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An Enhanced Artificial Bee Colony Based EELB-PWDGR for Optimized Route Selection in Wireless Multimedia Sensor Networks

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ABSTRACT

Energy efficient and load-balanced routing based on QoS requirements in Wireless Multimedia Sensor Network have been achieved using Energy Enhanced Load Balancing Pairwise Directional Geographical Routing (EELB-PWDGR). However, the process of path selection is a time-consuming one. Hence, Artificial Bee Colony (ABC) is used to select the optimal path satisfying QoS constraints. Though the ABC-EELB-PWDGR outperforms EELB-PWDGR, the ABC algorithm exhibits unsatisfactory performance with a lower search speed, poor population diversity, stagnation within working methods, and struck to the local optimal solution. This study uses an enhanced ABC algorithm in which the global best solution information is added into the solution search equations in order to find the new solution only around the best solutions of the previous iterations for improved exploitation. Since Population initialization is imperative due to its impact on convergence speed, an initialization approach which based on chaotic systems and opposition based learning method has been employed to balance the diversity and convergence capability of ABC. Thus the Enhanced ABC based EELB-PWDGR (EABC- EELB-PWDGR) constructs an initial population with a maximum diversity to provide the best search solutions and a high degree of accuracy. The experimental results prove that the proposed EABC-EELB-PWDGR provides better routing performance than ABC-EELB-PWDGR.

Keywords: Artificial Bee Colony, chaotic search method, EELB-PWDGR, learning mechanism, optimization, opposition-based, routing, wireless multimedia sensor networks

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INTRODUCTION

Wireless Multimedia Sensor Networks (WMSN) focuses on aggregating multimedia data over distant geographical locations. With efficient routing techniques, these enable networks multi-dimensional applications in tracking, home automation, and environment monitoring. Different routing approaches such as GPSR, DGR, and TPGF. have been evaluated (Al-Ariki, & Swamy, 2017) with the PWDGR (Wang, Zhang, Wang, Ma, & Chen, 2015) emerging as the best routing technique. However, the issues of high energy consumption and inefficient load balancing continue to remain. Generally, in Wireless Sensor Networks (WSN), compression techniques are used for high energy consumption problems. However, in WMSN, the maximal image compression schemes consume more energy. Additionally, the compression schemes are utilized in the camera-equipped node, making it further worse. Similarly, since the selection of nodes is mostly in trajectory lines, the general load balancing approaches cannot improve load balancing in WMSN. This results in load imbalance and also hinders multimedia transmission. EE-PWDGR and EELB-PWDGR (Al-Ariki, Mohammed, & Swamy, 2017a; 2017b) has been developed to overcome the limitations of PWDGR. EELB-PWDGR utilizing the cluster based Self Positioning Algorithms (SPA) (Srie Vidhya Janani, & Ganesh Kumar, 2015) and GPS free localization algorithms (Wang & Xu, 2010) for energy efficient localization algorithm to locate the local coordinates of the nodes in the geographically distant places. The triangulation method is then employed after merging the coordinates to locate the node positions. Following this, the loop-free paths with effective forwarding nodes based on the energy drain and distance measures are selected. The paths are then analysed for QoS values and based on these parameters, the priority is assigned. The high prioritized image contents are then allocated to the priority paths. However, EELB-PWDGR lacks the selection of an optimal route for effective transmission, which limits its overall performance.

This study utilizes the Artificial Bee Colony (ABC) algorithm (Karaboga, & Akay, 2009; Zhang, & Liu, 2015) in EELB-PWDGR to enable optimal selection of routing paths. However, the insufficiency in solution search operation of ABC reduces the efficiency. Hence, EABC-EELB-PWDGR has been introduced with two new solution search equations to reduce time latency. Additionally, the chaotic search method and the opposition-based learning mechanism have been employed in population initialization to enhance global convergence. Based on the two new solution search equations, the optimal path is chosen and the paths are compared with for ranking purposes, based on the priority within lesser search time.

Related works

Le Dinh and Nguyen (2010) proposed a greedy geographical routing with the path optimization for WSN. The approach provides optimal routing with void avoidance capacity and also improves the lifetime using ant routing optimization, as mentioned by Hu and Zhang (2010). Paschalidis and Li (2011) proposed energy optimized topologies for providing distributed routing in WSN using the graph-based algorithms of bi-directional spanning trees. Ye and Mohamadian (2014) proposed an adaptive clustering based dynamic routing using ant colony optimization for WSN. Zheng and Luo (2014) also proposed a novel routing protocol by using ABC to address the delay-energy trade-off problem. However, the average packet delivery ratio of this approach was found to be quite less. Ding, Tang and Ji (2016) proposed an optimized routing protocol with queuing model to reduce both energy consumption and congestion in WSN. Chatterjee and Das (2015) proposed Ant Colony Optimization (ACO) based dynamic source routing for MANETs in order to provide high packet delivery ratio with reduced delay. Selvi and Latha (2015) developed lifespan conservation method for the heterogeneous WSN using the ABC algorithm. However, in this method, the computational cost was found to increase due to the population of solutions. Cai, Duan, He, Yang and Li (2015) proposed Bee-Sensor-C, an energy-aware and scalable multipath routing protocol for wireless sensor networks based on the dynamic cluster and foraging behaviour of the bee swarm in order to balance energy consumption.

Azharuddin and Jana (2016) proposed the utilization of Particle swarm optimization (PSO) for the effective maximization of the network lifetime in WSN. This approach includes both routing and clustering algorithms to ensure energy efficient selection of cluster head and effective load balancing. Similarly, Xiang, Wang and Zhou (2016) proposed an energy-efficient routing algorithm for software-defined wireless sensor networks using the PSO algorithm. However, PSO easily suffers from the partial optimism, which results in lesser speed and direction for particles. Ari, Yenke, Labraoui, Damakoa and Gueroui (2016) introduced the concept of honey bee swarm intelligence based approach using ABC for achieving power efficient cluster-based routing. Zeng and Dong (2016) introduced an improved harmony search concept for the energy efficient routing in WSN, which also enhanced both the convergence speed and the accuracy of routing. However, since the vital QoS parameters were not well addressed, this approach seems directionless.

Rao and Banka (2017) had developed a routing algorithm based on chemical reaction optimization which clustered the network and optimized routing paths. However, this model does not consider the fault-tolerance and delay for forwarding the data which is a major drawback. Sirdeshpande and Udupi (2017) developed fractional lion optimization for cluster head based energy efficient routing. Similarly, Sohan, Mittal, Singh and Sohi (2018) also proposed a tree based routing model using PSO but this model had issues in load balancing. To their account, Gupta and Jha (2018) developed an integrated model with clustering using improved cuckoo search and routing using improved harmony search. However this sustainability of this model with communication voids and delay sensitivity was not examined. This literature survey provides an overview of the advantages and disadvantages of the optimization load balancing-based routing methodologies, whose functional scenarios are analysed for developing the approaches proposed in this study.

MATERIALS AND METHODS

Since EELB-PWDGR approach consumes more time to compare the routing paths based on the QoS values, waiting time for the high priority multimedia data transmission tends to remain considerably high. In order to overcome this problem, the Optimization algorithms have been utilized in this study. The Artificial Bee Colony based EELB-PWDGR (ABC-EELB-PWDGR) has been proposed to reducing the time consumed for route selection. ABC-EELB-PWDGR has similar processing stages as in EELB-PWDGR, the major difference being the route selection mechanism. However, ABC has certain drawbacks of ABC, which have been overcome in EABC-EELB-PWDGR.

Optimization-based EELB-PWDGR

Initialization. In the initialization process, the early assumptions are made for localising the nodes in the network without involving the use of the GPS approach. The following assumptions are made to detect the node locations and form efficient routes.

The observed network is a network of wireless devices

All the nodes are stationary

There are no landmarks for absolute location information of a node.

All nodes have the same technical characteristics

All wireless links between the nodes are bidirectional

The nodes use Omni-directional antennae

Priority is assigned to the multimedia data packets

The improved SPA such as cluster-based SPA and Backbone-based SPA (BSPA) have been employed for finding the geographical coordinates of the sensor nodes. The sensor nodes are deployed in a random manner; the node specialization as master, slave, and border nodes is performed using a waiting timer for each node. Following this, the image or video data packets to be transmitted are assigned as high, low and medium priority depending upon the quality and impact of the particular packets in the overall aggregation performance. These prioritized data packets are transmitted over the priority routing paths at the end of the route selection stage.

Energy Efficient Node Localization

The energy efficient node localization algorithm (Wang & Xu, 2010) focuses on detecting the local coordinates of the nodes and using them determines the geographical positions of the nodes. In the first stage, each sensor node of the network initiates its own local coordinate system based on the triangulation method. It then determines the coordinates of other nodes with respect to its coordinate system. Thus, the local coordinate systems of each node are determined. In the second stage, the individual coordinate systems are merged to form the global coordinate system. The transformation equation consisting of the transformation matrix is computed for each global coordinate system, whose solution is determined by the direction adjustment. The positions of each node can be located by resolving the transformation equations.

Route Construction

Detection of node locations is followed by route construction. The paths are constructed considering loop-free and disjoint route conditions. In order to ensure a loop-free path, the invariant conditions based on the sequence number, distance to destination, next hop to the destination and feasible distance are validated. The probability of disjoint is computed for the nodes in order to construct the disjoint routes with minimal loss.

Route Discovery

The sensor nodes that have the aggregated multimedia content then begin to transmit the data through best routing paths, which are also reliable. In order to discover the routes, the nodes broadcast the route request (RREQ) packets to the other nodes. The nodes, which can also perform as routers reply or to RREP packets that contain the sequence number of the nodes. On analysing the received packets, those nodes with the highest sequence numbers are chosen for routing. In order to visualize this concept, the nodes must know the coordinates of the other nodes, which can be detected effectively using the energy efficient node localization algorithm.

Route Selection

It is important that the constructed paths with loop-free and disjoint properties are ranked in terms of better QoS values. The QoS parameters namely energy drain rate, path reliability, average delay and link quality are computed for the constructed paths. The energy drain rate of a node in a route can be calculated by estimating the energy consumed during transmission Et, the energy consumed during reception Er, the energy spent when the nodes are in idle state Ei, and the energy spent for data sensing Es. This energy drain rate Ed is given as follows

$$E_d = E_t + E_r + E_i + E_s \tag{1}$$

Distance D between a selected node and the destination node is computed as follows:

$$D = d[i,j] + length\ [i,j] \tag{2}$$

Where $d[i,j]$ and $length\ [i,j]$ refer to the distance and length between node i and its neighbouring node j.

Path reliability (R_p) is the sum of packet loss rate and the bit error rate (BER) in the path p.

$$R_p = Packet\ loss\ rate + BER \quad (3)$$

Where

$$Packet\ loss\ rate = \frac{Number\ of\ packets\ lost}{Number\ of\ packets\ sent} \quad (4)$$

$$BER = \frac{Number\ of\ errors}{Total\ Number\ of\ bits\ sent} \quad (5)$$

The Average delay (Ad) is given as follows:

$$Average\ delay\ \ Ad = \frac{1}{(\mu - \lambda)} \quad (6)$$

Where μ refers to the number of packets handled per second and λ is the average rate at which the packets are arriving at the path.

Link quality () can be estimated in terms of the packets received undamaged in a link during t seconds.

$$Q_L = \frac{Packets\ received\ in\ t}{\max\ (Packets\ expected\ in\ t, Packets\ recieved\ in\ t)} \quad (7)$$

The energy drain rate and distance measures are obtained as in EE-PWDGR and the computed values of the path reliability, average delay and link quality, fuzzy rules are generated and used for selecting the routing paths, based on a priority of the weights calculated with better performance values.

$$Path\ priority = w1 * \frac{1}{Ed} + w2 * \frac{1}{D} + w3 * R_p + w4 * \frac{1}{Ad} + w5 * Q_L \quad (8)$$

Where $\sum w_i = 1$.

Based on the computation results, the paths are ranked in a descending order of routes, with better QoS values ranked higher. The prioritized multimedia contents are now allocated to the paths based on priority. However, in this approach of path ranking, the QoS values of all the routes are compared with one another in order to determine the best path. This comparison process consumes more time, thus increasing the waiting time for data transmission, which in turn could degrade the overall performance of time-constrained applications. These issues of increased time consumption for path ranking can be minimized by selecting optimal routes using optimization algorithms.

Artificial Bee Colony based Route Optimization

Route selection based on the optimization concept is more efficient than the general comparison based approaches. ABC optimization is a nature-inspired algorithm based on the swarm intelligent honey bee foraging behaviour. The general concept of food search in ABC is the basis for the route optimization in this study. ABC has few important control parameters such as population size, limit, and maximum cycle number. The main advantage of the ABC is its fast convergence speed due to the utilization of the efficient search process in the population initialization phase.

The number of employed bees or onlooker bees is assigned as equal to the number of nodes, with the multimedia data as the input. The routing paths to the destination node are considered as the food sources. The population of solutions is initialized and the employed bees generate a new candidate solution from its neighbourhood such that each employer bee exploits only one solution.

Initialize a random value *rand*. Let SN be the initial population of solutions of routing paths which is equal to the number of bees. The initial population of solution n_i can be found using the equation

$$n_i = n_{min} + rand(0,1) * (n_{max} - n_{min}) \quad (9)$$

Where $i \in (1,2,....SN)$, n_{max} and n_{min} are the lower and upper bounds of n_i

As each employed bee N_i generates new routing paths based on a solution search equation, the solution search equation of ith bee can be given as u_i.

$$u_i = n_i + \emptyset_i * (n_i - n_k) \quad (10)$$

Where $k \in (1,2,....SN)$ is the random index and also such that k is different from i. $\emptyset_i$ is a random number in the range of [-1,1].

Using this equation, the employed bee generates new routing solutions and compares then with the available solutions in memory. If the new routing solution is equal to the QoS values or better QoS values than the old one, the old solution is replaced by the new routing solution. If not, the old solution is retained and the corresponding information is shared with the onlooker bee. The onlooker bee then selects the routing solution based on the QoS values, depending on the probability associated with each solution. The fitness values are calculated based on the weight values of QoS parameters. The probability associated with each routing solution is given as follows:

$$pi = \frac{fitness_i}{\sum_{i=1}^{n} fitness_i} \tag{11}$$

Where $fitness_i$ is the fitness value of the routing solution that can be obtained by equation (12)

$$fitness_i = \begin{cases} \frac{1}{1+f_i} f_i \geq 0 \\ 1 + |f_i| f_i < 0 \end{cases} \tag{12}$$

Where $fitness_i$ is the objective function value which can be computed as

$$fi = w1 * \frac{1}{Ed} + w2 * \frac{1}{D} + w3 * R_p + w4 * \frac{1}{Ad} + w5 * Q_L \tag{13}$$

Where $\sum w_i = 1$.

If the new routing solution has equal or better QoS values than the old solution, then the new one replaces the old solution. After this process, the employed bees which abandon these routing solutions and look for new solutions by becoming scout bees.

Enhanced Artificial Bee Colony based Route Optimization

Since ABC-based Route Optimization has issues in solution search equation, an enhanced ABC with two improved solution search equation, employed bee and onlooker bee separately. The flow of the enhanced ABC for route optimization is shown in Figure 1. The process begins with setting the control parameters for the enhanced ABC while the node information are obtained from the routing tables. Then the number of possible, energy efficient routes with less probability of attacks and packet loss is identified. Then the bees are initialized to compare the routes with the comparison order changed after each iteration. These bees utilize the two new search equations to detect the paths and update them as per their fitness. The best routing path information is saved while the previous best are updated. Thus the routing process is determined. The solution search equations can be determined by the employed bees. After the initialization of population routing solutions, the employed bees generate new solutions based on the newly improved solution search equation (Karaboga & Akay, 2009) as given by the following equation:

$$u_i = n_{best} + \emptyset_i * (n_{best} - n_i) \tag{14}$$

Where n_{best} is the global best solution and $\emptyset_i$ is a random number in the range of [-1,1]. Thus each employed bee generates new routing solutions and shares the same with the onlooker bees. The use of the global best solution improves the search operation with maximum exploitation.

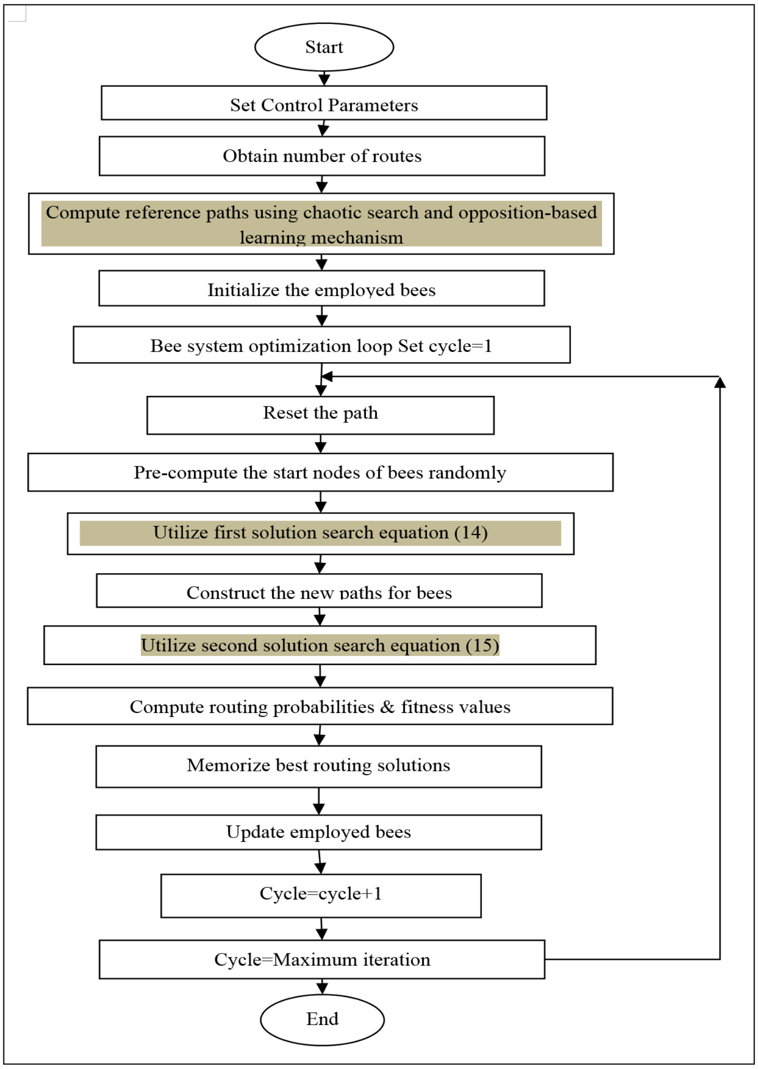

Figure 1. Flow of Enhanced ABC algorithm for Route Optimization

In addition to this equation, yet another improved search equation has also introduced for the search operation in onlookers. The equation makes the best use of the global best solution if the probability values are less than random number *rand*. When the probability using equation (11) is computed, it is compared with the random value initiated at the initialization phase.

$$u_i = n_{best} + \emptyset_i * (n_{best} - n_k) \tag{15}$$

where the index k is randomly selected from (1, 2, . . . , N), and different from the index n_i.

The probabilities of the routing paths are then computed and the best solutions detected. The new candidate solution only around the best solution of the previous iteration is selected using the enhanced ABC algorithm. The optimal routing paths thus obtained are the best routing path. The paths are ranked efficiently based on these paths to allocate the prioritized multimedia content for perfect transmission. This approach further enhances the search operation, results in attaining optimal routes.

In the case of Evolutionary algorithms, random initialization is essentially the most normally used process to generate candidate solutions. However, this affects the convergence speed and the quality of the final solution. To address this issue, the chaotic search algorithm (Alatas, 2010) and opposition-based learning mechanism (Xu, Wang, Wang, Hei, & Zhao, 2014) have been implemented in the initialization phase in order to enhance the solution search.

In chaotic function sinusoidal iterator is chosen and its equation is defined as follows:

$$Ch_{l+1} = \sin(\pi ch_k), \quad Ch_l \in (0,1) \tag{16}$$

Where k is the iteration counter and l is the pre-set maximum number of chaotic iterations.

The random function $\emptyset_i$ used in equation (14) and (15) is now changed as follows for employed and onlooker bees

$$u_i = n_{best} + \text{ch}_{\,l+1} * (n_{best} - n_i) \tag{17}$$

$$u_i = n_{best} + \text{ch}_{\,l+1} * (n_{best} - n_k) \tag{18}$$

Rahnamayan, Tizhoosh and Salama (2008) proposed an opposition based differential evolution (OBDE) to support the convergence speed of DE, which used opposite-based learning (OBL). The proposal of OBL was once offered by Tizhoosh (2005). The same idea can also be utilized in ABC to improve the convergence speed. If the randomized initialized solutions are closer to the global optima, then the required solution can also be determined with much less computational efforts but if the solutions are far from the optima, then it takes higher computational cost or at times, it would also not be infeasible to track the desired solutions. As instructed in these two works, the computational cost could be decreased via making use of the notion of OBL. In OBL, we take into account the easier solutions as good as their opposite counter phase solutions and combine them. The search strategy is then utilized to determine the fittest solutions among them.

$$ou_i = n_{best} + n_i - u_i \quad (19)$$

$$ou_i = n_{best} + n_i - u_i \quad (20)$$

The fittest individuals are found from set u (N) ∪ ou (N) as initial population for both the employed and onlooker bees. If a position update is not improved further for a pre-set number of iteration, then the scout bees discover new solutions ou_i to be replaced.

Procedures for Load Balancing Optimization

In the ABC model of delay-energy trade-off problem, then a number of the employed bees are equal to the number of solutions in the population. Each employed bee is associated with one food source. At the first step, a randomly distributed initial population which, is considered as the initial solution is generated. An onlooker bee chooses a food source depending on the probability value and this probability value P_i is calculated by Equation. (11)

1. Initialize Control Parameters of EABC Algorithm: Colony size CS, dimension of the problem D = 5, and

Limit for scout L = (CS*D)/2.

2. Initialize scout bee positions as per subroutine below:

2.1. Let s be the total no. of scout bees positions.

2.2. Evaluate the fitness of the positioning

3. Set no. of iterations for optimisation, MaxIt.

4. REPEAT for i = 1 to MaxIt

4.1. Assign k employee bee nodes, best out of s scouts, as k_i .

4.2. Produce new solutions for onlooker positions based on Opposition learning, as vij , for each k_i .

4.3 Apply greedy selection process between new nodes.

4.4 $v_{ij} = k_{best}$,i + r_{ij} (k_{best} ,i − k_i)

4.5. Determine the probability values out of their fitness values.

4.6. Produce new solutions for v_{ijout} of this check.

4.7. Record the best solutions yet.

4.8. Check for abandonment condition according to the QoS model,

$$fi = w1 * \frac{1}{Ed} + w2 * \frac{1}{D} + w3 * R_p + w4 * \frac{1}{Ad} + w5 * Q_L$$

& if satisfied replace with new solutions using Opposition based learning.

4.9. Increment i = i + 1.

EABC-EELB-PWDR Algorithm

Initialize nodes N

Get geographical information's of Node i //Node localization

For node i //Route construction

$$P = \sum_{\pi=\pi_i}(1-(1-\alpha)^{|\pi|}) \times \frac{1}{|\pi_i|} \quad \text{ion} \tag{21}$$

//Where α is the angle $\angle(p,i,j)$ between nodes i and j

Check for minPLT

If $(P(i) \leq 1$&& PLT=minPLT)

Node i→ $Path\ DR_i$

Else

Node= i+1

End if

End for

For node i //Route Selection

Compute Ed, D,Rp, Ad, Q_L using equation (1) to (7)

Determine path priority based on weight values using Equation (8)

If $(Path\ priority > 1)$

Assign DR_i = high rank

Else If $(0 > Path\ priority \geq 1)$

Assign DR_i =medium rank

Else If $(0 \leq Path\ priority)$

Assign DR_i =low rank

End if

End for

Initialization //EABC-EELB-PWDGR

Generate new candidate routing solutions u_i using Equation (19)

If $(u_i > n_i)$

$n_{ibest} \leftarrow u_i$

Iteration = 1

Else $n_{ibest} \leftarrow n_i$

Iteration = iteration + 1

End if

Compute probability pi using Equation (11)

If $(rand < pi)$

Generate new solutions u_i using Equation (20)

If $(u_i > n_i)$

$n_{ibest} \leftarrow u_i$

Iteration = 1

Else $n_{ibest} \leftarrow n_i$

Iteration = iteration + 1

End if

End for

If iteration =max

Replace n_i with new solution $n_i + 1$ using Equation (9)

End if

$N_i \rightarrow Scout\ bee$

$n_{ibest} \leftarrow DR_i$

Allocate data to DR

End

RESULTS AND DISCUSSION

In this research, the performance of ABC-based EELB-PWDGR and EABC-based EELB-PWDGR have been evaluated using Network Simulator (NS-2) and compared with that of PWDGR, EE-PWDGR, and EELB-PWDGR in terms of end-to-end delay, PSNR, energy per-packet, hop count and network lifetime in order to determine the efficiency of the proposed schemes. The video sensor nodes are utilized for collecting the multimedia data at different geographical locations with all the nodes considered as static nodes. The utilized sensor node is a 4-layer protocol with satisfactory QoS factors. In the whole network, only a few video monitoring nodes (VN) covering the monitoring area and the capacity of battery equipped for VN node are larger than that of common nodes. The responsibilities of other common nodes are transmitting data to the sink which has infinite energy through many hops. The energy of all the common nodes is equal. The node energy consumption is computed using the sending time, receiving time, idle time and overhearing time for the packet transmission. The NS-2 simulation settings are as followed as utilized in Al-Ariki and Swamy (2017) and Al-Ariki, Mohammed and Swamy (2017a, 2017b) and are given in Table 1.

Figure 2 and Table 2 shows the comparison of PWDGR, EE-PWDGR, EELB-PWDGR, ABC-EELB-PWDGR, and EABC-EELB-PWDGR in terms of End-to-end delay. The delay of EABC-EELB-PWDGR can always be seen to be lower than those by other methods. This becomes the selected path is very close to the bandwidth required by a video stream. Hence, the congestion and data loss are handled based on required QoS in EABC-EELB-PWDGR. It can be seen in Figure 2 and Table 2 that end-to-end delay from 1-Hop to 4-Hop of proposed two approaches is nearly 20% which is lesser than the PWDGR.

Figure 3 and Table 3 shows the comparison in terms of PSNR value. From the figure, it can be observed that ABC-EELB-PWDGR achieves higher PSNR than the EELB-PWDGR, which on an average is about 4dB. EABC-EELB-PWDGR achieves the highest PSNR, which on average is about 8 dB higher than that of EELB-PWDGR for all hop level with varies number of node used for simulation.

Figure 4 and Table 4 presents the comparison in terms of network life of PWDGR, EE-PWDGR, EELB-PWDGR, ABC-EELB-PWDGR and EABC-EELB-PWDGR for 1-Hop*,* 2-Hop*,* 3-Hop and 4-Hop level. From the results, it can be concluded that the network lifetime of EABC-EELB-PWDGR and ABC-EELB-PWDGR are significantly longer and stable than EELB-PWDGR in all Hop levels. EABC-EELB-PWDGR determines the best path. Further, the longevity of EABC-EELB-PWDGR is more than ABC-EELB-PWDGR. In analysis of lifetime with varied transmission ranges from 35 to 100, considering for all hop counts the lifetime is increased 17% on an average for EABC-EELB-PWDGR.

Figure 5 and Table 5 shows the comparison in terms of Hop count value. The hop count of ABC-EELB-PWDGR and EABC-EELB-PWDGR is lesser than that of EELB-PWDGR and EE-PWDGR. A hop count is lesser also implies energy consumption is also less. In this case, the average number of hop is reduced 8% for EE-PWDGR, 10% for EELB-PWDGR, 20% for ABC-EELB-PWDGR and 30% for EABC-EELB-PWDGR from PWDGR. EABC-EELB-PWDGR transmits the packets with adaptive distance and optimal path with QoS parameters which in turn reduces the overall hop count.

Figure 6 and Table 6 shows the comparison in terms of Energy per-packet value. Energy per-packet metric is used to measure how much energy is consumed to transmit one packet over a wireless link. The retransmission in the optimally selected path is reduced in the proposed approaches. The energy per-packet in the case of EABC-EELB-PWDGR is almost 60% lesser than PWDGR, while in the case of ABC-EELB-PWDGR approach it is 50% lesser than PWDGR. The scope of this routing protocol can be learnt from the performance improvement. The routing performance is mainly concentrated in terms of delay, power consumption and errors in transmission for which this research utilized five parameters to evaluate the performance. The optimization based routing protocols has the scope to be utilized in any energy constraint environment for various applications consisting of multimedia data.

Table 1
Simulation environment

Network Area (Size)	1000X1000 m^2
Network Topology	Randomized
MAC Layer (IEEE Standard)	IEEE 802.11
Data rate at MAC layer	2 Mbps
Link Layer	LL (Link Layer)
IFQ Type	Queue/DropTail/PriQueue
IFQ Length	50
Antenna Type	Antenna/OmniAntenna
Physical Type	Phy/WirelessPhy
Channel Type	Channel/WirelessChannel
Energy model	**EnergyModel**
Primary energy of common node	0.2 w
Primary energy of video node	5 w
Energy consumption at sending unit time	0.660 w/s
Energy consumption at receiving unit time	0.395 w/s
Energy consumption at overhearing unit time	0.195 w/s
Energy consumption at idle unit time	0.035 w/s
Packet loss rate	0.15%
Simulation Time	350 s
Data Transfer Protocol	TCP/UDP
No. of Sink Nodes	1
No. of Source Nodes	6
No. of Sensor Nodes	30
Maximum Transmission range	100m
Packet Size	2MB
No. of Paths	9

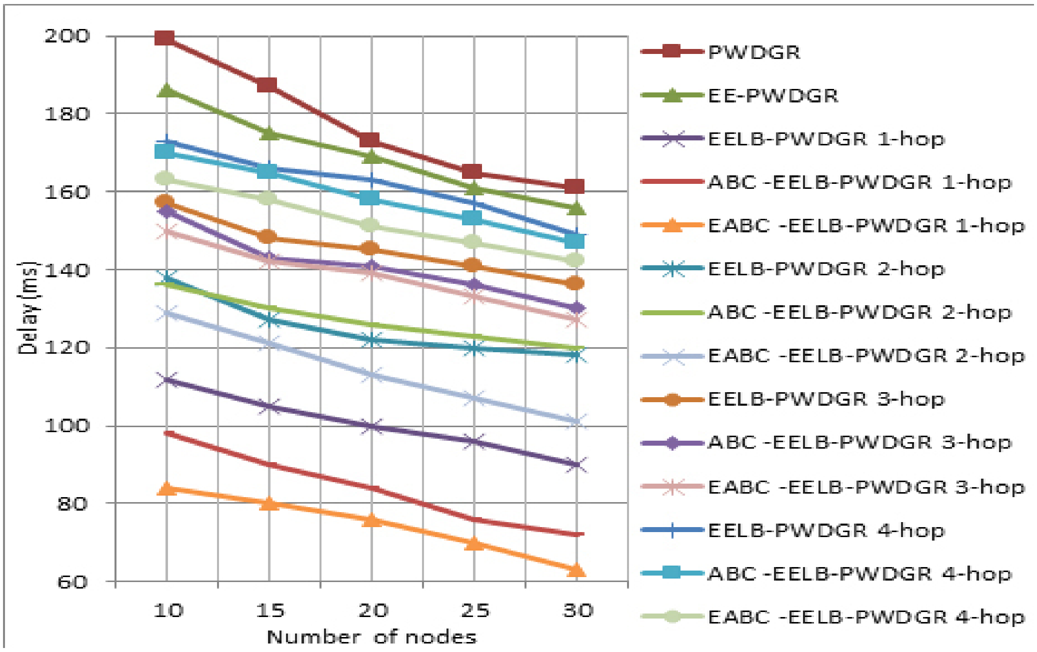

Figure 2. End-to End delay

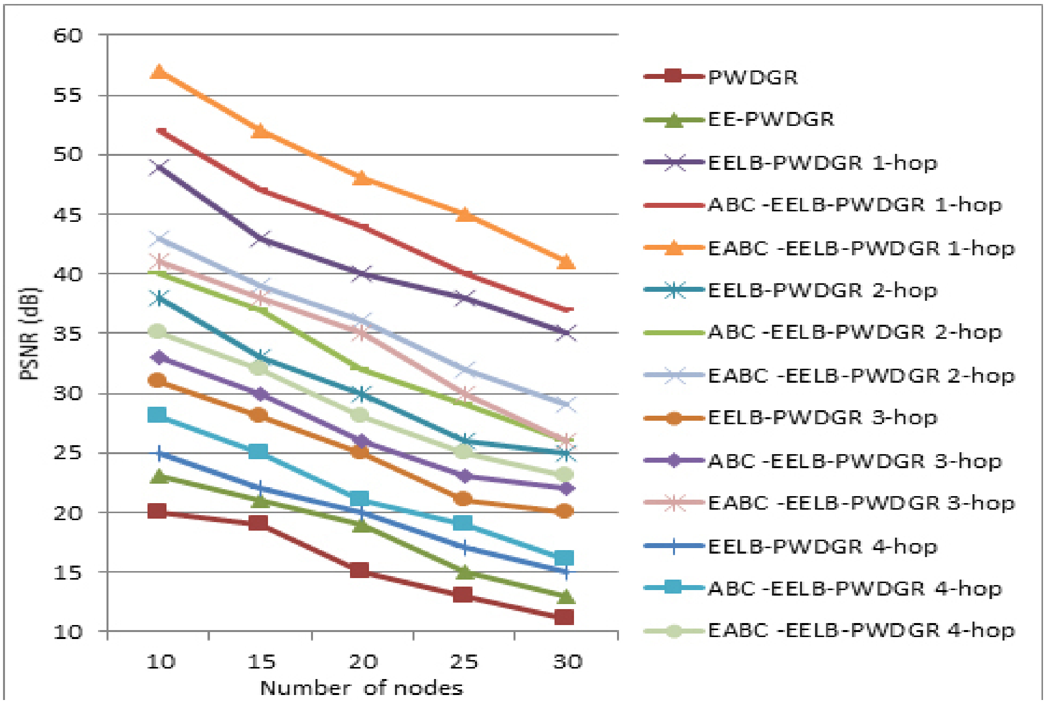

Figure 3. PSNR

Table 2
Comparison in terms of End-to-end delay (ms)

No. of sensor nodes	PWDGR	EE-PWDGR	EELB-PWDGR				ABC -EELB-PWDGR				EABC -EELB-PWDGR			
			1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop
10	199	186	112	138	157	173	98	136	155	170	84	129	150	163
15	187	175	105	127	148	166	90	130	143	165	80	121	142	158
20	173	169	100	122	145	163	84	126	141	158	76	113	139	151
25	165	161	96	120	141	157	76	123	136	153	70	107	133	147
30	161	156	90	118	136	149	72	120	130	147	63	101	127	142

Table 3
Comparison in terms of PSNR (dB)

No. of sensor nodes	PWDGR	EE-PWDGR	EELB-PWDGR				ABC -EELB-PWDGR				EABC -EELB-PWDGR			
			1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop
10	20	23	49	38	31	25	52	40	33	28	57	43	41	35
15	19	21	43	33	28	22	47	37	30	25	52	39	38	32
20	15	19	40	30	25	20	44	32	26	21	48	36	35	28
25	13	15	38	26	21	17	40	29	23	19	45	32	30	25
30	11	13	35	25	20	15	37	26	22	16	41	29	26	23

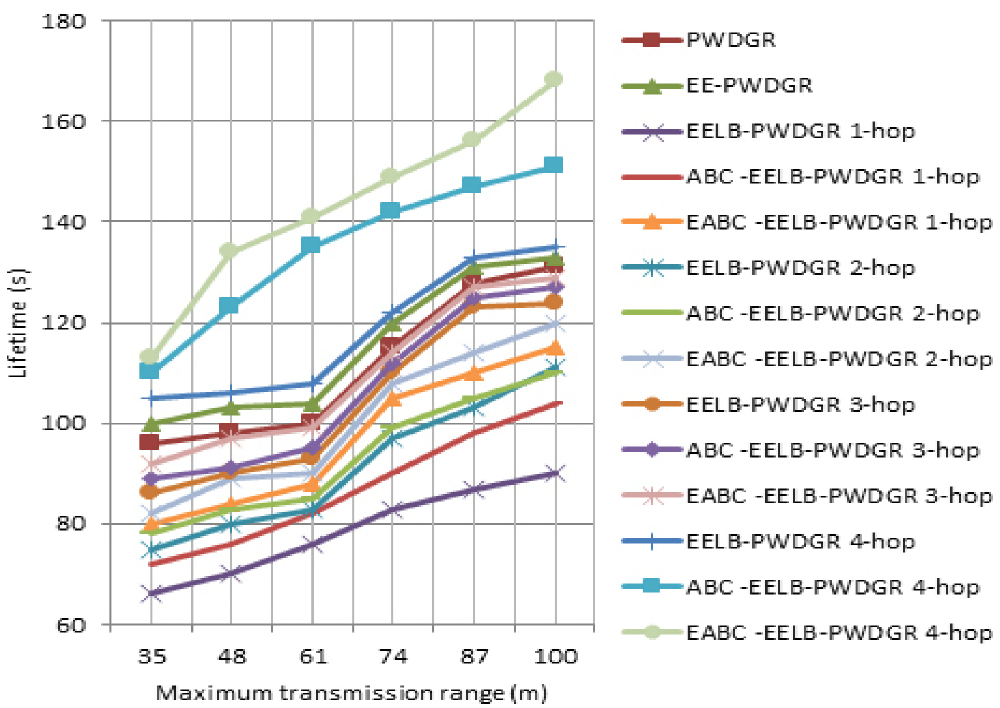

Figure 4. Lifetime

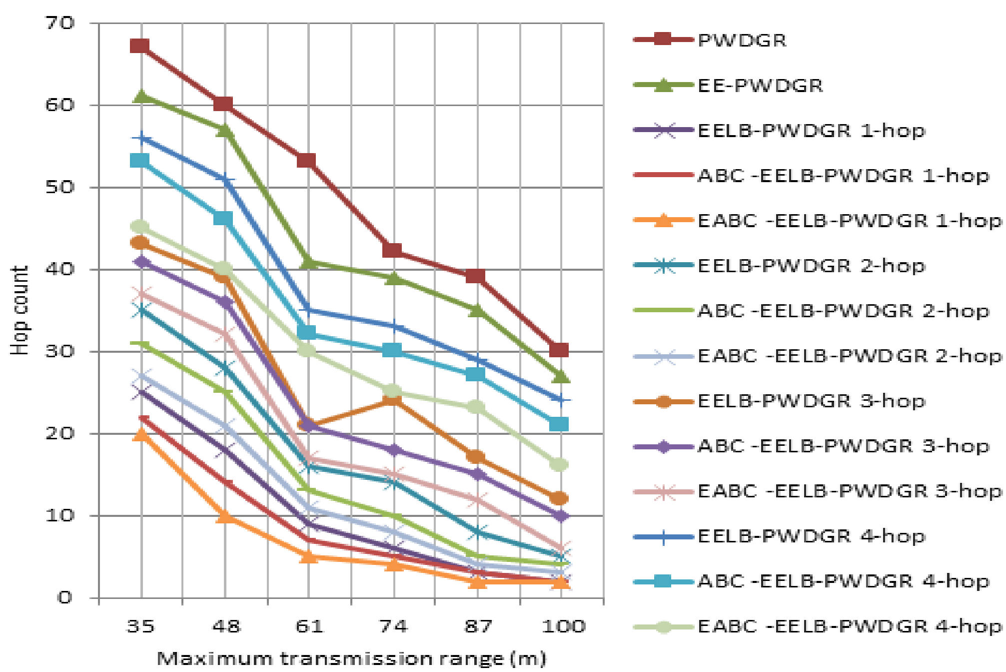

Figure 5. Hop count

Table 4
Comparison in terms of Lifetime

Max transmission range m	PWDGR	EE-PWDGR	EELB-PWDGR				ABC -EELB-PWDGR				EABC -EELB-PWDGR			
			1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop
35	96	100	66	75	86	105	72	78	89	110	80	82	92	113
48	98	103	70	80	90	106	76	83	91	123	84	89	97	134
61	100	104	76	83	93	108	82	85	95	135	88	90	99	141
74	115	120	83	97	110	122	90	99	112	142	105	108	114	149
87	128	131	87	103	123	133	98	105	125	147	110	114	127	156
100	131	133	90	111	124	135	104	110	127	151	115	120	129	168

Table 5
Comparison in terms of Hop count

Max transmission range m	PWDGR	EE-PWDGR	EELB-PWDGR				ABC -EELB-PWDGR				EABC -EELB-PWDGR			
			1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop	1-hop	2-hop	3-hop	4-hop
35	67	61	25	35	43	56	22	31	41	53	20	27	37	45
48	60	57	18	28	39	51	14	25	36	46	10	21	32	40
61	53	41	9	16	21	35	7	13	21	32	5	11	17	30
74	42	39	6	14	24	33	5	10	18	30	4	8	15	25
87	39	35	3	8	17	29	3	5	15	27	2	4	12	23
100	30	27	2	5	12	24	2	4	10	21	2	3	6	16

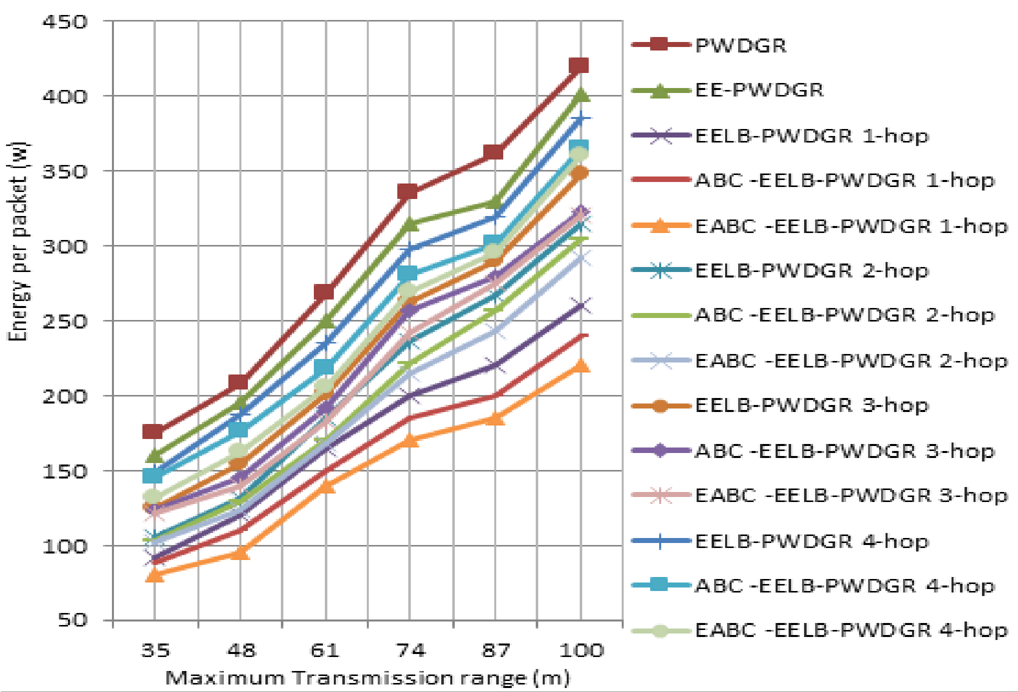

Figure 6. Energy per packet

Table 6
Comparison in terms of Energy per packet ($w/10^6$)

Max transmission range m	**PWDGR**	**EE-PWDGR**	**EELB-PWDGR**				**ABC -EELB-PWDGR**				**EABC -EELB-PWDGR**			
			1-hop	**2-hop**	**3-hop**	**4-hop**	**1-hop**	**2-hop**	**3-hop**	**4-hop**	**1-hop**	**2-hop**	**3-hop**	**4-hop**
35	175	160	92	105	125	149	88	103	124	145	80	102	121	132
48	208	195	120	132	154	188	110	129	145	176	95	124	140	162
61	268	250	165	185	201	235	150	170	192	218	140	168	183	206
74	335	315	200	236	263	298	185	222	257	281	170	215	242	269
87	361	330	220	267	290	319	200	257	280	301	185	243	275	295
100	419	401	260	315	348	385	240	305	323	365	220	292	320	360

CONCLUSION

Route optimization techniques reduce time consumption to rank routing paths based QoS priority. Hence, this study employs the optimization algorithms ABC and Enhanced ABC with EELB-PWDGR for reducing both latency and energy consumption based on QoS-based load balancing between paths. The Enhanced ABC algorithm consisting of two new improved solutions search equations and two functions for population initialization were used to further reduce the search time and to increase the convergence of ABC. The comparison of the proposed routing schemes shows that the EABC-EELB-PWDGR outperforms the other methods with a 20% less delay, 60% lesser energy consumption and a 17% higher lifetime. The multimedia content quality measured in terms of PSNR is also high for EABC-EELB-PWDGR than that of the approaches. Future research can focus on exploring the performance of EABC-EELB-PWDGR with node fault detection and correction. The event of node failures can significantly affect the overall process of routing and hence automatic fault detection and correction schemes are planned to be implemented along with these routing protocols in future.

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