



Quality of service aware energy efficient multipath routing protocol for internet of things using hybrid optimization algorithm

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Abstract

The Internet of Things (IoT) is evolving from a media term to a reality. We entered a new age of invention and creativity as a result of the development of IoT. Despite the fact that IoT has a lot of promise in the modern world, there are still a lot of obstacles. The main focus of this study is to improve the IoT's resilience by resolving energy optimization, routing, and other issues to increase network lifetime. In this research, we present an IoT hybrid optimization algorithm-based QoS aware energy efficient multipath routing (QEMR) protocol. The first step is to achieve optimal clustering using a modified teaching-learning-based optimization (MTLO) method. Next, we determine the cluster head (CH) using the nonlinear regression-based pigeon optimization (NR-PO) method. For routing and determining the optimum path, we use the Deep Kronecker Neural Network (DKNN). The NS-3 simulation tool is utilised to model our proposed routing QEMR system and assess its effectiveness. The proposed QEMR scheme's simulation findings are contrasted with existing techniques: REER, Rumor, and EOMR techniques in terms of the impacts of node density, node speed, and network traffic. In comparison of energy usage and the effect of node density, the suggested QEMR system uses less energy than the REER, Rumor, and EOMR schemes by 86.296%, 81.94%, and 75% respectively. The proposed QEMR scheme is used for studying the application of problem by enhancing the network performance and improving QoS by implementing DKNN based routing methodology to send data from source to the destination by selecting the optimal path.

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1 Introduction

Smart cities, agribusiness, weather forecasting, smart grids and waste management are some recent applications of Internet of Things (IoT). While IoT offers enormous promise in many applications, there are certain limitations [12]. The tremendous surge in popularity of IoT has led to massive data creation from diverse sensory devices. This has increased energy usage by linked gadgets [4]. Clustering routing algorithms are efficient in big IoT networks. For devices and other connected things like sensors, cameras, phones and other IoT infrastructure using location-based decision assistance reduces the routing complexity [25]. To integrate the recognized traditional computer advancements, the new IoT idea opens doors for inventive applications [23]. Although IoT devices offer automation, they use a lot of energy to link billions of objects. Unless regulated, energy consumption might be a hindrance to IoT system deployment [22]. Reliability of communication is also required for unattended network activities [2]. IoT also aids with pollution management and disaster prevention [21]. Data-driven models might forecast energy use. These models' accuracy and robustness need to be improved owing to considerable non-linearity between inputs and outputs [10]. In the IoT network, the resource allocation interfaces offer all important information to the end user, i.e. the device manager, who administers the large quantity of devices and data [20]. With so many IoT applications, end devices may be hard to access or unsafe, making routine maintenance and battery replacement inefficient and costly [8]. Increasing IoT adoption will need higher use of fossil fuels to power IoT industrial lines. This uneven squandering of precious metals and resources might become a major concern in the future [16].

In an existing study, for understanding of the independent variables, on the CASB (Cloud Access Security Broker) study, RSM (Research Surface Methodology) analysis was employed [1]. Despite the fact that IoT has a lot of promise in the modern world, there are still a lot of obstacles. Even though vital advancement has been carried out in this zone, obvious challenges stay to be tended to, which have been highlighted in this paper. The main focus of this study is to improve the IoT's resilience by resolving energy optimization, routing, and other issues to increase network lifetime. In this research, we present an IoT hybrid optimization algorithm-based QoS aware energy efficient multipath routing (QEMR) protocol.

1.1 Our contributions

A QoS aware energy efficient multipath routing (QEMR) protocol is suggested for further improving the IoT routing strategy. The following are the primary contributions of the suggested work:

- Optimal clustering is carried out using a modified teaching-learning-based optimization (MTLO) method.
- The cluster head (CH) is then calculated using the nonlinear regression-based pigeon optimization (NR-PO) method.
- We use the Deep Kronecker neural network for routing and choosing the best route (DKNN).

- The cluster head (CH) is then calculated using the nonlinear regression-based pigeon optimization (NR-PO) method.

1.2 Organization of paper

The remainder of the paper is structured as follows: The most current research on IoT routing algorithms is presented in Section 2. The issue approach and system model of the suggested routing technique are described in Section 3. In Section 4, a mathematical model and a description of the proposed routing technique are provided. In Section 5, results and performance comparisons of the proposed and existing routing systems are presented. The conclusion of the study is found in Section 6.

2 Related works

Strong residential and commercial integration with industry and utilities are required for smart city energy systems, as well as a higher share of heat and power sources. Smart Green Energy (IoT-SGE) for Smart Cities was suggested by X Zhang et al. [32] in 2021. IoT allows for omnipresent monitoring and safe connectivity, enabling smart cities to precisely control energy use. It focused on IoT-based deep reinforcement learning smart energy management systems. Results showed that IoT sensors might estimate energy demand in smart cities, monitor energy consumption, and generate cost savings. It is essential to create efficient IoT routes since sensor nodes have a limited energy supply.

J. Shreyas et al. [27] presented an energy-efficient optimum routing approach (2021). To choose the optimum path, the effective cluster head of a homogeneous IoT network is chosen. The recommended method used a genetic algorithm (GA) to discover the best route. It enabled message exchange from all network nodes while developing the ideal multipath routing. They presented an intricate evolutionary approach to IoT routing. By choosing a suitable path from the source cluster head to the sink, a longer network lifetime was attained. In terms of energy consumption, end-to-end latency, and the number of failed nodes, the recommended solution performed better than previously used methods in MATLAB. To improve the user experience in an IoT network with fog support, resource-constrained IoT devices may offload computation-intensive tasks to resource-rich neighbouring fog nodes. Compared to local processing, it uses less energy, but because of connection delays, operations take longer to complete.

Shahryari, et al. [26] (2021) examined the trade-off between task completion time and energy usage. User demands and remaining device battery energy were weighing variables for time and energy usage. Consequently, they classified the problem as an NP-hard mixed-integer nonlinear programme (MINLP). A hybrid genetic algorithm/particle swarm optimization strategy was used to resolve the problem. Numerous simulations confirmed the suggested algorithm's convergence and improved performance compared to standard methods. IoT enables a degree of intelligence that is advantageous to mankind. Connecting things and getting them to communicate with one another for applications in intelligent industrial processes, safety, and healthcare. The danger of unauthorised access is growing as more companies and applications are included in the Internet of Things. The cyberattacks on communication networks that occur nowadays are quite severe. This research has developed a smart approach or technique to thwart security vulnerabilities using Deep Learning

algorithms (Deep Belief Network). This sophisticated intrusion detection system searches the network for illicit activity and makes intrusion attempts.

Deep learning approach for embedding was studied by N Balakrishnan et al. [3] in 2021. The standard DGA and IDS algorithms were contrasted with the DBN security network upgrade. One of the main barriers to IoT application is the energy limitation of sensors. For IoT systems, extending network lifetime is essential. In the literature, metaheuristic methods have been used to solve the NP-hard energy optimization problem for scalable networks. In a number of optimization problems, quantum-inspired metaheuristics perform better than traditional metaheuristics.

A quantum-inspired green communication architecture for energy balancing using sensor-enabled Internet of Things devices was presented by S Kumar et al. [15] in 2020. (Q-EBIoT). For sensor-enabled IoT setups, we provide an energy optimization technique in which energy consumption was calculated as the cost of energy-oriented procedures. Then followed an optimization problem where quantum computing was used to represent, measure, and rotate the answers. Performance with cutting-edge technology was compared using the suggested technique. In terms of energy metrics for sensor-enabled IoT settings, the evaluation demonstrated the utility of the provided approach. For IoT-based adaptive systems, resource management, data security, and mobility management are major problems. All IoT-enabled smart networks must take these necessary requirements into account.

A resource allocation approach based on security, energy use, and cost was put up by S Pirbhulal et al. [17] (2020) for IoT-based systems. Additionally, MMSA combining security and mobility was developed. The provided MMSA outperformed conventional techniques in terms of mobility, latency, security, and criticality aspects, according to the findings of trials. Security levels, energy optimization, and dependability for the provided MMSA, conventional, and baseline techniques were 15%, 13%, 14%, and 9.78%, respectively. The suggested methodology thus outperformed previous methods in terms of reliability and mobility-enabled security.

Due to the clustering problem being NP-Hard, M Sadrishojaei, et al. [24] (2021) suggested a moth-flame optimization strategy. a successful communication technique inspired by the moth life cycle. The recommended fitness functions were distances, residual energy, and node degree. The experimental results were contrasted with clustering techniques such cuckoo search, novel chemical reaction optimization, and whale optimization. MATLAB simulation showed fewer cluster head nodes and more evenly distributed clusters. It extended life by at least 14.59% above the other methods. Devices connected to the internet of things (IoT) are essential for smart and sustainable settings. But since they run on batteries, IoT devices have a limited lifespan.

In order to lower the energy consumption of energy-harvesting IoT devices, VK Bhatia et al. [5] (2021) presented a Type-II fuzzy based clustering technique. After the type II fuzzy membership function elects cluster heads, the Dijkstra based inter-cluster data aggregation was used. Extensive testing was made possible by installing IoT devices at random. The suggested protocol performed better than the rival technique according to a number of performance metrics.

Y Du et al. [7] (2021) recommended an energy optimization and routing control strategy for the neotype MEIES employing ER using the bottom and top layers. It was carefully modelled at the lowest layer, where the electricity-heat-gas-cool multi-energy optimization technique is applied. The top layer normalised the energy flow in the electric, heating, and natural gas networks using precise mathematical logic (E-WAN). They developed a generalised multi-

energy network energy loss model using only one mathematical equation. The unified energy routing control strategy of least loss local absorption (MLLA) in the monopoly market and minimum loss multipath transmission (MLMT) in the competitive market was then suggested for various decision-makers. Two types of competitive market priority ranking ER transactions were provided in order to meet the required incentive objective by transferring the transaction's energy loss from one to the other. The feasibility and efficacy of the whole technique were finally confirmed by simulation and comparison. WSNs often use clustering and routing strategies to increase the network's longevity.

Prasad A. Y. et al. [18] (2020) developed a stimulated annealing strategy using a genetic algorithm to choose the best cluster head from a group of nodes. The performance parameters of the proposed approach were analysed in terms of live nodes, dead nodes, energy consumption, and data packets received by the BS.

Using the Cuckoo Optimization Approach and the TOPSIS multi-criteria algorithm, S Tabatabaei et al. [30] (2021) created a novel routing protocol to minimise energy usage in terms of throughput and end-to-end latency. The suggested method took four factors into account: the amount of bandwidth available, the amount of energy left, the speed, and the quantity of routing steps needed. To collect data and transmit it to the base station, also known as the destination node, wireless sensor networks are made up of several tiny sensor nodes that are positioned in various geographic locations. In larger search regions, the majority of well-known heuristic routing and clustering approaches have limitations. As the search space expands quickly, unoptimized clustering and routing operations uses sensor node resources.

To get beyond the limitations and restrictions of the present routing systems, Prasad A. Y. et al. [19] (2021) developed two new heuristics algorithms, gravitational approach based clustering and clustered gravitational routing. To determine the top cluster head nodes from each cluster, a fuzzy logic-based deductive inference system was also developed and used in their research. The simulation results showed that the recommended strategies increased network longevity and clustering accuracy while lowering energy use and latency.

The Grey Wolf Optimizer (GWO), developed by M. Ghalambaz et al. [9] minimized yearly energy use (2021). Grey wolf hunting behaviour served as the inspiration for the GWO meta-heuristic optimization method. The optimization method was created to optimise a building. According to our study, using 40 wolves gave GWO its best results. GWO's optimised solutions were contrasted with those of other optimization techniques and found to be better. Particle Swarm Optimization (PSO), one of the greatest optimization techniques in the literature, has an ideal objective function of 133.5, while GWO has 133. GWO looked into multi-objective building optimization. A valuable group of non-dominant optimal solutions could exist. Big data collection and storage are becoming harder to do. These data are gathered by several IoT sensors. In certain cases, data reduction is an effective way to reduce data gathering and maintain sensor energy. Spatial-temporal correlation is a valuable technique for data reduction in addition to the approaches mentioned above. The strategies differ in terms of complexity, data reduction, data quality, and sensor energy conservation.

M. Ibrahim et al. [11] suggested a hybrid data collecting and energy-saving technique for sensing-based IoT. (2021). The suggested approach enhanced various performance measurements by using already-in-use data reduction techniques. On, in, and node are the three stages of All-in-One. By data aggregation, compression, or prediction, the Cluster-Head (CH) may lower the data flow to each sensor node. During the second phase, each sensor could collect less data to investigate the state variation (in-period). The last level, such as in-node, employs

in-network correlation or data clustering to get rid of duplicate data collected by nearby nodes. To compare the effectiveness of their solution to other approaches, real sensor data was utilised.

3 Problem methodology and network model

3.1 Problem methodology

For WSN-based IoT applications with unfairness in the network under high traffic load, Jaiswal et al. [13] have developed an energy-efficient routing protocol (EOMR). The suggested protocol takes three factors into account while choosing the best path: longevity, dependability, and the volume of traffic at the next-hop node. When EOMR scheme performance is compared to that of other modern protocols, EOMR scheme outperforms other protocols in terms of energy savings, packet delivery ratio, end-to-end latency, and network longevity. The optimality factor, a measurement of three factors including the lifespan of a node, communication reliability, and traffic volume, is used by multipath routing protocols to design numerous pathways. The source node may choose a data transmission route among the detected numerous options using the EOMR protocol based on the calculated optimality factor (OF). More and more applications, including telemedicine and autonomous cars, are becoming sensitive to network latency and accuracy as a result of the growth of the Internet of Things (IoT) and 5G technologies. As a result, more flexible and effective routing systems are needed.

In the IoT, obtaining good QoS in cooperative systems is still a difficult challenge. High QoS may be attained, nevertheless, by maximising the transmission policy's bandwidth, coding rate, and carrier frequency parameters. However, the IoT parameters as a whole have not been optimised by the current routing algorithms. Learning-based routing systems with their benefits of great flexibility and accuracy are emerging as potential candidate solutions to address such an urgent demand. But in an Internet of Things (IoT) network, where link connections and access statuses change over time, routing becomes more difficult. As a result, learning-based routing systems must be able to quickly adapt to changing network conditions. We present a QoS aware energy efficient multipath routing (QEMR) strategy for the Internet of Things utilising a hybrid optimization technique in order to further improve the energy-efficient multipath routing system.

3.2 Objectives

The following are the major objectives of the proposed QEMR scheme:

1. A system for Internet of Things networks that is energy-efficient multipath routing (QEMR).
2. To provide effective clustering that assures energy-efficient data transmission, a modified teaching-learning-based optimization (MTLO) technique is presented.
3. To choose the best path among many source-to-destination routes, a hybrid optimization approach is provided.
4. The comparison study demonstrates how the suggested routing strategy performs better than the current methods in terms of several QoS criteria.

3.3 Network model of proposed QEMR scheme

Figure 1 depicts the network model of the proposed QEMR architecture. The network model demonstrates how to generate clusters, choose the best route, and choose the CH. Our suggested QEMR approach uses a hybrid optimization technique that includes of three steps: clustering, CH selection, and optimum route selection, with the goal of maximising throughput, minimising energy consumption, and improving the network’s fundamental QoS. The source node may choose a route from the collection of different pathways that have been found for data transfer using the routing technique.

4 Proposed QEMR protocol

In this part, we first go over how cluster creation works. The cluster head selection procedure is then discussed using the appropriate mathematical formulas. The method for computing the best route is finally described.

4.1 Clustering using modified teaching-learning-based optimization (MTLO) algorithm

The first step of our study objective is to achieve optimal clustering using a modified teaching-learning-based optimization (MTLO) method. By altering the topology of sensor nodes, clustering methods are utilised to overcome numerous hurdles to accessing the Internet of Things. The main goals of clustering techniques are high energy economy, bandwidth reuse, goal monitoring, data collection, and network lifespan. Clustering is a crucial energy-saving routing method, to sum up. Generally speaking, the main goal of teaching-learning is to improve mechanical component design [xy] while taking into account the teacher’s effect on the lesson. Teaching and learning are population-based approaches that use localised fixes in order to attain a universal fix. Population is seen as a collection or class of students. The

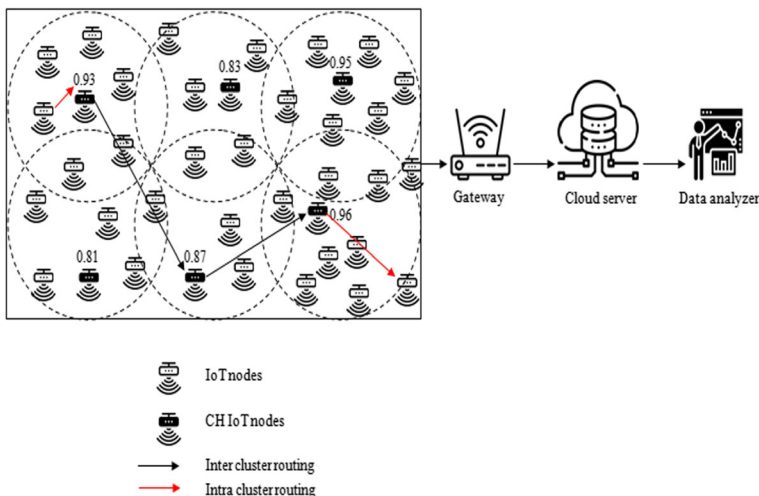


Fig. 1 Suggested scheme’s network model

teaching phase and the learning phase are the two main divisions of the teaching and learning process. Learning from a teacher is referred to as the teacher phase, while learning via contact with other learners is referred to as the learner phase.

Fish swarm optimization (FSO), which optimises the search range of the whole network by node location, position, and movement direction of IoT nodes, is the focus of the modified teaching-learning-based optimization (MTLO) approach that we have developed in this research.

The TLBO method denotes each solution as $X_{j,k,i}$, where j is the j th dimension and $j = 1, 2, \dots, m$; k denotes the k th population member or learner and $k = 1, 2, \dots, n$; and I denotes the i th iteration and $i = 1, 2, \dots, G_{\max}$, where the G_{\max} parameter denotes the maximum number of iterations.

Establishing an initial population of discrete people is the first stage in a discrete optimization approach. Simple methods are used to generate the first population. These two parameters are used in this pseudocode to identify a population's dimensions (Dim and Population Count) and the solutions in the population (Count). As a result of this, the best option or teacher seeks to raise the level of knowledge amongst the students and the class as a whole. X_{kbest} which represents the first step in this process, is used to discover the best answer. The average result $M_{i,j}$ of the students in the j th dimension will be calculated next. Using this formula, the teacher's impact on each student's average score may be calculated:

$$DM_{j,k,i} = r_{j,i}(X_{j,kbest,i} - T_f M_{j,i}) \quad (1)$$

To determine the new mean value, we use T_f as the teaching factor and $r_{j,i}$ is a random number between $[0, 12]$. When it comes to choosing T_f , it has an equal chance of being either number 1 or number 2.

$$T_f = \text{round}[1 + \text{rnd}(0, 1)\{2-1\}] \quad (2)$$

Based on Eq. 1, the value of $X_{j,k,i}$ should be calculated using the following formula:

$$X_{j,k,i}^{\text{old}} = X_{j,k,i} + DM_{j,k,i} \quad (3)$$

Since TLBO updates its population in a greedy manner, the current solution should be updated if the $X'_{j,k,i}$ fitness value is more than $X'_{j,k,i}$. Students may learn new information by interacting with one another throughout this period. To do this, each student chooses A and B at random from a group of three other students, whose $X'_{A,i} \neq X'_{B,i}$ values are updated by the instructor at the conclusion of the i th iteration. If $X'_{A,i}$'s fitness is higher than the $X'_{B,i}$'s fitness, Eq. 4 is employed; otherwise, Eq. 5 is used.

$$X_{j,A,i}^{\text{new}} = X_{j,p,i}^{\text{old}} + r_{j,p,i}(X_{j,A,i}^{\text{old}} - X_{j,B,i}^{\text{old}}) \quad (4)$$

$$X_{j,A,i}^{\text{new}} = X_{j,p,i}^{\text{old}} + r_{j,p,i}(X_{j,B,i}^{\text{old}} - X_{j,A,i}^{\text{old}}) \quad (5)$$

Random numbers in the range $[0,1]$ are used in these equations. Teacher phase input is based on all accepted function values from the learner phase.

The learner’s actions are used to pinpoint the target $x_T = s_T + \gamma P(r_{T+1}, \pi(r_{T+1} | \theta^{\pi})\theta^P)$ ’s position. The difference between the highest and lowest P-functions of a well-trained teacher is calculated in this teacher-initiated teaching experiment, $r \in \mathbb{R}$, to determine the requirement for network borders at the state level:

$$W(r) = \text{Max}(X_{j,A,i}^{new}) - \text{Min}(X_{j,A,i}^{new}) \tag{6}$$

The maximum and minimum P-functions are optimised using the FSO algorithm, which determines the control value for cluster boundaries. The undersea fish’s exceptional sensory capability serves as the model for the FSO algorithm. Fish will locate a nutrient-rich location whether they are alone or in groups. Fish exhibit a variety of behaviours, including swarming, jumping, pursuing, and searching for prey. The points and their placements are represented by the fish in the optimization tasks.

$$y_j^u = y_j + \text{Visual} * \text{rand} \tag{7}$$

$$y_{next} = y + \frac{y^u - y}{\|y^u - y\|} * \text{step} * \text{rand} \tag{8}$$

The fish randomly selects the following locations for food density:

$$y_i = y_j + \text{visual} * \text{rand} \tag{9}$$

The fish move together, search the ground for food, and then descend to the earth to flee the danger.

$$y_j^{T+1} = y_j^T + \frac{y_d - y_j^T}{\|y_d - y_j^T\|} * \text{step} * \text{rand} \tag{10}$$

Regarding the characteristics of fish echolocation, we make an assumption.

$$g_j = g_{\min} + (f_{\max} - g_{\min})\beta_j \tag{11}$$

$$U_j^T = U_j^{T-1} + (y_j^{T-1} - y^*)g_j \tag{12}$$

$$y_j^T = y_j^{T-1} + u_j^T \tag{13}$$

β is a random number between 0 and 1, T is a random number within the range, g is the frequency of the pulse, g_{\min} and g_{\max} are the lower and higher bounds of g, u is the velocity of the bat, y is the location of the batter, and y^* is the best global solution presently available. The index j in this instance corresponds to a bat (public solution) in this example.

$$B_j^{T+1} = \alpha B_j^T \tag{14}$$

$$s_j^{T+1} = s_j^0 [1 - \text{EXP}(-\chi)] \tag{15}$$

where the constants α and χ have a common value of 0.9. The MLTO technique considers the state feature to present as \hat{R}_j of the jth.

$$\hat{R}_j = B_j^{T+1}(r) + s_j^{T+1} : T + 1 \in R_{Ts}, r \in R_{rT} \tag{16}$$

A state feature mapping function, j , connects the source environment to the destination environment.

$$b = g_j(b_1, b_2, \dots, b_m) : b \in B_j^{T+1}, b_j \in B_{T_s} \tag{17}$$

$$b_j = e_j^b(b) : b \in B_{r_T}, b_j \in B_{T_s} \tag{18}$$

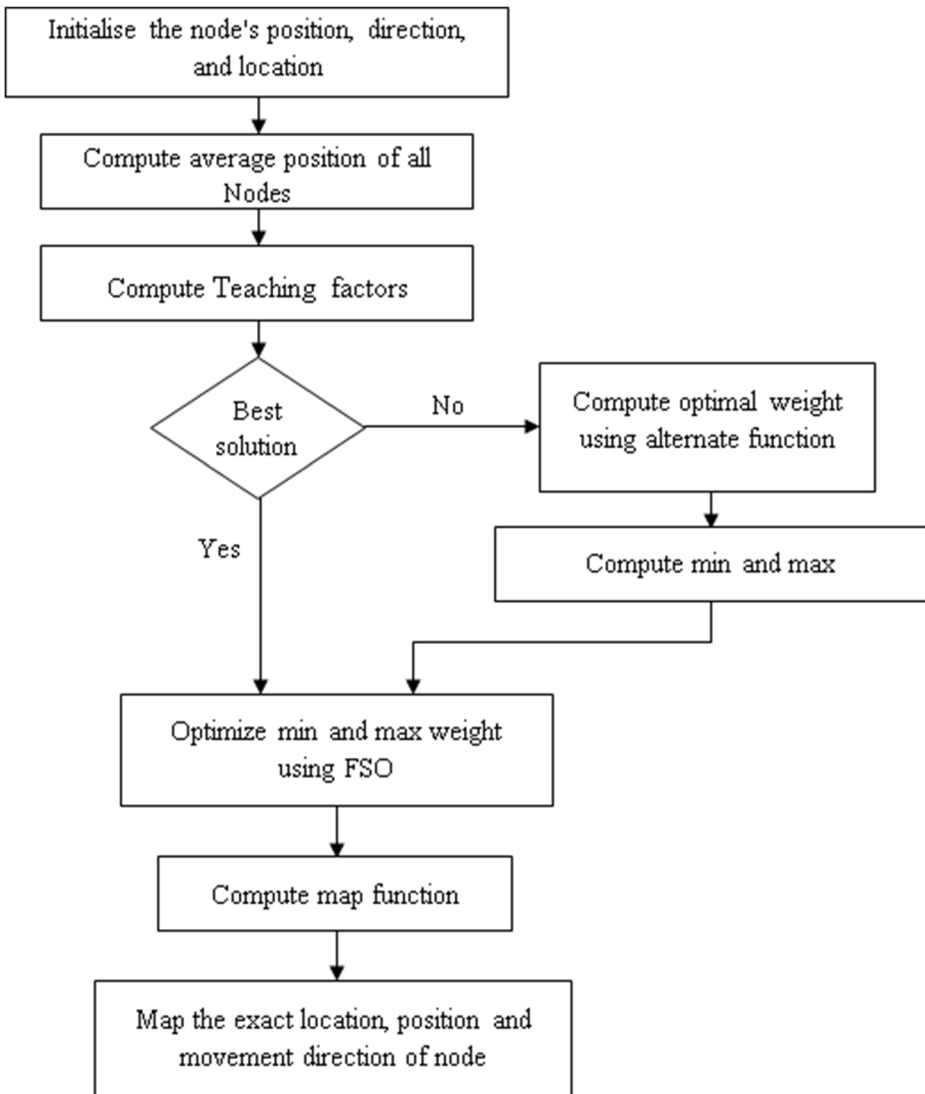
where $e_j^b(b)$ is the inverse mapping function of the agent, j . Algorithm 1 and Flowchart 1 describe the cluster generation procedure utilising MTLO.

Algorithm 1. Clustering using MTLO algorithm

Input: Function

Output: feature mapping

1	Initialize the parameters
2	Find out the average position of all Nodes. $DM_{j,k,i} = r_{j,i}(X_{j,kbest,i} - T_f M_{j,i})$
3	Calculate the Teaching factors $T_f = \mathbf{round}[1 + \mathbf{rnd}(0, 1)\{2 - 1\}]$
4	Compute the new solution $X_{j,A,i}^{new} = X_{j,p,i}^{old} + r_{j,p,i}(X_{j,A,i}^{old} - X_{j,B,i}^{old})$ $X_{j,A,i}^{new} = X_{j,p,i}^{old} + r_{j,p,i}(X_{j,B,i}^{old} - X_{j,A,i}^{old})$
5	Calculate the maximum and minimum function value $W(r) = \mathbf{Max}(X_{j,A,i}^{new}) - \mathbf{Min}(X_{j,A,i}^{new})$
6	Optimize maximum and minimum function value using FSO $B_j^{T+1} = \alpha B_j^T$
7	Compute the mapping function $b = g^b(b_1, b_2, \dots, b_m) : b \in B_{r_T}, b_j \in B_{T_s}$
8	End procedure



Flowchart 1 Work flow of cluster formation using MTLO algorithm

4.2 Nonlinear regression-based pigeon optimization (NR-PO) technique for CH selection

The second step of our study objective is to determine the cluster head (CH) using the nonlinear regression-based pigeon optimization (NR-PO) method.

4.2.1 Design parameters for CH selection

Using the following design parameters, we calculate the cluster head (CH) after cluster formation. The fundamental energy model, which takes into account the energy

needs of both the transmitter and receiver parts, is used to calculate the energy consumption of IoT sensor nodes. The total amount of energy needed by each network node to transmit and receive a -bit data packet is proportional to the square of the propagation distance (D) when it is less than the threshold distance (D_0); otherwise, it is proportional to (D^2).

$$E_{total} = T(n, D) + R(n) \tag{19}$$

where $T(n, D)$ and $R(n)$ are the transmitting and receiving nodes’ respective energy consumptions.

$$T(n, D) = \begin{cases} n \times E_{elec} + n \times \epsilon_{fs} \times D^2; & \text{if } D < D_0 \\ n \times E_{elec} + n \times \epsilon_{mp} \times D^4; & \text{if } D \geq D_0 \end{cases} \tag{20}$$

$$R(n) = n \times E_{elec} \tag{21}$$

The transmitter amplifier model is used to calculate the amplification energy for the free space model (ϵ_{fs}) and the multi-path model (ϵ_{mp}), where $T(n, D)$ is the threshold transmission distance. E_{elec} is the amount of energy required to run the transmitter or receiver circuit for each bit. The received signal intensity is determined by the distance and transmission energy (RSS). The RSS of the IoT sensor node may be expressed as follows if it transmits a packet with energy D_0 and a distance D :

$$RSS = \frac{T(n, D)}{4\pi D_i^2} + T_{a,a_1/a_2} \tag{22}$$

Mobility: Despite the possibility that the sample domain does not include any points that meet constraint $\Delta t_1 = \Delta t_2 = \Delta t$, sample locations that do are picked. Speed is correctly calculated based on distance and relative speed using the most recent signal intensity sample. A modified distance is determined using the cosines laws, where D_{i_1} , D_{i_2} and D_{i_3} stands for:

$$D_{i_1}^2 = D_{i_2}^2 + a_1 a_2^2 - 2D_{i_2} \cdot a_1 a_2 \cdot \cos(\alpha) \tag{23}$$

$$D_{i_3}^2 = D_{i_3}^2 + a_1 a_2^2 - 2D_{i_2} \cdot a_1 a_2 \cdot \cos(\beta) \tag{24}$$

Positions a_1 and a_2 at two independent reference points are possible destinations for Node a . Use the straightforward equation above and take into consideration (v) to get velocity $\cos(\alpha) = -\cos(\beta)$:

$$2a_1 a_2^2 = D_{i_1}^2 + D_{i_2}^2 - 2D_{i_3}^2 \tag{25}$$

$$v = \sqrt{\frac{2(D_{i_1}^2 + D_{i_2}^2 - 2D_{i_3}^2)}{2\Delta t}} \tag{26}$$

The movement time for IoT sensor nodes between the present location and the relocated place a_1 or a_2 is calculated using the following sign law as the distance $T_{a,a_1/a_2}$ divided by the node’s velocity:

$$T_{a,a_1/a_2} = \frac{R \cdot \sin \vartheta}{\sin \beta \cdot v} \tag{27}$$

Finally, we formulate the IoT sensor node mobility (M) model as follows.

$$M = T_{a,a_1/a_2} = \frac{\Delta t \cdot R \cdot \sin \vartheta}{\sin \beta \cdot \sqrt{\frac{(D_{i_1}^2 + D_{i_2}^2 - 2D_{i_3}^2)}{2}}} \tag{28}$$

The traffic rate (T) at time t is determined by counting the number of nodes in the network that have their middle neighbours set. The following criteria are used to calculate the node’s traffic rate at the base station’s time (t): (BS).

$$T(i, t) = \text{distance}(x_i(t), BS(t)) \tag{29}$$

4.2.2 Design parameter optimization using NR-PO algorithm

In order to maximise the specified design parameters, the nonlinear regression-based pigeon optimization (NR-PO) approach utilised here selects CH from a large number of cluster nodes. The information about the hidden state of earlier deadlines that is generated by nonlinear regression is provided to the regression rate in the following ways via the activation function:

$$H_r = v(X_r K^H + t_{r-1} v^H + b_H) \tag{30}$$

E_S is located near recall gate. X_r is input for each time step s, and T_{S-1} represents the hidden state T1 for time step 1. Z^e is the input layer’s weight, while v^e is the recurrent weight of the hidden state. The bias of the input layer is indicated by the b_e .

$$i_r = v(X_r K^i + t_{r-1} v^i + b_i) \tag{31}$$

$$\widetilde{E} \sim_s = \tanh(X_r Z^e + t_{r-1} v^e + b_e) \tag{32}$$

$$E_r = E_{r-1} * H_r + i_r * \widetilde{E} \sim_s \tag{33}$$

The maximum regression rate determines the hidden levels where the sigmoid activation function is expected.

$$Z_r = v\left(X_r X^Z + t_{r-1} v^Z + b_Z\right) \tag{34}$$

$$t_r = Z_r^* \tanh(E_r) \tag{35}$$

The regression weight is multiplied by the level buried at the previous time point, which is then multiplied by the current input. The sigmoid function, which computes one from zero and one, is used to aggregate the contributions of the two possibilities.

$$L_r = v\left(X_r X^L + d_{r-1} v^L + b_l\right) \tag{36}$$

Where Y_S is the input vector at a certain time step, c_{S-1} denotes the previous output from earlier units, and W_S denotes the updating gate. Finally, the regression rate is shown as,

$$s_r = v\left(X_r K^S + t_{r-1} v^S + b_S\right) \tag{37}$$

Pigeon optimization is used to calculate the greatest and lowest regression rate fitness function. When it comes to the optimization difficulty, each pigeon has a unique circumstance.

$$S_i = [x_{i1}, x_{i2}, \dots, x_{ic}] \tag{38}$$

where c is the size of the issue to be solved. 1, 2... The number of pigeons is M , M , and each one has the following velocity:

$$u_i = [U_{i1}, U_{i2}, \dots, U_{im}] \tag{39}$$

The difficulty may then be changed by repeating the subsequent steps as the quantity of repetitions pigeonholes.

$$u_i(r) = u_i(r-1) \cdot e^{-sr} + \text{Rand} \cdot (S_{FBest} - S_i(r-1)) \tag{40}$$

The following formula is used to determine the next x_i .

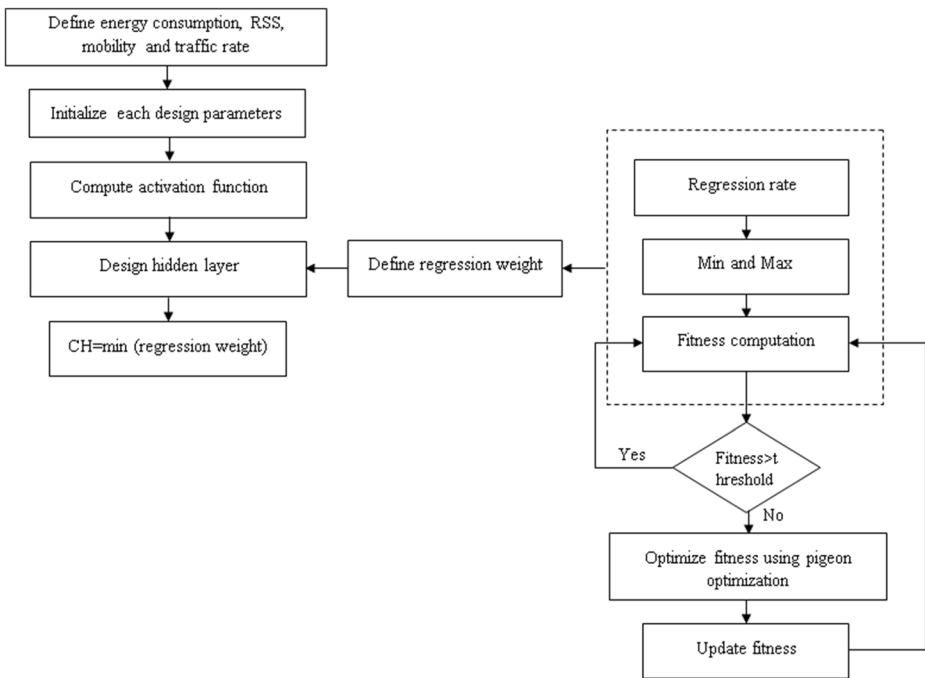
$$x_i(r) = x_i(H-1) + u_i(r) \tag{41}$$

where H is the current iteration's number and $H = 1, 2, \dots, H_{Max}$ is the total number of iterations during which the signpost operator is in use. It's critical to emphasise the significance of fitness:

$$\text{fitness}(S_j(r)) = H_{Max}(S_j(r)) \tag{42}$$

$$\text{fitness}(S_i(r)) = \frac{1}{H_{Min}(S_i(r)) + \varepsilon} \tag{43}$$

After each iteration, the pigeon will be located near to the centre point till the iterations approach the end R_{Max} . Flowchart 1 depicts the CH selection procedure utilising the NR-PO algorithm.



Flowchart 2 Workflow of the NR-PO algorithm for CH selection

4.3 Deep Kronecker neural network for selecting the best route (DKNN)

The third step of our study objective is routing and determining the optimum path by using the Deep Kronecker Neural Network (DKNN). We utilize DKNN to identify the optimum route between the source and the destination out of a multitude of possibilities after clustering and CH selection. The deep neural network (DNN) structure is built upon the hidden layer design.

$$Y_T^{i+1} = f \left(\sum_{j=0}^{R_i} \theta_{Tj} Y_j^i \right), T = 0, 1, 2, R_{i+1}.i = 0, 1, 2 \quad m \tag{44}$$

Where Y_j^i stands for the j th neuron in layer i , r_i for all of the neurons θ layer i , and Tj for the weight between neuron Y_j^i and neuron. The activation function, Y_T^{i+1} , $f(\cdot)$ m , denotes the total number of hidden layers. The estimated value that is correctly calculated is shown as,

$$R \leftarrow \beta R_{cl_j} + (1-\beta) cl_j^2 \tag{45}$$

$$l_j \leftarrow l_j - \alpha \frac{cl_j}{\sqrt{R_{cl_j}}} \tag{46}$$

where cl_j is the gradient that the weight computed. The scaling factors for the gradient are cl_j and R_{cl_j} , and the weight that the learning rate is updating is α . l_j stands for the

discounting factor for the historical gradient β . ReLU is a nonlinear transformation that looks like,

$$f(k) = \max(0, k) \tag{47}$$

The activation function of a sigmoid is calculated as,

$$f(k) = \frac{1}{1 + h^{-k}} \tag{48}$$

In order to tackle complicated issues, a wide-ranging network is necessary, but in practise, this network is challenging to employ. We add the hyper parameter to the activation procedure to accomplish this.

$$\sigma(bW_z(Z^{z^{-1}})) \tag{49}$$

The discovery of low loss functions is made possible by weights and dependencies, as well as the resulting block weight matrices optimization problem.

$$\begin{aligned} b^* &= \arg \min(I(b)) \\ b &\in S^* \setminus [0] \end{aligned} \tag{50}$$

The following are the revised block bias vectors:

$$b^{n+1} = b^m - \eta_w \nabla_{b^n} I^n(b) \tag{51}$$

a DNN feature for adaptive activation augmented by a Kronecker network. We found that the Kronecker network contains several times more neurons in each buried layer than other networks. However, the sole difference between a Kronecker product’s general parameters is. Additionally, the Kronecker network explicitly employs adaptive activation functions and summarises the current DNN class, is thought to be a new kind of neural network. The deep Kronecker neural network (DKNN) may be successfully built even without creating the block weight matrices (b^*) and block bias vectors (b^{n+1}).

This is how DKNN is expressed:

$$\delta^\kappa(z) = (\theta_{T_j} Y_T^i, \theta_{T_{j-1}} Y_T^{i-1}, \dots, \theta_T Y_T^\kappa)(z) \tag{52}$$

Thus the $\{\omega^l, \alpha^l\}$ trainable parameters determine an adaptive activation function at the l -th layer, which is no longer deterministic.

$$\theta_{T_j} Y_T^l(z), \omega^l \text{ and } \alpha^l = \sum_{\kappa=1}^{\kappa} (\alpha_\kappa^l \theta_{T_j} Y_T^l(z)), l = 1, 2, \dots, i-1 \tag{53}$$

The best route between the source and the destination is chosen using the DKNN algorithm. Here, the adaptive activation function is optimised via the Kronecker network, reducing the complexity of the DNN hidden layer. Algorithm 2 and Flowchart 3 provide the details of how optimum route selection using DKNN operates.

Algorithm 2. Optimal path selection using DKNN

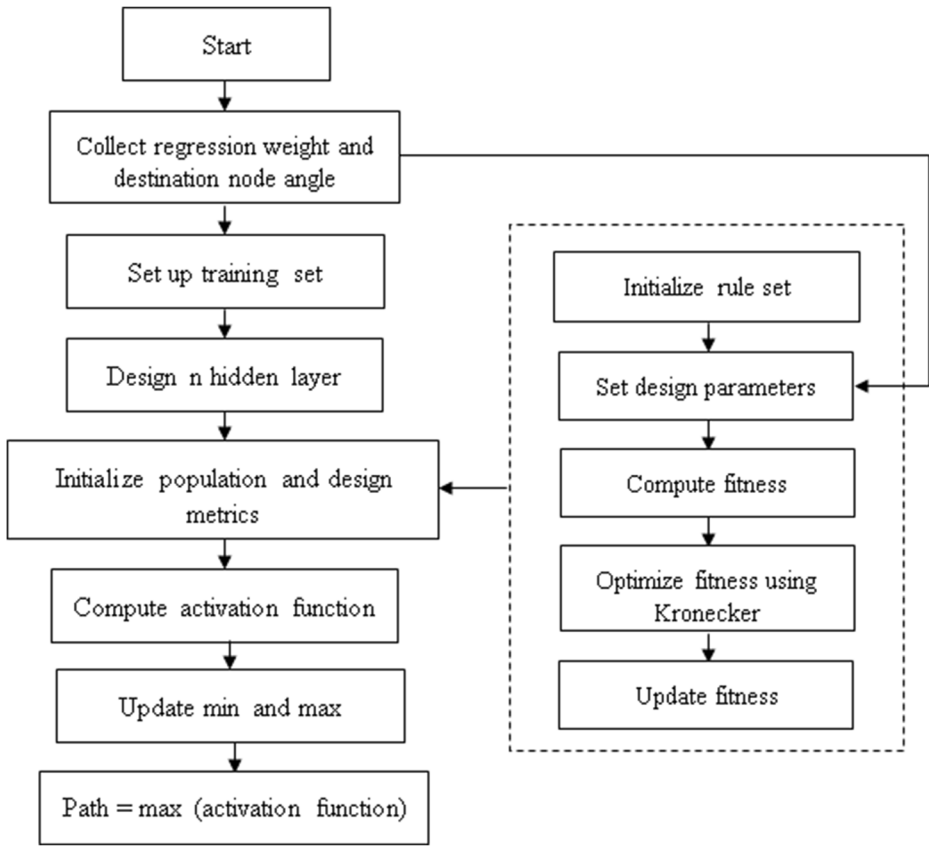
Input: Neurons

Output: Features

```

1      Initialize hidden layer parameters
2      for T= 0,1,2,..., do
3          set  $Y_T^{i+1} \leftarrow \theta$ 
4      end for
5      for i=1
6          compute activation function using  $R_{cl_j} \leftarrow \beta R_{cl_j} + (1 - \beta) cl_j^2$ 
7          compute nonlinear formulation using  $f(k) = \max(0, k)$ 
8          define hyper parameter  $\sigma(bW_z(Z^{z-1}))$ 
9          define block weight and vectors using eqns. (50) and (51)
10         set  $R_{cl_j} \leq b^{n+1}$ 
11     end for
12     for  $R_{cl_j} \geq b^{n+1}$ 
13         define adaptive activation function using eqn. (53)
14         set  $R_{cl_j} \leq \sum_{\kappa=1}^{\kappa} (\alpha_{\kappa}' \theta_{T_j} Y_T'(z))$ 
15     end for
16 end procedure

```



Flowchart 3 Work flow of optimal path selection using DKNN

5 Results and discussion

In this part, we use several simulation setups to assess the effectiveness of our suggested QEMR system. The standard NS-3 simulation programme is used to execute the suggested routing design and evaluate its efficacy. We took stationary nodes into consideration and dispersed them around a 500 m² network region. Euclidean distance between nodes determines their separation. We select the CBR type of traffic and the IEEE 802.15.4 MAC protocol. With a 250 kbps data transmission rate, we may have 200, 400, 600, 800, or 1000 IoT nodes. The sensor nodes’ initial transmission and receiving powers are 1.4 W and 1.0 W, respectively. Each node in the network initially uses 100 J of energy. The data capacity of each sensor node is 512 bytes. An overview of the simulation parameters is provided in Table 1.

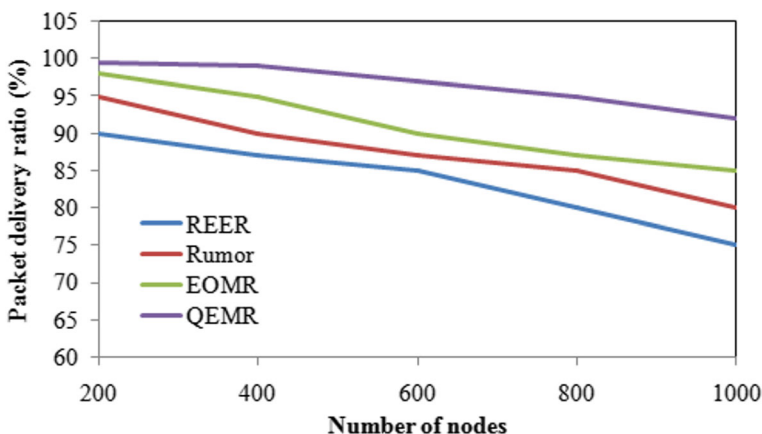
The simulation results of the proposed QEMR system are contrasted with the state-of-the-art REER [13], Rumor [13], and EOMR [13] approach in terms of packet delivery ratio, average end-to-end latency, normalised overhead, energy consumption, throughput, and packet loss rate, respectively.

Table 1 Setup for simulation

Parameters	Values
Simulation time	150 seconds
Node initial energy	100 J
Node transfer power	1.4 W
Node receiving power	1.0 W
MAC protocol	IEEE 802.15.4
Traffic type	CBR
Node density	200–1000
Data size	512bytes
Node speed	10–50kmph
Network size	500 × 500 m ²

5.1 Impact of node density

With a constant node speed of 100 m/s and 512 bytes of data, we vary the number of IoT sensor nodes in this simulated scenario from 200 to 400 to 600 to 800 to 1000. The discussion that follows explains the performance comparison between the recommended and real state-of-the-art routing systems. Figure 2 illustrates a comparison of the packet delivery ratio and the impact of node density. The image clearly shows that the packet delivery ratios of the proposed QEMR system are 5.1926%, 3.015%, and 1.507% higher than those of the existing REER, Rumor, and EOMR methods, respectively. Figure 3 compares the average end-to-end latency with the influence of node density. The graphic makes it evident that the proposed QEMR scheme has an average end-to-end latency that is 88.095%, 85%, and 80% shorter than those of the REER, Rumor, and EOMR schemes that are now in place, respectively. The normalised overhead comparison with the effect of node density is shown in Fig. 4. The graphic unmistakably demonstrates that the normalised overhead of the proposed QEMR scheme is, in comparison to the current REER, Rumor, and EOMR schemes, 85.46%, 84.074%, and 81.481% lower, respectively. The comparison of energy usage and the effect of node density is shown in Fig. 5. The graphic makes it evident that the suggested QEMR system uses less energy than the REER, Rumor, and EOMR schemes, respectively, by 86.296%, 81.94%, and 75%. The throughput comparison with the effect of node density is shown in Fig. 6. The

**Fig. 2** Ratio of packet delivery to nodes numbers

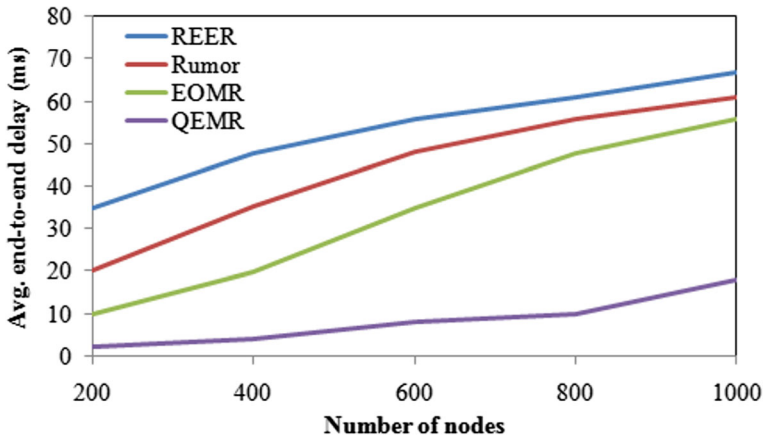


Fig. 3 Average end-to-end latency in relation to node count

graphic clearly demonstrates that the new QEMR scheme has a throughput that is 25%, 18.75%, and 12.5% greater than the corresponding current REER, Rumor, and EOMR schemes. Figure 7 illustrates a comparison of the packet loss ratio and the impact of node density. The graph clearly shows that the packet loss ratio of the proposed QEMR system is 90.078%, 89.11%, and 88.235% lower than that of the current REER, Rumor, and EOMR methods, respectively.

5.2 Impact of node speed

In this simulated scenario, the IoT sensor node speed is changed from 10, 20, 30, 40, and 50 kmph while the fixed node is kept at 1000 and the data size is kept at 512 bytes. The discussion that follows explains the performance comparison between the recommended and real state-of-the-art routing systems. Figure 8 illustrates a comparison of the packet delivery ratio and the impact of node density. The graph indicates unequivocally that the packet delivery ratio of the

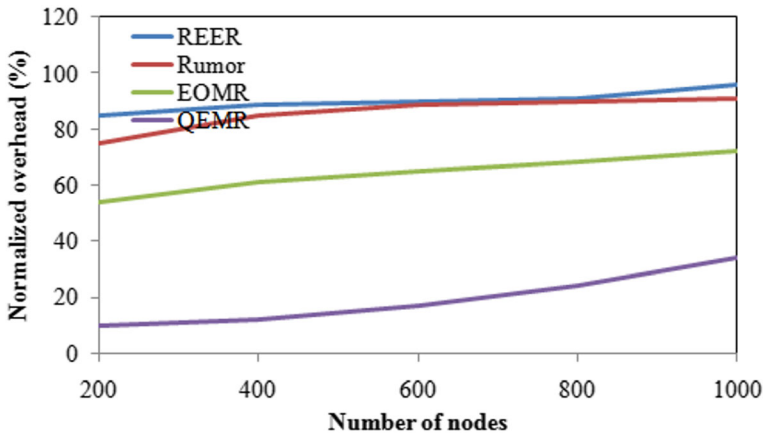


Fig. 4 Normalised overhead in relation to node count

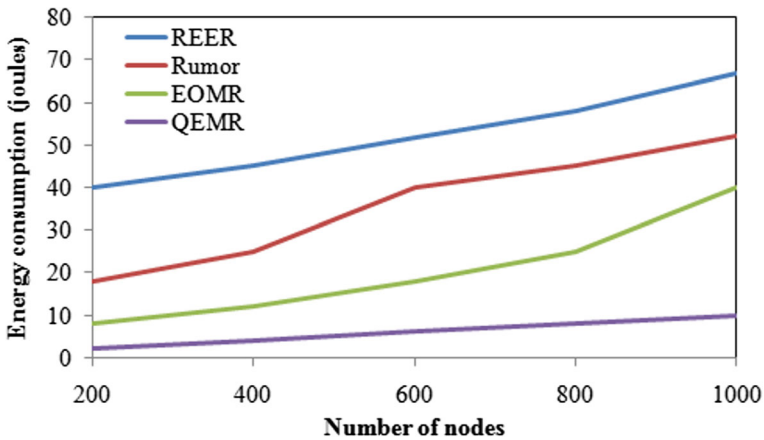


Fig. 5 Energy use in relation to the number of nodes

proposed QEMR method is 7.482%, 5.61%, and 3.061% higher than the existing REER, Rumor, and EOMR techniques, respectively. Figure 9 compares the average end-to-end latency with the influence of node density. The graphic unmistakably demonstrates that the average end-to-end latency of the proposed QEMR system is 66.465, 60.71, and 50% less than the current REER, Rumor, and EOMR schemes, respectively. The normalised overhead comparison with the effect of node density is shown in Fig. 10. The graphic makes it evident that the normalised overhead of the proposed QEMR scheme is lower than the current REER, Rumor, and EOMR schemes by 84.24, 83.105, and 80.327%, respectively. The comparison of energy usage and the effect of node density is shown in Fig. 11. The graphic makes it evident that the proposed QEMR system uses less energy than the REER, Rumor, and EOMR schemes, respectively, by 80.042%, 75.63%, and 66.66%. The throughput comparison with the effect of node density is shown in Fig. 12. The graphic makes it obvious that the proposed QEMR scheme has throughputs that are 28,57%, 21.428%, and 14.285% greater than those of

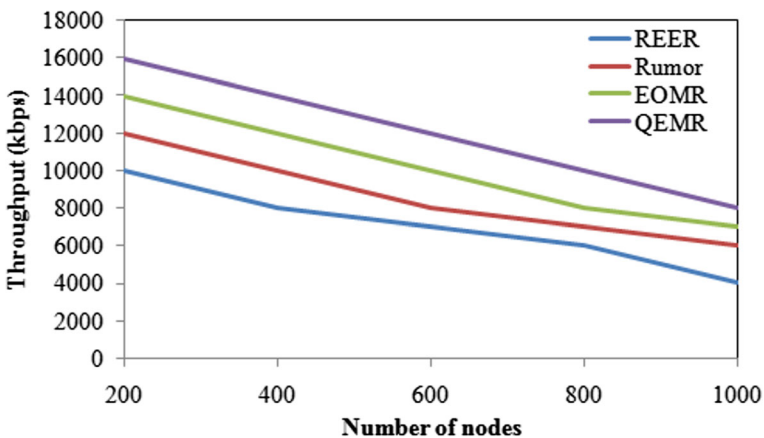


Fig. 6 Comparison of throughput and node count

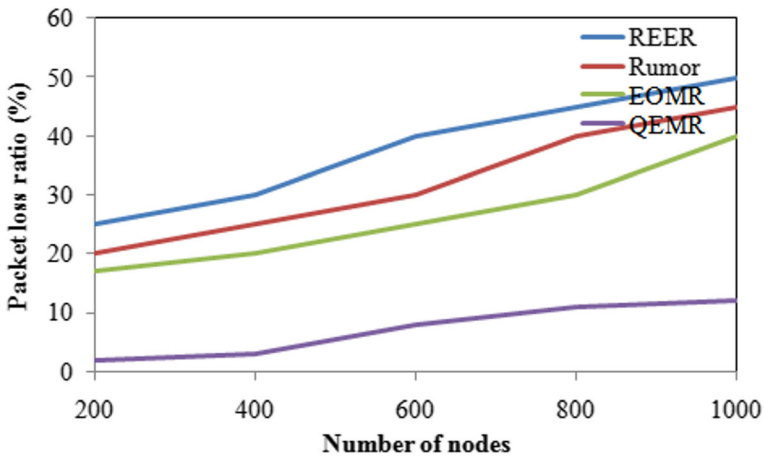


Fig. 7 Packet loss ratio in relation to node count

the REER, Rumor, and EOMR schemes that are now in place, respectively. Figure 13 illustrates a comparison of the packet loss ratio and the impact of node density. The graph indicates unequivocally that the packet loss ratio of the proposed QEMR system is, respectively, 70.462%, 67.916%, and 63.33% lower than that of the existing REER, Rumor, and EOMR methods.

5.3 Impact of network traffic

The fixed node in this simulation is 1000, and the speed is set at 50 kmph. We change the data rate to be 100, 200, 300, 400, and 500 bytes per second. The discussion that follows explains the performance comparison between the recommended and real state-of-the-art routing systems. Figure 14 compares the packet delivery ratio with the impact of node density. The graphic makes it evident that the proposed QEMR system has packet delivery ratios that are 8,

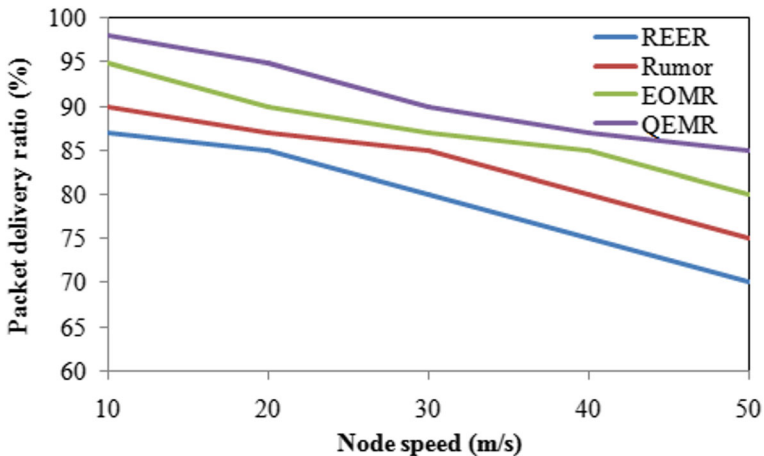


Fig. 8 Ratio of delivered packets to node speed

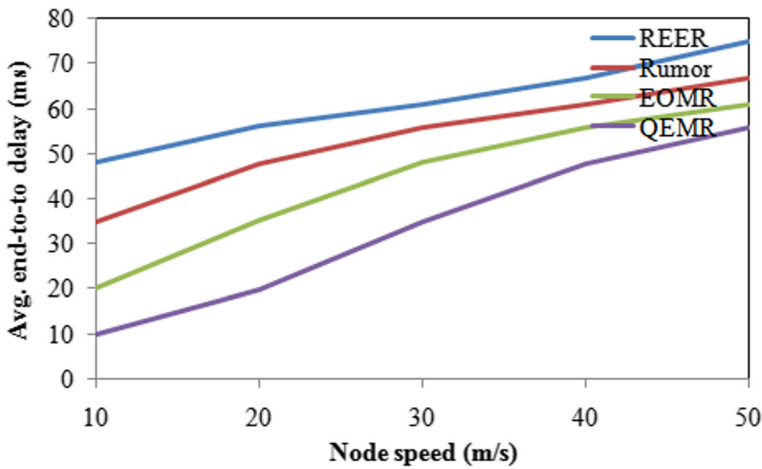


Fig. 9 Comparison of typical end-to-end latency and node speed

6, and 5.263 percentage points greater than the REER, Rumor, and EOMR schemes, respectively. Figure 15 compares the average end-to-end latency with the influence of node density. The graphic clearly demonstrates that the proposed QEMR system has an average end-to-end latency that is correspondingly 55.1587%, 50.59%, and 42.857% shorter than those of the current REER, Rumor, and EOMR schemes. The normalised overhead comparison with the effect of node density is shown in Fig. 16. The graphic clearly demonstrates that the proposed QEMR scheme’s normalised overhead is, respectively, 78.618%, 77.37%, and 73.846% lower than those of the current REER, Rumor, and EOMR schemes. The comparison of energy usage and the effect of node density is shown in Fig. 17. The graphic unmistakably demonstrates that the proposed QEMR scheme’s energy usage is, respectively, 78%, 75%, and 68% less than those of the present REER, Rumor, and EOMR schemes. The throughput comparison with the effect of node density is shown in Fig. 18. The graphic unmistakably demonstrates that the proposed QEMR scheme’s throughput is, respectively, 30.555%, 25%, and 16.667%

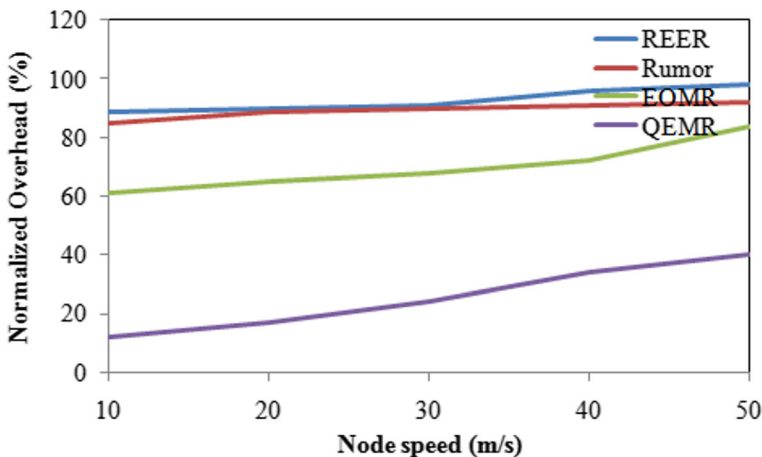


Fig. 10 Comparison of Normalised overhead and node speed

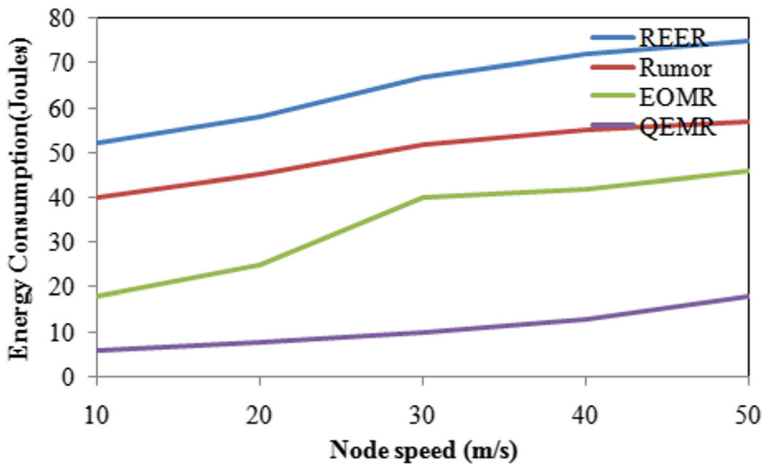


Fig. 11 Comparison of Energy use in relation to node speed

greater than that of the current REER, Rumor, and EOMR schemes. Figure 19 illustrates a comparison of the packet loss ratio and the impact of node density. The graphic clearly demonstrates that the proposed QEMR scheme’s packet loss ratio is, respectively, 73.11%, 71.666%, and 70% lower than those of the current REER, Rumor, and EOMR schemes.

5.4 Discussion

Jaiswal et al. [13] developed a EOMR scheme to design an energy-efficient routing protocol for wireless sensor network based IoT application having unfairness in the network with high traffic load REER [13] is based on the reliability of links that found an energy-efficient path to transfer the network data. Rumor [13] is based on those protocols that cannot be used for geographic routing criteria. The congestion at the relay node increased with the increase in

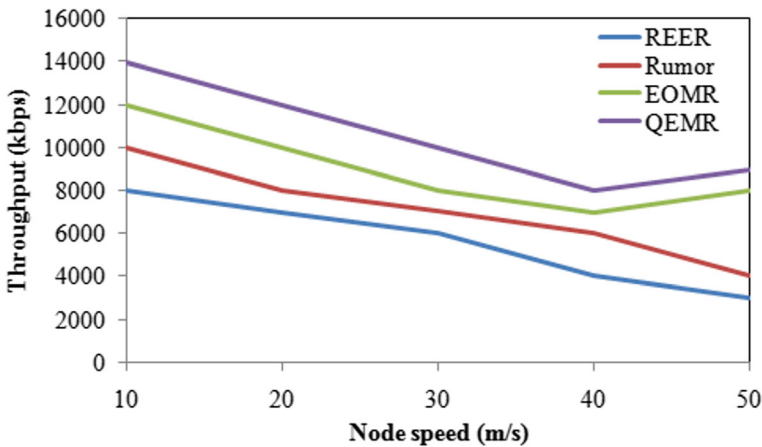


Fig. 12 Comparison of throughput and node speed

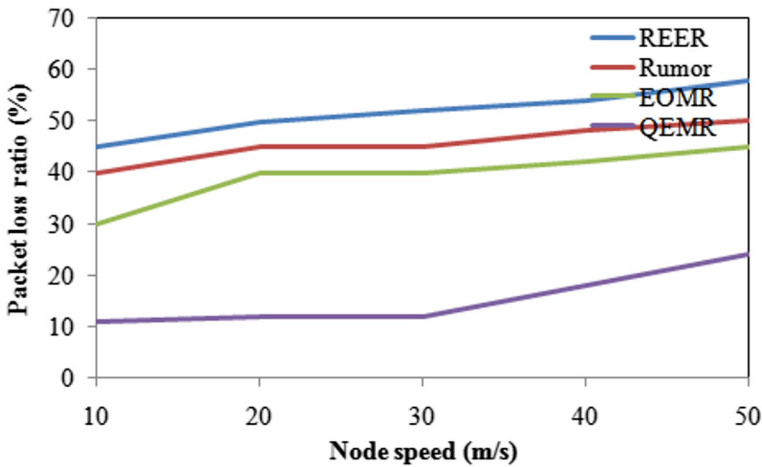


Fig. 13 Ratio of Packet loss in relation to node speed

traffic that adversely affected the packet delivery and increased the delay. REER and Rumor took much time to forward their packet.

Gray system theory by Khaleghnasab et al. [14] chosen the best paths used for separate routes to send packets. Ad hoc On-demand Multipath Distance Vector (AOMDV) packet format was altered and some fields are added to it so that energy criteria, link expiration time, and signal-to-noise ratio can also be considered during selection of the best route. Their developed method named RMPGST-IoT was introduced which chooses the routes with highest rank for concurrent transmission of data, using a specific method based on the gray system theory. Singh et al. [28] developed a multi-objective clustering strategy to optimize the energy consumption, network lifetime, network throughput, and network delay. A fitness function has been formulated for heterogeneous and homogeneous wireless sensor networks. This fitness function was utilized to select an optimum CH for energy minimization and load balancing of cluster heads. A new hybrid clustered routing protocol was developed based on

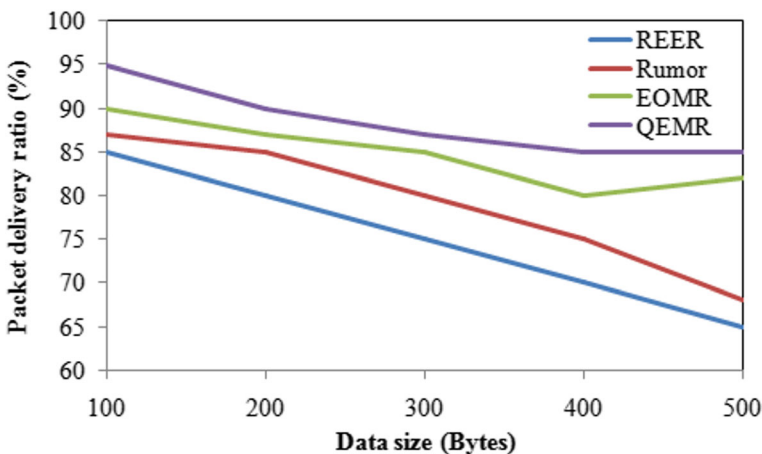


Fig. 14 Ratio of packets delivered per unit of packet size

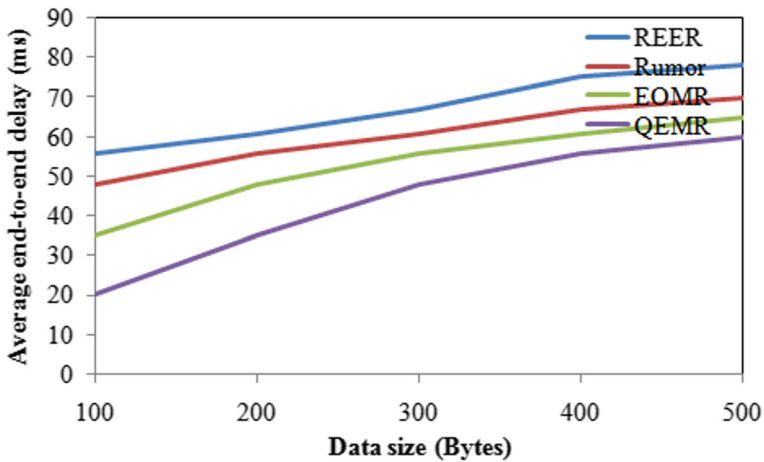


Fig. 15 Comparison of Typical end-to-end latency vs packet size

fitness function. Dogra et al. [6] developed the intelligent MIMO-based 5G balanced energy-efficient protocol which focussed to achieve Quality of Experience (QoE) for transmitting in clusters for IoT networks. The proposed protocol enhances the utilization of energy and lifetime of the network in which it showed 30% less energy. The fuzzy-GWO method and the energy-saving routing algorithm are developed and analyzed by Singh et al. [29]. The LEACH, HEED, MBC, FRLDG protocols, along with the developed protocol F-GWO is compared. From the obtained results, it was found that the network lifetime is increased.

Yang et al. [31] developed a non-uniform clustering routing protocol optimization algorithm from the energy loss of cluster head and clustering form algorithm in wireless sensor networks. At the level of cluster head calculation in wireless sensor networks, firstly, based on the adaptive estimation clustering algorithm, the core density was used as the estimation element to calculate the cluster head radius of wireless sensor networks. A fuzzy logic algorithm was developed to further solve the uncertainty of cluster head selection, integrate

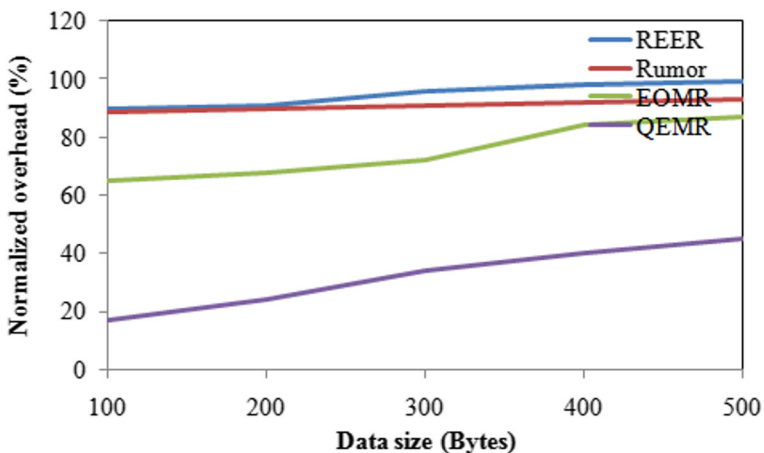


Fig. 16 Comparison of packet size with respect to normalised overhead

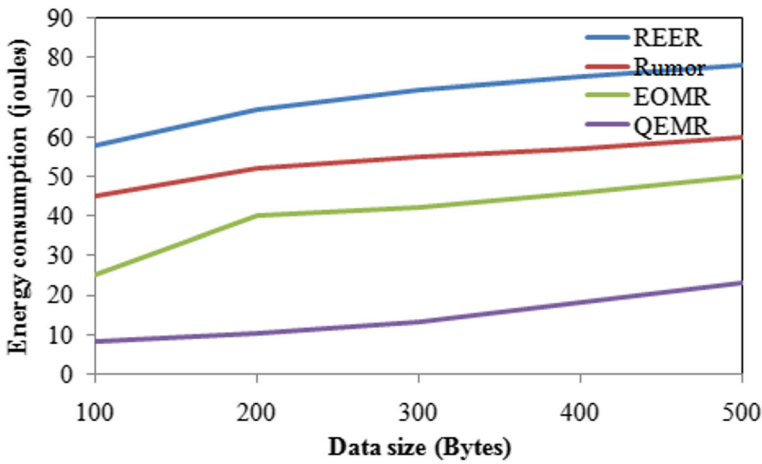


Fig. 17 Energy use in relation to packet size

the residual energy of cluster head nodes, and finally complete the reasonable distribution of cluster heads and realize the balance of node energy consumption. In order to further reduce the algorithm overhead of transmission between cluster heads and realize energy optimization, an inter-cluster routing optimization algorithm based on the ant colony algorithm is proposed. The pheromone was updated and disturbed by introducing chaotic mapping to ensure the optimal solution of the algorithm, and the optimal path was selected from the perspective of energy dispersion coefficient and distance coefficient, so as to optimize the energy consumption between cluster heads. Their experimental results showed that compared with the traditional algorithm, their non-uniform clustering routing protocol optimization algorithm prolongs the corresponding life cycle by 75% and reduced the total network energy consumption by about 20%. Therefore, their algorithm achieved the purpose of optimizing network energy consumption and prolonging network life to a certain extent and has certain practical value.

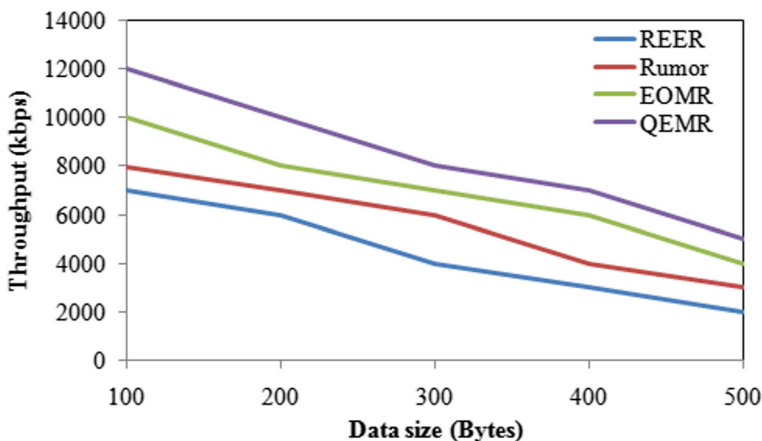


Fig. 18 Comparison of packet size vs throughput

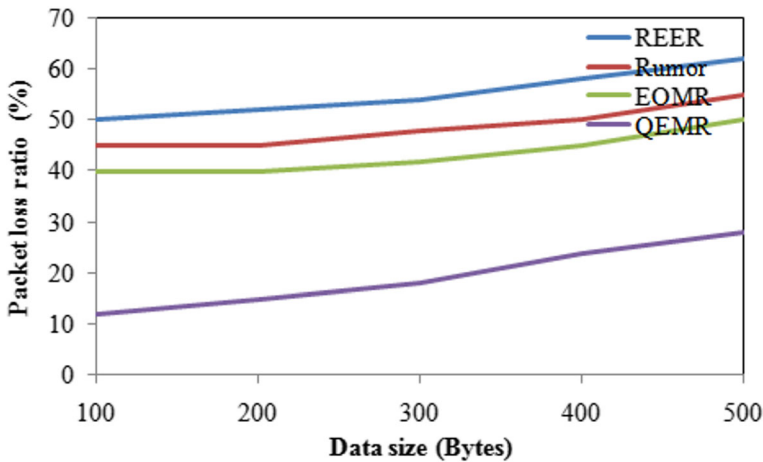


Fig. 19 Ratio of packet loss in relation to packet size

In our proposed QEMR strategy, the graphic clearly demonstrates that the proposed QEMR scheme's packet loss ratio is, respectively, 73.11%, 71.666%, and 70% lower than those of the existing REER [13], Rumor [13], and EOMR [13] schemes. The graphic unmistakably demonstrates that the proposed QEMR scheme's energy usage is, respectively, 78%, 75%, and 68% less than those of the present REER, Rumor, and EOMR schemes.

6 Conclusion

Energy optimization, routing, and other issues have been examined in this research as difficulties that must be resolved to improve the IoT's resilience. Using a hybrid optimization approach, a QoS-aware energy-efficient multipath routing (QEMR) strategy is suggested for the internet of things. To create an ideal clustering, a modified teaching-learning-based optimization (MTLO) method is applied. The cluster head (CH) of the cluster is determined using the nonlinear regression-based pigeon optimization (NR-PO) method. Deep Kronecker neural network (DKNN) is used to choose the optimum path between two nodes out of a large list of choices. In terms of the impact of node density, node speed, and network traffic, the NS3 simulation results showed that the proposed QEMR scheme surpassed the most advanced routing schemes at the time, REER, Rumor, and EOMR systems. In comparison of energy usage and the impact of node density, the suggested QEMR system uses less energy than the REER, Rumor, and EOMR schemes by 86.296%, 81.94%, and 75% respectively.

6.1 Limitations

In reality, IoT devices are exceedingly heterogeneous, and many of them have limited resources, making global communication a difficult task in the internet of things.

6.2 Recommendations

In our proposed QEMR scheme, QoS is a big challenge since multimedia data must be supplied in real-time and reliably.

Data availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest I have no conflict of interest.

References

- Ahmad S, Mehruz S, Mebarek-Oudina F, Beg J (2022) RSM analysis based cloud access security broker: a systematic literature review. *Clust Comput*:1–31
- Badi A, Mahgoub I (2021) ReapIoT: reliable, energy-aware network protocol for large-scale internet of things (IoT) applications. *IEEE Internet Things J* 8:13582–13592
- Balakrishnan N, Rajendran A, Pelusi D, Ponnusamy V (2021) Deep belief network enhanced intrusion detection system to prevent security breach in the internet of things. *Int things* 14:100112
- Bebortta S, Singh AK, Pati B, Senapati D (2021) A robust energy optimization and data reduction scheme for iot based indoor environments using local processing framework. *J Netw Syst Manag* 29(1):1–28
- Bhatia VK, Girdhar AKhurmi SS (2021) "Type-II fuzzy based clustering protocol for energy harvesting internet of things." *Materials Today: Proceedings*.
- Dogra R, Rani S, Babbar H, Krah D (2022) Energy-efficient routing protocol for next-generation application in the internet of things and wireless sensor networks. *Wirel Commun Mob Comput* 2022:1–10
- Du Y, Yin X, Lai J, Ullah Z, Wang Z, Jiakuan H (2021) Energy optimization and routing control strategy for energy router based multi-energy interconnected energy system. *Int J Electr Power Energy Syst* 133: 107110
- Famitafreshi G, Afaqui MS, Melià-Seguí J (2021) A Comprehensive Review on Energy Harvesting Integration in IoT Systems from MAC Layer Perspective: Challenges and Opportunities. *Sensors* 21(9): 3097
- Ghalambaz M (2021) Reza Jalilzadeh Yengejeh, and Amir Hossein Davami. "building energy optimization using Grey wolf optimizer (GWO)." *case studies in. Therm Eng* 27:101250
- Goudarzi S, Anisi MH, Soleymani SA, Ayob M, Zeadally S (2021) "An IoT-based Prediction Technique for Efficient Energy Consumption in Buildings." *IEEE Transactions on Green Communications and Networking*.
- Ibrahim M, Harb H, Mansour A, Nasser A, Osswald C (2021) All-in-one: toward hybrid data collection and energy saving mechanism in sensing-based IoT applications. *Peer-to-Peer Network App* 14(3):1154–1173
- Iwendi C, Maddikunta PKR, Gadekallu TR, Lakshmana K, Bashir AK, Piran J (2021) A metaheuristic optimization approach for energy efficiency in the IoT networks. *Software: Prac Exp* 51(12):2558–2571
- Jaiswal K, Anand V (2020) EOMR: an energy-efficient optimal multi-path routing protocol to improve QoS in wireless sensor network for IoT applications. *Wirel Pers Commun* 111(4):2493–2515
- Khaleghnasab R, Bagherifard K, Nejatian S, Parvin H, Ravaei B (2020) A new energy-efficient multipath routing in internet of things based on gray theory. *Int J Inf Technol Decis Mak* 19(06):1581–1617
- Kumar S, Kaiwartya O, Rathee M, Kumar N, Lloret J (2020) Toward energy-oriented optimization for green communication in sensor enabled IoT environments. *IEEE Syst J* 14(4):4663–4673
- Nižetić S, Šolić P, González-de D L-d-I, Patrono L (2020) Internet of things (IoT): opportunities, issues and challenges towards a smart and sustainable future. *J Clean Prod* 274:122877
- Pirbhulal S, Wu W, Muhammad K, Mehmood I, Li G, de Albuquerque VHC (2020) Mobility enabled security for optimizing IoT based intelligent applications. *IEEE Neww* 34(2):72–77
- Prasad AY, Balakrishna R (2019) A generic algorithmic protocol approaches to improve network life time and energy efficient using combined genetic algorithm with simulated annealing in MANET. *Int J Intel Unman Syst* 8(1):23–42 ISSN: 2049-6427

19. Prasad AY, Balakrishna R (2019) "Implementation of optimal solution for network lifetime and energy consumption metrics using improved energy efficient LEACH protocol in MANET" TELKOMNIKA (Telecommunication Computing Electronics and Control), V-17, No.4, pp.1758–1766
20. Praveen KV, Prathap PMJ (2021) Energy Efficient Congestion Aware Resource Allocation and Routing Protocol for IoT Network using Hybrid Optimization Techniques. *Wirel Pers Commun* 117(2):1187–1207
21. Rana B, Singh Y, Singh PK (2021) A systematic survey on internet of things: Energy efficiency and interoperability perspective. *Trans Emerg Telecommun Technol* 32(8):e4166
22. Raval M, Bhardwaj S, Aravelli A, Dofe J, Gohel H (2021) Smart energy optimization for massive IoT using artificial intelligence. *Internet of Things* 13:100354
23. Sadeeq MAM, Zeebaree S (2021) Energy management for internet of things via distributed systems. *J App Sci Technol Trends* 2(02):59–71
24. Sadrishojaei M, Navimipour NJ, Reshadi M, Hosseinzadeh M (2021) Clustered Routing Method in the Internet of Things Using a Moth-Flame Optimization Algorithm. *Int J Commun Syst* 34(16):e4964
25. Shad N, Mozhdeh MM, Moghadam MN (2021) GAPSO-SVM: An IDSS-based energy-aware clustering routing algorithm for IoT perception layer. *Wirel Pers Commun*:1–20
26. Shahryari O-K, Pedram H, Khajehvand V, TakhtFooladi MD Energy and task completion time trade-off for task offloading in fog-enabled IoT networks. *Perv Mob Comp* 74(2021):101395
27. Shreyas J, Chouhan D, Rao ST, Udayaprasad PK, Srinidhi NN, Kumar SMD (2021) An energy efficient optimal path selection technique for IoT using genetic algorithm. *Int J Intel Int Things Comp* 1(3):230–248
28. Singh P, Singh R (2019) Energy-efficient QoS-aware intelligent hybrid clustered routing protocol for wireless sensor networks. *J Sens* 2019:1–12
29. Singh J, Deepika v, Bhat JS, Kumararaja V, Vikram R, Amalraj JJ, Saravanan V, Sakthivel S (2022) "Energy-efficient clustering and routing algorithm using hybrid fuzzy with Grey wolf optimization in wireless sensor networks." *Security and Communication Networks* 2022.
30. Tabatabaei S (2021) A new routing protocol for energy optimization in Mobile ad hoc networks using the cuckoo optimization and the TOPSIS multi-criteria algorithm. *Cybern Syst*:1–21
31. Yang S, Long X'a, Peng H, Gao H (2022) Optimization of heterogeneous clustering routing protocol for internet of things in wireless sensor networks. *J Sens* 2022
32. Zhang X, Manogaran G, Muthu BA (2021) IoT enabled integrated system for green energy into smart cities. *Sustain Energy Technol Assess* 46:101208

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