Optimizing Network Lifetime of RPL Based IOT Networks Using Neural Network Based Cuckoo Search Algorithm

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Abstract:

Routing Protocol for Low-Power and Lossy Networks (RPLs) in Internet of Things (IoT) is currently one of the most popular wireless technologies for sensor communication. RPLs are typically designed for specialized applications, such as monitoring or tracking, in either indoor or outdoor conditions, where battery capacity is a major concern. Several routing techniques have been proposed in recent years to address this issue. Nevertheless, the expansion of the network lifetime in consideration of the sensors' capacities remains an outstanding question. In this research, aANN-CUCKOO based optimization technique is applied to obtain a more efficient and dependable energy efficient solution in IOT-RPL. The proposed method uses time constraints to minimise the distance between source and sink with the objective of a low-cost path. By considering the mobility of the nodes, the technique outperformed with an efficiency of 98% compared with other methods. MATLAB software is used to simulate the proposed model.

Keywords: *RPL, ANN-CUCKOO, IoT, low-cost path, sensors, energy efficiency*

1. Introduction

Sensor nodes serve as the main backbone in Routing Protocol for Low-Power and Lossy Networks (RPLs), which are among the most common wireless communication networks [1,2]. In terms of sensor designs, RPLs can have either homogeneous or heterogeneous sensors, with numbers ranging from hundreds to thousands. Most RPLs are tailored to a specific use case, and their sensor nodes typically offer fundamental functions including sensing, processing, computation, and communication. The communication is mostly done with neighboring nodes using radio frequency electromagnetic pulses [3].

Routing Protocol for Low-Power and Lossy Networks (RPLs) based on the Internet of Things (IoT) have recently opened up a new and interesting field for the creation of new sorts of applications [4]. RPLs are made up of several small sensing nodes that monitor their surroundings, analyse data (if necessary), and send/receive processed data to/from other sensing nodes. These sensing nodes, which are spread across the environment, are connected to a sink node – in centralised networks – or to other sensing nodes over a network. In centralised networks, the sink collects sensor data for end-user use. In certain situations, the sink can also send network pol to sensor nodes to activate them [5].Figure 1 depicts the basic general architecture of the RPLs encountered in this investigation. The massage is sent from the source sensor to the sink sensor via the most efficient way feasible, which includes the use of other random sensors [6-8].

In contrast to most existing research, which focuses on a specific element of RPLs [9], we define an Energy Driven Architecture (EDA) as a new architecture for decreasing the total energy consumption of RPLs.The architecture specifies the network's generic and important energy-consuming parts. RPLs are deployed using EDA as a constituent-based architecture based on energy dissipation through their components. This perspective on overall energy use in RPLs can be used to optimize and balance energy consumption while also extending network lifetime.The following contributions are highlighted in this paper in this regard:

1. Using ANN-CUCKOO based optimization technique for reducing total cost of the path.
2. The IoT-RPL is placed optimally to transfer message from sink to source with minimum time constraints.

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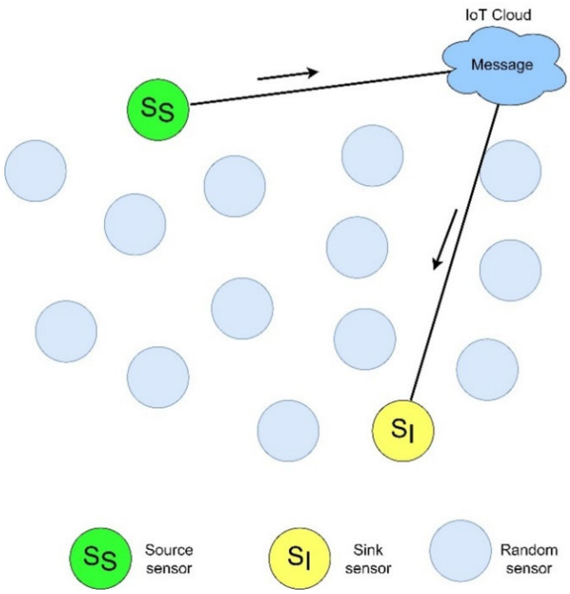

Figure 1. IoT-RPL architecture

2. IoT-RPL background and problem formulation

2.1 IoT-RPL architecture

Small batteries and power harvesting techniques power IoT-RPL sensors, which are often put in inaccessible places; replacing batteries is not an option [10]. Not only does using a battery shorten the sensor's lifespan, but it also makes RPL design and management more challenging. However, energy scarcity has prompted extensive study into RPLs at all layers of the protocol stack. The OSI model and the Internet, for example, are functional models arranged as layers, with each layer offering services to the layer above it (for example, the application layer delivers services to end users) [11].The quality of a network's service parameters is routinely evaluated, including delay, throughput, jitter, availability, dependability, and even security. However, there are various issues when it comes to energy consumption (EC), because there is no comprehensive model for analysing and optimising the network that includes EC..Most current energy minimization models [12] focus on sending and receiving data, while other parameters are ignored. The power consumption model in [13] and [14] focused on the cost of sending and receiving data and calculated the upper limit of single hop distance energy efficiency. This method proposes an intermediate node between the source and the destination in order to conserve energy during retransmission. Other ways use the power consumption model described in [13] to assess the energy efficiency of Routing Protocol for Low-Power and Lossy Networks.

For communication between wireless sensor nodes, a radio connection is required as a physical layer, and energy is consumed when the radio provides or receives data. In the transmitter, the physical layer modulates and codes data, and in the receiver, this layer must optimally decode the data. The radio channel has three modes: idle, sleep, and active. Thus, good energy management requires turning off the radio while the radio channel is not in use; to save energy, the time and energy required to switch between different modes and transmit and receive states must be reduced.

Furthermore, at the physical layer, a low-power listening strategy may be used, with the main idea being to turn on the receiver periodically to sample the incoming data. This duty-cycle method decreases the network's idle listening overhead [15]. Furthermore, the radio channel consumes the same amount of energy for sending and receiving data, so energy-efficient MAC protocols must maximize sensor sleep time [16]. The operating system (OS) is probably the best area to optimize and regulate energy usage of a RPL at the node level due to real-time monitoring and interaction with different elements of a sensing node.Clustering is another strategy for reducing energy consumption while ensuring that deadlines are met.Clustering, on the other hand, has a technical limitation: it can only be employed in wireless sensor clusters with DVS processors and compute capability [17-19]. To overcome this problem the paper, suggest a new approach as stated in next sections.

2.2 Problem formulation for energy module

The goal of this research is to reduce and conserve energy in RPLs. Cuckoo Search is used in the initial phase to construct static clusters to reduce the use of energy sensor nodes. According to[20], the radio model used is the most commonly used assumptions and models in sensor network simulation and analysis are listed below.

Nodes are spread in a 2-dimensional space at random in a uniform distribution, and all sensors are aware of the location of the Base Station (BS). Depending on the distance to the receiver, the nodes can transmit at different power levels. The nodes have no idea where they are. If the transmit power level is known, the nodes may estimate the approximate distance using the received signal intensity, and communication between nodes is not affected by multipath fading. Here, a network operating model based on rounds is used, similar to that of LEACH and HEED [21]. A clustering phase precedes the data collection phase in each round.

$$E_{ms} = \{l\,E_{eng} + E_a \cdot d^2\}\, for\; 0 \le d \le d_l \quad (1)$$

$$E_{ms} = \{l\,E_{eng} + E_a \cdot d^4\}\, for\; d \ge d_l \quad (2)$$

Equation 1 & 2 gives the amount of energy consumed for transmission E_{ms} of a l-bit message across a distance d.The energy expended per bit during the execution of the transmitter or receiver circuit is represented by theE_{eng}.E_a is energy consumed by the amplifier. The main aim of this research is to minimize the E_{ms}.

3. Proposed ANN-CUCKOO optimization modeling for IoT-RPL

The energy consumption of IoT-RPL is depends on the distance and the message bit. To have the efficient system ANN-CUCKOO based model is proposed as shown in figure 2. The CUCKOO search has three stage as described below:

1. Stage 1: Random placement of eggs.
2. Stage 2: The finest nest having good quality of eggs is selected and carried over for next generation.
3. Stage 3: Probability of getting discovered by the host bird nest.

Taking into account these three stages of CUCKOO search, it increases the system effectiveness for global optimizations by maintaining a balance between global random walk and local random walk. The output of CUCKOO search regarding to possible best nests is used as input for the ANN. The output of ANN is the best efficient path having the lowest cost in terms of path from source to sink leads to energy efficient system.

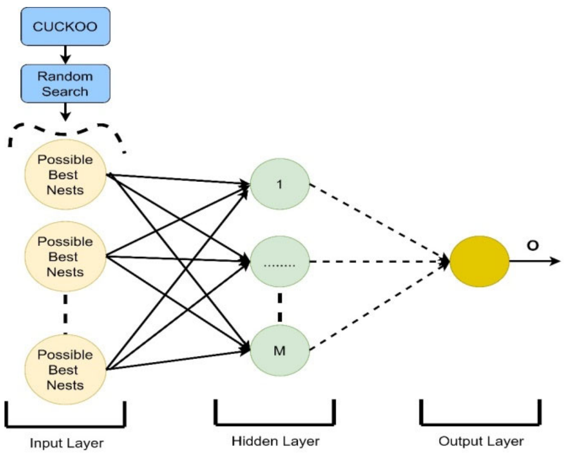

Figure 2. Proposed ANN-CUCKOO basic diagram

3.1 Proposed CUCKOO search modeling for possible best nests

The aim of the CUCKOO search in IoT-RPL is to find all the best possible path to send the message from the source sensor to the sink sensor by using the random sensors present in the vicinity. This is achieved using the nature of the cuckoo which lay eggs in the range of 2-10, which can be used as lower and upper limit of egg dedication to each cuckoo involved. The second habit is they try to lay eggs at maximum distance from their source habitat. The flow chart in figure 3, show the use of cuckoo search for finding the best possible route from source sensors to base/sink sensor. For selecting best sensor nodes for message transfer, the fitness function of each random node must be calculated using the equation:

$$f_n = \alpha_1 f_1 + \alpha_2 f_2 + \alpha_3 f_3 \quad (3)$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1 \quad (4)$$

Where α are the constants and having a value range from 0 to 1. The fitness 1,2 and 3 is calculated using the equations:

$$f_1 = \frac{1}{m} \times \sum_{n=1}^{m} \left(\frac{dist(S_S, S_I)}{m} \right) \quad (5)$$

$$f_2 = \frac{E_{ms}}{E_t} \quad (6)$$

$$f_3 = \frac{CK}{m} \quad (7)$$

Here m is the number of nodes in the system, S_S and S_I is the source node and sink/base node, E_t is the total energy of the node, CK is the number of cuckoos assigned. After calculating the fitness function of each node, the best nodes having high fitness values nodes are chosen for sending the message. For the selection of the best route cost of each route is evaluated using the equation:

$$cost = d_1 \times \gamma + d_2 \times (1 + \gamma) \qquad (8)$$

The d_1 is the function of distance between the random nodes present in the system and d_2 is the function of energy consumption of the nodes. The expression for d_1 and d_2 is given in equation 9 and 10.

$$d_1 = max\{\sum x(m, S_S, S_I)/CK\} \qquad (9)$$

$$d_2 = \sum_{n=1}^{m} E(m_n)/E_t \qquad (10)$$

Minimum value of d_1 and d_2 helps to obtain the best cost and subsequently best possible routes. The possible best route is served as input to the ANN network as shown in the figure 2. The next section gives the details about the ANN modeling regarding the best route and minimum time to send the message from source to base/sink sensor node.

3.2 Proposed ANN modeling for possible best solution

Thebest possible nodes are identified by the cuckoo search in the previous section. Using the best nodes and possibility of best path is used as input for the ANN model. In this model the best 3 possible input is considered from cuckoo search. A total of 30 hidden layer neurons is used to get the best output. The steps required to get the best solution consist of low cost and low energy uses using ANN is given below:

Step 1: Find the best possible routes using the fittest sensor nodes.

Step 2: Which routes has minimum number of sensor nodes involvement.

Step 3: Train the neural network for minimum cost leads to minimum energy consumption.

Step 4: If simulation round over stop, otherwise simulate for possible solution

Step 5: Compute the performance of the different parameters required.

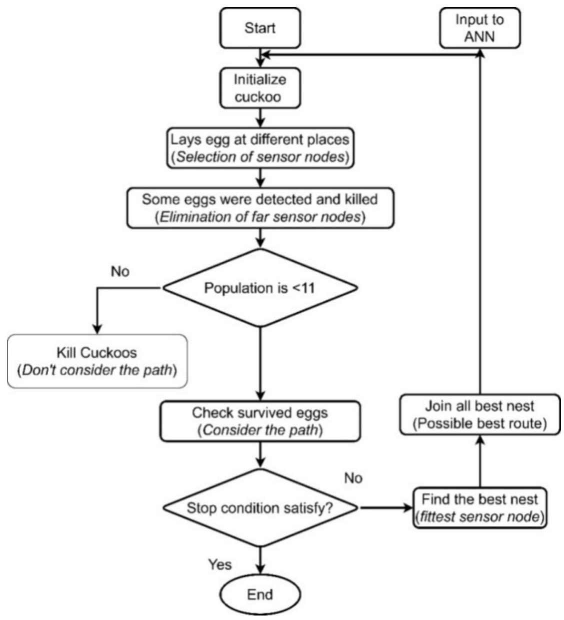

Figure 3. CUCKOO search for best sensor nodes

4. Result and Discussion

4.1 Simulation results

The following result is obtained from the proposed ANN-CUCKOO method. The simulation parameters required for the proposed method is given in the table 1. First the IoT-RPL are placed in two-dimension coordinates as shown in the simulation figure 4. The cuckoo search gives the fitness parameters for different rounds of simulation. Figure5 shows the last 10 best fitness parameters of simulation.

Table 1. Simulation parameters

Parameters	Value
Area	800 *800 m
No. of Sensors	80
Initial Energy	4W
Data packet size	2Mb/sec
No. of rounds	200
Motion coefficient	20
No. of possible nest	80
No. of cuckoos	5
Max. No. of cuckoos	20
No. of eggs in each nest	2
Radius coefficient	0.05
Cuckoo population variation	1e-10

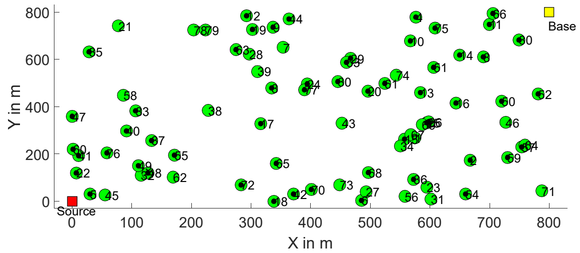

Figure 4. Random placement of IoT-RPL in two-dimension coordinates

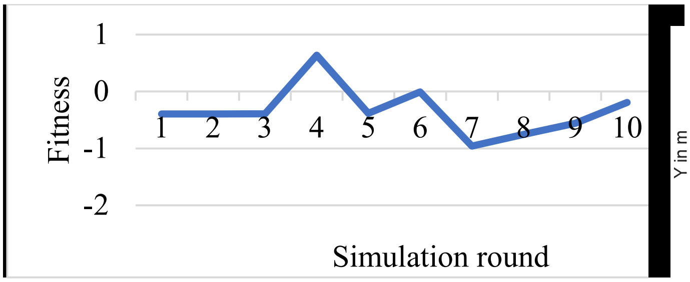

Figure 5. Best fitness for last 10 round of simulation

The cuckoo search finds the best sensor nodes which help the ANN to form the possible routes. The best possible routes find after the simulation is given in the table 2. The ANN estimate the cost of the route and find route 3 as the best route to transfer message from source to base/sink sensor. Through MATLAB simulation the cost of route 3 is found to be 2.145.

Table 2. Possible routes for transferring the message

Route 1	Route 2	Route 3
44	32	60
22	76	55
40	37	70
33	17	49
38	3	67
3	74	56
30	20	20
29	10	69
10	11	13
11	66	44

Figure 6 shows the simulation result for the cost and figure 7 shows the best path selected by the ANN-CUCKOO based model. The energy consumption for each round of simulation is showed in the figure 8.

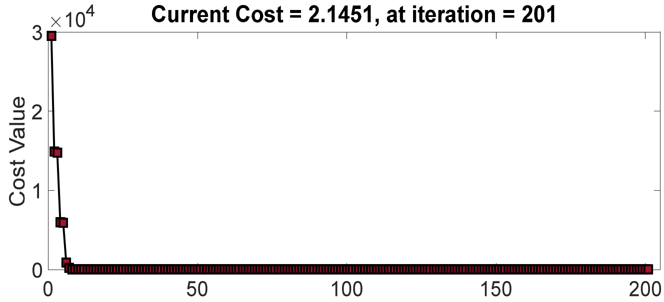

Figure 6. Best cost for simulation round

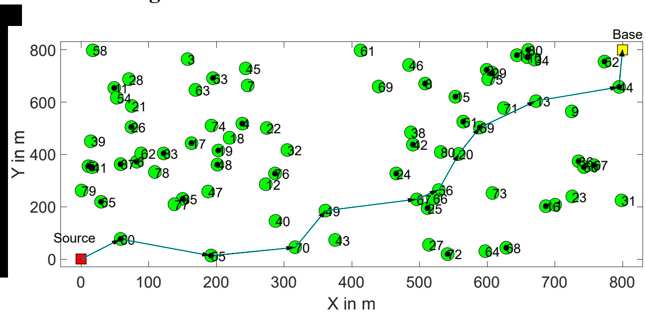

Figure 7. Best route found using ANN-CUCKOO based model

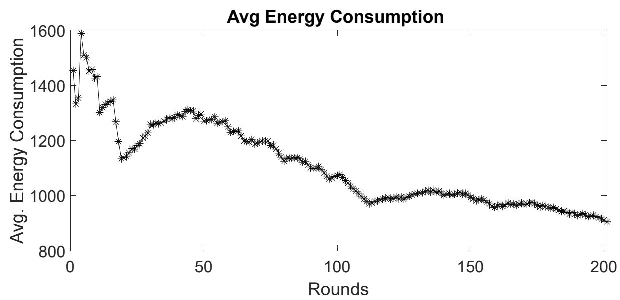

Figure 8. Average energy consumption of nodes during simulation

Figure 9 shows the predicted best nest and route compare with the real data. The error % is almost 2% which indicate the proposed model is very effective in nature.

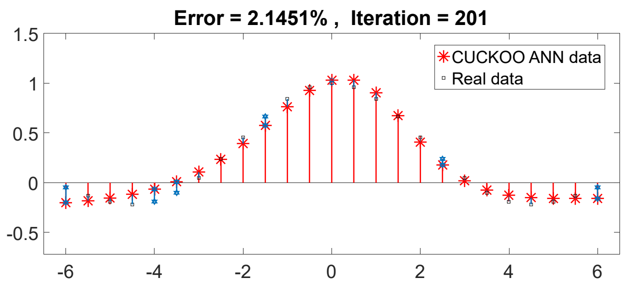

Figure 9. Error in predicted data set

4.2 Comparison with existing techniques

Table 3 shows the comparisons of several strategies, with parameters such as routing type, overhead, delay, scalability, and efficiency taken into account. The routing type indicate either the technique can be used foe single-hop (SH) or multi-hop (MH). The Overhead, sometimes known as overhead costs, is a recurring cost for the system.Scalability refers to ability to perform well as one or more of the network's fundamental parameters rise in value. Delay defines the time required to pass message from source to base/sink.

So, from the table 3 it is clear that ANN-CUCKOO perform well compare to the other existing techniques.

Table 3. Comparison with existing technique

Techniques	Routing	Overhead	Scalability	Delay	Efficiency
ANNR [22]	MH	High	Limited	Medium	90%
QLRR-WA [23]	MH	Low	Good	Low	87%
WL-DCNN [24]	MH	High	Good	Low	89%
ANN-CUCKOO	***MH/SH***	***Low***	***Good***	***Low***	***98%***

The fitness functions in the proposed model are RMSE and MMRE. In the literature, MMRE is the most extensively used performance metric for software cost estimation. The goal is to keep these numbers as low as possible. Equation 11 defines the RMSE function and equation 12 defines the function MMRE.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{((\vartheta-\theta)^2)}{n}} \qquad (11)$$

$$MMRE = \sum_{i=1}^{n} \frac{((\vartheta-\theta)^2)}{n} \qquad (12)$$

Where, ϑ is estimated time series and θ represents actual observations time series. Table 3 compare the RMSE and MMRE values for different techniques.

Table 4. RMSE and MMRE comparison [25]

Parameters	Technique	Values
RMSE	ANNR	0.052
	QLRR-WA	0.045
	WL-DCNN	0.48
	ANN-CUCKOO	0.035
MMRE	ANNR	0.75
	QLRR-WA	0.67
	WL-DCNN	0.49
	ANN-CUCKOO	0.14

5. Conclusion

IoT-RPLs are commonly installed in dense clusters in certain fields to monitor required parameter values. Any wireless sensor network's main goal is to extend the network's overall lifetime as much as feasible. As a result, energy efficiency is a critical parameter for every sensor network, and any effective management must emphasise it. In this research paper, a novel ANN-CUCKOO based optimization technique is used to achieve a more efficient and reliable energy efficient solution. First, the CUCKOO method finds the suitable/possible nodes which can help for fast message transfer. Then the ANN system finds out all the possible paths and then chooses the three best paths, those having the smallest number of nodes, and calculates the cost of the possible routes.

The simulation results show the cost of the best route is 2.14. Route 3 consists of 10 nodes and is the most suitable for message transfer from source node to sink node. The RMSE and MMRE values are 0.035 and 0.14, which indicate the best results. In contrast to other strategies used in the literature, we discovered that the ANN-CUCKOO model outperformed the majority of them.

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