Poisson Regressive Firefly Optimization for Energy Aware Data Aggregation in Wireless Sensor Network

**Prof.S.Kokilavani[1] and Dr.N.Sathish kumar[2]*

[1]Principal, Hindusthan Polytechnic College, Coimbatore-32, TamilNadu, India.

[2]Professor, Department of Electronics & Communication Engineering,

Sri Ramakrishna Engineering College, Coimbatore, TamilNadu, India.

[1]vani.msb@gmail.com, [2]nsk20022002@gmail.com

Abstract

Data aggregation is the process of collecting the data from the sensor node and sent to the sink node for further processing in WSN. To address the issue of high energy consumption during data aggregation, A Poisson Regressive Multi-objective Firefly Optimization-based Data Aggregation (PRMFO-DA) technique is introduced for improving the data gathering accuracy with lesser time consumption and energy consumption. In PRMFO-DA technique, residual energy is computed for every sensor node and poisson regression is used to analyze the energy level as well as to find the higher energy nodes and lesser energy nodes. The lesser energy sensor node transmits data packets to the neighboring optimal higher energy sensor node using multi-objective firefly optimization. It generates the population of fireflies and calculates the light intensity of every firefly based on the multiple objective functions. Then it ranks the fireflies according to the light intensity and identifies the best optimized higher energy sensor node to transmit the data packets to the sink node. Simulation results show PRMFO-DA technique efficiently improves the data aggregation and network lifetime with minimum time as well as energy consumption than the state-of-the-art-methods.

Keywords: *WSN, Data aggregation, residual energy, poison regression, multi-objective firefly optimization.*

1. Introduction

In WSN, sensor nodes are distributed in an environment and used the batteries as an energy resource for performing certain tasks and the nodes need additional energy. The higher energy utilization of the sensor nodes minimizes the network lifetime. Therefore, the energy-optimized data aggregation becomes a significant part of the sensor network to improve the network lifetime. In order to solve the issues, optimal sensor nodes are selected for performing the data aggregation.

A multi-mobile agent itinerary planning-based energy and fault aware data aggregation (MAEF) technique was introduced in [1] for minimizing the energy consumption. The designed MAEF technique failed to perform accurate data aggregation with minimum time. A hybrid ant colony optimization and particle swarm optimization (ACOPSO) technique were developed in [2] to increase the inter-cluster data aggregation. Though the designed ACOPSO technique enhances the network lifetime, data aggregation time was not minimized.

A ring-based in-network data aggregation method was introduced in [3] to minimize the energy cost as well as packet loss. But the performance of the data aggregation accuracy remained unaddressed. An optimization framework was developed in [4] for data collection using the mobile sink. The designed optimization framework minimizes the time complexity in data aggregation but the performance of network lifetime was not improved.

A Hierarchical Cover and Steiner Tree (HCST) algorithm were designed in [5] for data aggregation with minimum cost. But the algorithm failed to solve the issues of energy-optimized aggregation. A Mixed-Integer Linear Programming (MIP) was introduced in [6] to discover the optimal data-gathering tree and maximize the network lifetime. The technique failed to consider the distance function in the energy consumption model. A Maximum Lifetime Data Aggregation Tree Scheduling (MLDATS) method was developed in [7] to extend the network lifetime. The designed method failed to perform efficient data aggregation in dynamic WSN.

A Quantized Compressed Sensing and distributed compressive sensing theory was developed in [8] for data aggregation. Though the designed approach improves the energy-efficient data collection, accurate data aggregation was not performed. A Markov Decision Process (MDP) was developed in [9] for the measurement of data collection with minimum energy consumption. But the accurate data transmission was not performed.

An anchor selection algorithm was designed in [10] based on the energy to gather the zonal data. Though the designed algorithm minimizes the data transmission delay, the data aggregation accuracy was not improved.

The major issues are identified from the above-said methods such as lesser energy consumption, more time to perform data aggregation, lesser data aggregation accuracy and so on. In order to solve the above-said issues, the novel technique called PRMFO-DA is introduced.

The major contribution of the proposed PRMFO-DA technique is summarized as follows,

- The PRMFO-DA technique is introduced to obtain the optimal solution for energy-efficient data aggregation in a distributed manner. The PRMFO-DA technique uses Poisson regression to find the sensor nodes energy level. The nodes with higher residual energy are identified by setting the threshold value for data aggregation. This, in turn, minimizes energy consumption and improves the network lifetime.

- The firefly optimization algorithm is applied to find the optimal neighboring node based on the multiple objective functions such as higher residual energy and minimum distance. The sink node collects all the data from the optimal energy-efficient nodes resulting in improves the data aggregation accuracy and minimizes the data aggregation time.

1.1 Organization of the proposal work

The rest of this paper is organized into five different sections. In Section 2, the system model and the proposed Poisson Regressive Multi-objective Firefly Optimization-based Data Aggregation are presented. In Section 3, simulation settings are presented with certain parameters. The performance results of the proposed PRMFO-DA technique compared to other conventional technique are presented in Section 4. In Section 5, briefly describes the related works. Finally, the conclusion of the paper is presented in Section 6.

2. Methodology

The PRMFO-DA technique is introduced for energy-efficient data aggregation in WSN. In WSN, the limited energy capacity of the sensors node is not able to transmit the data directly to the sink at a longer period of time. In such a case, collected data may drop and the data aggregation process was not successful. Therefore, the major concern in the design of a WSN application is to improve the data aggregation with lesser energy utilization. The PRMFO-DA technique performs two processes such as regression and optimization. In PRMFO-DA technique, Poisson regression function is used to analyze the sensor node energy level. Then the optimization technique is applied to find the neighboring energy-efficient node for transmitting the data based on the two objective functions such as distance and energy. Hence the name is called as multi-objective Firefly Optimization. The following system model is used for organizing the PRMFO-DA technique.

2.1 System model

In this section, the system model of the PRMFO-DA technique is described. The WSN is designed in the graphical model $g\ (v, e)$ where $'v'$ represents sensor nodes $sn_1, sn_2, sn_3, \ldots. sn_n$ distributed in the square area $n * n$ to monitor the environmental conditions and continually forward to the sink node (SN). In the graph, 'e' denotes connections between the sensors nodes. The sink node collects the data $dp_1, dp_2, \ldots. dp_n$ from the energy efficient sensor nodes for further processing. The data gathering process of the sensor nodes considers the node residual energy R_E for increasing the network lifetime. The PRMFO-DA technique comprises two processes namely regression and optimization are explained in the following sections.

2.2 Poison regression-based sensor node energy evaluation

The first process in the PRMFO-DA technique is to find the energy level of the sensor nodes using Poisson regression. The distributed sensor node in the network has a similar energy level. Due to the sensing nature of the node, the energy level gets degraded. The lesser energy node does not withstand to longer duration resulting the network lifetime gets minimized. Therefore, the proposed PRMFO-DA technique finds higher energy sensor nodes for enhancing the network lifetime. The Poisson regression is the machine learning technique used to analyze the energy level of the sensor nodes in the network.

Figure 1 shows the Poisson regression-based energy-efficient node identification. For every sensor node in the WSN, the residual energy is computed using the following equation,

$$R_E = T_E\ (sn) - C_E\ (sn) \quad (1)$$

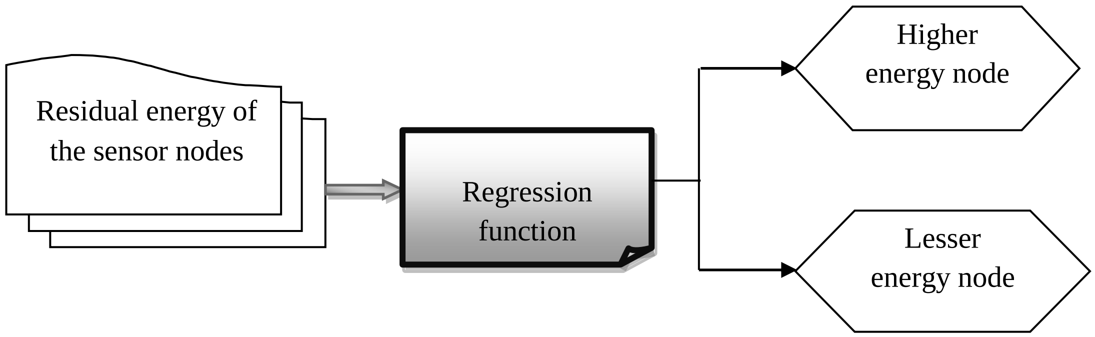

Figure 1 Poission Regression Based Energy-Efficient Node Identification

From (1),R_E denotes a residual energy of the sensor node, $T_E\ (sn)$ is the total energy of the node, $C_E\ (sn)$ is the consumed energy of the node. The Poisson regression analysis is performed using the following equation.

$$Y = \exp\ (\rho_t\ x_i) \tag{2}$$

In (2),Y denotes a regression outcome, ρ_t denotes regression parameters, x_i denotes an energy level of sensor nodes. After analyze the energy level it compared with the threshold value. If the energy level of the node is above the threshold, then the nodes are said to be a higher energy nodes. Otherwise, the nodes are said to be a lesser energy nodes.

$$Y = \begin{cases} x_i > t_h & ;\ sn_h\ (R_E) \\ otherwise & ;\ sn_L\ (R_E) \end{cases} \tag{3}$$

In (3), x_i denotes an energy level of the sensor node, t_h denotes threshold, $sn_h\ (R_E)$ represents the higher energy sensor nodes, $sn_L\ (R_E)$ is the lesser energy sensor nodes. The higher energy nodes are used for data aggregation process and it helps to extend the network lifetime. The algorithmic process of regression based nodes identification is described as follows,

Input: Number of sensor nodes $sn_1, sn_2, sn_3, \dots .\ sn_n$
Output: Find high energy and lesser energy sensor nodes
Begin
1. **for each** node sn_i
2. **C**ompute residual energy R_E
3. Measure the regression function $Y_i = \exp\ (\rho_t\ x_i)$
4. **if** $(x_i\ \geq\ th)$ **then**
5. sn_i is a higher energy nodes
6. **else**
7. sn_i is a lesser energy nodes
8. **end if**
9. **end for**

end

Algorithm 1 Poisson Regression-Based Energy-Efficient Node Identification

Algorithm 1 describes the energy-efficient node identification using Poisson regression. The regression process analyzes the residual energy of all the sensor nodes randomly distributed in the network. If the residual energy of the sensor nodes is greater than the threshold value, then the regression function correctly identifies the sensor nodes as higher energy node. Otherwise, the sensor nodes are identified as lesser energy. In this way, PRMFO-DA technique finds the energy-efficient sensor nodes for performing the data aggregation with minimum time.

2.3 Multi-objective firefly optimization based data aggregation

The second process of the PRMFO-DA technique is to perform the data aggregation by selecting the nearest energy-efficient node. The higher energy sensor nodes extend the network life but the lesser energy sensor node does not maintain the collected data at a longer period of time. In addition, the lesser energy nodes need more energy for transmitting their sensed data to the sink node. Therefore, PRMFO-DA technique solves the above-said issue by finding the nearest energy-efficient nodes to transmit the data packets using a multi-objective firefly optimization algorithm.

Firefly is a Metaheuristic optimization technique and it is designed based on flashing light intensity of fireflies. All the fireflies are unisexual where the firefly gets attracted to other fireflies based on their light intensity. In other words, the lesser light intensity fireflies get attracted by the brighter one. When the distance between the two fireflies is increased, the intensity of the fireflies is minimized. Therefore, a proposed PRMFO-DA technique uses the behavior of the firefly algorithm for selecting the optimal energy-efficient neighboring node for data aggregation. Initially, the populations of the higher energy sensor nodes (i.e. firefly) are generated randomly in search space to find the optimal neighboring node. Then the objective function of every sensor node is defined. Based on the objective function of the sensor nodes, more fit individuals are selected from the current population. For each firefly, the light intensity is related to the objective function.

$$\alpha(f) = f\ (x) \tag{4}$$

In (4),$\alpha(f)$ represents the light intensity of the firefly, $f\ (x)$ denotes an objective function. Here, the two objective functions are used such as residual energy and distance.

$$f\ (x) = higher\ R_E + min\ D_t \tag{5}$$

From (5), R_E represents the residual energy, D_t denotes a distance, min denotes a minimum function. In the search space, the lesser energy nodes find the nearest higher energy nodes with two objective functions. Let us consider the coordinate of the one node is (x_1, y_1) and the coordinate of another node is (x_2, y_2) in the two dimensional space. Then the distance between the nodes is computed using the following equation.

$$D_t = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{6}$$

In (6), 'D_t' represents the distance between the two nodes. The firefly 'i' move towards 'j' with minimum distance. Based on the distance measure and the energy of the node, the intensity for any pair of fireflies are updated as follows,

$$i_{(t+1)}(f) = f_{\mathrm{i}}^{\ t} + a * exp^{[-\gamma {D_t}^2]}\left(f_{\mathrm{i}}^{\ t} - f_{\mathrm{j}}^{\ t}\right) + \omega_t \epsilon_t \tag{7}$$

From (7), $i_{(t+1)}(f)$ represents an updated intensity of the firefly, $f_{\mathrm{i}}{}^{t}$, $f_{\mathrm{j}}{}^{t}$ denotes a position of the firefly at the time a 't','a' represents an attractiveness of the firefly, γ denotes a light absorption coefficient, D_t represents the distance between the fireflies, ω_t is the parameter controlling step size and ϵ_t represents a vector drawn from a Gaussian or other distribution. Finally, the fireflies are ranked based on their updated light intensity.

$$R_t \rightarrow \{f_1, f_2, f_3 \dots . f_n\} \tag{8}$$

From (8), 'R_t' denotes rank assigned to the fireflies $f_1, f_2, f_3 \dots . f_n$. The firefly which has higher energy and the minimum distance is top ranked than the other firefly. As a result, the firefly optimization technique selects the top ranked firefly as a globally optimal solutions to detect the nearest higher energy nodes. After finding the higher energy nodes, the lesser energy nodes transmits their sensing data to the nearest optimal energy efficient node. The sink node act as a data collector to gathers the data from the higher energy nodes instead of collecting from all the nodes. This helps to minimize the data aggregation time.

As shown in figure 2, multi-objective optimization based energy-efficient data aggregation in WSN. The red color node indicates the lesser energy node and the green color node represents the higher energy nodes. The lesser energy node finds the nearest higher energy node towards the sink node. Then the higher energy node sends the data to the sink node for further processing.

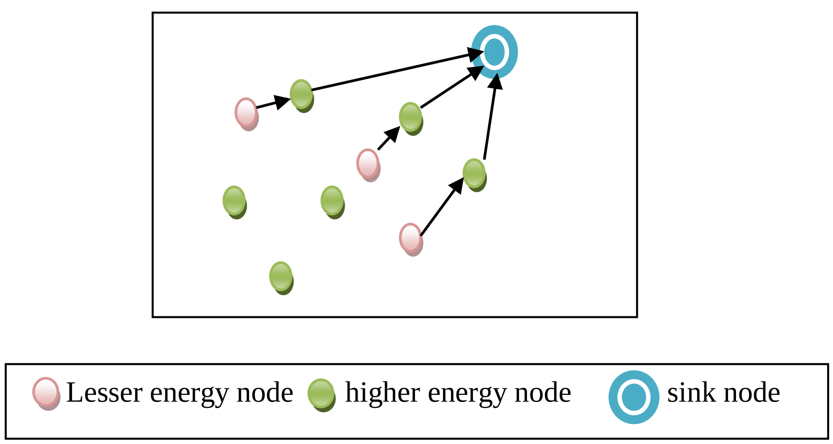

Figure 2 Multi-Objective Optimization Based Energy-Efficient Data Aggregation in WSN

Algorithm 2 describes an energy-efficient data aggregation in WSN to improve network lifetime. Initially, the populations of the sensor nodes are initialized randomly in search space and define the objective function for each sensor node. By applying the firefly optimization algorithm, the lesser energy node finds their optimal neighboring node. Then the data packet from the lesser energy sensor nodes transmits to the nearest higher energy nodes. Then the sink node receives the sensed data packets from higher energy nodes. This process improves the data aggregation efficiency and minimizes the aggregation time. As a result, the PRMFO-DA technique effectively performs the data aggregation with lesser energy consumption resulting improves the network lifetime.

The algorithmic process of data aggregation is given below,

Input: Number of sensor nodes $sn_1, sn_2, sn_3, \dots . sn_n$, data packets $dp_{1,} dp_2, dp_3, \dots . dp_n$
Output: Energy-efficient data aggregation
Begin
1. Initialize population of nodes $sn_1, sn_2, sn_3, \dots . sn_n$ i.e. fireflies
2. **for each f_i**
3. Define the objective function $f(x)$
4. Formulate light intensity $\alpha(f)$ based on objective function $f\ (x)$
5. **if $\left(\alpha(f_j) > \alpha\ (f_i)\right)$ then**
6. Firefly f_i moves towards f_j
7. Evaluate new solutions and update light intensity of firefly $i_{(t+1)}(f)$
8. **end if**
9. Rank the firefli**es** $R_t \rightarrow \{f_1, f_2, f_3 \dots . f_n\}$
10. Find current best nearest sensor node
11. Lesser energy node sends dp_i to higher energy node
12. SN aggregates dp_i from high energy node
13. **end for**
end

Algorithm 2 Multi-Objective Firefly Optimization Based Data Aggregation

The aforesaid algorithmic processes are implemented in the network simulator to show the performance of the PRMFO-DA technique against the existing techniques.

3. Simulation settings

The simulation is carried out with three different techniques namely proposed PRMFO-DA technique and existing methods MAEF [1] , ACOPSO [2] using NS2.34 network simulator. Totally 500 sensor nodes are randomly deployed in a square area of A^2 (1100 m * 1100 m). The random waypoint model is used as a mobility model. The movement speed of the sensor node is taken in the range from 0 to 20m/sec. The simulation time is set as 300 sec. The Dynamic Source Routing (DSR) protocol is used in the simulation setup for performing the energy efficient data aggregation. The lists of the parameters used for the simulation are shown in table 1.

There are four metrics are used for evaluating the performance of the proposed PRMFO-DA technique and the two existing methods. The metrics are listed given below,

- Energy consumption
- Network lifetime
- Data aggregation accuracy
- Data aggregation time

The simulation results of the different parameters with various techniques are discussed in the following section.

Table 1 Simulation Parameters Settings

Simulation Parameters	Values
Network Simulator	NS2.34
Square area	1100 m * 1100 m
Number of sensor nodes	50,100,150,200,250,300,350,400,450,500
Number of data packets	25,50,75,100,125,150,175,200,225,250
Mobility model	Random Waypoint model
Speed of sensor nodes	0 – 20 m/sec
Simulation time	300sec
Protocol	DSR
Number of runs	10

4. Results and discussion

In this section, the simulation results of proposed PRMFO-DA technique and existing methods MAEF [1], ACOPSO [2] are discussed with different parameters such as energy consumption, network lifetime, data aggregation accuracy and data aggregation time. The simulation results of three different techniques are discussed using graphical representation. For each section, the mathematical calculation is given to show the performance of the proposed technique as compared to the existing technique.

4.1 Simulation results of energy consumption

Energy consumption is a measurement of the amount of energy consumed by the sensor nodes to aggregate the data packets. The Energy consumption is mathematically calculated using the given formula,

$$EC = n * EC \ (one\ sn) \tag{9}$$

In (9), EC denotes energy consumption, n represents the number of sensor nodes, sn denotes a sensor node. The measurement unit of energy consumption is joule (J). The sample mathematical calculation for energy consumption is given below,

Mathematical calculation for energy consumption:

- **Proposed PRMFO-DA:** Number of sensor nodes are 50 and the energy consumed by single sensor nodes is $0.5 Joule$, then the overall energy consumption is computed as follows,
$$EC = 50 * 0.5 \ Joule \ = 25 \ Joule$$
- **Existing MAEF:** Number of sensor nodes are 50 and the energy consumed by single sensor nodes is $0.62 Joule$, then the overall energy consumption is computed as follows,
$$EC = 50 * 0.62 Joule \ = 31 \ Joule$$

➢ **Existing ACOPSO:** Number of sensor nodes are 50 and the energy consumed by single sensor nodes is $0.66 Joule$, then the overall energy consumption is computed as follows,

$$EC = 50 * 0.66\, Joule = 33 Joule$$

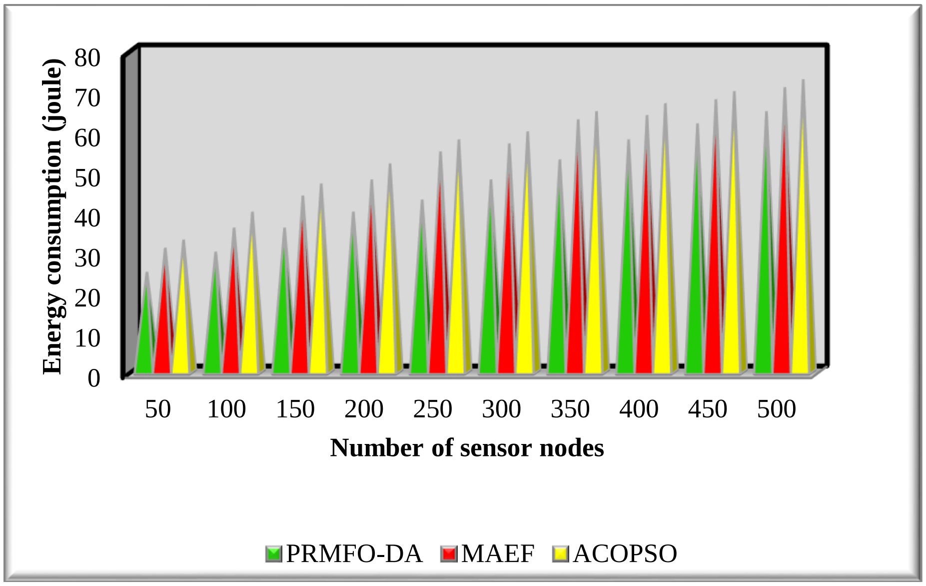

Figure 3 Comparative Analysis Using Energy Consumption

Figure 3 represents a comparative analysis of energy consumption versus a number of sensor nodes. As shown in figure 3, the different colors of the cone represent the energy consumption of the three different techniques namely PRMFO-DA technique, MAEF [1], ACOPSO [2]. The green color cone refers to the energy consumption of PRMFO-DA technique, whereas the cone represented in red and yellow color is the energy consumption using MAEF [1], ACOPSO [2] respectively. The performance of the three techniques was analyzed and the results show the proposed PRMFO-DA technique minimizes the energy consumption. This is because of the PRMFO-DA technique uses the poison regression to find the higher energy nodes for data aggregation. The higher energy nodes are identified with the threshold value. The regression coefficient identifies the higher energy node when their residual energy is greater than the threshold value. These higher residual energy nodes are used for data aggregation process since the node utilizes the lesser energy.

To evaluate the energy consumption of three techniques, 50 nodes are considered in the range from 50 to 500. Let us consider 50 nodes are taken in the first run, the energy consumption of PRMFO-DA technique is $25\, joules$. Similarly, the energy consumption of the MAEF [1], ACOPSO [2] are $31\, joule$ and $33\, joules$ respectively. Followed by, the remaining nine runs are performed with a number of sensor nodes. The outcomes of the proposed technique are compared with the existing results. The compared results prove that the PRMFO-DA technique minimizes the energy consumption by 15% and 20% as compared to MAEF [1], ACOPSO [2] respectively.

4.2 Simulation results of network lifetime

Network lifetime is defined as the number of higher energy sensor nodes are selected to perform the efficient data aggregation to the total number of sensor nodes. The network lifetime is calculated mathematically as given below,

$$Network\ lifetime = \left(\frac{Number\ of\ higher\ energy\ sn\ selected}{n}\right) * 100 \qquad (10)$$

From (10), n represents the number of sensor nodes, sn denotes a sensor node. The network lifetime is measured in the unit of percentage (%).

Mathematical calculation for network lifetime:

- **Proposed PRMFO-DA:** Total number of sensor nodes is 50 and the number of higher energy sensor nodes selected is 45. Then the network lifetime is mathematically evaluated as given below,

$$Network\ lifetime = \left(\frac{45}{50}\right) * 100 = 90\ \%$$

- **Existing MAEF:** Total number of sensor nodes is 50 and the number of higher energy sensor nodes selected is 41. Then the network lifetime is mathematically evaluated as given below,

$$Network\ lifetime = \left(\frac{41}{50}\right) * 100 = 82\ \%$$

- **Existing ACOPSO:** Total number of sensor nodes is 50 and the number of higher energy sensor nodes selected is 40. Then the network lifetime is mathematically evaluated as given below,

$$Network\ lifetime = \left(\frac{40}{50}\right) * 100 = 80\ \%$$

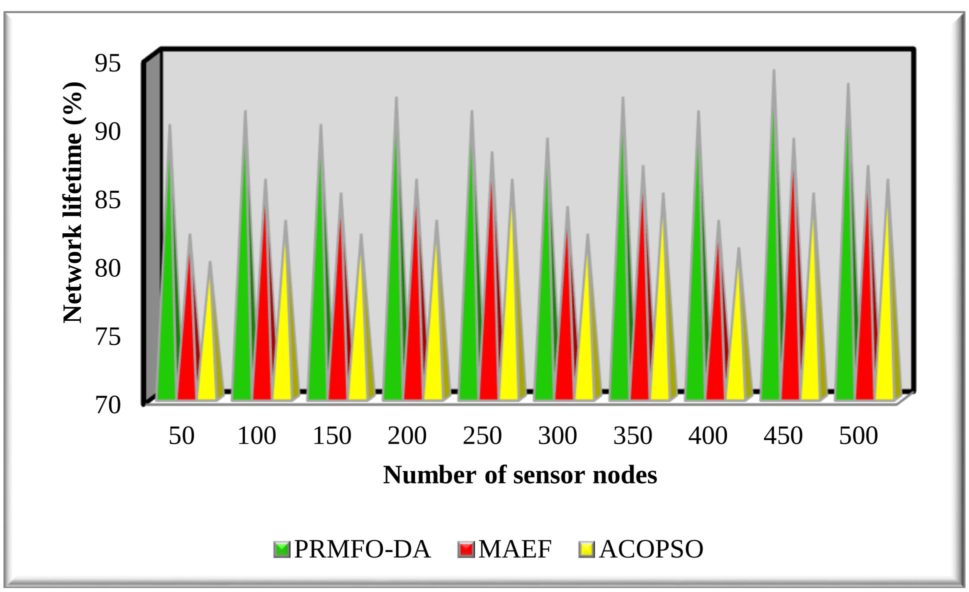

Figure 4 Comparative Analysis Using Network Lifetime

Figure 4 shows the comparative analysis of network lifetime using a number of sensor nodes varying in the range of 50 to 500. To evaluate the performance of network lifetime, ten different runs are considered. The lifetime of the network is enhanced by selecting the energy-efficient nodes for performing a certain task. The proposed PRMFO-DA technique effectively selects the energy-efficient nodes for data aggregation process. By applying multi-objective firefly optimization, the lesser energy nodes find their neighboring energy-efficient nodes for transmitting their collected data because the nodes with lesser energy not suitable for performing data aggregation at a longer duration resulting minimizes the network lifetime. Therefore the selected higher energy nodes used for data aggregation which in turn prolong the network lifetime. The comparison results proved that the PRMFO-DA technique extends the network lifetime by 7% as compared to the MAEF [1] and 10% compared to the ACOPSO [2].

4.3. Simulation results of data aggregation accuracy

Data aggregation accuracy is measured as the number of data packets gathered by the sink node to the total number of data packets sent from the higher energy sensor nodes. With this ratio analysis, the data aggregation accuracy is mathematically formulated as given below.

$$D_{AA} = \left(\frac{N_{dp}\ collected\ by\ sink}{N_{dp}}\right) * 100 \tag{11}$$

From (11), D_{AA} represents data aggregation accuracy, N_{dp} denotes the number of data packets. The D_{AA} is measured in the unit of percentage (%).

Mathematical calculation for data aggregation accuracy:

- **Proposed PRMFO-DA:** Number of data packets collected by the sink node is 23 and a total number of a packet sent is 25. Then the data aggregation accuracy is measured as given below,

$$D_{AA} = \left(\frac{23}{25}\right) * 100 = 92\%$$

- **Existing MAEF:** Number of data packets collected by the sink node is 21 and a total number of a packet sent is 25. Then the data aggregation accuracy is measured as given below,

$$D_{AA} = \left(\frac{21}{25}\right) * 100 = 84\%$$

- **Existing ACOPSO:** Number of data packets collected by the sink node is 20 and a total number of a packet sent is 25. Then the data aggregation accuracy is measured as given below,

$$D_{AA} = \left(\frac{20}{25}\right) * 100 = 80\%$$

Figure 5 shows the comparison of the data aggregation accuracy using a number of data packets varied from 25 to 250. Here, 'x^' axis represents the number of data packets and 'y' axis represents the data aggregation accuracy. With the number of data packets, data aggregation accuracy is said to be increased as compared to existing methods. This is because of the application of regression and optimization technique. The Poisson regression function analyzes residual energy of the nodes and finds the higher energy nodes. In addition, the firefly optimization is applied and detects the nearest energy efficient nodes. Then the higher energy nodes collect the data from the lesser energy node and send to the sink node. The sink node gathers the data from the higher energy nodes resulting in minimizes the data packet loss and improve the data aggregation accuracy.

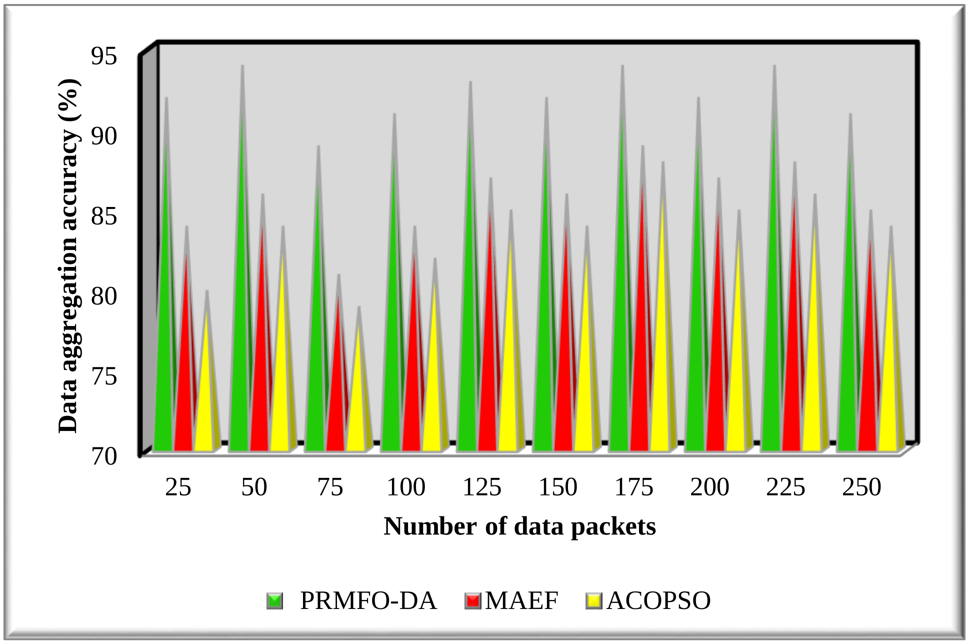

Figure 5 Comparative Analysis Using Data Aggregation Accuracy

For example, 25 data packets sent from the higher energy node, 23 data packets are collected by the sink node and the data aggregation accuracy is 92% using PRMFO-DA technique. Similarly, 21 data packets and 20 data packets are collected by sink node using MAEF [1] and ACOPSO [2] and their accuracy percentages are 84% and 80% respectively. Totally ten results are obtained with the different data packets. The results show that the data aggregation accuracy is significantly improved by 8% and 10% as compared to existing methods.

4.4. Simulation results of data aggregation time

Data aggregation time is measured as an amount of time taken by sink node to collect the data packets from the higher energy sensor nodes. The data gathering time is computed mathematically as follows,

$$DAT = N_{dp} * time(\,aggregating\ single\ dp) \qquad (12)$$

In equation (12), DAT represents the data gathering time, N_{dp} denotes number of the data packets. The DAT is measured in terms of milliseconds (ms).

Mathematical calculation for data aggregation time:

- **Proposed PRMFO-DA:** Number of data packets is 25 and the time for aggregating one data packet is $0.5ms$. Then the overall data aggregation time is mathematically evaluated as follows,

$$DAT = (25 * 0.5ms) = 12.5\ ms \sim 13ms$$

- **Existing MAEF:** Number of data packets is 25 and the time for aggregating one data packet is $0.8ms$. Then the overall data aggregation time is mathematically evaluated as follows,

$$DAT = (25 * 0.8ms) = 20ms$$

- **Existing ACOPSO:** Number of data packets is 25 and the time for aggregating one data packet is $0.9ms$. Then the overall data aggregation time is mathematically evaluated as follows,

$$DAT = (25 * 0.9ms) = 22.5ms \sim 22.5ms$$

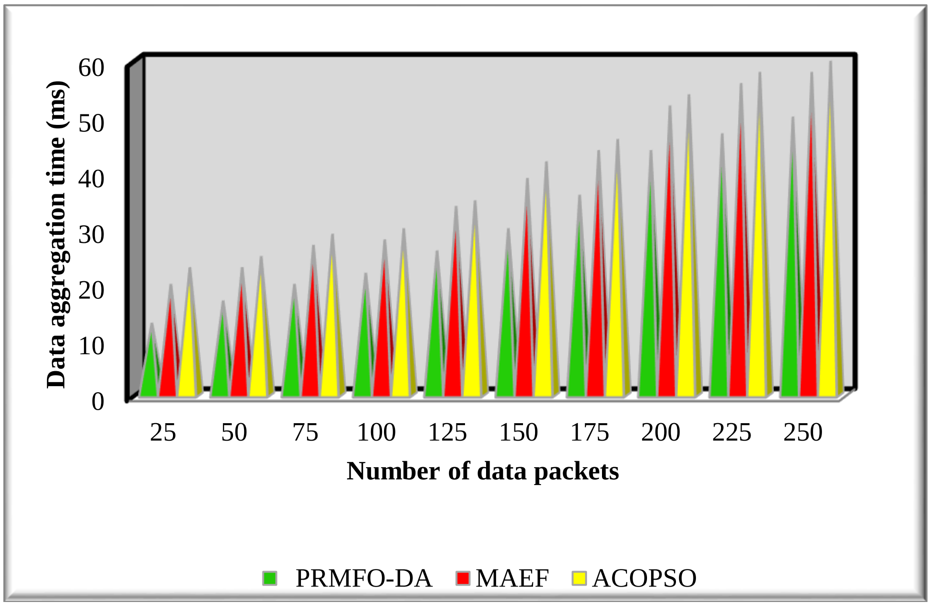

Figure 6 Comparative Analysis Using Data Aggregation Time

Figure 6 illustrates the simulation results of data aggregation time versus a number of data packets. The result of data aggregation time is considerably minimized using PRMFO-DA technique when compared to existing methods. In WSN, the sink nodes act as a data collector which aggregates the data only from the higher energy sensor nodes in the network rather than collecting all the nodes. If the sink node collects the data from all nodes directs a longer delay. But the PRMFO-DA technique collects the data only from the higher energy nodes. This helps to improve the data aggregation and minimizes the delay. Therefore, the PRMFO-DA technique takes a lesser amount of time for aggregating the data packets. Let us consider 25 data packets for calculating the data aggregation time. The time taken by the PRMFO-DA technique for aggregating 25 data packets is 13ms. Whereas, 20ms and 23ms time were taken by the MAEF [1] and ACOPSO [2] techniques. The discussion proves that the data aggregation time is significantly minimized by 22% and 26% when compared to state-of-the-art methods.

The above discussion clearly illustrates that the PRMFO-DA technique outperforms well as compared to the existing techniques.

5. Related works

A scalable method was designed in [11] for energy-efficient data collection. The designed method provides near-optimal performance and failed to offer optimal results. A Contact-Aware Expected Transmission Count was developed in [12] to improve the performance of data collection with minimum delay. The energy-optimized data collection was not performed.

A mobile data collector (MDC) method was developed in [13] for energy-efficient data aggregation and improve the network lifetime. But the method failed to minimize the data aggregation time. A distributed data gathering protocol was designed in [14] using a mobile sink for WSNs. But the mobile sink has utilized more energy to collect the data from all the sensor nodes in the network.

A Distributed Data Gathering Approach (DDGA) was introduced in [15] to perform the data collection with lesser energy consumption. But the data gathering accuracy was not improved. A simple adaptive and distributed energy balanced method was developed in [16] for data aggregation. But the designed method failed to minimize the data transmission delay since it failed to find the energy-efficient nodes.

An energy-efficient data gathering approach was designed in [17] based on mobile Sink with Fixed Points. The designed approach minimizes the time delay on data collection but the performance of network lifetime was not improved. A Two-Tier Distributed Fuzzy Logic Based Protocol (TTDFP) was designed in [18] to prolong the lifespan of the network. The designed protocol failed to use an optimization technique for efficient data aggregation.

An adaptive anchor selection algorithm was designed in [19] based on the sensor's energy level for performing the data aggregation with minimum latency. But the performance of the data gathering accuracy was not improved. A Mobile agent-based Energy-aware data aggregation (MAPE) scheme was introduced in [20] for collecting the data and send back to the sink. Though the scheme minimizes the execution time for data aggregation, the data aggregation accuracy was not improved.

6.Conclusion

A PRMFO-DA technique is introduced for improving the data aggregation accuracy with lesser time consumption in WSNs. This contribution is achieved by applying the Poisson regression and firefly optimization algorithm. The regression function is used to analyze the node energy level in the distributed network. Then the lesser energy node finds the neighboring higher energy nodes for data packet transmission. Finally, higher energy nodes send the collected data packets to the sink node for further process with minimum packet loss. This helps to improve the data aggregation accuracy and minimize the data aggregation time. The simulation of PRMFO-DA technique and existing methods are carried out with different performance metrics such as energy consumption, network lifetime, data aggregation accuracy and data aggregation time. Hence the results and discussions concluded that the PRMFO-DA technique effectively performs the efficient data aggregation with lesser energy consumption and improved the network lifetime than the state-of-the-art methods.

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