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Firefly Based Energy Efficient Routing of Charging Request in Wireless Rechargeable Sensor Network

SIRON ANITA SUSAN T.+ AND B. NITHYA
Department of Computer Science and Engineering
National Institute of Technology
Tiruchirappalli, 620015 India
E-mail: anitasusan.t@gmail.com+; nithya@nitt.edu

The on-time charging of Rechargeable Sensor Nodes (RSNs) prolongs the lifetime of the Wireless Rechargeable Sensor Network (WRSN). However, it necessitates the prompt and accurate transmission of Charging Requests (CRs) from RSNs to Mobile Charging Drones (MCD), and accordingly the charging trip is planned by MCD. Most of the existing algorithms attempted to forecast the shortest path, which may not be an optimal path for the current network traffic. This causes increased packet loss, retransmissions thus consuming more energy. To address this, Firefly-based Optimal Path Selection Algorithm (FOPSA) is proposed to find an optimum and stable path for the on-time delivery of CRs to MCD using firefly optimization. The proposed fitness function utilizes geometric mean of the residual energy, distance, and hop count to predict the routing path for the transmission of CRs. It ensures that the path has potential RSNs with adequate energy to avoid routing holes. The proposed algorithm is simulated and compared with the existing algorithms in terms of throughput, packet loss, residual energy, and delay.

Keywords: wireless sensor network, wireless rechargeable sensor network, mobile charging vehicle, charging requests, evolutionary computation, firefly algorithm, optimal path

1. INTRODUCTION

Wireless Sensor Network (WSN) is a huge collection of battery powered sensor nodes [1]. These batteries can be wirelessly recharged with Wireless Rechargeable Sensor Network (WRSN) to prolong the network lifetime [2]. The Rechargeable Sensor Nodes (RSNs) of WRSN [3] are used in various applications of data collections [4] where the unattended operability is required such as earthquakes, soil monitoring, and glacier movement monitoring. Wireless charging of batteries, as opposed to permanent batteries, provides more flexible, controllable, and predictable energy replenishment to reduce the number of dead nodes. Energy replenishment in sensor batteries initially demands the installation of external instruments such as wind turbines and solar panels to obtain renewable energy, which can help to extend network lifetime in certain circumstances. It is not possible to rely solely on these procedures because they are unable to function in

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+ Corresponding author.

the absence of energy sources. WRSNs use wireless energy transfer techniques and can be recharged by Mobile Charging Vehicle (MCV) [5], reducing the need for throwaway batteries thus extending the sensor node's operating life. If the RSNs are about to run out of energy, they send the charging request to the nearby MCV. Once the on-demand charging requests are received, the MCV will plan for the charging tour to recharge the RSNs which are in a situation to die.

Forest fires have become a major concern across the entire world, causing havoc on diverse dwellings and forest ecosystems [6]. There has been significant harm to society and the environment as it influences climatic changes and the environment pollution. Unfortunately, the fires are often discovered after they have spread across a broad area thus controlling and stopping the fire becomes arduous many times. As a result, it is necessary to detect forest fires early in order to reduce the amount of damage. If RSNs are deployed in the forest, they sense and detect the fire immediately. To have uninterrupted services, these sensors must have sufficient battery backup. However the following problems are inevitable due to the energy-characteristics of RSNs: (i) Replacing the energy-exhausted sensors in the dense forest is a tedious and risky process; (ii) During the communication process, if the intermediate sensors are energy depleted, it fails to relay the data to the sink nodes. To reduce the communication loss, the energy depleted sink nodes and intermediate nodes should be recharged on time before they die out of energy. In this scenario, MCV plays a vital role to recharge these RSNs thereby extending the network lifetime. But in the dense forest environment, there may not be the proper pathways for MCV to go and recharge RSNs in all the places. So, instead of vehicle, Mobile Charging Drones (MCD) can be utilized for recharging RSNs. The MCD will start from Base Station(BS) at the start of every tour and comes back to BS again for its maintenance and to recharge its backup battery. The deployment of sink or relay RSNs and member RSNs are depicted in Fig. 1. The member RSNs sense the temperature and will send the sensed data to its nearby Sink RSN and this sink RSN will relay these data to the BS. It may be further communicated to the remote station through an internet gateway.

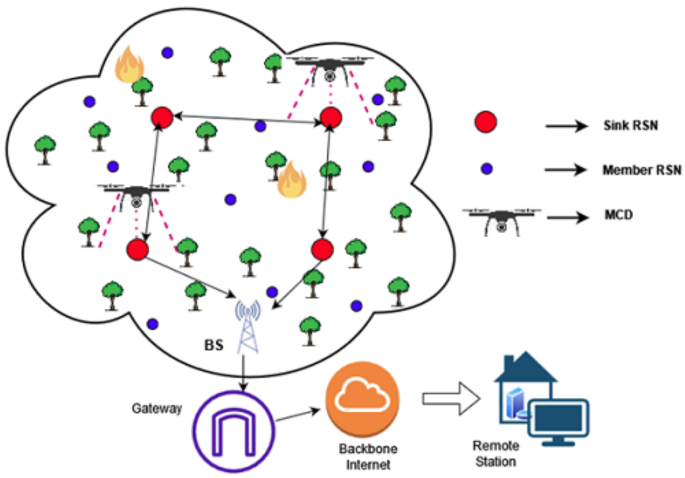

Fig. 1. WRSN network in forest area.

This recharging application of WRSN is made persuasive and capable with the aid of nature inspired optimization algorithms (NIOA) [7] and their contributions are inevitable for solving complex nonlinear and multimodal problems. These Metaheuristic algorithms are designed to perform global searches and to find the best solution for the derived problems. Particle swarm optimization (PSO) [8] is a population-based bio inspired technique inspired by the movement of flocks of birds and schools of fish. The Bat Algorithm (BA) [9] is a new heuristic optimization algorithm that is predicated on bat echo location behaviour. Ant colony optimization (ACO) [10] is a population-based metaheuristic based on food searching nature of the ants. The Firefly Algorithm (FA) [11] is a novel optimization technique which is based on the attraction of fireflies by its light intensity. The light emitted by fireflies is inversely proportional to distance. On comparing with the foresaid bio inspired algorithms, FA is superior for automatic subdivision as well as the ability to deal with multimodality problems. The convergence ratio is quite high in finding an optimal solution to the problem in the search space. Due to these reasons, the firefly algorithm is used to fix the routing problem in this paper.

1.1 Observations and Objectives of the Paper

From the above discussion, it is inferred that the charging request should reliably reach the MCD to enhance the efficient charging of RSNs. This may avoid profuse massive disasters and will rebirth the WRSN. The derivation of optimal path selection is carried out by inheriting the firefly algorithm. The optimal path selection for charging requests confronts two challenges: (i) determining the optimal path from RSN to MCD to circulate the charging request; (ii) constructing the fitness function with dynamic and critical parameters based on current network conditions. With these inferences, the following goals are focused in this paper.

1. Constructing an optimal path to circulate the charging request from sink RSN to MCD by inheriting FA. Evaluating the fitness function for an effective routing solution for multihop communication by considering certain network factors.
2. Proposing Firefly-based Optimal Path Selection Algorithm (FOPSA) with this fitness function. Simulating the proposed algorithm and comparing its performance with existing algorithms under varying scenarios.

The rest of the paper is structured as follows. Section 2 provides a rundown of the related work as well as a summary of it. Section 3 presents the proposed FOPSA along with the construction of fitness function. Section 4 shows the simulation results and comparisons, and the final section delivers the conclusion of the paper.

2. RELATED WORK

Bartomiej *et al*., [12] investigate the use of multicast routing and proposed an optimization model based on three mixed-integer programming problem formulations in order to increase packet traffic throughput. It optimizes TDMA frame composition by assuming fixed gateway locations and multicast routing trees. From the numerical analysis, it has been shown that the proposed work results in massive increase in traffic throughput. This model does not address the packet delay and energy consumption. Abdul *et al*., [13] proposed ACO based multipath transmission to balance the traffic load in the sensor network. The fitness function is evaluated based on node's residual energy, bandwidth and next hop. This multipath transmission diminishes the average delay and route load. The work load is eventually distributed to reduce traffic, but the major disadvantage with the algorithm is that the route has fewer hops and may suffer from delayed tranmission.

Rashmi *et al*., [14] proposed Destination-oriented Zone enabled Squirrel Search Algorithm (DZ-SSA) for providing green communication by balancing energy and packet loss. Steiner tree is built with all potential pathways. The DZ heuristic is then employed for effective search using SSA fitness calculations, where DZ implementation minimizes the search space, allowing the user to reach the destination direction faster. The tree construction is quiet complex and intricate to maintain. Santhana *et al*., [15] presented a stateless high power node multicasting approach to speed up packet delivery to multicast destinations. To minimize the costly neighbour table state information, this approach makes use of the precise placements of sensor nodes. Even though, the proposed Multicast routing has been demonstrated to provide higher success rates with lesser delay, shorter optimum transmission path is not guaranteed thus consuming more energy. Yongbin *et al*., [16] proposed the Localized Optimal Real-time Multicast Routing method (LORM), which discusses both real-time demands and transmission efficiency. LORM is divided into two phases for on-time delivery of packets: (1) the construction of a backbone line with a maximum distance constraint; and (2) the cost-effective branching of neighbouring destinations using a heuristic expectation maximisation allocation. The main advantage here is that it uses the least squares method to find ancillary shared paths. Furthermore, the method streamlines the entire computation for locating feasible ancillary shared paths.

Kavitha *et al*., [17] explored ACO based optimal routing algorithm to reduce node complexity and energy consumption. To build the premium path, the approach selects the best premier nodes based on energy and bandwidth. The ACO calculates the path's expiry time based on the ant's phremone evaporation time. Once all path constraints have been calculated and routes were calculated, packets are routed using DSDV via the best premium path. The algorithm has improved the throughput and shrinked the loss rate but it fails to minimize the number of intermediate hops and transmission path length. Ramin *et al*., [18] reinforced the Grey Wolf Optimization (GWO) algorithm to support cluster-based routing. The algorithm introduces a factor for balancing GWO's exploration and exploitation phases, and a mapping is performed in local search. The algorithm computes the best paths between the CHs by estimating fitness based on energy, distance, and cluster member count. This path selection conserves energy while shortening the distance of the routing path. However, the minimization of the hop count is not addressed.

Preetha *et al*., [19] proposed collision aware routing based on seagull optimization to reduce packet loss and transmission delay. It calculates the best CH for each cluster and then the routing path between the CHs based on the quality of the link, queue length, communication cost, and the node's remaining energy. The algorithm significantly reduced transmission delay and packet loss but failed to conserve energy to extend network lifetime. Mohit *et al*., [20] proposed a solar-based Modified Adhoc On-Demand Distance Vector (Solar-MAODV) algorithm to ensure energy harvesting and data transmission without causing congestion. The MCD obtains energy from solar power and uses it to recharge the Sink RSNs. The AODV algorithm is used to transmit packets between

RSNs by selecting the shortest path based on congestion level. The solar MCD may not be appropriate in certain locations and climates, and data transmission is concentrated on the shortest path rather than the optimal path. This model supports long-distance transmission, but the main drawback is that it increases network latency. Abdelkader *et al*., [21] proposes a gateway-based protocol for multihop routing in heterogeneous environments. In this protocol, sensors in the first field directly communicate with the BS, whereas nodes in the centre field send data to the BS via a gateway. Remaining nodes are clustered, CH is selected and it broadcast data to the gateway. Simulation results demonstrated that the network's throughput and lifetime are enhanced. However, as the number of hops and the delay in data transfer increase, the transmission time and path length are also increased.

Manisha *et al*., [22] addressed the issue of balancing energy and QoS aware routing by taking the trust factor of the nodes into account. Using ACO, the network's source node determines the path based on the lowest energy cost, shortest end-to-end delay, and highest trust factor. The path selection minimised node resistance while optimising energy consumption. It also improved QoS and security, but it increased the routing path's distance. Prachi *et al*., [23] explored an optimal route selection between the CHs and the BS. The CHs are chosen using the Butterfly Algorithm, with the fitness value derived from residual energy, distance, node degree, and node centrality. The route between the CHs and the BS is determined by the ACO algorithm, which takes into account residual energy, distance, and node degree. The algorithm increased the number of active nodes. The drawback is that data transmission time increased due to the increasing hop count. Zongshan *et al*., [24] improved the Artificial Bee Colony (ABC) algorithm as well as the ACO to determine a CH-based routing. The fuzzy C-means clustering algorithm is used by the author for network clustering, and the ABC algorithm is used to select the CH. The fitness function, calculated with average residual energy and distance, is then used to select the best path between CHs and BS using ACO. The hop count is not decreased by the algorithm, which enhances the nodes' energy dissipation. The choice and retention of CHs lead to complexity. Arun *et al*., [25] proposed an energy-aware routing scheme to handle real-time target tracking applications. The relay ability weight factor is calculated in advance based on energy and distance and is disclosed to sensor nodes by their CHs. The route is discovered with maximum relay capability to enhance the network throughput. However, the predefined calculation fails to include the residual energy of the nodes after each data transfer, resulting in an energy imbalance in route selection.

2.1 Inference and Contributions of the Paper

According to the preceding discussion, packet transfer must be optimised for effective data transmission without any delay. The unstable throughput attained by the existing system triggers frequent disruption during the packet transmission. Also, in some of the existing works, aggregated energy source is not well maintained resulting in less packer delivery ratio with increased packet loss. To alleviate these problems and to address the objectives mentioned in Section 1.1, the following contributions are made in this paper.

1. For optimal path selection, the paper proposes an efficient routing algorithm to circulate the charging request of sink RSNs to reach the MCD.
2. The proposed algorithm employs the Firefly algorithm to find the best path by taking into account the geometric mean of the nodes' residual energy, hop count, and

distance. This will aid the lossless and on-time arrival of charging requests, allowing the charging tour to begin sooner and avoid dead nodes.

3. The proposed algorithm is simulated and its performance is compared with the existing algorithms namely ACO [26], MAODV [20], GEAR [27] under varying the number of nodes.

3. PROPOSED FIREFLY BASED OPTIMAL PATH SELECTION ALGORITHM (FOPSA)

WRSN is a developing technology that aims to increase the network's lifespan by on-time charging the sensors. To facilitate the on-time charging, the requests must be routed to MCD through an optimal route. The proposed Firefly-based Optimal Path Selection Algorithm (FOPSA) optimizes the routing path for the on-time delivery of charging requests to the MCD. Once the charging requests are received and queued based on the demand, the MCD will plan its charging tour accordingly. The on time charging will increase the life of the RSNs thereby saving them before they become dead. The routing path to send this charging request is constructed by inheriting the Firefly Algorithm (FA). The fitness intensity of the firefly is calculated using three main factors namely distance, residual energy and hop count. In most of the existing routing path selection algorithms, the arithmetic mean of the residual energy is considered. In this case, there is a possibility of having the routing path that has some of the nodes with more energy and some of them are nearing their depleted state. However, this approach is an ideal case, where the energy depletion rate is common for all the RSNs. But in practical scenarios, the remaining energies of the nodes in the network are random and have a lot of variance. To address this problem, the proposed FOPSA utilizes the geometric mean of residual energy, hop count and distance as the decision parameters to choose the best path. The following section highlights the advantages of geometric mean in the routing process.

3.1 Impact of Geometric Mean

To reveal the impact of geometric mean in the routing path, consider a function $f(x) = e^x - 1 - x$ and its derivative $f'(x) = e^x - 1$. To find the critical points, substitute $f'(x)$ with 0.

$e^x - 1 = 0 => x - ln1 = 0$

$\therefore x = 0$ is a critical point. Further, to check if $x = 0$ is a valid critical point, apply $\lim_{x\to 0}$ on $f(x)$.

$$\begin{aligned} LHS &= \lim_{x\to 0^-} f(x) \\ &= \lim_{x\to 0^-} e^x - 1 - x \\ &= \lim_{h\to 0} e^{0-h} - 1 - (0-h), where\ h > 0 \\ &= \lim_{h\to 0} \frac{1}{e^h} - 1 + h \\ \therefore LHS &= \frac{1}{1} - 1 + 0 = 0 \end{aligned}$$

$$\begin{aligned} RHS &= \lim_{x\to 0^+} f(x) \\ &= \lim_{h\to 0} e^{0+h} - 1 - (0+h), where\ h > 0 \\ &= \lim_{h\to 0} e^h - 1 - h \\ \therefore RHS &= 1 - 1 - 0 = 0 \end{aligned}$$

Moreover, $f(0) = e^{(0)} - 1 - (0) = 0$

Since, LHS = RHS = $f(x)$ at x = 0, $\lim_{x\to 0} f(x)$ exists and equals to 0. In addition to this, the double derivation of $f(x)$ at x = 0 is greater than 0, function f attains minimum value at $x = 0$.

$\therefore f(x) \geq 0 \; \forall x$
$e^x - 1 - x \geq 0$
$e^x \geq 1 + x$

$$\text{But, } e^x = 1 + \frac{x}{1!} + \frac{x^2}{2!} + \frac{x^3}{3!} \ldots \tag{1}$$

From the above Eq. (1), the Arithmetic Mean (AM) of energy $e_1, e_2, e_3 \ldots e_n$ for n number of RSNs can be expressed as

$$AM = \frac{e_1 + e_2 + e_3 + \ldots + e_n}{\text{number of hops}}$$
$$\text{number of hops} = \frac{e_1 + e_2 + e_3 + \ldots + e_n}{AM}$$

Similarly, from Eq. (1), the Geometric Mean (GM) of energy of RSNs can be expressed as follows

$$GM = \sqrt[n]{e_1.e_2.e_3.\ldots.e_n}$$
$$e^{(\frac{e_1}{AM}-1)} \geq 1 + (\frac{e_1}{AM} - 1) = \frac{e_1}{AM}$$
$$e^{(\frac{e_2}{AM}-1)} \geq 1 + (\frac{e_2}{AM} - 1) = \frac{e_2}{AM}$$

Since e^y is positive for any y,

$$e^{(\frac{e_1}{AM}-1)}.e^{(\frac{e_2}{AM}-1)}.e^{(\frac{e_3}{AM}-1)}\ldots.e^{(\frac{e_n}{AM}-1)} \geq \frac{e_1}{AM}.\frac{e_2}{AM}.\frac{e_3}{AM}\ldots.\frac{e_n}{AM}$$
$$e^{\frac{e_1+e_2+e_3+\ldots+e_n}{AM}-n} \geq \frac{e_1.e_2.e_3\ldots e_n}{AM^n}$$

But $AM = \frac{e_1+e_2+e_3+\ldots+e_n}{n}$, the above equation is rewritten as follows

$$e^{\frac{e_1+e_2+e_3+\ldots+e_n}{AM}-n} = e^{n-n} = e^0 = 1$$
$$1 \geq \frac{e_1.e_2.e_3\ldots e_n}{AM^n}$$
$$AM^n \geq e_1.e_2.e_3\ldots e_n$$
$$AM \geq \sqrt[n]{e_1.e_2.e_3\ldots e_n}$$
$$AM \geq GM$$

Equality occurs when energy of all RSNs $e_1, e_2, e_3, \ldots e_n$ are exactly equal. Since the chances in all RSNs which have the exact amount of energy is negligible, it is concluded that $AM > GM$.

3.2 Objective Function Construction

The proposed FOPSA algorithm selects an optimal path by considering the three main factors such as residual energy (E_{GM}), hop count (HC) and distance (DS), which are discussed in the following subsections. With these metrics, the fitness function is derived for estimating the routing path.

3.2.1 Geometric mean of residual energy (E_{GM})

In WRSN, the packet transmission should be efficient and reliable without demanding frequent retransmissions as they consume more energy and shorten the network lifetime. As discussed in Section 3.1, geometric mean of residual energy of RSNs avoids the nodes with less energy during the path selection and it is estimated as given in the following Equation.

$$E_{GM} \leftarrow \left(\prod_{i=1}^{n} e_i\right)^{n} = \sqrt[n]{\prod_{i=1}^{n} e_i}$$

Where n is the number of nodes and e_i is the residual energy of the i^{th} node.

3.2.2 Hop count (HC)

The number of intermediate nodes will also decide the travelling time of the charging request. This request should reach the BS as early as possible making the MCV to initiate the charging tour on time without the delay.

$$HC \leftarrow \text{count}\left(\sum_{i=i}^{n} hop(i \to i+1) + \text{hop}(i+1 \to BS)\right)$$

where hop($i \to i$+1) gives the hop count between node to its next hop and gives the hop count between that node to BS.

3.2.3 Distance (DS)

It's the euclidean distance between the RSN and the next hop, as well as between them and the BS. It will use less energy if the distance is kept to a minimum. As a result, the goal is to reduce the distance between Sink RSN and BS which will increase the network's lifetime.

$$DS \leftarrow \frac{1}{\sum_{1=1}^{n} DS(Nd_i, Nd_{i+1}) + DS(Nd_{i+1}, BS)}$$

Where $DS(Nd_i, Nd_{i+1})$ is the distance between a node to the next hop and hop(i+1 $\to$ BS) is the distance between that next hop to BS.

3.2.4 Fitness function for FOPSA

The fitness function O_{fitness} for predicting the optimal path to transmit the charging requests is proposed in Eq. (2) with the above mentioned three metrics.

$$O_{\text{fitness}} = C1(F1) + C2(F2) \tag{2}$$

Where the sub-objective functions F1 and F2 are combined using weighted sum method to obtain a single fitness function and they are given as follows in Eqs. (3) and (4) respectively.

$$F1 = (E_{\text{GM}})^{1/HC} \tag{3}$$

$$F2 = DS \tag{4}$$

Here C1 and C2 are weights assigned to each sub objective, where Ci (0,1). With this fitness function, the proposed algorithm utilizes the firefly optimization technique to obtain the shortest path to transmit the charging requests.

3.3 Firefly-based Optimal Path Selection Algorithm (FOPSA)

The proposed FOPSA algorithm aims to find the quickest route between each sink RSNs and the MCD so that the charging requests are delivered as early as possible. To accomplish this goal, the firefly method is utilized with the above proposed fitness function that includes residual energy, euclidean distance, and hop count. To accurately build the Firefly model, two fundamental challenges must be addressed: attraction and variations in light intensity. Each firefly in the FOPSA algorithm represents a potential solution to the problem and each solution represents the data forwarding path from each RSN to the MCD. The brightness of the firefly is determined by the estimated fitness value that selects the optimum route. To reach the target MCD, the RSNs are drawn to the route with high intensity. The routing path selected by the proposed FOPSA has lesser number of hops thus minimizing delay, energy consumption, and distance.

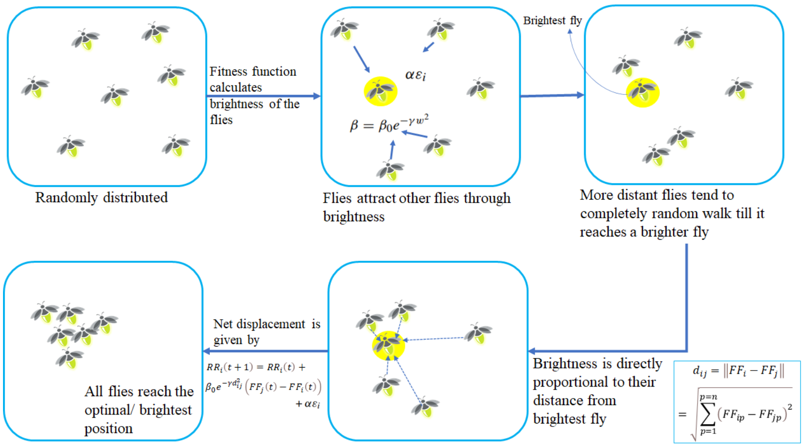

Fig. 2. Proposed FOPSA.

As depicted in Fig. 2, the steps in the proposed Firefly optimization algorithm are discussed as follow:

1. The FOPSA model initialises the firefly population as the various pathways between the sink RSNs and MCD.
2. The proposed fitness function discussed in Section 3.2 is used to evaluate the fitness O_{fitness} of each firefly. This fitness gives the light intensity for the flies.
3. Update the distance between two RSNs namely FF_{ip} and FF_{jp} is given by d_{ij} as illustrated in below Eq. (5).

$$d_{ij} = \|FF_i - FF_j\| = \sqrt{\sum_{p=1}^{p=n}(FF_{ip} - FF_{jp})^2} \tag{5}$$

4. The flies are ranked based on their fitness value and the best valued fly will be ranked first. The fitness intensity value for attraction is applied to find the optimal routing path for transmitting the charging request to MCD from the source RSNs.
5. The movement of firefly is evaluated using Eq. (6) in the search space towards the finding of next hop in the path and is repeated until the destination (MCD) is reached. The movement of fireflies comprises three features, the current position of ith firefly, attraction, and a random walk involving a variable named and a randomly formed integer ranging between [0, 1].

$$RR_i\,(t+1) \leftarrow\; RR_i\,(t) + \beta_0 e^{-\gamma d_{ij}^2}\,(FF_j\,(t) - FF_i\,(t)) + \alpha\varepsilon_i \tag{6}$$

where ε_i designate a random number, FF_i and FF_j is the position of ith and jth firefly respectively. β portrays the attractiveness and signifies the attraction level at $d = 0$. When $\beta_o = 0$ the movement is solely determined by random walks. The above steps are repeated till the maximum number of generations are reached which yields the optimal path for transmitting the charging request to MCD, which can then efficiently plan its charging tour to extend the life of the RSNs. The complete algorithm for the proposed FOPSA is given in Algorithm 1.

Algorithm 1 : Firefly-based Optimal Path Selection Algorithm (FOPSA)

Input: Initial Population FF_p, Residual energy e_i, Hop hop_i, Base Station BS.
Output: Geometric Mean E_{GM}, Hop count HC, Distance DS, Fitness $O_{fitness}$,

Initialize FF_p
while endcondition **do**
  for All FF_p **do**
    Get e_i, hop_i

$$E_{GM} \leftarrow \left(\prod_{i=1}^{n} e_i\right)^{n} = \sqrt[n]{\prod_{i=1}^{n} e_i}$$

$$HC \leftarrow \text{count}\left(\sum_{i=i}^{n} hop(i \to i+1) + \text{hop}(i+1 \to BS)\right) \tag{7}$$

$$DS \leftarrow \frac{1}{\sum_{1=1}^{n} DS\,(Nd_i, Nd_{i+1}) + DS\,(Nd_{i+1}, BS)}$$

    while $FF_p \leq$ n **do**

$$O_{\text{fitness}} \leftarrow C1\left((E_{GM})^{1/HC}\right) + C2(DS) \tag{8}$$

    end while

$$I_i = O_{fitness}(F_i)$$

  end for
  for All FF_p **do**
    if $I_i > I_j$ **then**

$$RR_i\,(t+1) \leftarrow\; RR_i\,(t) + \beta_0 e^{-\gamma d_{ij}^2}\,(FF_j\,(t) - FF_i\,(t)) + \alpha\varepsilon_i$$

    end if
  end for
  while $FF_p \leq n$ **do**
    Evaluate new $O_{fitness}$
    Update $O_{fitness}$
  end while
end while

4. SIMULATION RESULTS AND ANALYSIS

To evaluate the performance of the proposed FOPSA algorithm, the existing MAODV, ACO and GEAR algorithms are also simulated in MATLAB R2020b on an Intel(R) core(TM) i7-6700 CPU running at 3.40 GHz and 16 GB RAM. The metrics such as network throughput, packet delivery ratio, packet loss ratio, residual energy of the network, and delay are measured and analysed. The simulation is carried out by varying the number of sensor nodes from 50 to 250, which are deployed over a 100 m*100 m square area with a centralised base station. Each node's initial energy is set to 2J. The energy of power amplifier is set at 0.0013nJ/bits/m2 and the energy of transmitter and receiver are set at 0.04μJ/bit and 0.01μJ/bit respectively.

4.1 Throughput

Network throughput refers to the amount of data that can be transferred from source to destination in a given period of time. Figs. 3 and 4 depict the throughput performance at different time intervals and for varying number of nodes respectively. It is inferred from these figures that the throughput is degraded as the increased number of transmissions causes too many collisions among the nodes. However, the proposed algorithm FOPSA attains higher throughput than existing MAODV, ACO and GEAR algorithms. In order to accelerate packet transmission, the proposed FOPSA forecasts a shorter routing path with fewer hops. The more rapid and consistent data transmission rate has improved FOPSA's throughput. This is owing to the fact that the proposed algorithm elects the potential nodes based on the residual energy, hop count and distance thus leading an optimal path to relay the charging requests. Consequently, it avoids the transmission failures and retransmissions of the charging requests thus helping to preserve the residual energy of RSNs. Also, it facilitates the energy depleted nodes to be recharged before they die. As a result, the proposed algorithm prolongs the network lifetime by reducing dead nodes, and achieved higher throughput than that of other existing algorithms.

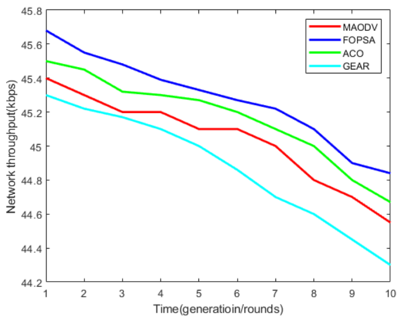

Fig. 3. Throughput vs. Time.

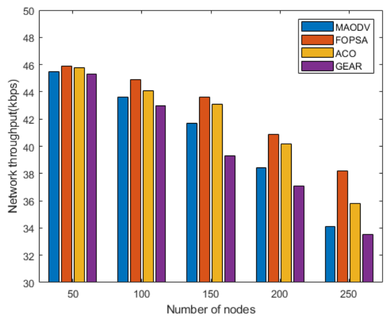

Fig. 4. Throughput vs. Number of nodes.

4.2 Packet Loss Ratio (PLR)

The packet loss ratio (PLR) is a ratio between the number of lost packets and the total number of transmitted packets. As mentioned in the previous subsection, proposed FOPSA algorithm predicts an optimal path with potential relay RSNs thus reducing packet loss, unwanted retransmissions and congestion of the network. From Figs. 5 and 6 , it is inferred that the proposed FOPSA curtails the packet loss than existing algorithms. Due to the enhanced fitness function with geometric mean and other factors, the congestion in the end-to-end path is significantly reduced which leads to lesser PLR than that of other approaches.

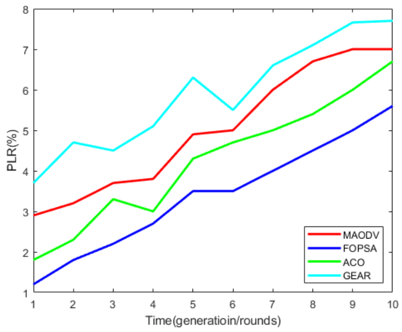

Fig. 5. Packet loss vs. Time.

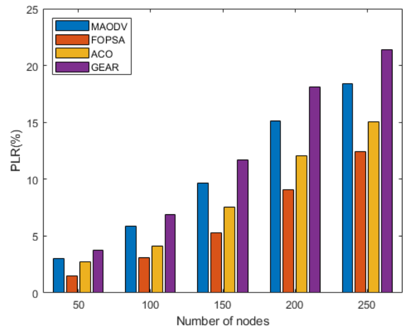

Fig. 6. Packet loss vs. Number of nodes.

4.3 Packet Delivery Ratio (PDR)

The packet delivery ratio (PDR) is the ratio between total packets received to total packets sent in a network from the source nodes to the destination nodes. The proposed FOPSA considerably reduces the cost of network routing by minimizing number of hops in the routing path thus raising the PDR. In Figs. 7 and 8, the proposed FOPSA algorithm comparatively shows higher PDR then existing MAODV ACO and GEAR algorithms due to decreased packet loss and network congestion. In the proposed FOPSA algorithm, optimal path selection with Geometric mean of residual energy reduces the frequency of dead nodes and guarantees stable routing path. As a result, there is no need to seek out alternate routes on a frequent basis. This reliable and consistent long-standing path selection boosts packet transmission rate.

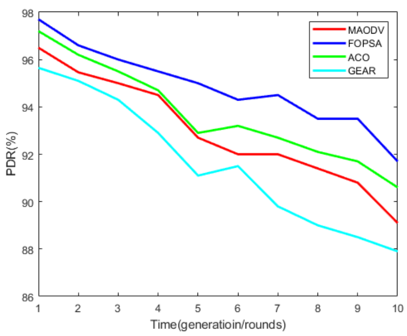

Fig. 7. PDR vs. Time.

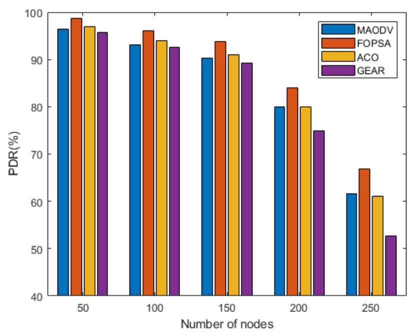

Fig. 8. PDR vs. Number of nodes.

4.4 Average Residual Energy

The proposed FOPSA manages energy loss during data transmission by evenly distributing the load across the network. The RSNs communicate their data over fewer hops and shorter distances, which saves network energy and extends the network's longevity. Figs. 9 and 10 show the average remaining energy which is the proportion of node energy consumption at the end of each round. Since power sources are limited, saving energy is essential for the network's longevity. In comparison to other current algorithms, the proposed FOPSA algorithm saves network energy by lowering packet loss and enhancing packet delivery rates as mentioned in the previous subsections.

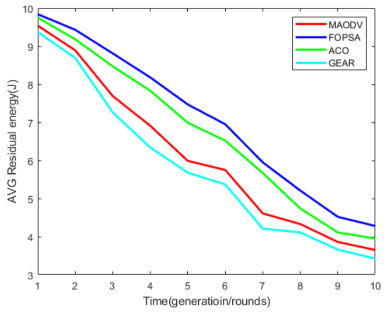

Fig. 9. Residual energy vs. Time.

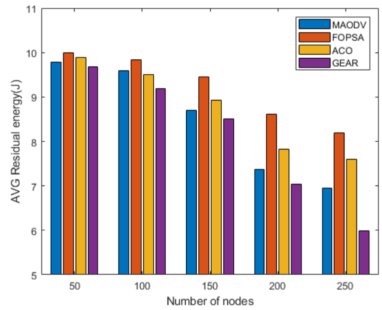

Fig. 10. Residual energy vs. Number of node.

4.5 Delay

The time that the packet takes to travel from its source to its destination across a network is measured and plotted in the Figs. 11 and 12 for all the algorithms. The proposed algorithm predicts the routing path considering the minimum hop count as one of its decision metrics. Moreover, all the relay RSNs in the routing path have sufficient residual energy which ensures the stable path among RSNS and MCD. This guarantees collision-free and on-time reception of the data with a lesser number of retransmission and congestion thus reducing delay. Whereas in the existing algorithms, the routing path with more number of hops caused more delay due to the processing and queueing delay in these hops.

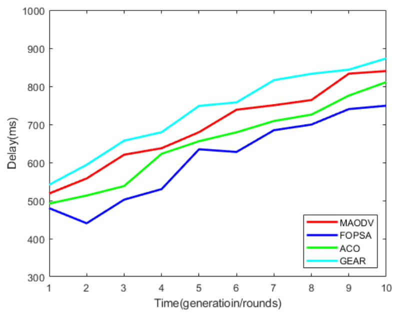

Fig. 11. Delay vs. Time.

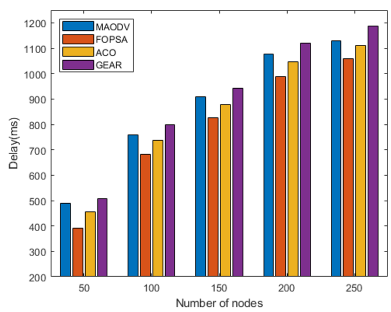

Fig. 12. Delay vs. Number of nodes.

5. CONCLUSION

The RSNs in the remote forest area must always have the sufficient battery backup with the aid of proper on-time recharging to facilitate the seamless data transmission. This paper proposes an optimal path selection algorithm based on Firefly optimization for predicting an optimal route to transmit the charge requests to MCD. The fitness function is constructed based on geometric mean of residual energy, hop count, and distance factor. It guarantees potential RSNs in the optimal path to ensure the on-time reception of charging requests by MCD thus replenishing energy depleted RSNs. From the simulation results, it is confirmed that the proposed FOPSA minimizes the packet loss and delay thus extending the network lifetime by reducing number of dead nodes. In the future, more run-time metrics, such as link reliability and node forwarding potential, will be used with hybrid optimization techniques to choose the best path. Additionally, the results will be tested in a real-world environment.

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First Author and Second Author equally contribute towards the idea, experiments, interpretation of results and paper write-up.

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Siron Anita Susan T. received the ME degree in Computer Science and Engineering from Kurinji College of Engineering and Technology, Tamilnadu, India. She is currently pursuing the Ph.D. degree in the Department of Computer Science and Engineering, National Institute of Technology, Tiruchirappalli, India. Her research interests include wireless sensor networks and optimization algorithms.

B. Nithya received Ph.D. degree from National Institute of Technology, Trichy in 2015. She is working as an Assistant Professor in National Institute of Technology (NIT) Trichy since 2007. Her research interests include in the wireless networks (mobile adhoc network, wireless sensor network, Internet of Things, wireless body area network, unmanned aerial vehicle, Internet of Vehicles), advanced data structures and optimization algorithms.