the given operations, correspondingly. Here, β_1, β_2 and β_3 indicates the parameters including delay, energy, and distance. The major conditions using these parameters can be represented as $\beta_1 + \beta_2 + \beta_3 = 1$. In Eq. (3), $W^a - C_d$ refers the distance among the normal node and sink node.

$$H_m = \gamma R_m + (1-\gamma) R_l \tag{1}$$

$$R_l = \beta_1 * R_i^{dis} + \beta_2 * R_i^{ene} + \beta_3 * R_i^{del} \tag{2}$$

$$R_m = \frac{1}{s}\sum_{a=1}^{s}\left\| W^a - C_d \right\| \tag{3}$$

The fitness value distance would be demonstrated in Eq. (4), thus $R_{(l)}^{dis}$ applies to packet transmission between CH to BS as well as from the normal node to CH. Here, R_i^{dis} the values [0, 1] must rely. If another distance between the CH and the normal node is large, therefore the R_i^{dis} value will be greater.

$$R_i^{dis} = \frac{R_{(l)}^{dis}}{R_{(m)}^{dis}} \tag{4}$$

$$R_{(l)}^{dis} = \sum_{a=1}^{P_a}\left[\left\| G_a - C_d \right\| + \sum_{b=1}^{P_b}\left\| G_a - W_a \right\| \right] \tag{5}$$

$$R_{(m)}^{dis} = \sum_{a=1}^{P_a}\sum_{b=1}^{P_b}\left\| W_a - W_b \right\| \tag{6}$$

In Eq. (5), and Eq. (6), $R_{(l)}^{dis}$ and $R_{(m)}^{dis}$ indicates the illustration respectively, and the W_a normal node in the a^{th} cluster, G_a describes the CH of the b^{th} cluster that determines the distance between the BS and the CH as $H_y - D_c$, $G_a - W_a$ indicates the distance between the CH and the normal node and $W_a - W_b$ corresponds to the distance between the two normal nodes, P_a and P_b relates to the node count that does not involve the node a^{th} and the b^{th} cluster.

Eq. (7) demonstrates the role of energy fitness. R_i^{ene} value turned out to be far more than one and the entire CH cumulative $R_{(l)}^{ene}$ and $R_{(m)}^{ene}$ improves the overall amount of energy and the upper CH count.

$$R_i^{ene} = \frac{R_{(l)}^{ene}}{R_{(m)}^{ene}} \tag{7}$$

Eq. (7) describes the fitness function of delay, which is directly related to all nodes involved within the cluster. Additionally, delay is minimized if the head of the cluster has lesser nodes. Eq. (8) involves determining the delay function of fitness. Therefore, P_P the denominator corresponds to the complete number of nodes found in WSN, and the numerator denotes the upper nodes of CH. Consequently, R_i^{del} value must be within [0, 1].

$$R_i^{del} = \frac{\max\left(\left\| G_a - W_a \right\|\right)_{a=1}^{P_d}}{P_P} \tag{8}$$

4. Determination of Energy and Distance Model of Network

4.1 Network Model

WSN includes several sensor nodes, as described to be stationary and have the similar properties. In the data transfer process, the node that functions as a CH has an effective sensor. In WSN, the clustering model includes the mixture of various sensor nodes. Extending WSN's lifetime is a great way too. Such pattern of CHS is employed in all clusters. Additionally, nodes were created in a specific cluster in such a way that the distance of CH might have been reduced. The information is gathered in sensor nodes starting in the planned area throughout most of the process, and transmitted in CH. Common CH actually passes on the information gathered to the BS.

In so many routing protocols the required CHS is known to be the principal restriction in terms of energy and position, particularly hierarchical routing. Usually a node needs a lot of energy to express a huge amount of data. The ideal CH positioning technique can lower the energy, allowing extra data to be transferred to the specific CH. Therefore, the node chosen as the CH leads the related nodes in the sensor for perfect coordination with the lowest energy usage.

4.2 Energy Model

Energy consumption is regarded as the most important problem in WSN. In fact, whenever the battery becomes weak (i.e.), there will be no power supply; the battery mounted in the WSN will not be re-energised. The entire energy consumption is represented in Eq. (9), throughout the message transmission. In Eq. (9), V_{el} indicated by the energy of electronics, relies on the various criteria of digital coding, filtering, spreading, etc. Here, $V_t(N:f)$ determines the amount of energy produced mostly during the transferred N packets at certain distance f. Eq. (10) refers to the electronic energy process, thus V_{ae} indicates to the energy consumed across the aggregation of data. Eq. (11) and Eq. (12) illustrate the energy produced available to execute N bytes of packets at a distance e throughout amplification. V_x Suggests the energy in the power amplifier, and V_y determines the critical energy as it identifies the concept of free space.

$$V_t(N:f)=\begin{cases}V_{el}*N+V_y*N*f^2, \text{if } f<f_0\\ V_{el}*N+V_x*N*f^2, \text{if } f\geq f_0\end{cases} \tag{9}$$

$$V_{el}=V_t+V_{ae} \tag{10}$$

$$V_r(N:f)=v_{el}N \tag{11}$$

$$V_{am}=V_y f^2 \tag{12}$$

$$f_0=\sqrt{\frac{V_y}{V_x}} \tag{13}$$

At last, the overall energy observed in the network is shown in Eq. (14), where, V_h corresponds to the energy needed in the inactive state, V_g suggests the energy cost in the sensing process. Decreasing energy output as demonstrated by Eq. (14) is crucial.

$$V_{total}=V_t+V_r+V_h+V_g \tag{14}$$

4.3 Distance Model

Once the distance of CH is high, the node is managed by a necessary cluster, and in reality sends messages to the correct CH. But at the other hand, if the distance of CH and node is greater than the distance in BS and node, the sensor node sends messages to the BS. The distance matrix $D(u*v)$ is represented in Eq. (15), where f_{L_o} corresponds to the Euclidean distance of CH suggested by L_o position information and $J_1, J_2, \ldots J_n$ responds to the sensor nodes as the normal node.

However, the two sensor nodes p^{th} and q^{th} with their positions E and F. Eq. (16) indicates the Euclidean distance. All the components throughout the distance matrix signify the distance of p^{th} node and q^{th} node inside the CH as described in Eq. (15). In the matrix rows the columns with the lowest value are paired with the previous one. Consider an element f_{L_{ov2},J_1} which requires the first column of the matrix even by shortest distance. The CH L_{o2} and the node p_1 also are related to each other as well.

$$D(u * v) = \begin{bmatrix} f_{L_{o1},J_1} f_{L_{o1},J_2} \ldots\ldots\ldots f_{L_{o1},J_n} \\ f_{L_{o2},J_1} f_{L_{o2},J_2} \ldots\ldots\ldots f_{L_{o2},J_n} \\ : \\ : \\ f_{L_{ov},J_1} f_{L_{ov},J_2} \ldots\ldots\ldots f_{L_{ov},J_n} \end{bmatrix} \tag{15}$$

$$f_{p,q} = \sqrt{(q_E - P_E)^2 + (q_F - P_F)^2} \tag{16}$$

Here, L_o indicates the time slot assigned to each node of the sensor during data transfer.

5. L-FF: A Hybrid Optimization Algorithm for Optimal Cluster Head Selection

5.1 L-FF algorithm

Based on the two distinct lion behaviours such as terrestrial defence and territorial conquest, the lion algorithm determines the optimal solution. The terrestrial defending occurs between the native males and the nomadic males, whereas the territorial conquest actually occurs between both the old territorial male and the new territorial male [16].

(i)Pride Generation: The original pride surround A^{ma}, A^{fem} and A^{nom} as the male territorial lion, female territorial lion and nomadic lion, correspondingly. Here, A^{ma} can be denoted as $A^{ma} = A_1^{ma} A_2^{ma} \ldots\ldots A_K^{ma}$. Likewise, A^{fem} is represented as $A^{fem} = A_1^{fem} A_2^{fem} \ldots\ldots A_K^{fem}$ .The solution vector length indicated as K . The arbitrary integer can be presented as A , in which $k = 1,2,3 \ldots K$ for A_k^{fem} and A_k^{ma} . The arbitrary integer must be created within the limit of $\left(A_k^{min}, A_k^{max}\right)$. The maximum and the minimum limit in solution space were determined as A_k^{min} and A_k^{max}, correspondingly. In addition, $e(A_k)$ can be indicated using the Eq. (17), that determines $e\left(A_k^{ma}\right)$ and $e\left(A_k^{fem}\right)$.The binary lions generation can be indicated using the Eq.(18).

$$e(A_k) = z(A_1) \sum_{k=2}^{K} 2^{K-1} A_k \tag{17}$$

$$z(A_k) = \begin{cases} 1; \text{if } A_1 = 0 \\ -1; \text{otherwise} \end{cases} \tag{18}$$

(ii)Fertility evaluation: A^{ma}, A^{fem} attain the global optima or local optima with saturated fitness value. In general, the fertility evaluation was carried out for eliminating the local optimal solutions. The solution update of both female and male can be indicated as A_{best}^{fem} and A_{best}^{ma}. The sterility rate $Q(j)$ makes certain fertility of A^{fem} and $Q(j)$ can be raised by 1 following the crossover process. The updating of A_{best}^{fem} by A^{fem} shown as per Eq. (19) and Eq. (20) here, the random integer is created in between the interval $[1, K]$ as k^* and the female renewal function is determined using φ . However, the random integers created in between the interval [0, 1] determined as jT_1 and jT_2 .

$$A_{best}^{fem} = \min\left[A_{k^*}^{max}, \max\left(A_{k^*}^{min}, \varphi_{k^*}\right)\right] \tag{19}$$

$$\varphi_{k^*} = \left\{A_{k^*}^{fem} + \left[0.1jT_2 - 0.05\left(A_{k^*}^{ma} - jT_1 A_{k^*}^{fem}\right)\right]\right\} \tag{20}$$

As per L-FF model, the concept of FF is related to LA model, which offers enhanced optimum solution. At first, a random number is chosen within the L-FF algorithm. If the random value exceeds 0.5 the solution will be updated with the FF. This approach renewal is achieved regarding the Eq. (21), where χ_0 indicates the maximum attractiveness known as the light absorption coefficientt. Moreover, O and w are two FF at position A_O and A_w .

$$A_{best} = A_O + \chi_0^{-\alpha x_{Ow}^2}(A_w - A_O) + \lambda\left(\text{rand} - \frac{1}{2}\right) \tag{21}$$

If the random value is better than 0.5, the solution would be revised by the LA and the best solution will be checked based on the Eq. (19).

(iii) Mating: At the conclusion of the crossover and mutation process four direct cubs and four mutant cubs are formed.

(iv)Lion Operation: If the new solution is a better one, it removes the existing contemporary solution and replaces it with the new solution in this process. The terrestrial takeover takes place as the age of the cub is greater than or equal to the maturity age.

(v)Termination: The termination process occurs when at least one of the termination criteria in Eq. (22) or eq.(23) gets satisfied. The error threshold and maximum number of generations is represented by T_e and Max_e .The target minimum is denoted as $Z(A^{opt})$.

$$Max_e > Max_e^{max} \tag{22}$$

$$\left\lfloor Z\left(A^{ma}\right) - Z\left(A^{opt}\right)\right\rfloor \leq T_e \tag{23}$$

6. Results and discussion

6.1 Simulation Procedure

The simulation of proposed CHS in WSN was simulated using MATLAB and the corresponding results were obtained. The L-FF model was compared with GA [17], FF [18] and DA [19] and the results were obtained. The experimentation outcomes were observed in terms of throughput (Kbps), network lifetime, mean residual energy and standard deviation and their outcomes were validated.

6.2 Analysis on Throughput and Lifetime

The analysis for throughput for the L-FF method over the traditional models is given by Table I. From the analysis, throughput is attained by the L-FF model over the other schemes for different number of sensor nodes. The proposed L-FF model is 42.85%, 51.78% and 64.28% better than other traditional algorithms such as GA, FF and DA for 1000th sensor nodes.

The analysis for network lifetime for the L-FF method over the conventional models is given by Table II. From the analysis, network lifetime is attained by the L-FF model over the other schemes for different number of sensor nodes such as 300, 600, 800 and 1000 nodes. The L-FF model is 18.75%, 37.5% and 43.75% better than other existing algorithms such as GA, FF and DA in 300th sensor nodes. Thus, the betterment of the L-FF method is proved from the results.

Table 1. *Analysis on throughput for L-FF model over conventional models*

Methods	Number of Sensor nodes			
	300	**600**	**800**	**1000**
L-FF	13	32	38	56
GA [17]	9	17	25	32
FF [18]	7	15	18	27
DA [19]	6	10	17	20

Table 2. *Analysis on network lifetime for the L-FF model over conventional models*

Methods	Number of Sensor nodes			
	300	**600**	**800**	**1000**
L-FF	32	27	26	22
GA [17]	26	21	19	15
FF[18]	20	15	12	10
DA [19]	18	12	8	7

6.3 Analysis on Mean Residual Energy

Table III demonstrates the mean residual energy of the L-FF method over other conventional schemes. On observing the outcomes, it is known that the L-FF algorithm provide better outcomes than the other compared models for the five different sink positions.

Table 3. *Analysis on mean residual energy for the L-FF model over conventional models*

Methods	Different sink positions				
	50-100	**100-100**	**100-200**	**150-50**	**200-100**
L-FF	98	99	99	98	99
GA [17]	78	72	79	72	70
FF [18]	56	50	52	50	54
DA [19]	36	26	26	30	32

6.4 Analysis on Standard Deviation

The results on standard deviation in throughput for different sink positions analysis are given by Table IV, from which the betterment of the L-FF method can be observed. Here, for all the five different sink positions, higher standard deviation in throughput is attained by the L-FF method over the other traditional methods like GA, FF and DA.

Table 4: *Analysis on Standard Deviation in throughput-sink positions for the L-FF model over conventional models*

Methods	Different sink positions				
	50-100	100-100	100-200	150-50	200-100
L-FF	16	16	16	16	16
GA [17]	12	11	11	10	10
FF[18]	9	9	8	8	8
DA [19]	7	7	7	7	7

7. Conclusion

This work introduced the L-FF method for identifying the optimal CHS in WSN. The CHS node was chosen using L-FF method by considering the factors like energy, delay, and distance. The L-FF method was founded better performance than the traditional methods such as throughput, network lifetime, mean residual energy and standard deviation. From the analysis, the L-FF model is 18.75%, 37.5% and 43.75% better than other existing algorithms such as GA, FF and DA in 300th sensor nodes. Finally, for all the five different sink positions, higher standard deviation in throughput is attained by the L-FF method over the other compared methods like GA, FF and DA. Thus, the enhancment of the presented scheme was validated in an effective manner.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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