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RESEARCH ARTICLE

Adaptive RPL Routing Optimization Model for Multimedia Data Transmission using IOT

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Abstract

Objectives: The main objectives of this research endeavor encompass the development of the Adaptive RPL Optimization (ARPLO) model to enhance data transmission efficiency within IoT networks. This includes constructing a grid-based network structure optimized for data transfer, selecting the most suitable nodes as grid head nodes to maximize network lifespan while minimizing energy consumption, implementing an innovative objective function-driven approach to optimize parent node selection, and integrating an Adaptive Deep Neural Network (ADNN) to accurately classify medical data. **Methods:** The research methodology entails several key steps. A grid-based network structure is established with IoT nodes and root nodes, where a DODAG process incorporating DIO messages is utilized for node ranking. To enhance energy efficiency, the Trickle algorithm is employed for control message optimization. Grid head nodes are chosen based on metrics such as root node fairness, residual energy, and load influence index. The novel Middle Order Optimal Routing (MOOR) objective function is utilized to optimize routing decisions. ADNN is implemented for precise medical data classification. The proposed model's performance is evaluated through simulation in a Python environment. **Findings:** The research findings demonstrate that the ARPLO model yields notable benefits compared to existing models. It achieves higher energy efficiency, improved throughput, enhanced packet delivery ratio (PDR), and an extended network lifespan. The Trickle algorithm contributes to efficient control message optimization. The MOOR-based routing approach improves multimedia medical data transfer. Moreover, the integration of ADNN enhances the accuracy of data classification, particularly in healthcare applications. The research outcomes align with the broader field's existing values and reports while offering novel insights that contribute to enhancing the existing knowledge base. ARPLO protocol performance reveals that there is increase of throughput of 31.2%, PDR by 7.12%, lifetime of 10.7 % with reduction of energy consumption by 12.72%, control overhead by 31.01% and end-to-end delay by 33.01%. **Novelty:** The novelty of this research lies in its comprehensive approach that integrates a grid-based network structure, MOOR-based optimization, and ADNN-based classification. The incorporation of the Trickle algorithm for energy-efficient communication is an innovative feature. The introduction of new metrics for grid head node selection, along with the application of the MOOR objective function for multimedia medical data routing, showcases the research's innovative contributions.

Keywords: Internet of Things (IoT); RPL (Routing Protocol for LowPower and Lossy Networks); Optimization; Routing; Multimedia; Healthcare

1 Introduction

The Multimedia Internet of Things (MIoT) is a versatile platform for connecting sensors and transferring data over a dynamic system without the need for human participation[(1)]. When used in conjunction with a sophisticated embedded system, it has an integrated revolutionary data aggregation approach that improves the reliability and efficiency of information access[(2)]. Because of the rapid technological advancement of sensors, the wired structure is gradually being replaced by the wireless model in the automation field[(3)]. This is only possible because of the combination of Wireless Sensor Networks and the IoT platform. An IoT network is formed by the connecting of sensing nodes[(2)]. Routing protocol for low power and lossy network (RPL) acts as an efficient platform for the routing operation of the IPv6 nodes[(4)]. Meanwhile, RPL suffers from certain drawbacks, which include QoS parameter degradation and energy distribution. Internet Engineering Task Force (IETF) has provided many amendments to tackle some of the challenges faced by RPL. However, still, some open issues are to be tackled for the efficient routing of information among IoT networks[(5)]. Based on the application of the implementation of this IoT Network, RPL performance gets degraded and fails to keep the QoS parameters of the packet intact. Load balancing is one of the significant challenges faced by RPL-based low-power lossy networks[(6)]. Because all the nodes in Low power lossy networks (LLN) are battery-operated, the lifetime of these nodes are dependent on the routing traffic of the nodes which are actively involved[(7)]. Hence, the foremost thing to do is to maximize the lifetime of a particular node rather than increase the overall lifetime of all the nodes in the network[(8)]. In an IoT network interoperability among different nodes and technologies is essential; hence RPL has provided some guidelines for overcoming such challenges of issues based on interoperability. IoT networks need to integrate software and hardware side because they might belong to different vendors[(9)]. Therefore, the integration of these two domains is a prime issue that needs to be resolved. Recent applications of IoT network has extended its service not only to fixed and static network but also mobile. In dynamic networks such as the Internet of Vehicles (IoV), Vehicular Ad-Hoc Networks (VANET), etc., here the traffic is changing concerning time and the network is dynamic in the sense the neighbour node discovery and parent node selection becomes an integral part of Routing[(10)]. Conventional RPL does not support mobility, and it also advocates that mobile nodes should not participate in the data transmission procedure.

In this scenario, RPL faces very high packet loss and also frequent parent changes. The main challenge for RPL during interference is reliable packet delivery to the destined node[(11)]. This issue of interference has been widely studied, and many researchers have come up with cross-layer solutions to mitigate the problem of interference[(12)]. Security threat is a significant challenge in RPL as it is for all the routing

Protocols [13]. Two types of security attacks frequently occur in a dynamic system, such as internal and external. Internal attackers are those nodes which freely involve in the network as authenticated nodes and transmit packets [14]. External attackers are intruders who deliberately try to enter the network and malign the packets. RPL provides protection against External attacks, but it is optional, and it is weak against internal attacks [15]. RPL assumes an essential part in the IoT network because of its conveniences, for example, low energy utilization effectively adjusts to the organization and makes network courses solidly [16]. The vast majority of the works in the RPL put together IoT network centered concerning the Objective Function based Directing. The setting mindful goal capability-based steering likewise acted in an RPL-based IoT network [17]. In any case, none of the works have focused on the information setting (i.e., Touchy and Non-Delicate information) based steering in the RPL organization [18]. In the meantime, load adjusting likewise packed in a portion of the attempts to adjust the heap in the IoT hubs present in the organization [19]. In load adjustment, the majority of the work focused on the boundaries, for example, youngster count and line usage to adjust the heap in the organization. Be that as it may, these two boundaries are not adequate to adjust the heap solidly [20–23]. In the predetermined number of works, bunch-based directing is acted in the RPL organization to adjust the heap and diminish energy utilization [24]. In any case, there is none of the works have focused on developing a framework-based network in RPL directing and load adjusting. The same context-centric approach has been applied to a mobile network for addressing the issue of mobility and load balancing in this Internet of Vehicles has been chosen as the area of implementation of the work. Heterogeneous types of data are considered here for routing the information and parent node selection is based on the type of data also mobility flag has been added to the DODAG Advertisement Object (DAO) message structure to recognize the mobility of nodes [25].

The Multimedia Internet of Things (MIoT) offers a versatile platform for sensor connectivity and data transfer in dynamic systems without human intervention, enhancing information access efficiency when integrated with sophisticated embedded systems. The shift from wired to wireless models in automation, facilitated by Wireless Sensor Networks and the IoT platform, underscores technological progress. However, the Routing Protocol for Low Power and Lossy Networks (RPL), a key element in MIoT, faces challenges. While it efficiently routes IPv6 nodes, it encounters issues like quality of service (QoS) parameter degradation and uneven energy distribution. Load balancing in battery-operated nodes presents a significant challenge, as maximizing the lifetime of specific nodes is prioritized over overall network longevity. RPL addresses interoperability issues among nodes and technologies but struggles with mobility in dynamic networks, leading to high packet loss and frequent parent changes. Interference, a common issue in dynamic systems, is a significant challenge for RPL, prompting researchers to propose cross-layer solutions. Security threats, both internal and external, pose a challenge, with RPL offering optional and weak protection against internal attacks. Despite these challenges, RPL remains crucial in IoT networks due to its energy efficiency and robust network routing. In addressing challenges, recent works focus on load balancing, emphasizing cluster-based routing and context-centric approaches. While some efforts incorporate sensitive and non-sensitive data-based routing in RPL, the exploration of system-based network development in RPL remains limited. A context-centric approach is also extended to mobile networks, specifically in the Internet of Vehicles (IoV), introducing considerations for heterogeneous data types, mobility flags, and parent node selection based on data types to address issues of mobility and load balancing. Despite advancements, there is a need for further exploration and development of system-based networks in RPL for efficient routing and load balancing in IoT scenarios.

1.1 Contribution and Organization of Paper

The research focuses on developing an Adaptive RPL Optimization (ARPLO) model for efficient data transmission in an Internet of Things (IoT) environment, specifically targeting medical multimedia applications like ECG, EEG, Heart Sound (HS), and wireless capsule endoscopy (WCE). The ARPLO model consists of various phases, including grid construction, grid head selection, optimization, and classification. The goal is to optimize the routing path in the IoT network to ensure seamless and reliable transmission of multimedia data in healthcare settings. The constructed ARPLO model ranks nodes based on factors like hop distance and power levels, considering the specific requirements of medical multimedia IoT systems. This ranking helps in determining the most suitable nodes for information exchange. Additionally, the model incorporates optimization techniques to enhance the performance of the IoT network.

The research evaluates the ARPLO model through simulation analysis, considering different numbers of nodes ranging from 20 to 100. Several performance parameters, such as energy consumption, packet delivery ratio (PDR), control overhead, end-to-end delay, throughput, and the number of alive nodes, are analyzed. A comparative analysis is conducted between ARPLO and existing protocols like PE-WMOT and MOOR. The simulation results demonstrate that the ARPLO model achieves superior network performance compared to the state-of-the-art methods. It exhibits higher PDR and throughput while minimizing end-to-end delay, energy consumption, and control overhead. Furthermore, the number of live nodes is effectively maintained, ensuring the robustness and reliability of the IoT network.

The paper is organized as follows: Section 1.1 provides the contributions of our work while section 2 presents the overview of the proposed methodology. Simulation environment is highlighted in section 3. The result analysis is discussed in section 4. Lastly, conclusion of the present work has been reported.

2 Methodology

The developed Adaptive RPL Optimization (ARPLO) for the data transmission over multimedia IoT environment. The ARPLO model uses the constructed graph G= N, L with a set of IoT nodes utilized based on root nodes denoted as N, and the link between the nodes is stated as L. Initially, the ARPLO model performs construction process with the utilization of DODAG process with the transmission of DIO messages through root nodes for the neighbouring node ranking, The ARPLO model constructs the DODAG with consideration of path between roots to the head node those are in static. The complete data transmission process with the ARPLO model is presented in Figure 1 .

The construction process comprises the 4 modules such as grid construction, ranking of selection in Grid Head, Data Transmission based on Reputation, and Dual Context Oriented Objective Function. With the construction of the grid, the network area is computed for the different grid levels through load balancing and network energy consumption. Secondly, the node in each grid is selected and ranked with the random walking process for the selected node to perform multimedia data transmission with the Random Walking process. Thirdly, the scheduling is performed for the grid head based on member node with the Reputation Scheduling with estimation of value and each member reputation values are computed for every grid member. With the dual context-oriented objective function the routing of the node is performed with the MIoT sensed data. The classification is performed with the received nodes with consideration of members in the nodes through an Adaptive Deep Neural Network (ADNN). The designed objective function is based on the transmission of multimedia data. The ARPLO model uses the Middle Order Optimal Routing (MOOR) objective function for the optimal parent node selection for multimedia medical data transmission. The overall architecture model for the proposed ARPLO model is presented in Figure 1.

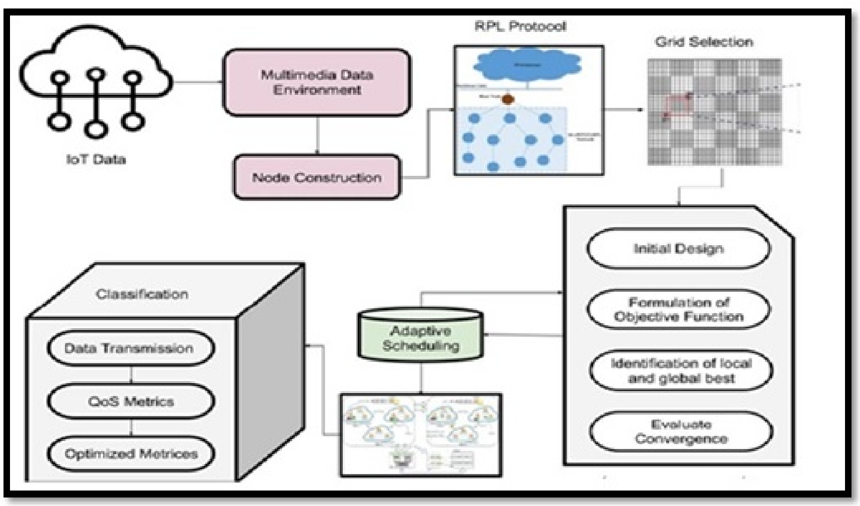

Fig 1. Data Transmission Process with the ARPLO model

2.1 Experimental data set

The performance of the proposed ARPLO algorithm was tested using the biomedical data comprising ECG, EEG, Wireless Capsule Endoscopy (WCE) image, and Heart Sound as used in our prior works. The detailed results are discussed in subsequent sections of the article.

2.2 Grid Construction

The ARPLO model uses the objective function-based optimization model for the selection of the parent optimal node to transfer the multimedia data transmission with MOOR. The ARPLO of the network node is observed as in static factor for the transmission and optimization of the control message, which is constructed with the DODAG graph with Trickle algorithm. The

ARPLO model constructs the network with different levels of grid construction for the broadcasting of the data towards rank nodes with the node ranking and transmission of DIO message packets towards other neighbours. The constructed ARPLO model constructs the network with different level of transmission of multimedia data that transfer the DIO message packets toward the neighbour nodes. In the network, every network has its level based on grid size for the computation of root nodes. The estimation expressed that root node distances are increased based on level, and the grid number at each level is minimized. In this contrast, the grid size increases with the increase in distance between the level and root nodes. In this manner, the network splits the data transmission multimedia data with minimized energy loss, imbalance of loss, and overhead.

2.3 Grid Head Selection

With the ARPLO model elect the head node in the optimal grid to achieve the effective lifetime to evaluate the heavy traffic of multimedia in the IoT environment for data transmission. The grid head selection is initiated based on control message reception with the root node through constructed DODAG. Initially, the root nodes in the network are ranked with a selection of head nodes. The MIoT model with the ranking process for the selection of grid in each node with consideration of different metrics such as root node, residual energy, and load influence index. The parameters computed in the grid head selection model are presented as follows:

Definition 1- Root Node Fairness (F_R): The fairness computed to minimize the delay utilized for effective data transmission. The evaluation is computed based on the estimation of the distance that lies between the grid node and the root node. The fairness of the node is presented in Equation (1).

$$F_R = \sqrt{(R_x - N_x)^2 + (R_y - N_y)^2} \tag{1}$$

In the above Equation (1), the root node (R) positions x, and y are denoted as Rxy, and grid node positions are stated as Nxy.

Definition 2- Residual Energy (Re): The IoT network for multimedia data transmission is constrained to resources that are utilized for the residual energy computation with grid selection. The selection of a frequent grid minimizes the loss of energy computed as in Equation (2).

$$R_e = T_e - C_e \tag{2}$$

Here, $T_e$represents the node energy level and $C_e$consumed energy of the nodes in the IoT environment.

Definition 3- Load Influence Index (LI^2): The node selects the evaluation with consideration of different load condition for multimedia data transmission. The computation is performed based on the transmission ability, probability of data forwarding, and metrics of buffer size are presented in Equation (3).

$$LI^2 = \sum (T_a B_z) \tag{3}$$

Where, $B_z$denoted size of buffer and data transmission ability $T_a$calculated as in Equation (4).

$$T_a = \frac{N_{p,t}}{T} \tag{4}$$

In above Equation (4)$N_{p,t}$ represented the packet count transmitted over time T.

With consideration of different metrics ARPLO algorithm computes every node rank with the computation of the highest rank in the selection of the head node in the grid. The ARPLO model computes node rank with consideration of different ranks such as positive edges (pe), negative edges (ne), tiredness probability (γ), and hopping probability (ε). Through the estimation of variables probabilities are computed in the range of π- and π+. Here π+ denoted the grid node probability for the estimation of grid positive rank and estimation of grid negative rank. The steps in the ARPLO ranking process are stated as follows:

Step 1: It allocates the same values for the range $\pi^{+(0)}$ and $\pi^{-\,(0)}$.

Step 2: It computes network positive edge and implement the values between sources towards the destination nodes.

Step 3: It computes the network negative edges and embraces the value between sources to destination node.

Step 4: Each node probability is ranked with estimation of positive and negative values.

Step 5: The error tolerance value is computed (ε) and compared with the estimated threshold value (φ). If the process is minimal than the threshold the process is terminated or process is continued for the minimal than threshold value.

In ARPLO model MOOR based model is implemented for the estimation of ranks for the computation of each node rank in the grid. Here, the nodes that have the highest rank in the grid are elected as the head node in the grid. The information is transmitted and selected based on the member node in every node. The IoT member nodes transmit the data to the root node towards the grid node. This IoT network provides significant transmission to provide an efficient network lifetime with the minimized node depletion energy effectually.

2.4 Selection of Optimal Path with Objective Function

The ARPLO uses the context adaptive function selection to achieve significant RPL routing in the IoT network for the transmission of multimedia data. The model uses the MOOR objective function routing protocol for the RPL concentrated on the transmission of multimedia data in an IoT environment. Here, the sensitive data is evaluated based on medical data for monitoring and so on. The medical data transmission with route selection is performed for the aware data to minimize packet loss and increases the packet delivery ratio. In this medical data, context is computed for the selection of optimal path based on objective function with RPL routing. The estimation of objective function with the MOOR model is computed as follows in a multimedia IoT environment**.**

Context 1-Objective Function: The objective function computes the transmission of data towards the root node. The objective function formulated are presented in Equation (5).

$$Obj\,1 = \sum_{i=0}^{n} SD_i \quad i = 1, \ldots.., n \; //using\; OF \tag{5}$$

Here, SD_idenoted the multimedia IoT data for transmission between roots to parent node selection.

Context 2-Objective Function: The multimedia data transmission is computed for the objective function as in Equation (6).

$$Obj\,2 = \sum_{i=0}^{n} NSD_i \quad i = 1, \ldots.., n \; //using\; MOF \tag{6}$$

In above Equation (6)NSD_i represented the multimedia data transmission through root nodes with MOOR model for the selection of parent node.

2.5 Data Classification

The routing path in the network of the ARPLO model performs the Deep Neural Network (DNN) to perform data classification. The constructed DNN model comprises the Adam learning rate Estimation with optimization. The adaptive learning process computes the learning rate for the determination of each parameter state. Through adaptive learning based Adam learning process to compute individual learning rates with consideration of different factors to perform adaptive estimation of the moment. The classification-based deep learning model comprises of convolutional layer, hidden layer, and softmax layer for the processing. With the utilization of the convolutional layer input packet features are computed to perform convolution operation. The connected convolutional layer to achieve output comprises hidden layers estimated with input value weights. The constructed model uses the Adam Optimizer model to compute the learning rate with an estimation of features as illustrated in Figure 2.

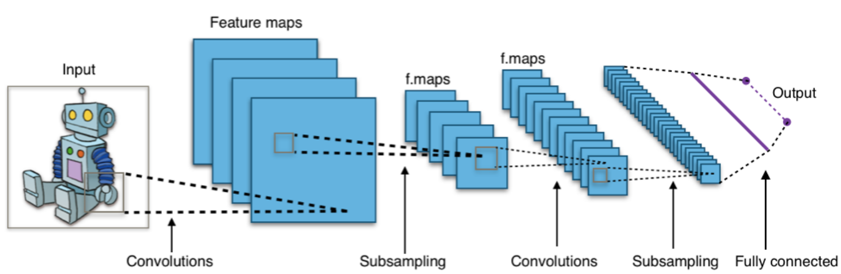

Fig 2. Optimizer with DNN model

The decaying gradient estimation with average for the past squared is denoted as $m_d$ands_d. The computation process is presented as in Equations (7) and (8).

$$m_d = \beta_1 m_{d-1} + (1 - \beta_1)\, G_d \tag{7}$$

$$s_d = \beta_2 s_{d-1} + (1 - \beta_2)\, G_d^2 \tag{8}$$

In above Equations (7) and (8) first and second moment are computed as $m_d$and s_d. The constant value of 1 denoted as $\beta_1$and β_2. The updated rule is computed as in Equation (9).

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{s_d + e}} \widehat{m_d} \tag{9}$$

In the above Equation (9) the learning rate is stated as η and input parameters are denoted as θt with consideration of the packet header information. The expression is estimated based on the evaluation of hidden layers to compute weights for the input layer. The information for the classification is performed with the soft-max layer for the transmission of multimedia data transmission

2.5.1 Multimedia Data Transmission

Multimedia data is transmitted with the consideration of medical information as illustrated in Figure 3. Through the consideration of the constructed grids with the optimal data transmission with a selection of optimal path between nodes. The data transmitted is optimal through the path selection with the identification of the best path for the parent node with the use of Hashing algorithm. The medical data are transmitted with the selection of the optimal node in the parent with consideration of the parent node chain with the root nodes. The selection of a parent node provides significant data transmission with multimedia information exchanges. The medical information transmission comprises the objective function of the selection of nodes with an RPL-based IoT network. The performance of the ARPLO model performance is compared with the conventional heuristic algorithm for the grid node selection in the network. The fitness is estimated with the identification of the selection of each optimal parent path for the packet delivery.

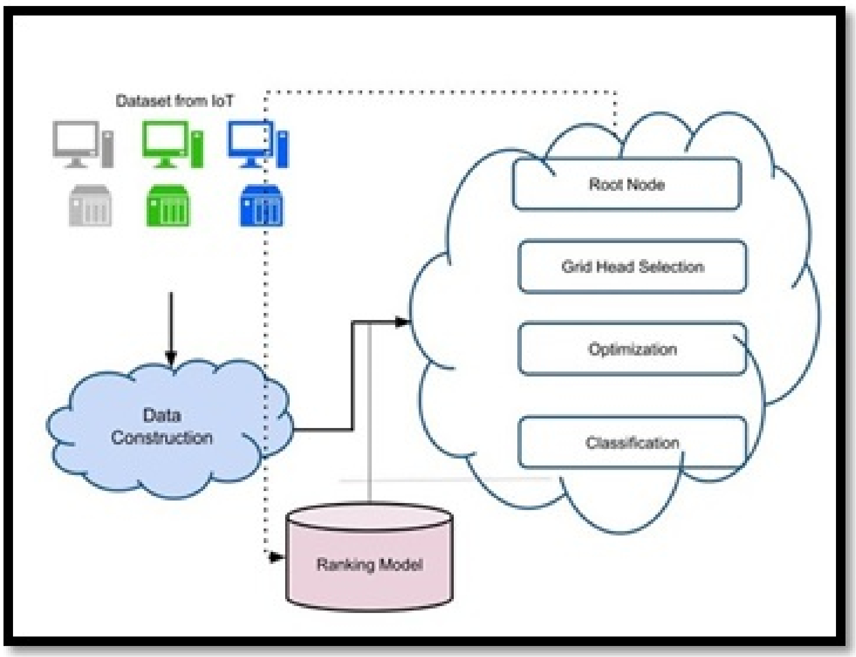

Fig 3. ARPLO Optimization for routing of medical data

The estimation of fitness function is computed with the different metrices such as latency, reliability of links, rank of parent, size of buffer, data rate and expected load. The metrices considered for the analysis are presented in Table 1.

Table 1. Matrices in ARPLO for Multimedia Data

Parameters	Definition	Equation
Latency	It provides the time taken by the packet for the information transmission between sources to destination.	$L = \frac{P_{sg}}{t}$ Where, P_{sg} denoted the size of packets and t represented the time taken for the packet to perform data transmission.
Link reliability	It provides the link strength lies between the nodes in source to destination.	l_{re}
Parent Rank	The number of hops is minimized between the sources to destination.	$R(n) = P(R) + ETX$ Where, $P(R)$ denoted the range of parent and ETX stated the transmission count.

Continued on next page

Table 1 continued

Buffer Size	It minimizes the congestion in the routing path with the elimination of packet loss through the reduction of load in the parent node.	$B_g = \frac{n_p}{T_{bl}}$ Here,$n_p$denoted the data packet count and T_{bl}denoted the buffer total length.
Data Rate	The significant data transmission is evaluated with the RPL data routing to increase the packet delivery ratio.	$D_r = B * log_2(1 + SNR)$ Where,Bdenoted the bandwidth and SNRstated the signal to noise ratio
Expected Load	It provides the load balance between the parent nodes with the estimation of the load in the path previously. In this manner the load balance is computed for the effects on the parent nodes.	$E_l = \sum_{i=0}^{n} \frac{N_{dp,i}}{t_i}$ Here, $N_{dp,i}$ denoted the transmission of data packed over path 'i' for the specified time 't',

The constructed ARPLO model uses the objective function-based routing technique with improved mobility features and content-centric features. Conventionally, the RPL nodes perform the detection, and routing performance is minimal with the ARPLO model the mobility features are implemented in RPL through the signal handshaking. Through mobility features the packets are broadcasted to neighboring nodes with the implementation of data forwarding. With the movement of the node, the information related to the present position is computed with the parent node and computed with the selected parent node with the computation of neighbors of the parent node. Upon the incorporation of the mobile node within the network information about parents moving in the network is updated with the mobile flag as stated in Figure 4.

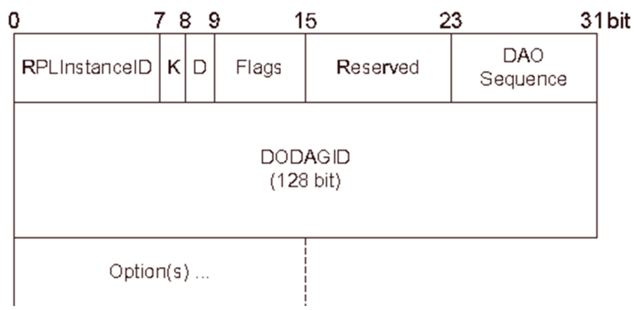

Fig 4. Structure of DAO messages

With the information estimation parent node compute the information those are stored in the mobility table. The data algorithm performs the phase of data forwarding without any ACK reception. In that scenario, the routing packets destination is computed in downward with the evaluation of the mobile node those paths are updated in mobility tables. The mobile nodes that are higher than the trial number are broadcasted with the old parent for all the neighboring packets in the received parent node. The algorithm for the ARPLO for the data forwarding phase is presented as follows:

Algorithm 1: ARPLO Data Forwarding Phase

Packet Forward_noack ()
If (compute table_mobility(packet_destination_IP) ==TRUE)) then
If (packet_Transmission Count>Maximum_Transmission) &&(Type_Packet=="A")
Then
Packet_MAC_address=Broadcast address_1
else
If(packet_Transmission_Count>Maximum_Transmission)&&(Type_Packet=="B")
then
Packet_MAC_address=Broadcast addr2
Send(packet)
else if(packet_Transmission_Count<= Transmission_Count_Maximal Value) then
Packet_Transmission_Count++
Retransmission(packet)
end if
end if

The proposed ARPLO model flow chart is presented in Figure 5 is presented for the effective routing for the multimedia data transmission.

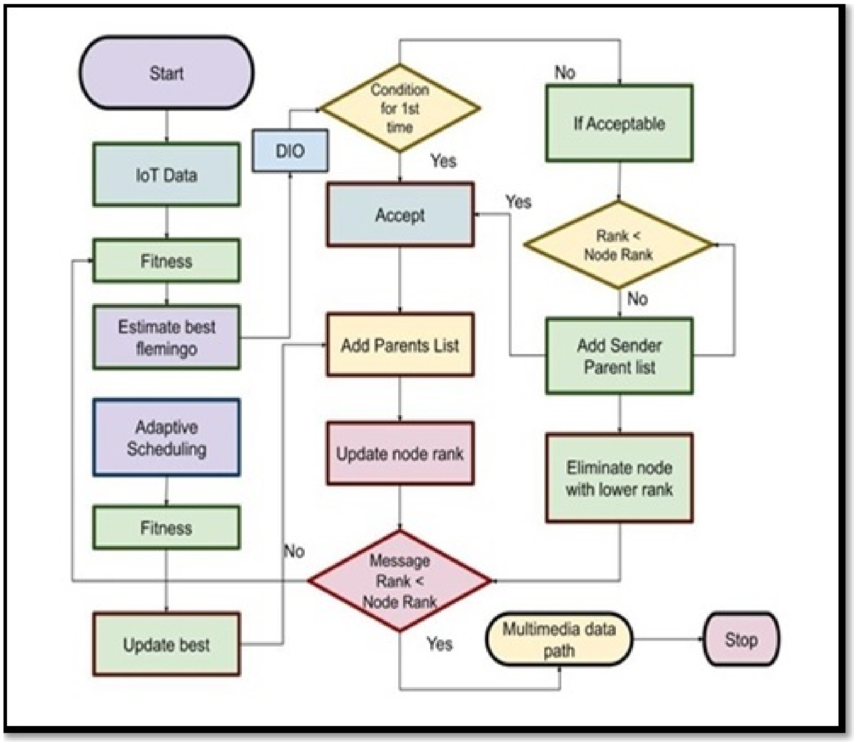

Fig 5. Flow chart of ARPLO

3 Simulation Environment

The analysis is performed for the ARPLO model implemented in Python simulation environment. With the developed model data transmission between root nodes and border root are computed. The parameters implemented for the ARPLO model are evaluated with consideration of standard values. The simulation parameters used for the implementation of the ARPLO model are defined as network, packet, traffic, and communication parameters. The simulation parameters considered for the analysis are presented in Table 2.

Table 2. Simulation Setting

Parameters	Value
Simulation Duration	500s
Simulator Software	Python
IoT Nodes	105
Root Node	2
Initial Energy	50J
Range of Transmission	100m
Power for Transmission	-20dBm
Format of Packet	IPv6
Number of Packets	~1000
Size of data packet	60bytes
DIO length	17bytes
DAO packet length	17bytes
DIS packet length	2bytes
Packets Interval	1,2.5,3s

Continued on next page

Table 2 continued

Traffic Type	Constant Bit Rate (CBR)
Traffic Rate	15,25,35,45,80pkt/min
Protocol utilized in network	IP based
Routing Protocol	RPL
Standard for the Physical and MAC layer	IEEE 802.15.4

4 Results and Discussion

The ARPLO model computes the ranking of nodes in MIoT for healthcare multimedia data transmission. With the ARPLO model, the feature and node ranks are computed with the estimation of the optimal path for multimedia data transmission for healthcare data. The examination is based on consideration of multimedia data such as .jpg, .txt, .mp3, .mp4, and .mat files. The analysis for the .jpg file for the data transmission is presented simulation results. The test.jpg file evaluates the network transmission packet count of 402913. The network node and ranking are stated as [(1 2 10 9 11 13 0 8 14 5 4 7 12 6 3)]. The simulation analysis is considered based on consideration of energy consumption, Packet Delivery Ratio (PDR), End-to-End Delay, Control Overhead, Throughput, lifetime of CH, and number of alive nodes.

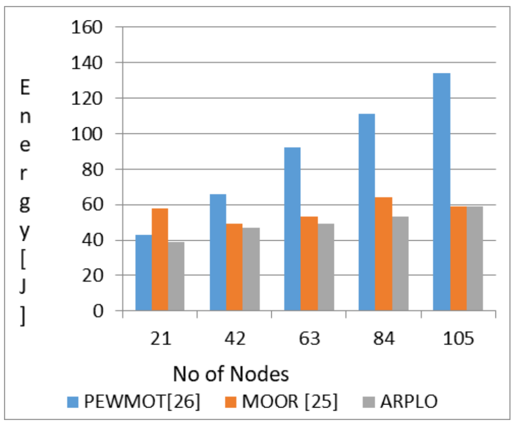

Fig 6. Performance comparison of energy consumption (mJ)

Figure 6 provides the measured energy consumption for the proposed ARPLO for the varying number of nodes. Similarly, for the varying number of nodes PDR, End-to-End Delay, Control Overhead, and Throughput are presented in Figures 7, 8, 9 and 10.

The energy consumption estimation for the varying number of nodes stated that with an increase in the number of nodes inFigure 6, the energy consumption of the ARPLO model is minimal. The energy consumption is higher for the 60 nodes. The PDR computation expressed that for 40 nodes the PDR value is achieved as higher compared to the other nodes. With the ARPLO model for varying numbers of nodes, the energy consumption is minimal with the higher PDR.

In Figures 8 and 9, the end-to-end delay and control overhead of the nodes is minimal for the proposed ARPLO model. The estimated delay is minimal for the node count of 80. In the case of the ARPLO model the control, overhead is minimal for the node count of 60. The estimation expressed that the proposed model significantly minimizes the end-to-end delay and control overhead. In Figure 11 the lifetime of CH node measured for the varying number of nodes are presented.

In Figure 10 stated the measurement of throughput for the varying node count of 21, 42,63, 84, and 105. The estimated throughput value of the node count is significantly minimal than the other node count of 60. The existing model of ARPLO is compared with PE-WMOT and MOOR models. The performance of ARPLO compared with the existing model exhibits significant performance compared with the PE-WMOT and MOOR. The performance of the ARPLO model is comparatively examined with the conventional PE-WMOT and MPR model for the node count of 21, 42, 63, 84, and 105.

Figures 6, 7, 8, 9, 10 and 11 illustrate comparative analyses with state-of-the-art protocols evaluated by varying the number of nodes as 21,42,63,84 and 105 nodes. Metrics like energy consumption, PDR, End-to-End delay, Control overhead, Throughput, and Alive nodes have been considered for study. The proposed ARPLO model is ~23%. Packet Delivery Ratio provides the number of packets delivered to the destination for the total number of packets transmitted the ARPLO model achieves the ~12% higher performance. In the case of End-to-End Delay and control overhead of the ARPLO model is ~21% - ~27% less

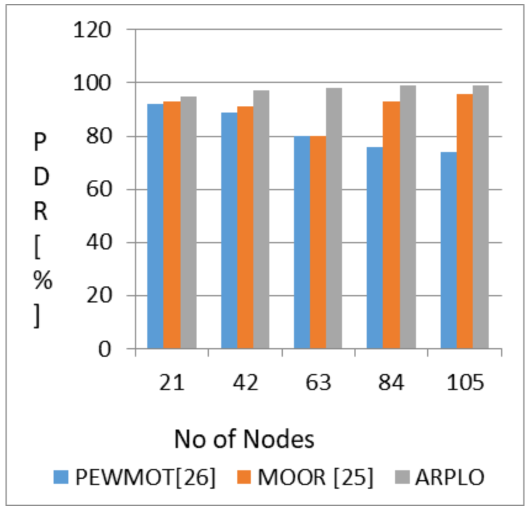

Fig 7. Comparison of R(%)

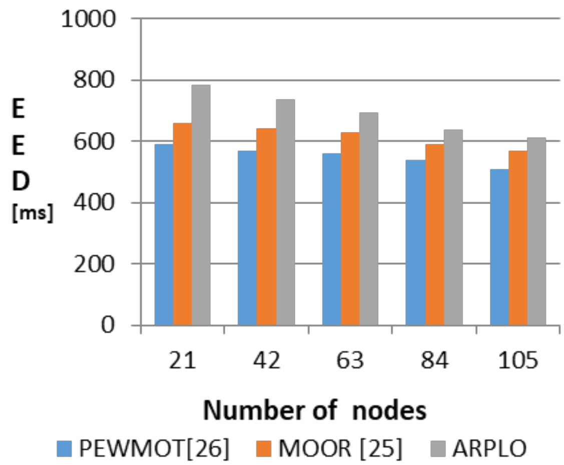

Fig 8. Comparison of End-End Delay

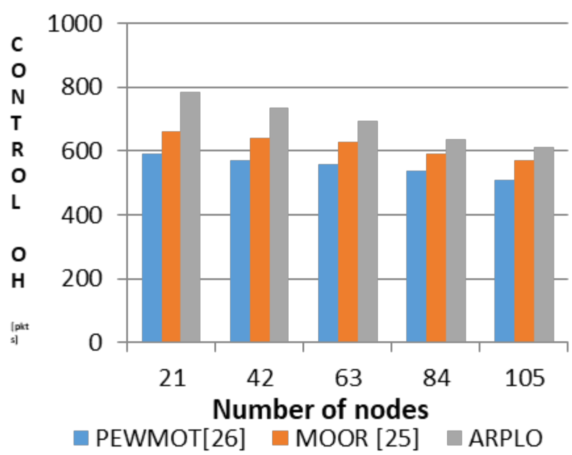

Fig 9. Comparison of Control overhead

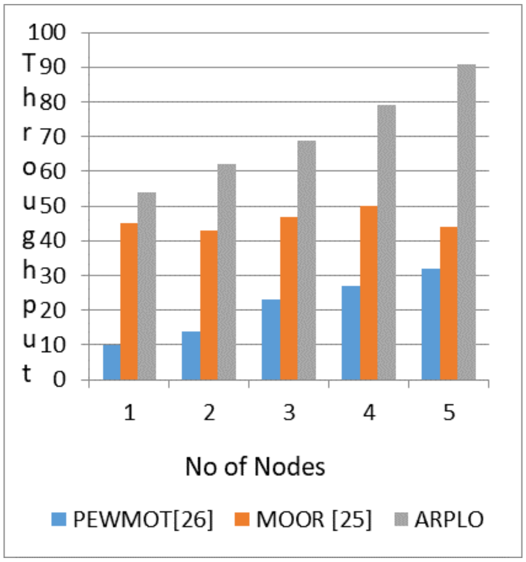

Fig 10. Comparison of Throughput (Kbps)

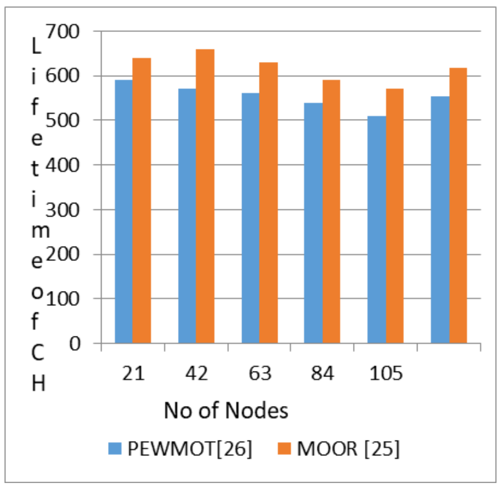

Fig 11. Comparison of Lifetime of CH (secs)

than the PE-WMOT and MOOR. The throughput model of the ARPLO model is ~23% higher than PE-WMOT and MOOR. Similarly, in the case of several alive nodes, the estimation after the data transmission is higher than the conventional PE-WMOT and MOOR methods.

A comparative analysis of the ARPLO routing model with PE-WMOT and MOOR, across various key performance metrics presented in Table 3. These metrics are essential for evaluating the efficiency and effectiveness of routing protocols within the context of IoT networks. "Energy Consumption (J)," which measures the amount of energy consumed during data transmission. ARPLO demonstrates an energy consumption value of 49.4J, indicating its ability to conserve energy while efficiently transmitting data. In contrast, PE-WMOT and MOOR have slightly higher energy consumption values, suggesting that ARPLO is relatively more energy-efficient in this regard. "Packet Delivery Ratio (PDR)," which reflects the percentage of successfully delivered packets to the destination. ARPLO achieves a commendable PDR of 97.6%, implying its reliability in ensuring packet delivery. In comparison, PE-WMOT and MOOR also have respectable PDR values but fall slightly behind ARPLO, reinforcing its efficiency in packet delivery. "End-to-End Delay (msec)" measures the time it takes for data packets to traverse the network. ARPLO excels in this aspect with an end-to-end delay of only 14.2milliseconds, demonstrating its capability to minimize delays in data transmission. On the other hand, the reference methods PE-WMOT and MOOR have longer end-to-end delays, indicating that ARPLO can offer quicker data delivery.

Table 3. Comparative Analysis

No. of Nodes	Energy Consumption (J)			PDR (%)			End-to-End (msec)		
	PEW-MOT [26]	MOOR [25]	ARPLO	PEW-MOT [26]	MOOR [25]	ARPLO	PEW-MOT [26]	MOOR [25]	ARPLO
21	43	58	39	92	93	95	10	10	07
42	66	49	47	89	91	97	14	14	09
63	92	53	49	80	80	98	23	23	14
84	111	64	53	76	93	99	27	27	19
105	134	59	59	74	96	99	32	32	22
AVG	**89.2**	**56.6**	**49.4**	**82.2**	**90.6**	**97.6**	**21.2**	**21.2**	**14.2**
No. of Nodes	**Control Overhead (Pkts)**			**Throughput (Kbps)**			**Lifetime of CH [Sec]**		
	PEW-MOT [26]	**MOOR [25]**	**ARPLO**	**PEW-MOT [26]**	**MOOR [25]**	**ARPLO**	**PEW-MOT [26]**	**MOOR [25]**	**ARPLO**
21	1100	1000	900	10	45	54	590	640	783
42	2800	2700	1900	14	43	62	570	660	735
63	4400	3900	2600	23	47	69	560	630	693
84	6300	4800	3200	27	50	79	540	590	638
105	8100	6300	4300	32	44	91	510	570	612
AVG	**4540**	**3740**	**2580**	**21.2**	**45.8**	**71**	**554**	**618**	**692.2**

The "Control Overhead (Pkts)" metric quantifies the number of control packets used for network management. Here, ARPLO shows a lower control overhead of 2580 packets, signifying its efficiency in managing the network with fewer control packets. In contrast, the reference methods PE-WMOT and MOOR require more control packets for network management. Regarding "Throughput (Kbps)," which measures the rate of successful data transmission, ARPLO boasts a higher throughput of 71 Kbps, implying its capacity to transmit data at a faster rate. While the PE-WMOT and MOOR also achieve reasonable throughput, ARPLO stands out with a notably higher value. Finally, "Lifetime of CH (sec)" measures the duration for which cluster heads remain active within the network. ARPLO maintains a relatively longer cluster head lifetime of 692.2 seconds, indicating its ability to prolong the operational lifespan of cluster heads. In contrast, PE-WMOT and MOOR have shorter cluster head lifetimes. The comparative analysis demonstrates that ARPLO exhibits superior performance in terms of energy efficiency, packet delivery, end-to-end delay, control overhead, throughput, and the lifetime of cluster heads when compared to the referenced methods. These findings suggest that ARPLO is an efficient and effective routing protocol, particularly suitable for IoT networks.

5 Conclusion

This paper proposed the ARPLO model for effective multimedia healthcare data transmission for information exchange. The ARPLO model consists of different phases such as the construction of the grid, selection of head, optimization, and classification. The ARPLO model computes the optimization model for the computation of the routing with the optimal path identification with the node ranking process. The ADNN model performs classification for the medical data information exchange. The simulation analysis stated that the ARPLO model achieves increased throughput, PDR, and more alive nodes with reduced energy consumption, control overhead, and end-to-end delay. ARPLO protocol performance reveals that there is increase of throughput of 31.2%, PDR by 7.12% lifetime of 10.7 % with reduction of energy consumption by 12.72%, control overhead by 31.01% and end-to-end delay by 33.01%. It achieves higher energy efficiency, elevated Packet Delivery Ratio (PDR), reduced End-to-End Delay, decreased Control Overhead, improved Throughput, and extended Cluster Head (CH) node lifespans, resulting in a more reliable and efficient network for healthcare data transmission. Furthermore, ARPLO consistently outperforms existing protocols by approximately 23%, highlighting its practical utility and effectiveness. The novelty of ARPLO, stemming from its comprehensive approach and innovative features, promises to shape the future of IoT network optimization, not only in healthcare but also in other domains. With ARPLO include real-world deployment, enhanced security measures, scalability assessments, and cross-domain applications. Future direction can be considered by employing compressive sensing based routing algorithms on all the input multimedia data.

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