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Employing Genetic Algorithms for Energy-Efficient Data Routing in Internet of Things Networks

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Employing Genetic Algorithms for Energy-Efficient Data Routing in Internet of Things Networks

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Abstract

The Internet of Things (IoT) connects a vast number of smart objects for various applications, such as home automation, industrial control, and healthcare. The rapid advancement in wireless technologies and miniature embedded devices has enabled IoT systems to be deployed in various environments. However, the performance of IoT devices is limited because of the imbalance of data traffic on different router nodes. Nodes that experience high data volume will have a higher energy depletion rate and, as a result, will reach the end of their life quicker than other routers that have less data traffic. Genetic Algorithms are a well-known technique used to solve routing problems, but it is essential to pay more attention to designing data routing protocols that take into account a router's data traffic load and position in the overall network topology.

The objectives of this thesis are two-fold. First, we propose a GA-based routing protocol for hierarchical multi-hop IoT networks that identifies heavily congested routers and ranks them based on their potential load. Second, we present a centralized approach to determine optimal routing paths for IoT networks by utilizing a priori knowledge of the network topology. Additionally, we conduct comparative analysis on the existing GA-based multi-hop routing protocols using simulation data.

Our research has revealed that distributing the data load evenly on nodes can noticeably enhance the network lifetime in comparison to other routing protocols. Our extensive simulations have demonstrated that the routing approach that we have proposed, based on Genetic Algorithm (GA), can significantly reduce energy consumption and improve network reliability.

Citations

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1 Introduction

1.1 Motivation

Internet of Things (IoT) have evolved from simple to complex scenarios due to the rapid development of sensor technologies [1,2]. IoTs are now used to send large and complex information, which increases the energy consumption of nodes and exacerbates the energy imbalance of the whole network [3]. The energy of the nodes is the most critical factor in the network's lifetime, and reducing and balancing energy consumption is a significant challenge. Dividing the network into clusters for data transmission can help balance energy consumption and prolong network lifetime [4]. However, this approach requires a considerable message overhead, and the energy consumption of data transmission in this way is higher than that of plane routing. Due to its cost effectiveness, hierarchical multi-hop routing for large-scale hybrid IoT networks has become very popular. This approach enables IoT users to act as intermediate relaying nodes, reducing routing overhead and eliminating the need for a fixed routing table [5]. The hierarchical routing protocol also increases network bandwidth by transmitting data through multiple short hops, making it ideal for the hybrid IoT network architecture.

Genetic algorithms (GAs) are widely used in modern metaheuristics, with numerous applications in the routing problem domain, including sensor network routing [], vehicle routing problems [], and school bus routing [23]. However, GAs have not made a significant impact on the multi-hop based data routing for sensor networks yet. This study aims to propose a straightforward GA for the basic centralized multihop IoT network, which is competitive with other modern heuristics in terms of solution quality and computing time. The study also explores different operators of GA to find optimal routing path. Computational results are presented for the proposed algorithm, along with some of the well-known results obtained using network simulation.

1.2 Background

In this part, the outline of a few key ideas and foundation material that have been to a great extent utilized all through this paper is given.

1.2.1 What is Internet of Things

A network of linked sensors called the Internet of Things (IoT) makes it possible for humans and machines to communicate with each other easily [6]. It is made up of wirelessly communicating

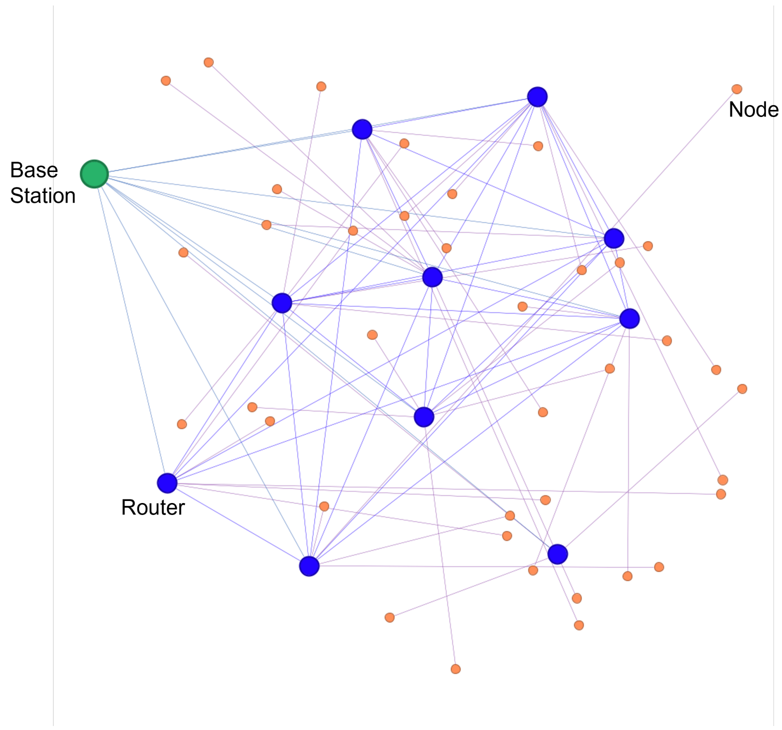


Figure 1.1: Representation of an IoT network in general. To be able to route data to the base station, end nodes forward data to the nearest router.

sensors, actuators, and routers that provide real-time sensory data. The router is connected to the inexpensive sensor nodes, sometimes referred to as end-nodes, which help in data collection and decision-making [7]. After then, a remote server receives the sensory data for data gathering, analysis, and real-time device control. Multiple routers and end nodes are part of the Internet of Things architecture, as Fig. 1.1 illustrates.

The Internet of Things (IoT) aims to connect people with their surroundings through various context-aware and reactive IoT devices [8]. This opens up a wide array of applications across multiple disciplines. The applications of IoT are diverse, ranging from energy efficiency, such as smart grids and household energy control systems, to automation, including industrial and automobile control systems [9]. Additionally, there has been a recent surge in interest in IoT-based healthcare applications for patient assistance, exercise regimens, and personal health monitoring. Thanks to advancements in sensor technology, the Internet of Things can now be easily utilized for agricultural and environmental purposes [10]. Some of the current IoT applications for the environment include water quality monitoring, wildfire monitoring, and pollution monitoring.

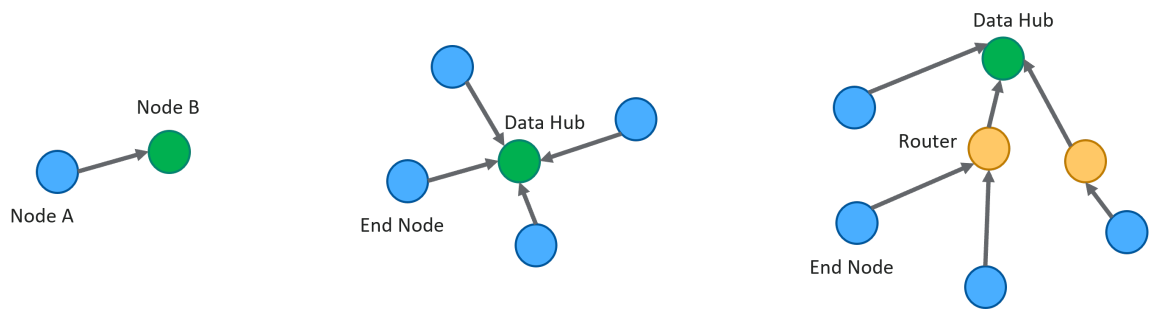


Figure 1.2: Example of various topologies used in IoT networks: (a) point-to-point, (b) star, (c) mesh and (d) hybrid mesh topology.

1.2.2 IoT Architecture

IoT devices can work alone or together for practical applications and communicate via network topology. Deployment can be random or predetermined. In predetermined topology, routes are planned, and nodes know neighbors' locations. In random deployment, nodes discover neighbors during routing. IoT networks use point-to-point or multi-level configurations.

- Point-to-point topology: As shown in Fig. 2.1, this is the most fundamental architecture that links two end devices, for instance a smartphone and a single sensor node.
- Star topology: If end nodes are close to the base station in a small IoT network, they can communicate directly with it without the need for a repeater node. As the hub for all data transmission, the base station serves as a central node in such networks.
- Mesh topology: IoT applications often require many devices to cover a large area, with the base station outside the end nodes' range. In mesh networks, nodes communicate via multiple router nodes, acting as repeaters. Hybrid mesh networks use sparse connections to reduce redundancy and are easier to install.

In this work, we consider a hierarchical IoT network, where nodes can function as either routers or sensors. Sensor nodes are responsible for data collection and transmit it to a remote base station via routers. At the base station, data from all sensors is processed, and routing decisions are made in a centralized manner. This centralized approach provides greater control while minimizing complexity. Hierarchical IoT networks strike a balance between resource efficiency, fault tolerance, and scalability, making them an excellent choice for various IoT and sensor-based applications. In contrast, mesh networks offer robustness in handling failures and adapt well to diverse scenarios. However, they come with the trade-off of redundant paths, which can increase energy consumption for sensor nodes with limited battery life. Despite this, hierarchical networks play a crucial role in different industries. For instance: Continuous Patient Monitoring: hierarchical IoT networks facilitate continuous monitoring of patients' vital signs and health conditions [11]. Efficient Hospital Resource Management: hospitals benefit from hierarchical structures for managing medical equipment, patient data, and communication systems [12]. Traffic Light Control: hierarchical networks contribute to efficient traffic light management, ensuring smooth traffic flow and safety [13]. Utility Consumption Monitoring: real-time monitoring of utility consumption (e.g., electricity, water) is achievable through hierarchical IoT networks [14]. Environmental Monitoring: hierarchical networks enable timely data collection and analysis for environmental parameters such as air quality, temperature, and pollution [15]. As a result, we leveraged multi-hop hierarchical network structure for our work to investigate the energy efficient routing of IoT networks.

1.2.3 Routing Techniques for IoT networks

IoT routing protocols are designed to be energy-efficient and non-redundant due to the limited power, and capabilities of IoT devices [16]. While IoT network topology is mostly static, some applications may involve mobile routers or sink nodes, which affect the network structure and require dynamic updates to routing paths. Routing protocols can be classified into different sub-categories based on network structure, as shown in Figure 1.

- Location based: This category routes sensory data using node positions determined by localization methods or GPS. [17] describes examples of delivering data using nearby geographic information.

- Hierarchical: Hierarchical networks have nodes designated as routers or end nodes based on their energy levels and capabilities. Cluster-based approaches in protocols help minimize power consumption in IoT devices.

- Flat-based: In flat-based network topology, nodes use broadcasting to deliver data to all neighboring nodes until it reaches its destination. Enhanced versions of this architecture, such as directed diffusion protocol and negotiation-based protocol, have been proposed to reduce data redundancy and energy consumption.

IoT networks with fewer routers are more cost-effective but out of range for power-constrained devices. Hierarchical multihop routing solves this by allowing users to act as relaying nodes for their nearest neighbors [18]. This reduces routing overhead and increases network bandwidth by transmitting data through multiple short hops. The advantages of such networks make it an ideal candidate for the work proposed herein.

1.2.4 Genetic Algorithm based Routing for Hierarchical IoT Networks

Cluster-based routing protocols are commonly used in hierarchical IoT networks. These protocols split the network into clusters, with each cluster led by a cluster head [19]. Clusters reduce communication overhead by aggregating data within them. The cluster heads handle intra-cluster communication, simplifying routing. There are several examples of cluster-based routing methods. The Water-Cycle Algorithm is an algorithm that clusters dense, randomly distributed, and heterogeneous IoT networks [20]. It combines clustering with software-defined networking (SDN) using the Water-Cycle Algorithm (WCA) for enhanced efficiency [21]. The Hybrid Energy Efficient Distributed clustering technique was adopted for IoT networks based on wireless sensor networks (WSNs). It organizes nodes into clusters, with cluster heads responsible for local communication. While cluster-based routing approaches offer benefits such as scalability, data aggregation, and optimized channel utilization in hierarchical networks, they have some limitations compared to GA-based routing approach. GA-based routing approaches have several advantages over cluster-based algorithms. For example, GAs explore a wide solution space by maintaining a diverse population of candidate solutions. This diversity allows them to discover novel and non-obvious solutions. In contrast, cluster-based algorithms often focus on grouping data points into clusters, which may not explore the entire solution space comprehensively [22]. Similarly, GAs adapt to changing environments by evolving solutions over generations. They can handle dynamic scenarios where the problem landscape evolves. Cluster-based algorithms may struggle with abrupt changes or noisy data [23]. In summary, genetic algorithms offer versatility, adaptability, and global exploration, making them advantageous for various optimization tasks beyond clustering.

The Genetic Algorithm compares a problem to an environment, where feasible solutions are treated as individuals [24–26]. These individuals can be binary digits or symbols taken from a finite set. Each individual is encoded and represents a solution to the problem [27]. Certain operations are performed on these individuals to find the best optimal solution. This sections explains the terminology and operators used in Genetic Algorithms to achieve a good solution for terminating conditions [28].

1.2.4.1 Terminologies of GA A genetic algorithm starts with an initial population, selects parents for mating, applies crossover and mutation operators to create new offspring, replaces existing individuals with offspring, and repeats the process [29]. This mimics human evolution to some extent. In GA, the population is a subset of all possible encoded solutions to a problem. A chromosome is a solution to the problem and consists of genes [30]. A gene represents an element position of a chromosome, and an allele is the value a gene takes for a particular chromosome. Genetic algorithms use genotype and phenotype populations to find solutions. The genotype population is used in the computation space, while the phenotype population is used in the real-world space. Decoding and encoding are used to transform solutions between the two spaces [31]. A fitness function evaluates the suitability of the solution as output. The fitness and objective functions may be the same in some cases, while they may differ in others.

1.2.4.2 Genetic Operators Genetic algorithms use selection, crossover, and mutation methods to optimize solution. The selection method ensures that the highest-performing chromosomes are used for breeding in the next generation. The crossover method involves splitting two strings at a random point of crossover, reassembling them to form a pair of new chromosomes, and assessing their fitness in the following generation [32]. Mutation involves flipping a random gene's bit to help escape potential local minima.

- Crossover: Crossover combines two parent solutions to create a child solution, improving the quality of solutions in a population. Single-point crossover is commonly used in traditional genetic algorithms [33]. Other crossover algorithms exist, but too many crossover points can reduce performance by disrupting building blocks. More crossover points can help search the problem space more thoroughly.

- Mutation: After crossover, genetic strings undergo mutation to prevent the algorithm from becoming trapped in a local minimum. Mutation helps recover lost genetic materials and randomly disturbs genetic information, acting as an insurance policy against the irreversible loss of genetic material. It helps explore the entire search space while maintaining genetic diversity in the population. Different kinds of representations require different mutation forms [34]. However, care should be taken as this operator might reduce the population's diversity and cause the algorithm to converge towards local optima.

1.3 Research Objectives and Organization

The central question that this thesis aimed to answer was: how can GA-based routing techniques improve link reliability and energy efficiency in resource-constrained IoT devices transmitting high-volume data in multi-hop IoT networks?

The research aimed to achieve two specific objectives. Firstly, a comparative analysis was conducted between the proposed GA-based approach and the primary static following neighbor routing-based protocol. Secondly, end-to-end network reliability and energy consumption assessments were performed for the existing GA-based multi-hop routing techniques.

The thesis is divided into several sections. Section 2 describes the IoT network, systems model and sensor details. In Section 3, we present the proposed GA-based routing technique that takes advantage of the hybrid IoT network architecture and ranks router nodes based on their position in the topology. This ranking helps distribute the load evenly, prevents data congestion, and enhances network lifetime and reliability. In Section 4, simulation results are presented and performance of the proposed GA approach is discussed. The results clearly demonstrated the benefits of identifying potential highly-congested router nodes and showed how the proposed technique outperformed comparable approaches. Section 5 summarizes the conclusions and provides avenues for future work.

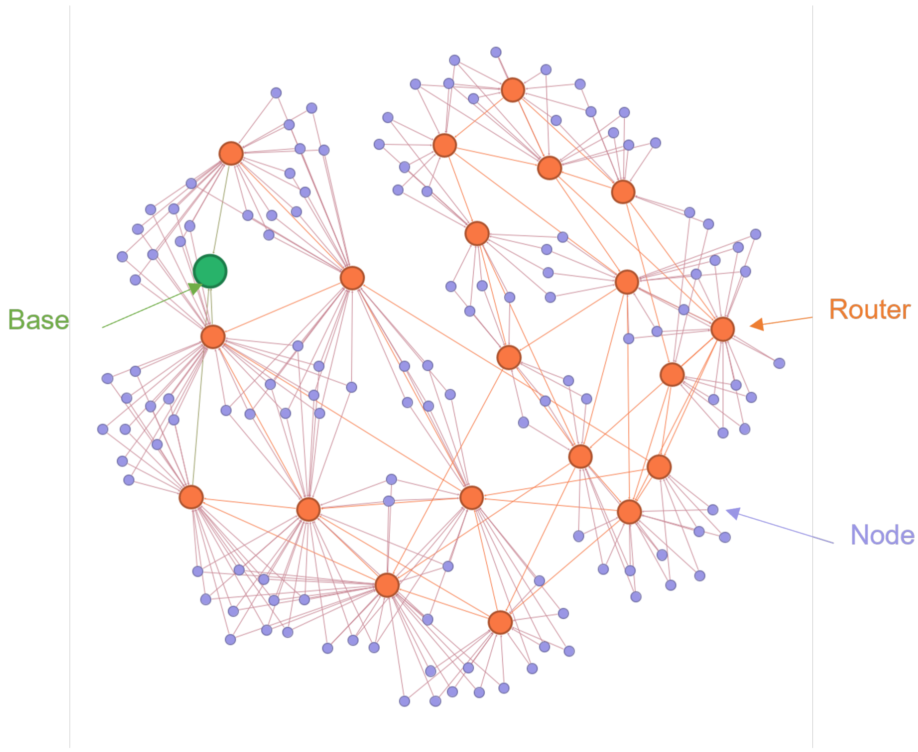


Figure 2.1: An IoT network with sensor nodes, routers and base station. As can be seen, some routers are closer to the base compared to others, resulting in receiving higher data flow that will eventually increase their energy consumption.

2 System Model

Different IoT network architectures may be of interest depending on specific applications in indoor environments [35]. For our work, we consider a network with sensor nodes and routers that have limited energy, insubstantial memory, and limited processing capabilities. Sensor nodes are deployed randomly in an area to monitor and send periodically sensed data. Router nodes relay the received data from the sensors in a multi-hop manner to a remote base station.

An example of such an application is IoT networks used for spatio-temporal analysis in indoor environments [35]. When a node joins the network, it sends an acknowledgment message to the nearest neighbors. Routers within the reception range of the node that sends acknowledgment receipts are added to the neighbor list of that node. We assume that the base station has all the topology information and leverages that information to plan data routing paths for all the sensors. Running the algorithm centrally by the base station is advantageous as the routes can be adjusted easily if any changes occur in the topology by newly joined or disconnected nodes compared to decentralized routing protocols. Additionally, energy efficiency is increased by reducing computation performed at the sensor nodes [36].

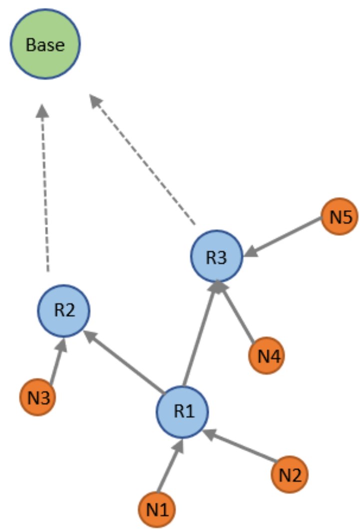
Figure 2.1 illustrates an example IoT network where sensor nodes are randomly deployed, and only router nodes can relay the sensed data. The base station aggregates all sensed information, processes the data, and acts accordingly. Due to limited memory, we assume that the nodes and router do not have any global network knowledge. Hence, our proposed algorithm is run by the base station, where it finds near-optimal routes for each of the nodes that are present in the network. The algorithm also identifies the routers that will have a higher energy consumption rate when the routing paths are implemented. Once the routing paths are established, each node receives local information only to ensure that routes determined by the algorithm are followed.

3 Proposed GA Based Routing Protocol

GA is commonly used in routing problems due to its robustness and simplicity. It guides a search by copying and swapping partial strings, yielding promising results [37]. Unlike traditional methods that search from a single point, genetic algorithms search in parallel from a population of points, avoiding being trapped in local optimal solutions [38]. Random-search-oriented optimization algorithms, including GA, do not require any information about the structure of the function being optimized and treat it as a Black Box—in contrast to classical optimization methods. This section describes how our proposed technique applies GA to solve data routing problems for IoT networks.

3.1 Generating the Initial Population

Genetic algorithms (GAs) are problem-solving search heuristics that simulate natural selection. They employ biologically-inspired operators such as mutation, crossover, and selection to generate high-quality solutions [39]. Here are the basic steps of a GA: First, generate a random population of chromosomes that represent suitable solutions for the problem. Then, evaluate the fitness of each chromosome. Next, create a new population by repeating the following steps until the new population is complete. To create offspring, GAs use a genetic operator called crossover or recombination, akin to sexual reproduction, as it combines genetic material from both parents to produce offspring [40]. For an IoT network, the number of hops required for a packet to be delivered to the base may vary depending on the sensor node's position (see Fig. 2.1). Therefore, our proposed GA runs the route optimization individually for all the nodes in the network, and chromosome length varies according to the node's position. For example, if a data packet generated by a sensor node can be forwarded to the base via three routers, then the chromosome length will be five, as shown below:



Node	Rank
N1	1
N2	1
N3	1
N4	1
N5	1
R1	1+1+1 = 3
R2	1+1+3 = 5
R3	1+1+1+3 = 6

Figure 3.1: An illustration of the ranking of nodes and routers in an IoT network. The ranking represents the probability of data flow in and out of a node in the IoT network. The higher the node's ranking, the higher the likelihood of receiving data from other nodes.

$$\text{Chromosome} = [\text{Node} \mid \text{R1} \mid \text{R2} \mid \text{R3} \mid \text{Base}] \qquad (1)$$

Here, 'Node' is the sensor transmitting the data packet, and R1, R2, and R3 are the routers relaying the data to the base station. The encoding of the chromosomes for the proposed GA consists of node or router ID instead of binary 0 or 1. Thus, each gene represents the next hop neighbor of the previous gene in the real network. Therefore, 'Node' will forward the data packet to 'R1', and they must be in each other's neighbor list to be within the transmission and reception range. Similarly, R3 has to be in the neighbor list of R2 and base to receive data packets from R2 successfully and forward them to the base.

3.2 Individual

During the creation of each individual, it is assigned an ID, rank, a neighbor list of nearest one-hop neighbors, fitness score, and chromosome. An individual's rank is defined based on its connectivity. Each sensor node has a default rank of 1. A router's rank depends on the number of neighbors and their type. Fig. 3.1 illustrates the ranking of routers. Here, router R1 has two sensor node neighbors from which it will receive sensed data corresponding to a rank of 3. Router R2, on the other hand, has one sensor node and one router (R1) neighbor from which it will receive data and has a higher rank of 5. Note that only incoming data flow is considered in the ranking of the nodes. Since the network is hierarchical, the data will always be from bottom to top. Thus, the routers near the base

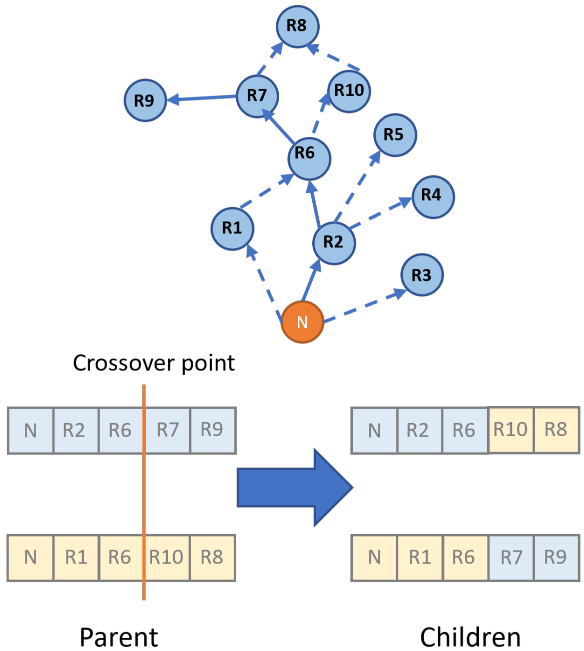


Figure 3.2: An illustration of 1-point crossover procedure. Crossover point is randomly selected during reproduction except it can't be the first or last position of the gene.

will have higher ranks and correctly represent their data congestion.

3.3 Crossover

In GA, crossover is used to produce children from parents with an expectation that the reproduction process will create better individuals. Crossover is done in three steps. First, a pair of parents is selected randomly from the population. Next, a cross-site is chosen randomly from the chromosome length. We use a single-point crossover, where cross-site is randomly selected along the string length. Consider a chromosome with length 'L' where (L-1) cross-sites are available. Since each chromosome consists of a sensor node at the beginning and a base station at the end, cross-site must be greater or less than (L-1). Finally, the position values are swapped between the two parents in the last step based on the crossover point. This concept is illustrated in Fig. 3.2, where router R6 is familiar to both parents. Therefore, when crossover occurs, the newly produced offspring do not have a disconnection, as R7 and R10 are neighbors of R6.

3.4 Mutation

Mutation is a simple but very effective operation that prevents the GA from being stuck in a local minimum. For our proposed GA, genes are randomly selected except the first and last, which are

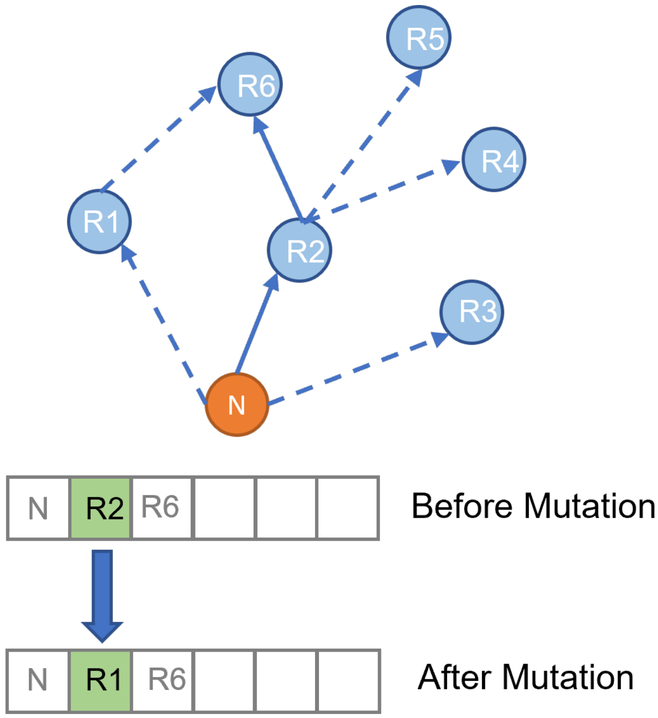


Figure 3.3: An illustration of mutation procedure where a gene (i.e., router) can be replaced by another router randomly to ensure diversity of the population

the sensor node and base, respectively. However, when a router is replaced in the chromosome, and the new router in the modified string is not in the neighbor list of the nodes before and after the router in the string, the newly produced individual will have a disconnection in the routing path. For example, in Fig. 3.3, the mutation is applied in the second gene where R1 replaces R2. Since R1 and R2 are in the neighbor list of N and R6, respectively, the resulting offspring is a new solution that may be better than the earlier chromosome. To make the mutation meaningful, the proposed algorithm randomly selects a gene, finds all the mutual neighbors of the nodes before and after the selected node, and then swaps the selected router with another mutual router.

3.5 Fitness Function

The fitness of an individual route in the GA represents how suitable the route for data forwarding. The objective function evaluates the fitness of its individuals and indicates how good the solution is. In our case, we have multiple criterion - how congested the routers are and how long the route is. In multi-criterion optimization problem like ours, there is often some solutions that are better for one criterion but worse for another. For example, we may have a solution that is the shortest path from a sensor node to the base but the routers in the path have higher ranking. Fig. 3.1 illustrates a scenario, where data from N1 (sensor node) can routed via two routes as below:

$$S_1 = [\text{N1} \mid \text{R1} \mid \text{R2} \mid \ldots \mid \text{Base}] \qquad (2)$$

$$S_2 = [\text{N1} \mid \text{R1} \mid \text{R3} \mid \ldots \mid \text{Base}] \qquad (3)$$

Although both solutions S_1 and S_2 have same route length, weights will be different since rank of R3 is higher than R2. Therefore, S_1 (Eq. 2) has lower fitness score and represents a better solution than S_2 (Eq. 3).

Our fitness function tries to find a route that includes routers will low rank while also try to find a shorter path for data transmission. We define our objective function as below:

$$f = \sum_{i=0}^{L} r_i * L \qquad (4)$$

The objective function adds the rank of nodes in a chromosome and multiplies the result by the chromosome's length. Therefore, if the route is longer, the fitness score will be high, and if it consists of high-ranked routers, the fitness score will be high as well. We aim to find routes with less congested routers while routing the packets via the shortest routes. Thus, the algorithm will try to find solutions with lower fitness scores, which implies a better solution.

3.6 Algorithm

We now describe the pseudocode used to implement the proposed GA-based routing algorithm. The algorithm is run centrally by the base station. Since each node has a different set of neighbors and routes to forward the sensory data to the base station, the algorithm runs GA for each node in the network individually. Once the routes are determined, each node will update its next-hop neighbor routers, transmitting the sensory data. We start with a network of size P and assume that a node has N number of neighbors, which can be parsed from the network topology.

4 Simulation results

In this section, the performance of the EEGA is evaluated via simulations, and the results are analyzed. First, we describe the simulation setup and related parameters used to study the algorithm. Next, we describe the results obtained during the simulation.

Comparison with related work: We conducted a comparison of the performance of EEGA

Algorithm 1: Algorithm for GA based routing

```
Input: Network topology including next-hop neighbor list for each node
Output: Near optimal routes for each node
Init: - Extract neighbor information of each node
      - r_i^P ← 1 + w_j, i = 1, ..., P and j = 1, ..., N
foreach Node i from 1 to P do
    /* Find near optimal route */
    for t = 1 to T do
        Select parents from population
        Produce children from selected parents
        Mutate the children
        Extend the population by adding offspring
        Reduce the extended population
    end
end
return The best route found
```

and AMRBEC [41], the current state-of-the-art GA for centralized routing in power-constrained IoT networks. We compare our approach to AMRBEC with and without the feedback confirmation mechanism (ACK). Previous experiments by Liu et al. [41] demonstrate the superiority of AMRBEC over four representative algorithms in various network scenarios, involving up to 200 nodes. These algorithms included MR-GA, a multipath method based on the GA, a low-cost path selection algorithm; EB-CRP, an energy-efficient and energy-balanced cluster-based routing protocol; and IS-k-means, an improved clustering algorithm. AMRBEC outperformed all four by a significant margin, and we therefore selected it as a benchmark to compare our proposed technique. Additionally, we examined the nearest neighbor approach, where nodes forward data to the closest neighbor regardless of their energy status, as a baseline for comparison.

Simulation setup: We generated an IoT network for simulation with 20 router nodes and 130 sensor nodes. We deployed all the nodes randomly and let each node connect to the nearest neighbor nodes. Each node maintains two node lists: direct and indirect neighbor lists. The first is the next-hop neighbor list, which includes the node's routers to send a data packet. The second list collects all nodes transmitting or receiving from the node. Fig. 3.4 demonstrates an example network used during simulation. Each sensor node and router has multiple next-level router neighbors where it can transmit data. As can be seen in Fig, some routers appear to be closer to base compared to other routers. Similarly, some routers have more connections, i.e., data flow compared to other routers. The heterogeneity of the routers can impact the network's performance, and our algorithm tries to adapt the routing according to that.

Ranking: Fig. 3.4 shows how the ranking of the routers can successfully address the heterogene-

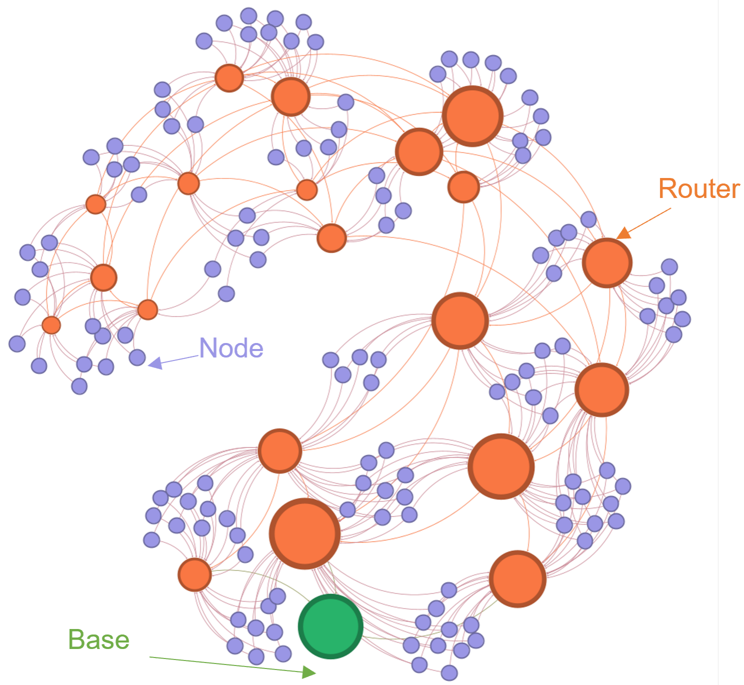


Figure 3.4: Example IoT network with 150 nodes used during simulation, where size of the routers represent their rank. A higher ranked router will experience higher data flow compared to a lower ranked router.

ity of the nodes. We assigned each node in the network a rank based on the number of connections and the probability of incoming data flow. Higher-ranked nodes are likely to receive more data packets, which will result in higher energy depletion compared to lower-ranked nodes. Therefore, rank also represents the significance of the node in the network. Our fitness function incorporates the rank of the nodes and tries to minimize the load on the most significant nodes by selecting low-ranking routers. The resulting routes will consist of less congested routers and effectively balance the data load on all the routers.

GA Operators: We ran the GA under various conditions: crossover only, mutation only and using both crossover and mutation together. While slightly better results were obtained when only crossover was used, the other two modes also yielded quite similar result. Since we used a small-scale network of 150 nodes, where the largest route length from sensor node to the base station is less than 10, chromosome length were always smaller. We experimented with different termination point for the proposed technique by allowing the number of iterations to be dynamic. During simulation, we monitor the fitness score of the best individual of a generation and compare the score with the next generation. As noted, the fitness can be considered settled if it remains same approximately for more than 10 iterations. Therefore, instead of using a fixed number of generations, adapting the

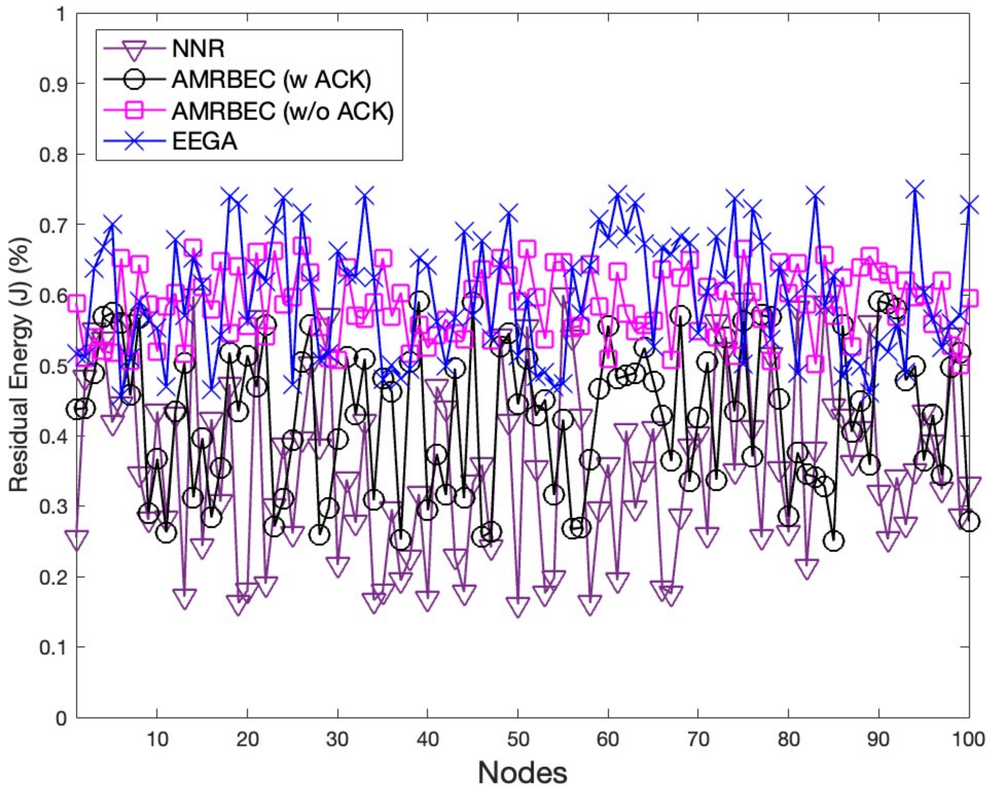


Figure 4.1: Comparison of residual energy between EEGA, AMRBEC, and NNR in a network with 150 nodes

iteration number will reduce time and accelerate the convergence of the algorithm.

Energy Consumption. Fig. 4.1 illustrates the residual energy of 130 end nodes after running 300 rounds for different algorithms. It can be seen that remaining energy in several nodes are higher when EEGA is used compared to other techniques. While AMRBEC uses load balancing approach to find optimal solution, it also transmits same data over multiple paths, causing increased energy consumption. Additionally, nodes using NNR technique consumed 12% more energy than EEGA (see Fig. 4.2) since nodes were forwarding packet to their neighboring nodes only without being aware of their load or energy status.

Throughput Performance. Throughput performance is crucial for IoT networks that process time-sensitive data. Fig. 4.4 shows how our proposed EEGA approach outperforms NNR for various numbers of data transmission and reception rounds. While for a small number of packets, both algorithms perform similarly; as the number of packet transmissions increases, the packet drop rate for NNR also increases (more than 10% for 300 or more data packets). Since EEGE determines the routing path based on routers' rank and load, the likelihood that a packet will be dropped or needs

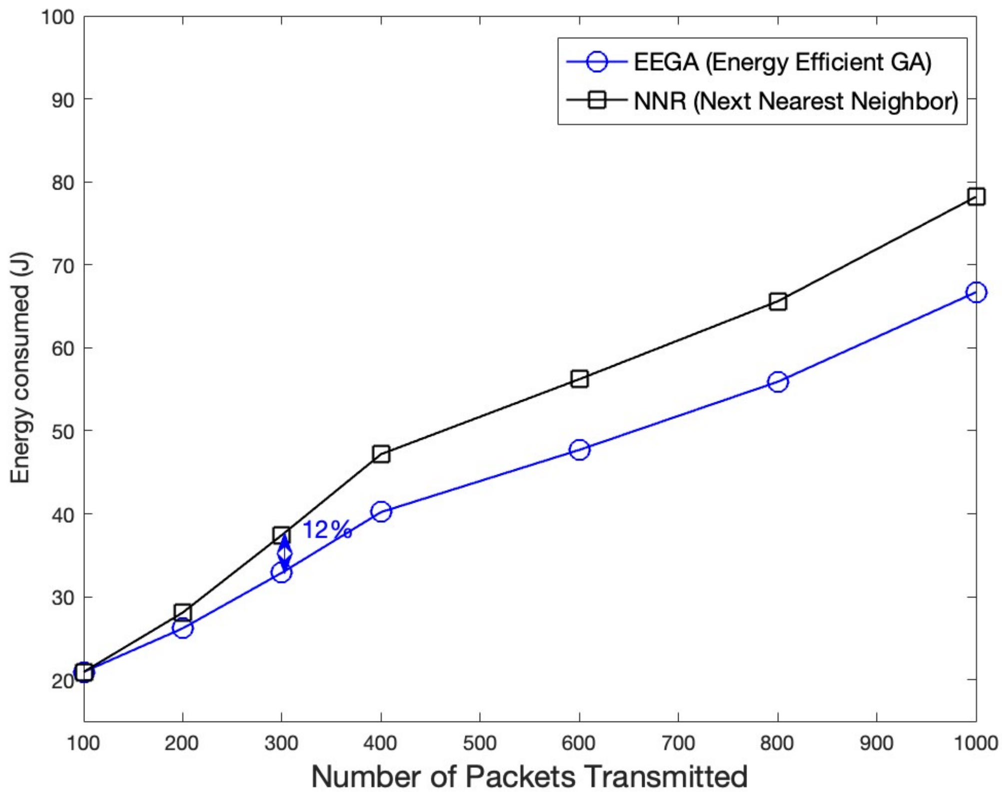


Figure 4.2: Comparison of energy consumption between EEGA and NNR in a network with 150 nodes

Table 4.1: Comparison of Energy consumption, Network lifetime and Packet Delivery between EEGA, ABRBEC and NNR

Nodes	Parmeters	NNR	AMRBEC (w/o ACK)	AMRBEC (w ACK)	EEGA
500	Avg. Residual Energy (%)	58.7	62.1	65.6	69.2
	Dead Nodes	150	139	130	117
	Packet Delivery Ratio (%)	85.4	88.3	90.2	96.6
1000	Avg. Residual Energy (%)	57.8	61.2	64.6	68.3
	Dead Nodes	430	387	361	318
	Packet Delivery Ratio (%)	83.7	86.5	88.4	94.4
1500	Avg. Residual Energy (%)	54.4	57.6	60.8	64.8
	Dead Nodes	720	640	576	511
	Packet Delivery Ratio (%)	81	83.7	85.5	91.7

re-transmission reduces significantly compared to NNR.

Network Lifetime. Fig. 4.3 shows the network lifetime of EEGA and the other 3 approaches. Generally, network lifetime means the number of rounds before the first node dies. When 80% of all the nodes run out of energy, the whole network will stop working. As shown in Fig. 4.3, when the EEGA approach is used, the network lifetime increases by 10% and 28%, compared to AMRBEC and NNR, respectively. The approximately straight curve for EEGA also shows that many nodes in the network have similar lifetimes. On the other hand, under the AMRBEC approach, sending the same data over multiple paths causes faster energy depletion, which can be minimized by deactivating acknowledgment messages after data transmission. However, EEGA is still significantly better than the rest of the approaches.

Finally, we analyzed the performance of EEGA for various network sizes. Table 4.1 shows the simulation performance of all 4 algorithms for different network sizes. The measurements were collected after 5000 rounds of data transmission during simulation. It is clear that EEGA not only reduces energy consumption but also improves throughput of the network while reducing number of dead nodes.

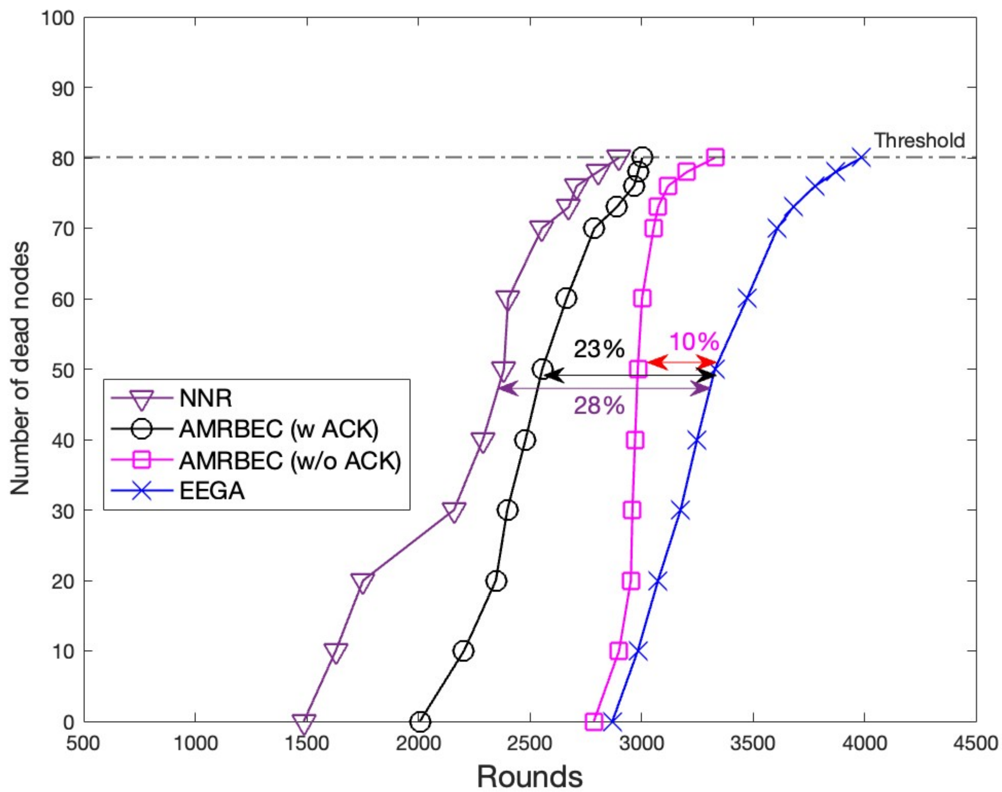


Figure 4.3: Comparison of network lifetime between EEGA, AMRBEC, and NNR in a network with 150 nodes

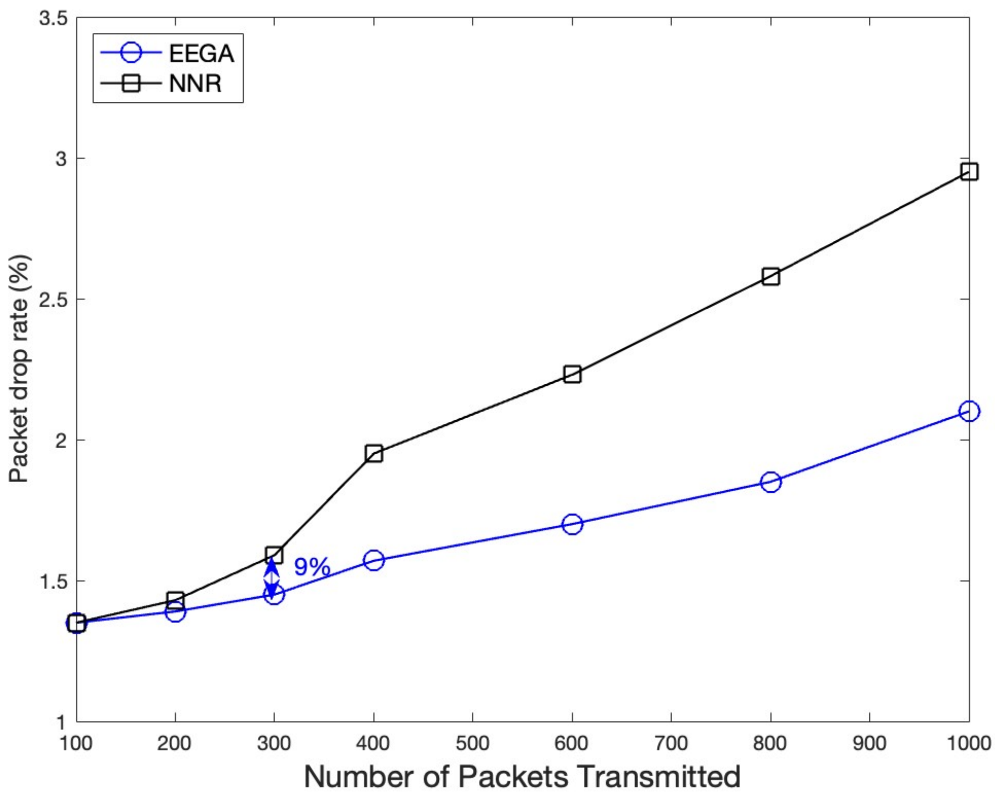


Figure 4.4: Comparison of packet drop rate between EEGA and NNR after 1000 data packets transmission with 150 sensor nodes

5 Conclusion and Future Work

The purpose of our study was to evaluate the performance of GA-based routing strategies in Internet of Things networks. According to the research, hierarchical Internet of Things networks may greatly improve link reliability and energy efficiency by implementing a load-aware GA-based multi-hop routing strategy. The section includes a summary of research findings, future work recommendations, and final remarks. The summary highlights the research's value and contributions, while future work suggests enhancing IoT routing performance. We conclude by discussing how sensor networks and IoT will play an important part in the coming years.

5.1 Summary

The Internet of Things (IoT) is a network of physical objects that are interconnected through sensing, limited data processing, and sharing capabilities. IoT devices are expected to perform autonomously, using standard wireless communication protocols with minimal human intervention. IoT devices are energy-constrained due to battery power, and they are often deployed in remote areas where replenishing energy is costly and time-consuming. To improve the performance of IoT networks, dynamic routing techniques are needed to move data in an energy-efficient manner through the network. This work aims to investigate the performance of a multi-hop GA-based routing technique in an IoT network consisting of low-cost, low-powered, and small IoT devices. By leveraging the network topology and nodes' status, the proposed work performs better than recent multi-hop routing techniques. A comparison with recent multi-hop routing techniques is also provided to illustrate the superiority of the proposed work.

We introduced a multi-hop routing protocol that uses genetic algorithm (GA) to find the optimal path for hierarchical IoT networks. GA is a suitable solution for solving multi-criteria problems and producing various solutions. The individuals in the final population, which are part of the "Pareto front," represent all optimization solutions that are better than any other individual in at least one phenotype. Therefore, using a genetic algorithm to optimize values of multiple phenotypes in a population is a wise choice. Our simulation results demonstrate that the proposed routing approach can significantly enhance the packet delivery rate compared to existing recent multi-hop routing techniques. Furthermore, the results indicate that considering the load on the router nodes during routing path selection can improve network lifetime and energy consumption.

5.2 Future Research Directions

There are various avenues for extending the work presented in this thesis, which can be outlined as follows.

5.2.1 Improving Baseline Approach for Comparison

In this study, we conducted a thorough comparison between our proposed GA-based approach and the Next Nearest Neighbor technique, which we used as a baseline. We found that NNR is not an ideal approach because it simply forwards data packets to the nearest router without considering the status of the router. Instead, we recommend using the Open Shortest Path First (OSPF) approach, which is more realistic and efficient. OSPF involves nodes establishing relationships with routers within the transmission range and selecting the best path based on different matrices, such as bandwidth, delay, and reliability. Research has shown that OSPF is an effective approach for large-scale hierarchical networks [42–44]. Despite requiring additional routing updates and potentially increasing energy consumption, OSPF remains a better alternative to NNR as a baseline comparison approach for future works.

5.2.2 Modifying Convergence and Selection Criteria for GA

Genetic Algorithm is a widely used optimization technique for evolving models and feature selection, among other applications. However, it does have some limitations. To help the GA reach an optimal or sub-optimal solution more quickly, different selection techniques can be used to choose parents for crossing, such as roulette wheel selection [45] and random selection [46]. The final stage of breeding, replacement, involves maintaining the population using different methods, such as generational and steady-state updates [47]. Search termination criteria can vary, including stopping after a specified number of generations or discontinuing the search if there is no improvement in the objective function for a sequence of consecutive generations [48, 49]. All the techniques mentioned above need to be experimented to understand the performance of GA in multi-hop IoT networks.

5.2.3 Evaluating Effectiveness Across Different IoT Architectures

Choosing the right routing strategy is crucial in IoT networks to ensure efficient packet delivery while conserving energy. Various energy-efficient routing protocols have been developed for IoT-based sensor networks [50, 51]. Different network architectures and routing protocols suit different IoT applications. Researchers have studied centralized [52], decentralized [53], hierarchical [54], and clustered network [55] topologies. While hierarchical routing can be advantageous in certain scenarios, it may not be suitable for the dynamic and decentralized nature of mesh networks. A mesh IoT network is a local network where devices are connected directly in a non-hierarchical manner to route data across the network [56]. Unlike traditional star network topologies, where devices communicate through a central hub, mesh networks allow each device to participate in data transmission. Mesh networking is an attractive choice for small-scale battery-powered IoT applications because it doesn't require expensive hardware. The self-healing capability of mesh networks ensures robustness, meaning that if one repeater fails, data can be rerouted through an alternative path. Mesh networks are particularly useful for applications like industrial automation [57], smart metering [58], and environmental monitoring [59] because they can distribute data efficiently and enhance overall network performance. Optimizing EEGA for Mesh Network: Implementing EEGA in a mesh network involves integrating the structured approach of hierarchical routing with the often decentralized and flexible nature of mesh networks. To optimize EEGA for mesh network requires several steps and considerations such as network segmentation, backbone formation, hybrid routing, resource management, and performance optimization. Network segmentation involves dividing the mesh network into smaller segments with local leaders or gateways [60]. Backbone formation establishes a backbone of interconnected gateways for inter-cluster communication [61]. Hybrid routing combines proactive and reactive routing protocols [62]. Resource management reduces the overhead of routing information dissemination. Performance optimization involves continuous monitoring and adjustment of network parameters. Overall, a hybrid genetic-algorithm based routing protocol will be required that combines the advantages of both hierarchical and flat architectures.

Our research has demonstrated that if routing algorithms take into account the topology of the network as well as the data load of nearby nodes, then network performance may be enhanced. Nevertheless, existing research only considers a centralized multi-hop network, which leaves performance analysis with open questions. The network's size is directly proportional to the packet drop rates and energy consumption. Assessing the performance of routing protocols is essential for various network topologies in IoT applications.

5.2.4 Real-life Implementation Combined With Testbed

Research on routing protocols for IoT has primarily focused on simulation [63, 64]. However, it is crucial to validate their performance through hardware implementation. To enable the implementation and experimentation of other protocols, it is essential to have a large-scale experimental platform with battery-powered sensor nodes placed in different locations. Moreover, the infrastructure must be affordable and low-cost to ensure easy access for the broader research community to validate different routing techniques related to IoT networks. Therefore, the next step in the practical implementation of routing protocols is to develop the framework of the IoT testbed.

5.2.5 Adapting to Sensor Mobility

Managing node mobility in a hierarchical routing protocol can be quite challenging due to the structured nature of hierarchical networks. However, there are several strategies to handle this issue. One approach is to introduce logical subnets within the hierarchy to manage groups of mobile nodes [65]. This concept is similar to the Home Agent in Mobile IP, which keeps track of mobile nodes' locations. Another method is to implement soft state protocols like WHIRL (Wireless Hierarchical Routing Protocol with Group Mobility), which adapt to changes in the network topology caused by node mobility [66]. Cluster-Based Routing is another effective technique that uses a two-layer hierarchical cluster-based routing protocol [67]. It exploits node heterogeneity and organizational structure to mitigate the impact of rapid topology changes. Incorporating location management techniques is yet another way to handle node mobility. It keeps updating the hierarchical partitioning continuously as nodes move. By employing these methods, we can maintain the efficiency and scalability of hierarchical routing while accommodating the dynamic nature of mobile nodes.

5.3 Final Comments

The work presented in this thesis demonstrates the significance of energy-efficient routing protocols in low-powered IoT networks. It aims to bridge the gap between general and load-aware routing techniques in multihop IoT networks. By utilizing the router's topology position and the number of neighbors, the work shows the potential for improving network reliability while enhancing energy efficiency.

We hope this work will inspire researchers to develop routing techniques specifically designed for low-cost energy-constrained IoT devices that need to transfer large volumes of data based on their application. The decreasing costs of embedded devices enabled by semiconductor technology has led to the deployment of new IoT applications that require high reliability and faster data rates. Using software-defined radios, cognitive radios, and IoT devices can lead to a hybrid network, and diverse routing techniques are necessary to adapt the routing strategy based on the dynamic network architecture.

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