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Multipath Data Transmission in IoT Networks Using Fractional Firefly Algorithm and Chicken Swarm Optimization

Salem Abdulla Awadh Ba Hmaid[1]* **Vasanthi Varadharajan[2]**

[1]*Computer Science Department, Rathinam College of Arts and Science, Bharathiar University, Coimbatore, India*
[2]*Department of Information Technology, Sri Krishna Adithya College of Arts and Science, Bharathiar University, Coimbatore, India*
* Corresponding author's Email: salem100323@gmail.com

Abstract: Integration of Wireless Sensor Networks (WSN) with the Internet Protocol (IP) has led to the development of Internet-of-Things (IoT) networks with high connectivity and improved data transmission with limited power supplies. Hence, it is necessary to utilize a high performance multi-path routing protocol to avoid energy constraint problems and network connectivity issues. This paper presents an optimal multi-path routing protocol using multi objective algorithms namely Fractional Firefly algorithm with Chicken Swarm Optimization (FFA+CSO) to resolve the energy constraint problem. First the network is clustered and a Cluster Head (CH) is selected to initiate inter-cluster and intra-cluster communication. Fractional Firefly algorithm (FFA) has been developed for this purpose by overcoming the slow convergence and local optima problem of firefly algorithm. FFA selects CH based on energy, delay, link quality and lifetime. Then the routes are formed and optimal route is selected using Chicken Swarm Optimization (CSO) based on energy, inter and intra-cluster delay, link quality, lifetime and hop count. The proposed FFA+CSO routing protocol is evaluated using Network Simulator-2. Results obtained for 100 nodes showed that FFA+CSO provided efficient multipath data transmission for WSN based IoT networks with 24% less delay, 28% greater throughput, 18.7% lesser energy consumption, 21.6% longer lifetime, 20% higher PSNR and 37.5% less number of hops than the existing routing models.

Keywords: Wireless sensor networks, Internet-of-things, Energy constraint problem, Multipath routing, Cluster head, Firefly algorithm, Fractional firefly algorithm, Chicken swarm optimization.

1. Introduction

Internet-of-Things (IoT) is an innovative paradigm that has gained immense attention due to its efficient and novel pattern of turning objects into smart devices to enable connection to internet [1]. Recently, the research interest in IoT has been rapidly increasing in the fields of academia; health-care, smart cities, environmental monitoring and industrial automation that utilize IoT primarily for efficient data gathering and transmission [2]. In recent years, IoT applications have utilized the concepts of wireless sensor networks (WSN) which has garnered significant attraction for research applications [3]. In combination with the radio frequency identification (RFID) technology, the IoT employs the WSN technology to support applications in various domains such as smart systems, smart cities, smart healthcare systems, environmental monitoring, traffic monitoring, military applications, etc. WSN based IoT ensures better connectivity among the connected things and enable them to provide effective transmission. This collaboration allows the WSN based IoT to utilize the WSN routing protocols for data transmission but the battery constrained nature of the network limits the power utilization and reduce the overall lifetime.

Energy efficiency is one of the serious concerns in the mass organization of WSN based IoT applications. In IoT, sensor nodes are restricted by limited batteries and transmission range. Hence the

WSN techniques must be ensured to provide energy efficiency and only then the WSN based IoT can be economically feasible for its enormous applications [4]. The routing protocol must also assure the characteristics of WSN, such as dynamic topology, limited power, memory capacity, and high transmission for IoT applications [5]. The existing routing protocols do not consider all the energy components and hence does not provide complete energy efficiency to IoT sensors. Hence energy-efficiency and the quality-of-service (QoS) parameters are prominent in routing protocols [6]. Most protocols are built upon either Adhoc On-Demand Distance Vector (AODV) or Dynamic Source Routing (DSR) models [7]. In WSN based IoT networks, AODV models are preferred for the objective of minimizing the broadcast with better tackling of the issue of loops in routing in WSN based IoT networks. The majority of routing algorithms prefer the selection of optimal paths for providing efficient routing with minimizing the total energy consumption [8]. However, the optimal path concept divides the network and creates the energy-hole problem due to continuous usage of single optimal path and also the non-uniform energy drain rate in the network nodes. These problems contradict the efficiency of minimized total energy consumption and fail the routing protocol to achieve the intended results.

This paper emphases on resolving these problems and develop an energy efficient multi-path routing protocol using FFA+CSO based on multiple objectives. The important considerations are load balancing, reduced and uniform energy consumption, minimized packet retransmission and less packet drop rate. To realize these goals, the proposed FFA+CSO based routing model considers the parameters such as energy, delay, link quality and lifetime for CH selection while energy, inter and intra-cluster delay, link quality, lifetime and hop count for optimal path selection. These improvements enable the network to prolong its lifetime with effective solution for energy-hole problem and non-uniform energy drain rate problems. The rest of the paper is ordered as: section 2 presents the discussion on related works. Section 2 introduces and explains the proposed FFA+CSO based routing model. Section 4 presents the simulation and evaluation results and section 5 presents a conclusion of this paper.

2. Related works

Many recent works have aimed to address the energy constraint problem for improving the data transmission in real-time WSN based IoT applications. Machado et al, [9] developed a WSN routing protocol based on energy and link quality for IoT applications. However, it is much suitable for the small scale applications only due to proportional performance on node density. Shen et al, [10] presented energy efficient centroid-based routing protocol for WSN-assisted IoT which reduces the energy drain rate by selecting CH on rotational basis. This model supports only single-hop transmission while multi-hop transmission are not effective as the base station is mostly situated at the network center. Nguyen et al, [11] introduced energy-harvesting-aware routing algorithm for WSN-based IoT applications using energy back-off parameter. This approach has also been extended by Nguyen et al, [12] to develop distributed energy-harvesting-aware routing algorithm. Both these routing algorithms have provided better data transmission in IoT, but the models do not reduce the packet delay and subsequent packet drops.

CH selection plays a prominent role in energy consumption and also deciding the routing performance. Singh and Lobiyal, [13] proposed the use of particle swarm optimization (PSO) for CH selection based on the residual energy, minimum average distance and number of head nodes. Rana and Zaveri, [14] proposed Synthesized CH selection and routing using Genetic algorithm (GA) to improve network lifetime. Rao et al, [15] also employed PSO for CH selection based on intra-cluster distance, sink distance and residual energy of sensor nodes. Kumar et al, [16] developed FABC+ Exponential Ant Colony Optimization (EACO) algorithms for energy efficient routing. CH selection is done using FABC based on energy, delay and location while routes are optimized using EACO based on energy, distance, intra cluster delay and inter cluster delay. Similarly, Dhumane and Prasad, [17] proposed Fractional Gravitational Grey Wolf Optimization (FGGWO) based energy aware routing in which the Fractional Gravitational Search Algorithm (FGSA) selects the CH and FGGWO selects optimal path based on energy, inter and intra-cluster distance, delay and lifetime. These approaches reduce the cost of locating optimal CH but the energy balancing properties are not satisfied during transmission.

From the literature, it can be inferred that the optimal route selection models have performed significantly better than other models. It can also be seen that these models too have their own limitations in terms of energy-hole problem. To overcome these limitations, the proposed model

Table 1. Notations and definitions

Notation	Definition
P_i	Initial node power
P_T	Power consumed for transmission
P_R	Power consumption for reception
i, j	Sensor nodes
D_t	Distance between nodes i and j
P_{cons}	Constant power
P_{amp}	Power amplification
D_0	Threshold distance
n_1, n_2	IoT nodes redefined
t	Time
(u_1, v_1) and (u_2, v_2)	Current location of nodes
(u_1', v_1') and (u_2', v_2')	Updated new locations of nodes
T_{ri}	Receive time of i-th packet
T_{si}	Sending time of i-th packet
n	Total number of data packets
d	Distance between source and destination nodes
ε_0	total non-rechargeable initial energy
λ	average broadcasting rate
$\mathbb{E}[E_w]$	expected unused energy
$\mathbb{E}[E_r]$	expected reporting energy
L_q	Link quality
AG_r and AG_t	antenna gain of receiver and transmitter
n_x^y	fraction of n at location (x, y)
l	Dimension of fractional input
c	Coefficient of fractional input
γ	Absorption coefficient
$F\beta$	Fractional attractiveness
β_0	Initial attractiveness
FT^α	Fractional time period
$F\alpha$	Fractional number of iterations
m	Number of iterations
$D^\alpha(r)$	minimum distance of fireflies with required intensity
α	non-integer parameter for step-size control
S^α	increasing intensity index
α_F	fractional parameter to control the step size
ϵ	Gaussian distribution vector
F_p	fitness function for path selection
W	Path transmission range
ρ	Density of node deployment
$rand(0, \sigma^2)$	Gaussian distribution with mean 0 and standard deviation σ^2
$X_{i,j}^T$	location of current best chicken
$X_{i,j}^{T+1}$	location of next best chicken
S_1, S_2	coefficient of social factors in search space
$r1, r2$	Index of rooster and chicken
f_i, f_{r1} and f_{r2}	fitness of i-th hen, rooster with index $r1$ and rooster/hen with index $r2$
$abs(f_i)$	absolute value of fitness
ε	smallest constant to avoid zero-division error
$X_{m,j}^T$	location of the j-th chick's mother
fl	Food forage parameter of chick
X(i, j)	Data objects

introduces FFA+CSO algorithms in the routing protocol.

3. Methodology

Table 1 presents the list of notations used in this paper and their definitions.

3.1 System model

WSN is composed of N sensor nodes, which can sense and obtain data. Each node in the given network is capable of shifting their transmission energy and also has the capacity to act as both CH as well as the member nodes. The sensor nodes are clustered into groups and each of the group is headed by a CH selected based on certain objectives [17]. Each IoT node collects the data and transmits them to the BS through the CH but it consumes considerable amount of energy for these processes. Hence the CH is selected on energy and distance. Assign a simulation area with dimension, BS, and k IoT nodes distributed as clusters each headed by a CH. The proposed scheme could be employed in any WSN based IoT routing protocols to implement cooperation among nodes.

3.1.1. Energy model

Considering each sensor has an initial energy P_i and if the key factors of energy consumption is based on packet reply and broadcast. P_T is the power utilization of node i to transmit a data packet to its nearby node j and P_R is the power utilization of node i while receiving a data packet from its nearby node j. If the sink node reflects unlimited energy and maintains movement until the end of the network lifetime, which is denoted as the time until the first node expires due to energy depletion. The objective of optimization problem is the selection of optimal routing strategy and the optimal CH selection at each sink location thus the network lifetime is maximized for a given order of node locations. It provides better network lifetime by using linear programming model. Power consumption for transmitting L bits of data at distance D_t is given in Eq. (1) and power consumption for receiving L bits of transmitted data packets is given in Eq. (2).

$$P_T = \begin{cases} P_{cons} \times L \times P_{amp} \times D_t^2 & if\ D_t < D_0 \\ P_{cons} \times L \times P_{amp} \times D_t^4 & if\ D_t \geq D_0 \end{cases} \quad (1)$$

$$P_R = P_{cons} \times L \quad (2)$$

Where P_{cons} is the constant power, P_T power consumption for transmission of packets, L is bits of data, P_{amp} is power amplification, D_t is distance among nodes, D_0 is threshold distance, P_R is power consumption while receiving the packets. The power consumption is reduced significantly in this model during the data transmission and shortest routing path can also be ensured effectively.

3.1.2. Mobility model

The mobility model [18] represents the measure of the WSN based IoT nodes in the system based on the location, speed and hop. It discovers the implementation of the scheme in the network for packet data communication. Consider n_1 and n_2 be two IoT nodes located at (u_1, v_1) and (u_2, v_2), respectively. At a time t = 1, both the nodes move to a new position (u_1', v_1') and (u_2', v_2') such that the link of the nodes is within a particular region. The Euclidean distance among these nodes is given as

$$d(0) = |u_1 - u_2|^2 + |v_1 - v_2|^2 \quad (3)$$

The distance among the WSN based IoT nodes at any time l in the new positions is calculated as follows,

$$d(l) = |u_1{}' - u_2{}'|^2 + |v_1{}' - v_2{}'|^2 \quad (4)$$

Here $(u_1{}', v_1{}')\ and\ (u_2{}', v_2{}')$ are the new locations obtained via the nodes n_1 and n_2 respectively.

3.1.3. Routing model

The routing is performed by the protocol built upon the AODV routing algorithm to reduce the amount of retransmissions through generating routes on-demand with high effectiveness. This protocol forms the routing table when source node needs to broadcast data [19]. The loop-free, single path, distance vector protocol based on hop-by-hop routing approach of AODV is utilized and the two main strategies employed are: Route discovery and Route maintenance. The network is grouped into clusters of similar nodes and a CH is selected in each cluster using newly developed FFA. Based on the CH, the inter-cluster routes are formed and the routing paths are selected optimally using CSO.

3.2 Cluster head selection

The objective parameters namely energy, delay, lifetime, and link quality are considered for selecting the optimal CH in the WSN based IoT network. The network is categorized into regions of similar nodes called cluster and each cluster contains a set of characteristically similar sensor nodes. The network lifetime can be improved in better way with optimal selection of CH which reduces the non-uniform energy drain rate. The primary objective is to avert the excess energy consumption and avoid the packet loss owing to various delays. This two metrics will significantly contribute to the increase in network lifetime. The formula for calculating delay, energy, lifetime, and link quality are given below:

$$delay\ (T_d) = \frac{\sum_{i=1}^{n}(T_{ri} - T_{si})}{n} \quad (5)$$

Here T_{ri} is the receive time of i-th packet, T_{si} is the sending time of i-th packet and n is the total number of packets.

$$Energy\ (e) = (2 \times i - 1)(P_t + P_r)d \quad (6)$$

Here i is the data packet, P_r denotes the reception power and P_t denotes the transmitter power of the packet i and d is the distance from the source to the destination node.

Lifetime is the time a network operates until the first sensor node or the group of nodes in the network runs out of energy. It can be simply defined as the overall network lifetime that is determined by the remaining energy in the network.

$$Lifetime\ \mathbb{E}[L] = \frac{\varepsilon_0 - \mathbb{E}[E_w]}{P + \lambda \mathbb{E}[E_r]} \quad (7)$$

Where P is the constant continuous power depletion of the whole network, ε_0 is the total non-rechargeable initial energy, λ is the average broadcasting rate, $\mathbb{E}[E_w]$ is the anticipated misused energy or unused energy when the network dies and $\mathbb{E}[E_r]$ is the expected reporting energy consumed by all sensors.

Link quality (L_q) can be estimated based on link expiration time or link energy drain rate based on the reception power as L_q is directly proportional to reception power.

$$L_q \propto P_r \tag{8}$$

$$P_r = P_t \times AG_r \times AG_t \times \frac{\lambda^2}{(4\pi d)^2} \tag{9}$$

Where AG_r and AG_t are the antenna gain of receiver and transmitter respectively, and λ is the average broadcasting rate. These four parameter values are used to form the fitness function or objective function for CH selection and formulated fitness function has to be resolved to obtain pareto-optimal solution.

The fitness function F is formulated as the combination of weighted functions of all these four objective parameters.

$$F = w(T_d) \times f(T_d) + w(e) \times f(e) + w(\mathbb{E}[L]) \times f(\mathbb{E}[L]) + w(L_q) \times f(L_q) \tag{10}$$

Where $f(e)$ is the energy function, $f(T_d)$ is the delay function, $f(\mathbb{E}[L])$ is the lifetime function and $f(L_q)$ is the link quality function and $w(T_d)$, $w(e)$, $w(\mathbb{E}[L])$, $w(L_q)$ are the weight functions of delay, energy, lifetime and link quality parameters, respectively. The energy parameter is given high priority in this model to ensure energy efficiency and hence the higher weights are assigned to $w(e)$ when the optimal CH is selected. The CH is selected using FFA which is an improved version of FA using the fractional theory concept.

3.2.1. CH selection using FFA

FFA selects the optimal CH node for each cluster in the given network. Though efficient, the FA algorithm is not effective for larger networks and hence fails to expand the network lifetime in such cases. This is predominantly due to the exploration and exploitation property of the traditional FA [20]. Hence the theory of fractional calculus [21] is applied to form fractional FA which works better in larger networks and can be applied as fractional groups in each of the regions of the network to improve the search ability. Fractional calculus assumes the use of pseudo-differential operators with real powers of the differential operator. FFA algorithm selects the best node as CH node based on energy, delay, lifetime, and link quality parameters. FFA improves the memory and hereditary properties of the processes by generalizing the derivative or integral of a function to non- integer orders. This process increases the convergence rate and avoids sinking into local optimum cycle.

First the population of fractional fireflies is initialized as $Fx_i, (i = 1,2,..n)$. The fractional theory is applied to the general FA. The fractional formula [21] used for this modification is given by

$$n_x^y(l+1) = \gamma n_x^y(l) + \frac{1}{2}\gamma n_x^y(l-1) + c^i(l+1) \tag{11}$$

Where n_x^y is the fraction of n at location (x, y), l is the dimension of the fractional input and c is the coefficient of fractional input with absorption coefficient γ. The cost estimation must be performed to determine the feasibility of using fractional FA. The cost function is formulated as

$$cost = F\beta \times f_1 + (1 - F\beta) \times f_2 + (1 - F\beta^2) \times f_3 + \cdots + (1 - F\beta^n) \times f_n \tag{12}$$

Here $F\beta, F\beta^2, \ldots, F\beta^n$ is the fractional attractiveness of the n fireflies and $f_1, f_2, \ldots, f_n$ is the individual fitness of n fireflies. The cost of FFA is significantly lesser than the FA and hence it is recommended to utilize the FFA in place of FA. The fitness can be computed using Eq. (10) while the Fractional attractiveness $(F\beta)$ can be computed as

$$F\beta = \frac{1}{FT^\alpha}\beta_0 \exp(-\gamma r^{m+F\alpha}) \tag{13}$$

Here FT^α is fractional time period and $F\alpha$ is the fractional number of iterations at m iterations. Then the fractional light intensity (FI) is formulated as

$$FI = D^\alpha(r). I_0 \exp(-S^\alpha \gamma r^2) \tag{14}$$

Here $D^\alpha(r)$ is a minimum distance of fireflies with required intensity, α is the non-integer parameter for step-size control and S^α is the increasing intensity index. The distance and other metrics are computed as in FA. The fractional fireflies are updated using

$$Fx_i = \alpha_F x_i + \frac{1}{2}\alpha_F \beta_0 e^{-\gamma r_{i,j}^2}(x_j - x_i) + \alpha\epsilon \tag{15}$$

Here ϵ is the Gaussian distribution vector, α is the non-integer parameter for step-size control, α_F is the fractional parameter to control the step size of the fireflies.

Once the FFA completes its search process, the best node in the cluster is identified which has best fitness function. This node will be selected as the

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CH and its fitness equation will return the following form

$$F_i = w(e) \times f_i^{low\,e} + w(T_d) \times f_i^{less\,T_d} + (L_q) \times f_i^{high\,L_q} + w(\mathbb{E}[L]) \times f_i^{high\,\mathbb{E}[L]} \quad (16)$$

There is diversity amid the members in every population of live creatures in terms of quality and fitness. Global solution of firefly algorithm is aimed to increase the performance of the agents (network) in determining more appropriate solutions by modifying them, develops the quality of firefly's society, thereby the probability of finding the multiple optimal solution can be increased. Algorithm 1 shows the CH selection process using the above developed FFA.

Algorithm 1. FFA based CH selection

Generate n nodes to cover k randomly initialized fractional fireflies
Select the closest nodes i and j as primary fractional fireflies for comparison
Map the randomly assigned locations along with closest co-ordinates
Begin
While (m<Max generation)
If (any fractional firefly (node) is with less lifetime)
    Keep the firefly in new location stochastically
    Update the solution set
End if
Select the mapped location of i, j along with closest co-ordinates
Estimate the cost function using Eq. (12)
For i=1 to n (all n fireflies)
    For j=1 to n (all n fireflies)
    Compute fractional theory based generation (assume I_j and I_{i+1} are same)
    Compute the energy, delay, link quality and network lifetime parameters
    Compute fitness using Eq. (10)
    If ($F_j > F_i$)
    Move i towards j;
    End if;
    Sort the fractional fireflies
    Update the node's locations (fractional firefly update) using Eq. (15)
    Restrict the frequent change in the node locations using attractiveness $F\beta$
    Update the solutions list
    End for j
End for i
Rank the fireflies and determine the current best
Return CH
End

The position of the fireflies (nodes) is updated using FA along with the fractional concept. This can resolve the issues in the search process that occur in FA, offering improved location update of nodes. The fractional algorithm is used for the rapid evaluation of the centroid CH node selection. The fractional algorithm, evaluates the cluster centroid point in the given network. The centroid points initialized are subjected to the intensity and brightness. Once the new points are produced, the fractional calculus based solution point is produced based on the constraint of the random solution points. Therefore several solution points are produced and using the computed solution point, the fitness estimation is performed. After the fitness computation, the centroid point along with the optimal fitness is assumed as the CH and the procedure of FFA is iterated until the best CH is ensured. FFA metaheuristic is chosen for its capability of providing optimal solutions for multi-objective problems in larger networks with highly accurate exploration property to avoid stagnation in local optimum position. CH node selection is performed by using FFA algorithm based on the lower energy consumption, less distance (estimated using delay metric) and higher packet delivery and lower number of hop count nodes. Thus selected CH performs the functionalities of the leader until it runs out of energy or a better node in the cluster takes its position.

3.3 Routing path selection using CSO

The routing path is selected using the CSO optimization algorithm [22] for multipath data transmission. The fitness function is formed based on energy, inter-cluster and intra-cluster delay, link quality, hop count and lifetime.

Delay is computed for path selection as the sum of inter-cluster delay ($delay\ (P_{d\ (inter)})$ and intra-cluster delay ($delay\ (P_{d\ (intra)})$. It is given by

$$Path\ delay\ (P_d) = delay\ (P_{d\ (inter)} + delay\ (P_{d\ (intra)})) \quad (17)$$

Both intra-cluster delay and inter-cluster delay are computed based on the time for transmitted packets to reach destination in intra-cluster and inter-clusters respectively. The hop count is computed as the number of adjacent forwarding nodes in transmission. For a path with transmission range W and density of node deployment (ρ), hop count can be estimated as

$$Hop = \left\lceil \frac{Distance\ to\ destination}{\frac{W}{2}\cos(\frac{1}{2}\arcsin\frac{4}{\rho W^2})} \right\rceil - 1 \quad (18)$$

Here $\left\lceil \frac{D}{\frac{W}{2}\cos(\frac{1}{2}\arcsin\frac{4}{\rho W^2})} \right\rceil$ is the expected number of regions.

The fitness function for path selection (F_p) is formulated similar to Eq. (10) of CH selection and it is given by

$$F_p = w(P_d) \times f(P_d) + w(e) \times f(e) + w(\mathbb{E}[L]) \times f(\mathbb{E}[L]) + w(L_q) \times f(L_q) + w(Hop) \times f(Hop) \quad (19)$$

Here $f(P_d)$ and $f(Hop)$ are the functions of path delay and hop count while $w(P_d)$ and $w(Hop)$ are weight functions of path delay and hop count, respectively.

The roosters with highest fitness values are selected as the leader of the group with high priority in accessing the food source. For ease, this case is performed via the location that the roosters with improved objective values can search for food in a broad range of locations than that of the roosters with worst fitness values. This rooster movement and location update can be given as

$$X_{i,j}^{T+1} = X_{i,j}^{T} \times (1 + rand(0, \sigma^2)) \quad (20)$$

Where $rand(0, \sigma^2)$ is a Gaussian distribution with mean 0 and standard deviation σ^2, $X_{i,j}^{T}$ is a location of current best chicken for food source and $X_{i,j}^{T+1}$ is the location of next best chicken.

Since the hens have to take care of the young chicks, they can search food through their group-mate roosters and can arbitrarily take the high-quality food found by other chickens. The new leading hens include the benefit in competing for food than the new passive ones. These phenomena of the hen formulate the movement and location update which are given as:

$$X_{i,j}^{T+1} = X_{i,j}^{T} + S_1 \times rand \times \left(X_{r1,j}^{T} - X_{i,j}^{T}\right) + S_2 \times rand \times \left(X_{r2,j}^{T} - X_{i,j}^{T}\right) \quad (21)$$

Where Rand is a uniform random number over [0, 1], S_1, S_2 are the coefficient of social factors in search space; $r1 \in [1, \dots, N]$ is an index of the rooster and $r2 \in [1, \dots, N]$ is an index of the chicken (rooster or hen) randomly chosen from the swarm with $r1 \neq r2$. $S_2 < 1 < S_1$ and i, j are hen's group mate. S_1 and S_2 are computed as $S_1 = \exp((f_i - f_{r1})/(abs(f_i) + \varepsilon))$ and $S_2 = \exp(f_{r2} - f_i)$. Here f_i, f_{r1} and f_{r2} are the fitness of i-th hen, rooster with index $r1$ and rooster/hen with index $r2$ while $abs(f_i)$ is the absolute value of fitness and ε is the smallest constant to avoid zero-division error.

The chicks move around their mother to forage for food. This is given as the movement and location update equation.

$$X_{i,j}^{T+1} = X_{i,j}^{T} + fl \times (X_{m,j}^{T} - X_{i,j}^{T}) \quad (22)$$

Where $X_{m,j}^{T}$ is the location of the j-th chick's mother (index m belongs to [1, N]), fl is a parameter, that the chick pursue its mother to forage for food. Assuming the individual differences, the value of fl of every chick would be randomly chosen between 0 and 2. Depends on these values and the residual energy, a new route is determined over the network from source to destination. The overall route selection process is summarized in algorithm 2.

Algorithm 2. CSO based route selection

Form paths for routing
Initialize a population of N chickens and define the related parameters;
Assign the paths as chickens
Evaluate the N chickens' fitness values using Eq. (19), iterations m=0;
While (m< Max_Generation)
If (m% G == 0) /// m is a fraction of G steps of chick movement
    Rank the chickens' fitness values and launch a hierarchal swarm order;
    Classify the swarm into many groups of paths
    Fix the relationship amongst the chicks and mother hens in a group;
    Compare the paths i, i+1;
    Rank the paths to transmit packets
    Until termination conditions achieved
End if
For i = 1 : N
If i == rooster, then update its location via (20)
End if
If i == hen, then update its location via (21)
End if
If i == chick, then update its location via (22)
End if
Evaluate the new solution;
If the new solution is superior than its previous one, replace previous solution;
Obtain the multiple shortest optimal routes by destination
Assign each group for multi-path transmission
End for
End while

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Table 2. Simulation parameters

Simulator	NS-2.34
No. of Nodes	100
Area Size	1000 X 1000 m
Channel type	Wireless Channel
Propagation model	Two Ray Ground
Link Layer	LL
Antenna model	Omni Antenna
Traffic type	CBR
Mobility model	Random Way point
MAC	802.11
Initial energy	100 Joules
Radio Range	250m
Simulation Time	300 seconds
Number of packets	1000
Packet rate	8 packets/sec
Data payload	512 bytes/packet

CSO minimizes the energy drain rate, inter and intra cluster delay, and hop count nodes to build best shortest path route. In the proposed WSN based IoT network, all nodes are worked cooperatively and efficiently by sharing multiple information based on inter and intra cluster delay, link quality of the node and partial routes. Hence the FFA based CSO utilizes the best CH for the multipath routing through multiple objectives.

4. Experimental results

The proposed FFA+CSO based routing model is simulated in NS-2 simulator. The existing models namely Fractional Artificial Bee Colony-Enhanced Ant Colony Optimization (FABC+EACO) [16], Fractional Gravitational Search Algorithm-Fractional Grey Wolf Optimization (FGSA+FGWO) [17], and FA+CSO are compared in terms of end to end delay, throughput, energy consumption, hop-count, PSNR and network lifetime parameters. The simulation settings are given in Table 1.

4.1 Performance metrics

(i) End-to-end delay is estimated as the average time taken by the packets to transmit from source to the destination nodes across the network and it includes the inter-cluster and intra-cluster delay, buffer delay, queuing delay, etc. High delay results in the packet loss and subsequent energy wastage for the retransmissions.

(ii) Throughput is the rate of successful data packets transmission in a network. It is estimated in bits per second (bit/s or bps). It is also specified by units of information processed over a given time slot. It can be computed by

$$\text{Throughput} = \frac{\sum \text{Number of packets recieved by destination}}{\text{Simulation time}} \times \frac{8}{1000} \tag{23}$$

(iii) Energy consumption refers to the average energy necessary for transmitting, receiving or forwarding operations of a packet to a node in the network during a period of time. It is measured in Joules per second.

(iv) Network lifetime is the total lifespan of a network calculated by the time to first dead node or a group of nodes in the network.

(v) PSNR value should be high for the proposed method. It is defined to determine the quality of received data packets and is estimated as the ratio of maximum power of received packet to the noise associated with it. It is computed by

$$\text{PSNR (dB)} = 20 \log_{10} \frac{2^{s}-1}{\sqrt{\text{MSE}}} \tag{24}$$

Here MSE is the mean square error given by $\text{MSE} = \frac{1}{N_1 \times N_2} \sum_{i}^{N_1} \sum_{i}^{N_2} [X(i,j) - \hat{X}(i,j)]^2$ with $X(i,j)$ denoting the data objects.

(vi) Hop count: In networking, a hop count is the total sum of transitional devices such as routers or nodes via which information must pass from the source to destination, rather than flowing straight over a single wire. Along the information path, every node forms a hop, with data moving from one node to another node.

4.2 Results and discussion

Fig. 1 illustrates the comparison of (a) end to end delay, (b) throughput, (c) energy consumption, (d) network lifetime, (e) PSNR and (f) hop count results between the FABC+EACO, FGSA+FGWO, FA+CSO and the proposed FFA+CSO routing models. Fig. 1(a) shows that the proposed FFA+CSO model has less delay than the other models because of the selection of optimal CH and routes that reduces the overall time for data transmission and ensures energy efficient delay-less transmission. For instance, while the number of nodes is 100, the delay of FFA+CSO is 0.95ms

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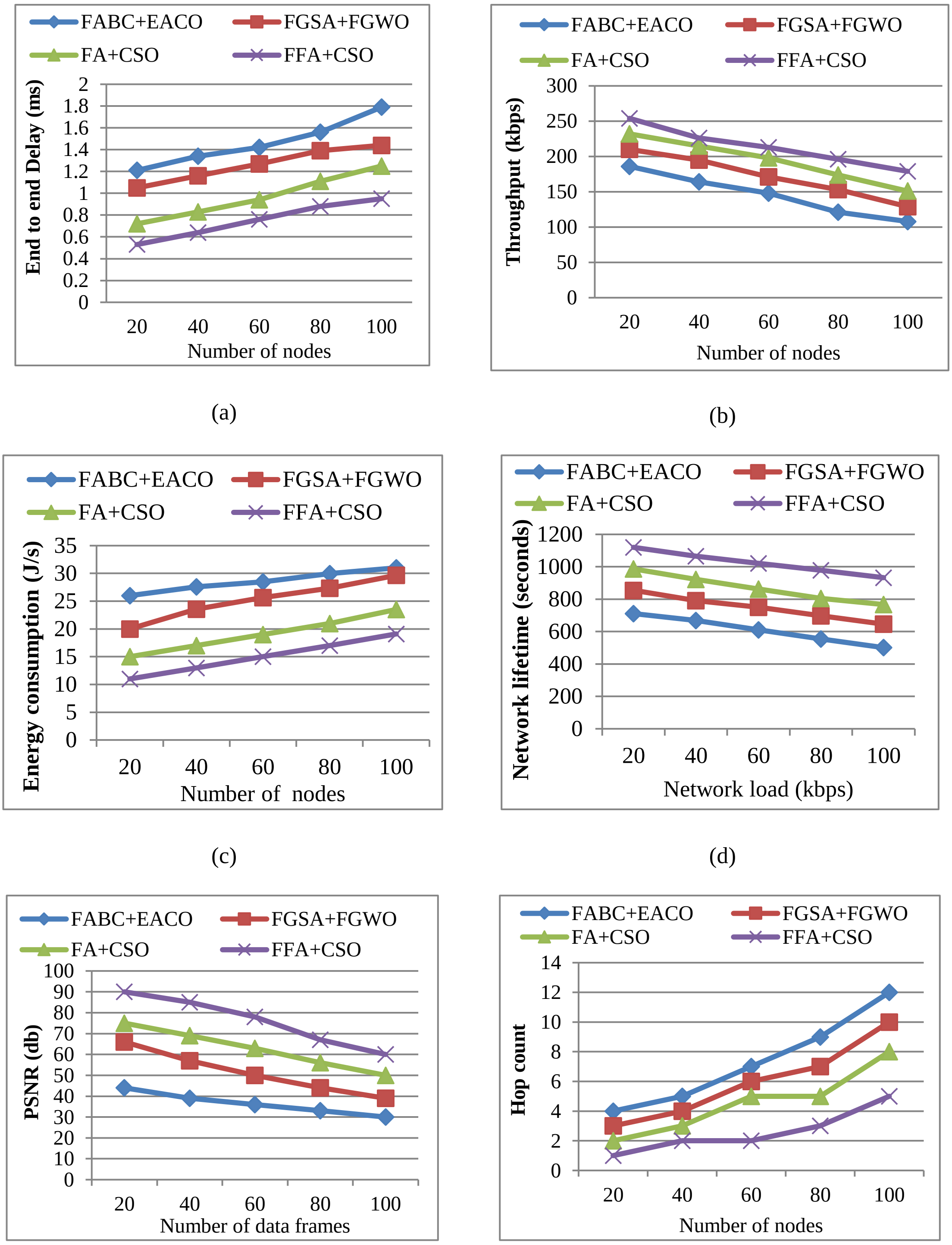

(a) (b) (c) (d) (e) (f)

Figure. 1 Performance comparison: (a) end-to-end delay, (b) throughput, (c) energy consumption, (d) network lifetime, (e) PSNR, and (f) hop count

which is around 24% less than the second best FA+CSO model while 34% and 46% less than FGSA+FGWO and FABC+EACO models respectively.

Fig. 1 (b) shows that the proposed FFA+CSO model has high throughput than the other models. For instance, while the number of nodes is 100, the throughput of FFA+CSO is 179kbps which is around 28%, 38% and 65% greater than the FA+CSO, FGSA+FGWO and FABC+EACO models respectively. This is because of the reliable multi-path transmission of FFA+CSO in ensuring energy-efficient data transmission with reduced need for packet retransmission due to packet loss. From Fig. 1 (c), it is observed that the proposed FFA+CSO have low energy consumption than the other models. When the number of nodes is 100, the energy consumption of FFA+CSO is 19.1J/s which is 18.7%, 35% and 38% lesser than the FA+CSO, FGSA+FGWO and FABC+EACO models respectively. The better energy conservation is due to the uniform energy drain rate through balanced energy consumption of FFA+CSO model.

Fig. 1 (d) shows that the proposed FFA+CSO model has high network lifetime due to effective resolving of the energy-hole problem and the non-uniform energy dissipation problem. When compared at 100 kbps of network load, the network lifetime of FFA+CSO is 933s which is 21.6%, 44.4% and 86% higher than the FA+CSO, FGSA+FGWO and FABC+EACO models respectively.

Fig. 1 (e) illustrate that the proposed FFA+CSO model has high PSNR than other models due to the minimum loss of packets during transmission. When compared at 100 data frames, the PSNR of FFA+CSO is 60dB which is 20% higher than the second best FA+CSO model due to its superior routing behaviour.

Similarly, from Fig. 1 (f), it can be observed that the proposed FFA+CSO model has less hop count than other models due to energy-efficient and optimal path selection. When compared at 100 nodes, the FFA+CSO has 5 hops which is 37.5% less than the second best FA+CSO model due to its superior routing behaviour. Similarly, it also outperforms the FABC+EACO and the FGSA+FGWO models. The competence of the FFA+CSO is attributed to the fractional firefly based CH selection which improves the exploration ability of the FA algorithm and hence increases the efficacy of the routing models. These results prove the significance of the proposed FFA+CSO routing model for efficient data transmission in WSN based IoT applications.

5. Conclusion and future work

This paper presented the development of energy proficient routing protocol using FFA+CSO for multipath data transmission in WSN based IoT networks. The proposed FFA+CSO model utilized FFA for optimal CH selection and CSO for optimal route selection. This model averted the problems of energy-hole problem and non-uniform energy dissipation issue by balancing the energy and load so that single path does not suffer from early expiration of nodes. The simulation results performed in NS-2 proved that the proposed FFA+CSO routing model outperforms the other existing routing models significantly with 24% less delay, 28% greater throughput, 18.7% lesser energy consumption, 21.6% longer lifetime, 20% higher PSNR and 37.5% less number of hops for evaluation with 100 nodes. This proves that the FFA+CSO are more suitable for smart applications of WSN based IoT networks.

In future, the multi-objective optimization problem can be extended to include more parameters without increasing the cost and complexity using novel adaptive and advanced optimization principles. Another direction for future research is the extending the proposed FFA+CSO model to achieve fault tolerance in WSN based IoT without considerably affecting data routing and end-to-end delay.

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