EFFICIENT ROUTING OPTIMIZATION MODEL FOR SOLAR ENERGY WIRELESS SENSOR NETWORK USING LINEAR FUNCTION MAYFLY ALGORITHM

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Abstract: A wireless sensor network (WSN) is a collection of sensor nodes that work together to monitor and control their immediate surroundings. However, such a network needs to contend with frequent topological changes, and constrained communication, memory, and energy resources. For effective and seamless operation of WSN, the nodes must be driven by a sustainable solar energy source, resulting in a Solar Energy Wireless Sensor Network (SE-WSN). This research work has therefore developed a routing protocol for SE-WSN to find the optimal link between the source and destination using the Linear Function Mayfly Algorithm (LFMA). The developed technique was simulated in a MATLAB environment. The result of the study was compared with Fractional Firefly Chicken Swarm Optimization (FF-CO) and Particle Swarm Optimization Routing Protocol (PSO-RP) using end-to-end delay and energy consumption as performance metrics. For end-to-end delay, our technique recorded 0.62 ms, FF-CO has 0.70 ms while PSO-RP recorded 0.72 ms at 50 intermediate nodes. For the energy consumption, at 30 nodes, this study result showed 0.2 J/sec of energy consumed; FF-CO and PSO-RP showed 0.4 and 0.8 J/sec respectively. From the result analysis, it is therefore evident that the LFMA routing technique as proposed in this work has demonstrated a better performance.

Keywords: Solar Energy Wireless Sensor Network, Routing Protocol, Linear Function Mayfly Algorithm

Introduction

The development and use of wireless technology have grown substantially in recent years. Modern developments in digital wireless communication circuits have made it feasible to create low-cost, small, and power-efficient sensor nodes (Abidoye et al., 2012). Among the varieties of wireless networks is the Wireless Sensor Network (WSN). WSN is an infrastructure-free network technology that monitors the system using numerous sensor nodes. Additionally, there may be a lot of low-cost micro-sensor nodes connected wirelessly to form a multi-hop self-organizing network, or it can be a collection of geographically dispersed wirelessly connected sensor nodes (Kandris et al., 2020; Anwer et al., 2022). The use of sensor networks for data collection and monitoring has increased due to networking techniques and semiconductor technology. It can also monitor the movement of mobile targets or environmental parameters like temperature and humidity (Li et al., 2019; Krishna Karne et al., 2021). WSNs do have certain limitations, such as routing protocol challenges, energy-saving optimization, and limited resources in system monitoring. Because of their small size, WSNs are fitted with tiny batteries that have a finite amount of energy, repeated topology changes, constrained memory, and communication resources (Abidoye et al., 2012; Kaushik et al., 2016). Owing to these difficulties, WSN needs a battery and external power source to sense and send data seamlessly. The battery has to be replaced or recharged after its energy is exhausted, and this has become a crucial component of routing protocols for wireless sensor networks (WSNs) which has become an area of significant research (Li et al., 2019). Even though battery capacity is a major limitation for WSN applications, solar-powered wireless sensor networks can serve as a better alternative since they can guarantee the highest power density and best efficiency. Among all, it also has a long lifespan and requires relatively little maintenance (Himanshu et al., 2018).

Through the SE-WSN, rechargeable batteries may obtain energy from the environment while simultaneously improving network performance (Qian et al., 2023). However, several unavoidable circumstances (like shadows, solar panel orientations, and placements) enable the energy distribution in the nodes to be inconsistent. The energy remains sleeping until sufficient energy is amassed to energize the nodes when they are ready to go into a deep slumber. As such, nodes need to be kept awake for a longer period to maximize network energy efficiency given the power constraints. By enhancing the average awake time of each node and putting in place a strong routing architecture, SE-WSN integrity may be effectively preserved (Li et al., 2020). To handle further problems such as topology distortion that arise from a node failing due to energy loss, efficient routing methods are necessary. This will support the long-term operations management and communication strategies for energy saving. Among the main SE-WSN research topics that needed additional focus are routing optimization algorithms, energy management, and node hardware design. Nevertheless, there is a paucity of research on routing algorithms for addressing SE-WSN routing difficulties (Wu et al., 2021). The Mayfly algorithm is one of the most efficient bio-inspired algorithms that have been applied to solve complex routing optimization problems in many engineering and science applications (Jasmine & Chenthalir, 2022). Mayfly combines the advantages of particle swarm optimization (PSO), genetic algorithm (GA), and firefly algorithm (FA). This makes it a powerful optimization technique. However, it also has the shortcomings of these combined (PSO, GA, and FA) algorithms. This makes it (mayfly) suffer from insufficient search capability and low convergence speed (Fortes et al., 2022). Therefore, this study is about the development of an improved mayfly algorithm known as the linear function mayfly algorithm (LFMA) for routing optimization in SE-WSN. The developed model was simulated in a MATLAB environment. The end-to-end latency and energy consumption of a SE-WSN were considered while selecting a routing protocol. A number of the techniques that have been used in several studies to improve the working operation of sensor nodes (both WSN and SE-WSN) are presented here. Yadav et al. (2018) utilized particle swarm optimization (PSO) which is one of the bio-inspired algorithm methods for assessing the network lifespan of the WSN. The most crucial component of WSNs is their energy balancing, and data transmission is one of several clustering techniques that have been created to maximize this harmony. The main purpose of these techniques is to increase the lifespan of sensor networks. Load balancing and methods that save energy are implemented in the clustering algorithms. The PSO technology is the foundation for the network lifetime improvement approach. Both group building and cluster head (CH) selection are supported by it. After putting the developed method through a rigorous testing process and comparing the outcomes to earlier approaches like Low Energy Adaptive Clustering Hierarchy Protocol [LEACH] among others. It is determined that the PSO-based clustering algorithm produces superior outcomes. In Solomon & Olusesi (2019), the authors developed a model for Mobile Ad Hoc Network (MANET) energy management that employs the adaptive information bat algorithm, which is inspired by nature, to optimize and control the energy of nodes in MANETs. As a result, there were fewer connection failures and an extended network lifespan. Similarly, Liu et al. (2019) developed an improved energy-efficient LEACH (IEE-LEACH) protocol, which accounts for the remaining node energy and the average energy of the network. To enable accomplishing optimal results in terms of reducing sensor usage, the developed IEE-LEACH was responsible for the number of ideal CHs and forbids the nodes that are closer to the base station (BS) from joining in the cluster formation. In addition to a new threshold for choosing CHs among sensor nodes, the planned IEEE-LEACH employs single-hop, multi-hop, and hybrid communications to increase network energy efficiency. The result significantly lowers WSNs' energy usage compared to a few of the current routing schemes. A clustering routing protocol to lengthen the network's life was developed in Ari et al. (2016). This protocol uses the artificial bee colony (ABC) method to solve the routing and clustering problems. The clustering problem was solved by developing an efficient fitness function for ABC that considers node energy and neighborhood data. The protocol does not account for the load balance across cluster heads, which impacts network performance. Yarinezhad & Hashemi (2019), proposed a brand-new cluster-based routing algorithm that addresses the load balancing problem in wireless sensor networks (WSN) by utilizing a Fixed-Parameter Tractable (FTP) approximation technique. By establishing a virtual grid infrastructure with several equal-sized cells, the FTP approximation technique is also made appropriate for large-scale WSNs. The procedure runs separately for each cell. Merit is designed to assess the cell based on the average energy of its nodes, the distance between the base station and the cell center, and the gateway's starting energy. This is done in an attempt to increase the network's longevity and balance energy usage across nodes. El-Hageen et al. (2022) developed an agile lossless reduction for big data of SE-WSN. Three stages make up the suggested algorithm. Unwanted data are eliminated in the first stage. To save a significant amount of storage space, the second phase organizes date and time data and transforms it into values of seconds that reflect the difference between the current and prior rows. Lastly, to further reduce the amount of storage space, the third step makes use of the qualities of the data and gathers them in a single row. Kosunalp et al. (2016) proposed an energy prediction algorithm for energy-harvesting WSN (EH-WSN) with Q-Learning. For EH-WSNs, the solar energy prediction technique is presented. It utilizes the use of prior information on energy generation from previous days as well as the most current weather conditions. The suggested method, a solar energy prediction algorithm with Q-learning (QL-SEP), is predicated on the idea that solar energy behaves as a periodic energy source, splitting time into equal-length slots and repeating them daily. The algorithm performs better in long-term evaluations, as confirmed by the performance results. By intelligently controlling the energy level of the sensor nodes, it can be integrated into the creation of the present and future MAC protocols to predict the quantity of energy to be harvested within a specific time slot, thereby enhancing the performance of WSNs. Qi et al. (2019) designed an adaptive energy management technique to increase the battery life of solar-powered WSNs. Initially, the supercapacitor (SC) serves to collect solar energy and supply the node with power as required. When there is not enough solar energy and the charge is low, the battery charges the SC to keep it from running out. Furthermore, the power required to charge the SC from the battery is directly correlated with the node's average power consumption. As a result, this approach adjusts to the node load situation. Additionally, the suggested approach is adaptable to changing weather conditions. This technique lowers the battery's charging power by battery state of charge [SOC] when the node is exposed to intense sunshine, causing the solar power to become excessive and perhaps damaging the battery. The battery is shielded from high current charging damage in this way. To confirm the robustness and availability, simulation parameters like SC capacity, event frequency, and stimulated load power are changed. The suggested approach yielded minimal battery deterioration in all situations, according to the results. Continuing in this trend, the study in Junior et al. (2018) came up with a network policy in solar power sensor networks that optimizes the minimum energy among the sensor nodes within the network. An algorithm known as Renewable Energy-Based Routing (REBORN) was introduced. Because every sensor node has a small solar cell built into it, it can recharge its batteries based on the amount of sunlight strength that is available, which changes during the day/night cycle. Unlike the majority of suggested solutions, REBORN decides whether to send and/or forward data based on both the residual battery level and the intensity of the available energy. When the sink node sends a controlled flood message with its position in the grid included, the REBORN begins. A variable that indicates whether the packet was received by the node is kept to manage flooding. Dehwah et al. (2017) proposed a spatial routing algorithm with energy awareness that can control both available and residual energy in WSN. A stationary sensor that is capable of sensing flooding as well as traffic was developed to facilitate remote computing while reducing power usage. This was done to address the issue of optimizing the sensor network's energy margin over a predetermined time horizon to ensure energy availability during flood events, when solar energy may be in short supply owing to atmospheric coverage. Results indicate that it is especially well-suited to low-power wireless sensor networks because of its minimal memory and computational power needs.

Conclusively, all the studies presented above have chronicled the work done so far by researchers aimed at providing insight into the use of several techniques for routing protocols in wireless sensor networks. This present study is now proposing a unique algorithm called LFMA for routing optimization in SE-WSN.

Materials and Methods

The working operation of SE-WSN was presented here, along with the developed mathematical model of the linear function mayfly algorithm (LFMA). Figure 1.0 shows the basic building block diagram of a SE-WSN arrangement.

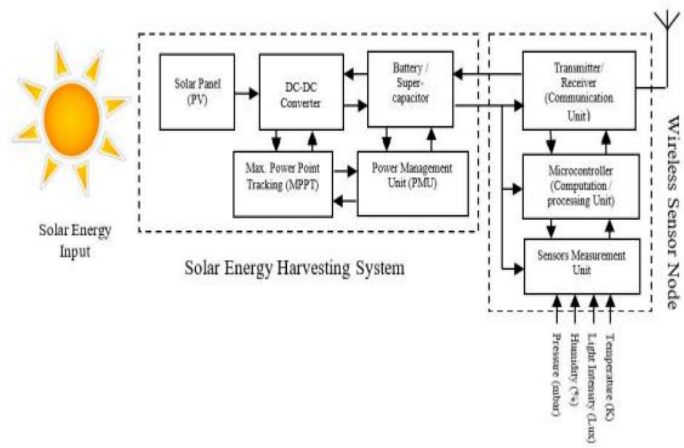

Figure 1: Block diagram of SE-WSN (Himanshu et al., 2018)

As shown above, the arrangement consists of two units; solar energy unit and wireless sensor unit. The solar unit is made up of a solar photovoltaic cells, converter, maximum power point tracker (MPPT) and energy storage device (battery super capacitor storage). While the wireless sensor unit consists of the sensor board measurement unit, processing unit (microcontroller) and communication unit (transmitter and receiver).

In their operation, the solar panels capture ambient light energy from the sun and transform it into electrical energy which is the direct current (DC) voltage. The WSN node load can be powered directly by this DC voltage, or it can be saved for later use in a rechargeable battery. This DC voltage is controlled by the DC-DC converter in order to charge the battery. The sensor measurement unit is used by the WSN node to measure the necessary physical quantity (such as temperature, light, humidity, and pressure). In the processing unit, this detected data is processed by a microcontroller. Using a transmitter unit, the measured or sensed data is wirelessly transmitted in the form of data packets to the neighboring network node (Sharma et al., 2018). The main applications of SE-WSNs are air quality monitoring in transportation, smoke monitoring, light intensity monitoring, humidity monitoring, pressure monitoring, temperature monitoring, and environment monitoring. Figure 2.0 shows a WSN node with its external power supply connection attached to two solar panels (Himanshu et al., 2018).

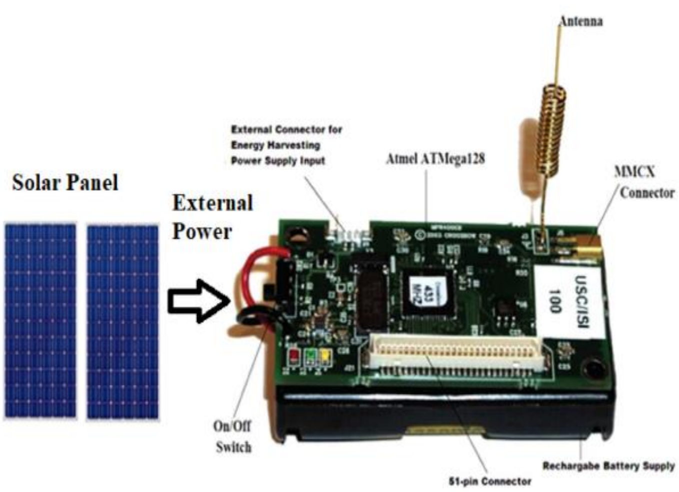

Figure 2: WSN Node Connected to Solar Panels (Himanshu et al., 2018)

Mayfly Algorithm

The mayfly algorithm was developed by fusing the principles and benefits of three optimization algorithms: Fire Fly Algorithm (FA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) (Zhang et al, 2022; Zervoudakis & Tsafarakis, 2020).To address optimization problems, some researchers have used either the standard mayfly method or the enhanced mayfly algorithm (Oladimeji et al., 2022)

Movement of Male Mayfly

Mayflies are initialized separately for males and females. Every mayfly adjusts its position in response to its experiences as well as those of others. The mayfly's current position is considered to be $x_j^t$and its position changes when velocity is applied to its current location. The search space is represented as i at a time t. It may be found using following Equation 1 (Jasmine & Chenthalir, 2022)

$$V_{ij}^{t+1} = V_{ij}^{t} + a_1 e^{-\alpha r_p^2}(pbest_{ij} - x_{ij}^t) + a_2 e^{-\alpha r_g^2}(gbest_{ij} - x_{ij}^t) \quad (1)$$

where v_{ij}^t is the male mayfly velocity, x_{ij}^t is the position of male mayfly, a_1 and a_2 are positive attraction constants, $pbest_{ij}$ is the best position which the male mayfly has ever visited, i is the number of mayfly, $j = 1, \dots \dots \dots . n$ which is searching space, t is the time step, a_1 and a_2 are the constants which measure the contribution constants that is used in social and cognitive component, α this is the visibility co-efficient that limits the visit of the mayfly to other mayflies, r_p and r_g is the distance between x_i, $pbest_i$ and $gbest_i$. Assume x_i^t is the current position for mayfly i in the search space at time t. The present position is changed by adding velocity v_i^{t+1} to the present positon. This turns the current positon to be update as shown in Equation 2 (Zervoudakis & Tsafarakis,2020)

$$x_i^{t+1} = x_i^t + V_{ij}^{t+1} \quad (2)$$

Movement of Female Mayfly

The attractiveness of males and females is determined by the quality of the present solution. The best-performing man is drawn to the finest female, and so on until all mates have been identified. Likewise, the present whereabouts of female mayflies might be represented as shown in equation 3 [11].

$$y_i^{t+1} = y_i^t + V_i^{t+1} \quad (3)$$

While the second-best female mayfly attracts the second-best male, the best female mayfly attracts the best male. After updating the female's velocity, the equation is expressed in equation 4 [11].

$$V_{ij}^{t+1} = \begin{cases} v_{ij}^t + a_3 e^{-\beta r_{mf}^2}(x_{ij}^t - y_{ij}^t), if\ f(y_i) > f(x_i) \\ v_{ij}^t + fl * r\ if\ f(y_i) \le f(x_i) \end{cases} \quad (4)$$

where v_{ij}^t is the female mayfly velocity, y_{ij}^t *and* x_{ij}^t is the position of male and female velocity.
a_2 is the positive attraction constant, β is the fixed visibility coefficient, r_{mf} is Cartesian distance between male and female mayfly, fl is the random walking coefficient which is used when the attraction between male and female failed, r is the random number between -1,1

Mating Between Mayflies

Through mating, male and female mayflies carry out their mating ritual. This makes the Mayfly algorithm capable of doing a worldwide search. When male and female mayflies have the same individual fitness mate, their progeny is shown in Equations 5 and 6 (Wang et al., 2022; Hassan et al., 2021) to illustrate the generation of the fitness value, which is utilized to choose parents for mating and producing two offspring.

$$offspting1 = L * male + (1 - L) * female \quad (5)$$

$$offspting2 = L * female + (1 - L) * male \quad (6)$$

male denotes the presence of male parent
female denotes the presence of female parent
L is a random number within a range 0 to 1.
offspring1 and offspring2 are initial velocity which are both assumed to be zero

Algorithm 1: Mayfly Algorithm (Wang et al., 2022)
Input: *male and female population sizes* N_1 *and* N_2*; maximum iterations* $iter_{max}$*;*
visibility coefficient β*; learning factors* a_1 *and* a_2*; nuptial dance coefficient* d*;*
random flight coefficient fl*; objective function* $f(x)$
$\boldsymbol{Output}$: $Optimal\ solution\ g_{best}$
Start
Initialize the male and female velocities V_m *and* V_f
Evaluate all solutions according to the objective function $f(x)$
Find the best value from all solutions (g_{best})
for $iter = 1\ to\ iter_{max}$ **do**
Adjust the speed of a female mayfly using Equation 3
Adjust the position of a female mayfly using Equation 4
Adjust the speed of male mayfly using equation 1
Adjust the position of male mayfly using equation 2
Sort the mayflies and rank them based on $f(x)$
Perform crossover and generate male and female offspring
Mutate the offspring
Divide offspring into male and female at random
Update the worst individuals with finest new ones
Update p_{best} *and* g_{best}
End for
End

Conceptual Model of LFMA Routing Protocol for SE-WSN

The sender and destination are connected to the nodes of the SE-WSN, as illustrated in Figure 3.0. The development of an effective routing method is challenging due to the dynamic nature of the sensor nodes in SE-WSN. This study presented a linear function with inertia weight w in response to the disadvantages of the mayfly algorithm, which include the inability to balance exploration and exploitation and the tendency to stagnate into local optima. During the optimization phase, the linear function inertia weight is used to balance the mayfly algorithm's capacity for exploration and exploitation while also adjusting the location and velocity of the mayflies. This proposed optimization technique has a strong hybrid mathematical architecture and is based on adjusting and improving the mayfly algorithm technique. The greatest outcomes come from combining this method with a routing mechanism of SE-WSN by generating an optimized routing path based on the new position of each node within the network using Equation 13. The shortest path to the destination was established by the dashed lines connecting the sender to nodes 1, 2, and 5 out of the different numbers of links in the network, as shown in Figure 3.

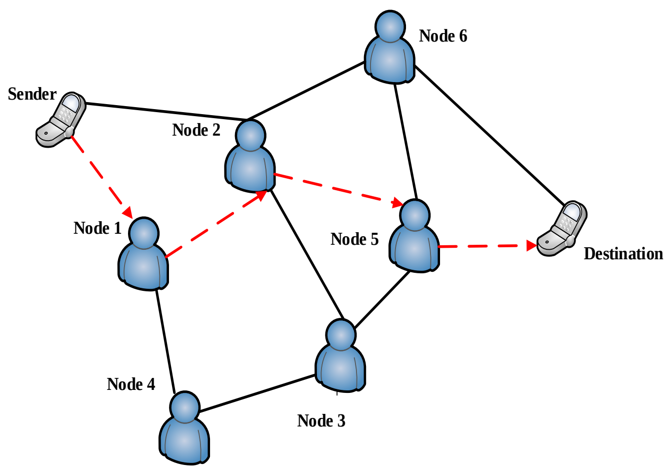

Figure 3: Conceptual Model of Routing Protocol in SE-WSN

The mathematical model of LFMA is as described below:

$$lf_w = l_w \times DF_t \times AF_{iter} \quad (7)$$

$$l_w = \left(\frac{Iter_{max} - iter}{iter_{max}}\right)(w_{min} - w_{max}) + w_{max} \quad (8)$$

lf_w is linear function inertia weight, l_w is the linear weight, $iter_{max}$ is the maximum number of iterations, $iter$ is current iteration numbers, w_{min} and w_{max} are the minimum and maximum inertia weight values, DF_t and AF_t is diversity and the adjustment function and they are represented as shown in Equations 10 and 11

$$DF_t = 1 - \frac{2}{\pi}\arctan(G_f) \quad (9)$$

$$G_f = \frac{1}{N}\sum_{i=1}^{N}(f_{(x_i)} - f_{avg})^2 \quad (10)$$

$$f_{avg} = \frac{1}{N}\sum_{i=1}^{N}(f_{(x_i)}) \quad (11)$$

$$AF_t = e^{\left(\frac{-iter^2}{2\rho^2}\right)} \quad (12)$$

where $\rho = {iter}/{3}$

N is the searching space size , $f_{(x_i)}$ is the fitness of mayfly i , f_{avg} is the current average fitness of the network size. The linear function inertia weight was introduced in this work to enhance the performance of the mayfly algorithm by balancing the exploitation and exploration, changing the node velocity update in equation 1 to the velocity update as shown in Equation 13

$$V_{ij}^{t+1} = lf_w V_{ij}^t + a_1 e^{-\alpha r_p^2}(pbest_{ij} - x_{ij}^t) + a_2 e^{-\alpha r_g^2}(gbest_{ij} - x_{ij}^t) \quad (13)$$

Also, the velocity update of the female mayfly in equation 4 becomes;

$$V_{ij}^{t+1} = \begin{cases} lf_w v_{ij}^t + a_3 e^{-\beta r_{mf}^2}(x_{ij}^t - y_{ij}^t), & if\ f(y_i) > f(x_i) \\ lf_w v_{ij}^t + fl * r & if\ f(y_i) \le f(x_i) \end{cases} \quad (14)$$

Equations 13 and 14 for the two velocities balance the search process while also preventing mayfly entrapment within local optima.

The LFMA algorithm for routing protocol in SE-WSN is shown below in Algorithm 2

Algorithm 2: LFMA Algorithm

Input: *Generate randomized hexadecimal value*

Output: *Optimal solution* g_{best}

Start

Generate randomized hexadecimal value.
Convert to decimal and generate decimal value
// Perform key generation
Input: *male and female population sizes* N_1 *and* N_2; *maximum iterations* $iter_{max}$; *visibility coefficient* β; *learning factors* a_1 *and* a_2; *nuptial dance coefficient* d; *random flight coefficient* fl; *objective function* $f(x)$

Output: *Optimal solution* g_{best}

Initialize the male and female velocities V_m *and* V_f
Evaluate all solutions according to the objective function $f(x)$
Find the best value from all solutions (g_{best})
for $iter = 1$ *to* $iter_{max}$ ***do***
Adjust the speed of female mayfly using Equation 14
Adjust the position of female mayfly using Equation 3
Adjust the speed of male mayfly using Equation 13
Adjust the position of male mayfly using Equation 2
Sort the mayflies and rank them based on $f(x)$
Perform crossover and generate male and female offspring
Mutate the offspring
Divide offspring into male and female at random
Update the worst individuals with finest new ones
Update p_{best} *and* g_{best}
End for

End

2.6 Simulation of the Proposed LFMA Routing Protocol

The work was simulated in a MATLAB environment using release R2020a. The system configuration is an Intel Core i5 processor running at 2.5GHz frequency, 8GB of RAM, a 250GB solid state drive (SSD) and running on a Windows 10 Ultimate 64-bit system. The input parameters, which correspond to the mobile nodes, are from 10 to 80 randomly generated values. A fixed number of 100 running iteration times was applied to each randomly produced node. Additionally, as indicated in Tables 1 and 2, LFMA was compared with existing fractional firefly chicken swarm optimization (FF-CO) (Hmaid et al., 2022) and particle swarm optimization routing protocol (PSO-RP) (Mohammed et al., 2022) in order to assess the performance of this study. The performance metrics used in this simulation work are energy consumption and end-to-end delay.

Results and Discussion

Table 1 and Figure 4 show the test result using the end-to-end delay metric.

Table 1. End to End Delay (ms)

Nodes	FF-CO	PSO-RP	LFMA
10	0.2	0.40	0.10
20	0.5	0.54	0.30

25	0.51	0.58	0.45
30	0.54	0.6	0.48
35	0.52	0.62	0.50
40	0.60	0.67	0.55
45	0.62	0.64	0.57
50	0.70	0.72	0.62
55	0.73	0.75	0.66
60	0.8	0.83	0.73
65	0.84	0.88	0.79
70	0.86	0.91	0.82
75	0.89	0.94	0.86
80	0.92	0.97	0.89

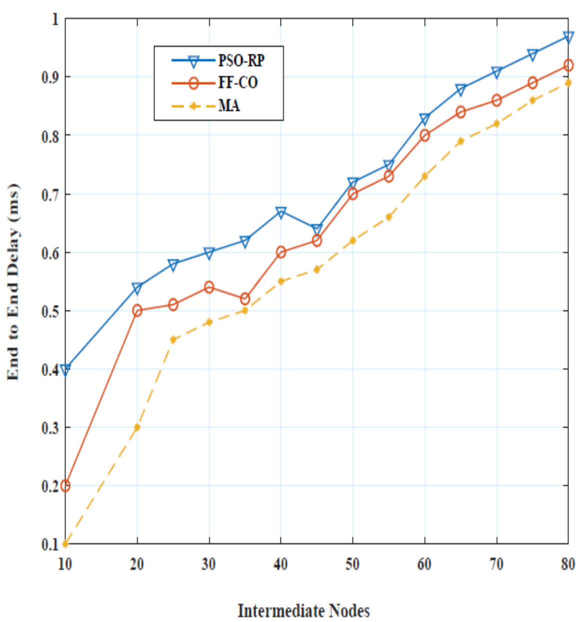

Figure 4: End to End Delay

From the plot (Figure 4) above, it can be seen that LFMA demonstrated minimized and optimal routing protocol compared with FF-CO and PSO-RP. On the overall average, LFMA recorded 0.59 ms which is the least and minimal delay compared with FF-CO which recorded 0.66 ms and PSO-RP measured 0.72 ms. Also, on the plot and at 30 intermediate nodes, the end-to-end latency for this LFMA was 0.48 ms, but for FF-CO and PSO-RP the measured end-to-end delay were 0.54 and 0.60 ms, respectively. With 70 intermediate nodes, the end-to-end of the LFMA was 0.82 ms, while the end-to-end delays for FF-CO and PSO-RP were 0.86 and 0.91 ms respectively. This result confirms the effectiveness and efficiency of our proposed technique (LFMA) as a routing protocol.
Another metric used in evaluating the performance of this model is the level of energy consumption, which is measured in Joules/second. The result of testing using this metric is presented in Table 2 and Figure 5.

Table 2. Energy Consumption (Joules/sec)

Nodes	FF-CO	PSO-RP	LFMA
10	1.25	1.27	0.5
20	0.3	0.6	0.2
25	1.27	1.3	0.7
30	0.4	0.8	0.2
35	1.36	1.71	0.9
40	0.2	0.4	0.1
45	2.1	2.3	1.1
50	0.2	0.4	0.1
55	1.7	1.9	0.8
60	0.5	0.8	0.3
65	1.3	1.6	1.1
70	0.8	1.1	0.6
75	1.6	1.8	0.9
80	0.3	0.5	0.1

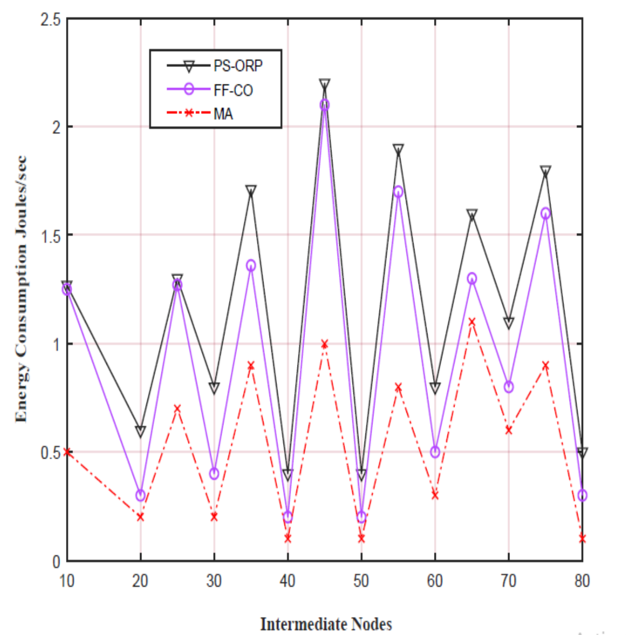

Figure 5: Energy Consumption

As shown in the Table 2 and Figure 5 above, LFMA consumes the least energy during the process of data transmission and reception. On the overall average, LFMA consumed 0.54 J/sec of energy, while FF-CO and PSO-RP consume 0.95 and 1.18 J/sec, respectively. These two techniques have consumed more energy due to poor routing decisions made between intermediate nodes within the network. Also, at node 45, LFMA recorded 1.1J/sec while FF-CO measured 2.1J/sec and PSO-RP measured 2.3J/sec. Among all the test parameters and techniques used in this study, PSO gave the worst performance, while LFMA shows the best performance in terms of energy consumption and latency.

Conclusion

Finding the most advantageous link inside a wireless network is the goal of routing techniques. It is an important field of study for wireless networks. Furthermore, it is crucial because the network's transmitting and receiving nodes must be connected via the best route possible. Numerous meta-heuristics and bio-inspired algorithms have been employed in earlier research over the years to solve the routing difficulties that SE-WSN faces as a result of the dynamic topology of the sensor nodes. This study proposed the LFMA routing protocol model with the goal of enhancing SE-WSN routing and lowering the difficulties associated with determining the shortest path between the source and destination. The result of this study showed that it outperformed existing work and thereby improved the node and the network lifetime. However, the identification and extraction of solar PVC characteristics in SE-WSN remain open for further research. Additionally, it is well recognized that environmental factors like pollution and weather patterns have an impact on solar panels. Further effort must be put into designing suitable solar PVC that can endure some of the environmental difficulties. Additionally, this will extend the lifetime of the network and reduce energy consumption when operating SE-WSN.

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