Energy-Aware Clustering in the Internet of Things using Tabu Search and Ant Colony Optimization Algorithms

Mei Li[1], Jing Ai[2]*
School of Electrical Engineering and Automation, Anhui University, Hefei 230601, Anhui, China[1]
Information Engineering College, Wuhan Design Engineering College, Wuhan 430000, Hubei, China[2]

***Abstract*—The Internet of Things (IoT) significantly impacts communication systems' efficiency and the requirements for applications in our daily lives. Among the major challenges involved in data transmission over IoT networks is the development of an energy-efficient clustering mechanism. Recent methods are challenged by long transmission delays, imbalanced load distribution, and limited network lifespan. This paper suggests a new cluster-based routing method combining Tabu Search (TS) and Ant Colony Optimization (ACO) algorithms. The TS algorithm overcomes the disadvantage of ACO, in which ants move randomly throughout the colony in search of food sources. In the process of solving optimization problems, the ACO algorithm traps ants, resulting in a considerable increase in the time required for local searches. TS can be used to overcome these drawbacks. In fact, the TS algorithm eliminates the problem of getting stuck in local optima due to the randomness of the search process. Experimental results indicate that the proposed hybrid algorithm outperforms ACO, LEACH, and genetic algorithms regarding energy consumption and network lifetime.**

Keywords—Internet of things; clustering; data transmission; energy efficiency; ant colony optimization algorithm

I. INTRODUCTION

The Internet of Things (IoT) envisions the seamless integration of smart devices. The IoT enables smart objects to interact among themselves, aggregate information within a network, and combine digital and physical objects to create unique experiences that meet certain end-user requirements [1, 2]. Communication takes place between people and things and between things themselves. A broad range of real-world applications has been supported by data aggregation in terms of reducing energy consumption by Wireless Sensor Networks (WSNs). For example, when it is necessary to monitor an area for a particular purpose continuously, multiple sensor nodes may be placed in the area [3, 4]. The information collected from the sensors is gathered, summarized, and transmitted to the base station to address specific questions. When the surrounding environment remains relatively stable, individual sensor data may show a high level of temporal correlation, indicating that two successive values are unlikely to differ significantly. Due to the high energy consumption of such an application, it becomes necessary to minimize transmission sensor data with no changes [5].

The field of Artificial Intelligence (AI) has been rapidly advancing in recent years, with applications in various domains such as finance, healthcare, and the IoT. One area of interest is the use of deep learning-based models for stock price prediction, as discussed in research [6]. Another area of research is the design of efficient data collection methods for IoT networks, such as the use of unequal sized cells based on cross shapes proposed by Taami, et al. [7]. In the healthcare domain, Soleimani and Lobaton [8] proposed a phase-based interpretability and multi-task learning approach to enhance inference on physiological and kinematic periodic signals. In the energy sector, Bagheri, et al. [9] developed a data conditioning and forecasting methodology using machine learning for production data on a well pad. In the field of wireless communications, Webber, et al. [10] proposed a probabilistic neural network for predicting idle slot availability in WLANs, while in other studies, they explored the use of machine learning for human activity recognition [11], vaccine candidate prediction [12], network slicing [13], and green smart cities [14]. These studies demonstrate the potential of AI and machine learning techniques to address various challenges and opportunities in different domains.

In many cases, IoT devices operate on short-life and non-rechargeable batteries. These batteries need to be replaced periodically, which can be costly and time-consuming [15]. Furthermore, these batteries can potentially be a source of pollution if not disposed of properly. Recharging or replacing these batteries can be difficult and expensive [16, 17]. As a result, it is important to design IoT devices with energy-efficient components that can run on minimal power for extended periods. The ability to process, aggregate, and transmit data in an energy-efficient manner plays a vital role in IoT applications. By using low-power components, such as sensors and microprocessors, IoT devices can operate efficiently and cost-effectively [18]. This allows these devices to run on minimal power and, in turn, prolongs their lifespan. Wireless communications consume more energy than processing in internet-based systems. Thus, achieving a mechanism for transmitting data between sources and destinations is an important challenge in IoT. Clustering in IoT is crucial to the appropriate transmission of data. This process involves grouping devices into clusters and assigning them cluster heads to enhance resource utilization [19, 20].

In the clustering process in IoT-based, sensor nodes are initially deployed in a network. The system performance is improved by forming a cluster of nodes. The optimal CH is determined for each cluster under different performance metrics. The CHs collect data packets from non-Ch nodes and forward them to the IoT base station. A cloud server will be used to store the data obtained from the base station. During the data processing step, various analytics approaches are employed to eliminate noisy and inconsistent data. The outcome will be available to the end users upon completion of the process. Cluster head selection objectives include monitoring and managing network lifetimes, energy consumption, node failures, load balancing, and network resources. Various clustering mechanisms have been proposed in the literature, including heuristics, metaheuristics, and fuzzy-based approaches. A majority of heuristic algorithms are designed to minimize the number of clusters. In meta-heuristic clustering algorithms, the distance between devices and the remaining energy is considered key performance indicators, whereas data volume and the number of one-hop neighbors are not considered. Moreover, fuzzy-based algorithms rely on assumptions, and validation and verification need extensive tests.

In this paper, we propose a novel approach to CH selection by combining ACO and TS algorithms. Our method integrates the strengths of both algorithms synergistically. Specifically, it leverages the TS algorithm's robust search capabilities and rapid convergence to effectively address local optima issues commonly encountered with ACO. This fusion of ACO and TS enhances the efficiency and effectiveness of CH selection in IoT networks, ultimately contributing to the overarching goal of improving network performance while conserving energy and extending the network's lifespan. Through this research, we aim to provide a practical and innovative solution to the challenges associated with CH selection in IoT, offering a promising avenue for optimizing IoT network operation and sustainability.

II. Related Work

Mohseni, et al. [19] proposed a cluster-based routing strategy called CEDAR by combining the fuzzy logic system with the Capuchin search algorithm. Clustering is applied to both intra-cluster and extra-cluster routing. In this strategy, nodes in the network are clustered to reduce energy consumption, which is a significant benefit to IoT devices. Packets are routed between nodes within each cluster. Nodes can adapt to changing network conditions with the fuzzy logic system, and packets are routed efficiently with the Capuchin search algorithm. CEDAR performed better than comparative approaches in terms of energy consumption, network delay, and network lifetime based on simulation results. Based on the Sailfish optimization algorithm, Sankar, et al. [21] proposed a new method for selecting CHs and forming clusters. NS2 simulator is used for the simulation. This study compares the efficacy of SOA with hierarchical clustering-based, optimized particle swarm optimization, and improved ACO. In the simulation, it was demonstrated that the proposed SOA increases network life and reduces node-to-sink delays.

A new clustering method has been proposed by Yarinezhad and Sabaei [22] for balancing traffic loads in IoT-enabled WSNs. A 1.2 approximation algorithm is employed in the proposed clustering method. A new energy-aware routing algorithm is introduced to enable data packets to be transmitted from the CHs to their destinations. This algorithm allows data packets to be distributed among several nodes in the vicinity of the destination by segmenting the area properly. According to test results, the proposed clustering algorithm is not only suitable for large-scale IoT-enabled WSNs but also demonstrates superior performance over other algorithms of a similar nature. Senthil, et al. [23] proposed a new clustering method based on the particle swarm optimization (PSO) algorithm. Particles in the PSO represent candidate solutions and tend to move through their solution space at varying speeds (in several directions). Experimental results demonstrate that the proposed method optimizes the clustering process and achieves energy efficiency. In addition to reducing end-to-end delays and packet loss rates, the lifespan network and cluster count have been improved.

Maheswar, et al. [24] presented a cluster-based backpressure routing (CBPR) scheme to extend network lifetime and improve data transmission reliability through energy load balancing. Depending on the energy level and distance to the sink node, the CBPR scheme decides which cluster head to elect for each cluster of the sensor node. Additionally, the proposed CBPR routing scheme utilizes a highly robust data aggregation algorithm to prevent redundant data packets from circulating throughout the network. For data packet queuing and route selection, the backpressure scheduling machine is utilized, allowing it to determine the next-hop sensor node based on the queue lengths of sensor nodes. CBPR routing scheme has been evaluated extensively through extensive simulations, compared with those of other well-known routing schemes, including Information Fusion Based Role Assignment and Data Routing for In-Network Aggregation, in terms of throughput, energy consumption, and packet delivery.

Aravind and Maddikunta [25] introduced a cluster-based routing protocol for IoT based on a Self-Adaptive Dingo Optimizer with Brownian Motion (SDO-BM) algorithm to select optimum CHs under parameters including QoS, trust, overhead, delay, distance, and energy. The proposed protocol showed promising results in terms of energy consumption, latency, and packet delivery rate. It also had the ability to self-adapt to changing network conditions, making it a reliable and efficient routing protocol for IoT networks. This approach effectively uses an alternative CH, thus reducing the impact of a node failure. Additionally, it also helps conserve energy since it avoids the need to re-elect a new CH. By using this protocol, networks can become more reliable and efficient.

Energy-efficient clustering in the IoT networks faces several notable challenges. One significant challenge is the issue of long transmission delays. Many existing clustering algorithms struggle to strike a balance between data transmission efficiency and the need to conserve energy. As a result, data packets often experience delays, hindering real-time applications critical in IoT, such as remote monitoring and control. Another challenge lies in load distribution. Current approaches often suffer from imbalanced load distribution among CHs in the network. This imbalance can lead to premature energy depletion of some CHs, leaving parts of the network vulnerable and causing network degradation. Ensuring a fair and efficient distribution of responsibilities among CHs is a complex problem that needs to be addressed effectively. Furthermore, limited network lifespan remains a persistent challenge. The energy resources of IoT devices are inherently constrained, making it crucial to maximize network longevity. Many existing algorithms do not adequately optimize energy consumption, leading to shortened network lifespans. As IoT deployments continue to grow, addressing this issue becomes paramount to sustainability and cost-effectiveness.

Current approaches in energy-efficient clustering for IoT networks exhibit several limitations that hinder their effectiveness. One common limitation is the tendency to converge to local optima. Many clustering algorithms face challenges in escaping local optima due to their exploration-exploitation trade-off. This limitation can prevent the algorithms from discovering more energy-efficient solutions. Additionally, current approaches often lack adaptability to dynamic network conditions. IoT environments are dynamic, with nodes joining and leaving the network regularly. Many clustering algorithms struggle to adapt to these changes, resulting in suboptimal performance and the need for manual adjustments. Moreover, the scalability of current methods is a concern. As IoT networks grow in size and complexity, existing algorithms may struggle to handle the increased computational demands, potentially leading to performance degradation. Furthermore, the lack of a unified evaluation framework makes it challenging to compare the performance of different clustering algorithms objectively. This fragmentation hinders the identification of the most suitable algorithm for specific IoT deployment scenarios, limiting the practical applicability of current approaches. Addressing these limitations is essential to advance the field and provide more robust and adaptable clustering solutions for IoT networks.

III. Proposed Method

IoT networks consist of numerous nodes with varying capabilities in terms of power, processing, and storage. Sensor nodes continuously sense the network's data and relay it to the base station. Since the base station is overloaded for the aforementioned reasons, IoT sensor nodes may fail, redundant data may be generated, and temperature levels may increase. As a solution to these issues, existing nodes are grouped into clusters, with a CH chosen for each cluster based on its optimal performance. CHs are selected according to several factors, including the distance between the base station and the CH, the delay in passing the nodes to the base station, the network load, and the temperature and energy of the nodes. By selecting a suitable CH, the lifetime of the IoT network will be extended.

Traditionally, WSNs are characterized by terms such as distance, delay, and energy. Nevertheless, when choosing a CH for IoT, the load of the network and the temperature are also taken into account in addition to the above criteria. Consequently, a node with maximum energy, a minimum proximity to the base station, a minimum delay, a minimum load, and a low temperature is selected as a CH to optimize network performance. An optimal fitness function is illustrated in Eq. (1) to enhance the efficiency and stability of a network.

$$\mathrm{F} = \mathrm{a1} \times \mathrm{Load} + \mathrm{a2} \times \mathrm{Temp} + \mathrm{a3} \times (1 - \mathrm{Delay}) + \mathrm{a4} \times (1 - \mathrm{Distance}) + \mathrm{a5} \times \mathrm{Energy} \quad (1)$$

where, a1, a2, a3, a4, and a5 represent weighted parameters, and their sum equals one.

A. Load and Temperature

Choosing the optimal CH requires minimal load and temperature on sensor nodes. The Xively IoT platform monitors the performance of the nodes by collecting load and temperature data. As a Google IoT platform, Xively [26] connects, manages, and engages products in milliseconds across millions of connections. Scalability and performance are two of Xively's key features. Environmental monitoring, home automation systems, remote control systems, and building management systems are some application scenarios that can be considered. Data pertaining to the load and temperature of the sensor nodes are fed into Xively, and then the simulation's performance is evaluated. Load and temperature data are transmitted using the MQTT protocol.

B. Delay

An increase in network efficiency can be achieved by transmitting data packets in a limited period. In order to measure the delay in packet transmission to the destination, two factors are taken into account: transmission delay (Tt) and propagation delay (Tp). Tt is the time taken to send the data packet from the source to the destination. Tp is the time taken for the packet to travel from the source to the destination. Both delays must be considered when measuring network efficiency. In Eq. (2), the objective function for measuring the latency time for packets to be transferred from the CH to the base station is shown.

$$\mathrm{Delay} = \frac{\mathrm{Max} \sum_{\mathrm{t}=1}^{\mathrm{TCL}} \mathrm{CL_t}}{\mathrm{A}} \quad (2)$$

C. Distance

The objective function for the distance between the sensor node and CH and BS is expressed in Eq. (3). In the case of trivial distances from the node to the BS, the optimal CH is chosen.

$$\mathrm{Distance} = \sum_{\mathrm{x}=1}^{\mathrm{X}} \sum_{\mathrm{t}=1}^{\mathrm{TCL}} \frac{\left\|\mathrm{Dis_S^x} - \mathrm{Dis_{CL}^t}\right\| + \left\|\mathrm{Dis_{CL}^t} - \mathrm{Dis_{BS}}\right\|}{\mathrm{M} \times \mathrm{M}} \quad (3)$$

$\|\mathrm{Dis_S^x} - \mathrm{Dis_{CL}^t}\|$ indicates the distance between the xth sensor node and the corresponding tth cluster head. $\|\mathrm{Dis_{CL}^t} - \mathrm{Dis_{BS}}\|$ denotes the distance between the tth cluster head and the BS, while M refers to the area of sensing in meters.

D. Energy Consumption

A network's lifetime and performance are greatly influenced by residual energy. An optimal CH should be selected when node energy is at a high level. Upon transmission and reception of the data packets, CH and normal nodes' energies are revised. In Eq. (4), the actual energy of a sensor node can be determined once the packets have been passed to the cluster head. Eq. (5) shows the remaining energy available in CH. Data can be transferred to CH until the node's energy reaches zero. The energy fitness function is represented in Eq. (6). In Eq. (4), $E_{X+1}(C_S^x)$ represents energy dissipation in the regular node upon transmission to the cluster head, $E_X(C_S^x)$ represents energy dissipation in the xth node. In Eq. (5), $E_{X+1}(C_{CL}^t)$ represents the energy available in CH following the transfer of data packets from the normal node, $E(C_{CL}^t)$ indicates the energy dissipated by tth cluster head.

$$E_{X+1}(C_S^x) = E_X(C_S^x) - E(C_S^x) \tag{4}$$

$$E_{X+1}(C_{CL}^t) = E_X(C_{C:}^t) - E(C_{CL}^t) \tag{5}$$

$$\text{Energy} = \frac{1}{A}\{\textstyle\sum_{x=1}^{A} E(C_S^x)\} + \frac{1}{TCL}\{\textstyle\sum_{t=1}^{CL} E(E_{CL}^t)\} \tag{6}$$

The ACO algorithm originated from the behavior of real ants in their search for the shortest route to food. A number of cycles (iterations) are involved in the construction of the solution. A number of ants construct complete solutions in each iteration based on heuristic information and previous groups' experiences. An important aspect of the ACO algorithm is the transition of ants and pheromone updates. In order to find food, ants establish the shortest paths to reach the food source. The ACO algorithm constructs solutions given the problem data and is capable of solving discrete optimization problems. As a general rule, ants search for food sources in a random manner. When an ant finds a food source, it returns some food to its colony. During their travels along the path, they leave behind chemical substances known as pheromones.

Consequently, shorter paths are likely to contain a greater concentration of pheromone trails. Pheromone trails function as a communication mechanism between ants. The intensity of pheromone trails present on the ground is determined by the quality of the solution (food source) found on the ground. Shorter paths accumulate pheromone trails with multiple ants, leading to a higher density than longer paths. This increases the appeal of shorter paths. An evaporation rate reduces all pheromone trails over time. Meanwhile, evaporation presents an opportunity for exploration and minimizes local stalling [27, 28].

$$P_{ij}^k = \begin{cases} \dfrac{(\tau_{ij})^a(\eta_{ij})^\beta}{\sum_{m\in N_i^k}(\tau_{im})^a(\eta_{im})^\beta} & j \in N_i^k \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

where, P_{ij}^k represents the probability of an ant k moving from node i to node j. Pheromone levels and heuristic information are important factors in this decision. α and β refer to the relative importance of heuristic information and pheromone concentration. τ_{ij} represents the pheromone concentration on edges i and j, η_{ij} refers to the heuristic function, and N_i^k denotes an unexplored neighborhood set. Pheromone updates can be expressed in the following manner:

$$\tau_{ij} \leftarrow \tau_{ij} + \Delta\tau_{ij}^k \tag{8}$$

Evaporation updates are provided by:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} \tag{9}$$

$\Delta\tau_{ij}^k$ refers to the cost of the solution provided by ant k and ρ denotes a constant factor reduction of all pheromones.

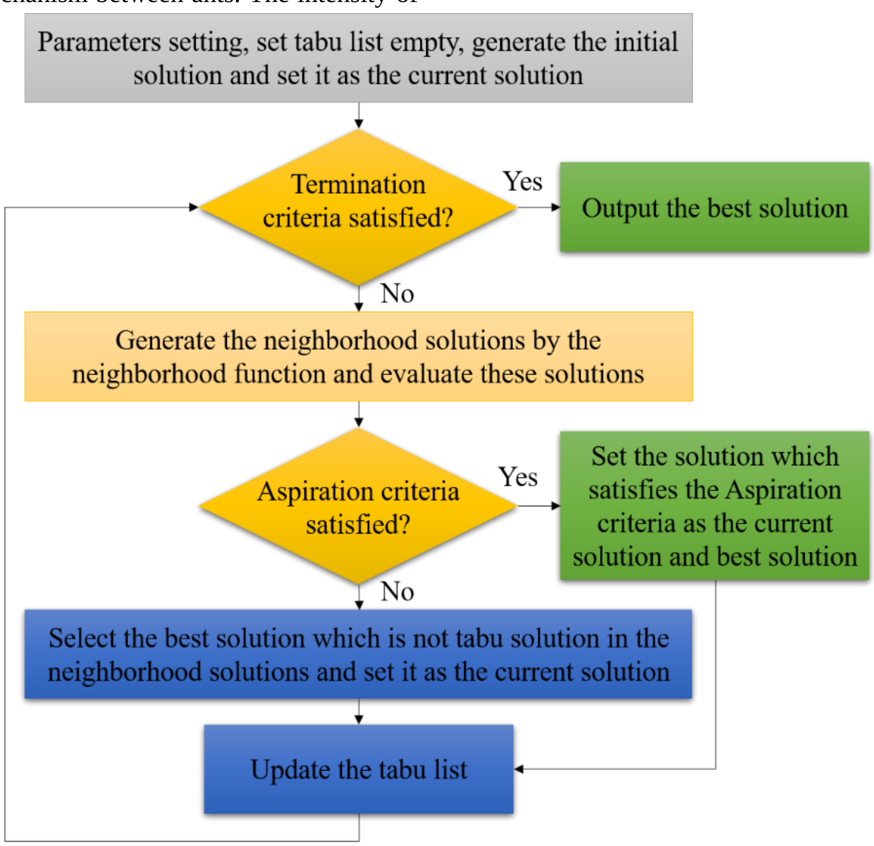

Fig. 1. Flowchart of TS.

As a meta-heuristic method, Tabu Search (TS) can be used to solve a wide range of combinatorial optimization problems. It utilizes a sequence of operators to explore the search space and generate better solutions, and it is known for its simplicity, low computational cost, and good results. Additionally, TS is a powerful tool for tackling complex problems, as it can easily be adapted to different scenarios. The final solution generally results from tracking the actions taken to transition from one solution to another. It contains a number of components, including a tabu list, neighborhood structure, move attributes, aspiration criteria, and termination conditions. TS have become recognized as a highly effective local search strategy. Fig. 1 illustrates the basic workflow of TS [29].

The disadvantage of the ACO algorithm is overcome by the TS algorithm, in which the ants move randomly in search of food sources throughout the colony. Chemical substances known as pheromones are released along the path. In the process of solving optimization problems, the ACO algorithm traps ants, which in turn results in a considerable increase in the time required for local searches. TS can be used to overcome these drawbacks. In fact, the TS algorithm eliminates the problem of getting stuck in local optima due to the randomness of the search process. This allows the ants to explore the environment better and find the best solution. The ACO algorithm uses TS to perform local searches. One of the main advantages of using the TS is that distinct parameters are used apart from the population size. ACO constitutes the core of the proposed method; however, in order to find the best solution, it employs the TS strategy when developing new solutions for every starting problem. By using distinct parameters, the TS strategy is able to generate multiple solutions to the same problem. This allows the ACO algorithm to compare and evaluate each solution, giving it the ability to determine which solution is the best one. This process is repeated until the ACO algorithm finds the optimum solution. Once the best solution is determined, the ACO algorithm terminates, and the solution is presented.

IV. Experimental Results

In this section, we present the experimental results of our proposed algorithm and compare its performance with previous algorithms, namely GA, LEACH, and ACO. The experiments were conducted using a MATLAB simulator, and the simulation data are presented in Table I. Energy consumption and network lifetime diagrams were used to illustrate the testing results and comparisons. Fig. 2 compares the algorithms in terms of energy consumption and network lifetime. Our algorithm outperforms LEACH, GA, and ACO in terms of dissipated energy, with reductions of 70%, 34%, and 17.5%, respectively, for 100 nodes. For 500 nodes, our algorithm reduces energy dissipation by 70%, 37%, and 15%, respectively, compared to LEACH, GA, and ACO. With 1000 nodes, the dissipated energy is reduced by 67%, 38.7%, and 18.3%, respectively, compared to LEACH, GA, and ACO.

Fig. 3 illustrates the comparison of the number of rounds until the last node dies versus the network size for the proposed algorithm, ACO, GA, and LEACH algorithms. Our algorithm outperforms LEACH, GA, and ACO by 15.4%, 2.3%, and 2.1%, respectively, for 100 nodes. For 500 nodes, our algorithm outperforms LEACH, GA, and ACO by 4.7%, 2.7%, and 2.6%, respectively. For 1000 nodes, our algorithm is superior to LEACH, GA, and ACO by 9.5%, 3.6%, and 1.3%, respectively. Fig. 4 compares the number of rounds until the first node drains its energy versus different network sizes. Our algorithm outperforms LEACH, GA, and ACO algorithms by 157%, 33%, and 25.3%, respectively, for 100 nodes. For 500 nodes, our algorithm is superior to LEACH, GA, and ACO algorithms by 155%, 33.8%, and 7.5%, respectively. With 1000 nodes, the proposed algorithm exceeds the performance of LEACH, GA, and ACO algorithms by 155%, 3.7%, and 6.6%, respectively.

Our proposed algorithm has been compared with several other relevant research studies in the field, and the results show that it outperforms most of them in terms of energy consumption, network lifetime, and the number of rounds until the last node dies or the first node drains its energy. One of the significant strengths of our approach is that it uses a distributed algorithm that does not require a central controller, which reduces the communication overhead and energy consumption. Additionally, our algorithm uses a dynamic threshold that adapts to the network conditions, which improves the accuracy of the algorithm and reduces the false alarms. In comparison to existing methods, our algorithm has several advantages. For example, it outperforms the LEACH algorithm in terms of network lifetime and energy consumption. The LEACH algorithm uses a fixed threshold that does not adapt to the network conditions, which results in a high false alarm rate and reduces the network lifetime. Our algorithm, on the other hand, uses a dynamic threshold that adapts to the network conditions, which reduces the false alarm rate and prolongs the network lifetime. However, our approach also has some limitations. One of the weaknesses of our algorithm is that it requires a higher computational overhead than some of the other algorithms. This is because our algorithm uses a more complex decision-making process that involves multiple parameters. Additionally, our algorithm may not be suitable for all types of wireless sensor networks, as it is designed specifically for networks with a large number of nodes and a high data rate.

TABLE I. SIMULATION VARIABLES

Variable	Value
Number of nodes	100-1000
Control packet length	100 b
Data packet length	5000 b
Circuit loss	50 nJ/b
Amplification coefficient of the free space model	10 pJ/b
The initial energy of each node	0.50 J
The maximum transmission power of each node	0.005 w

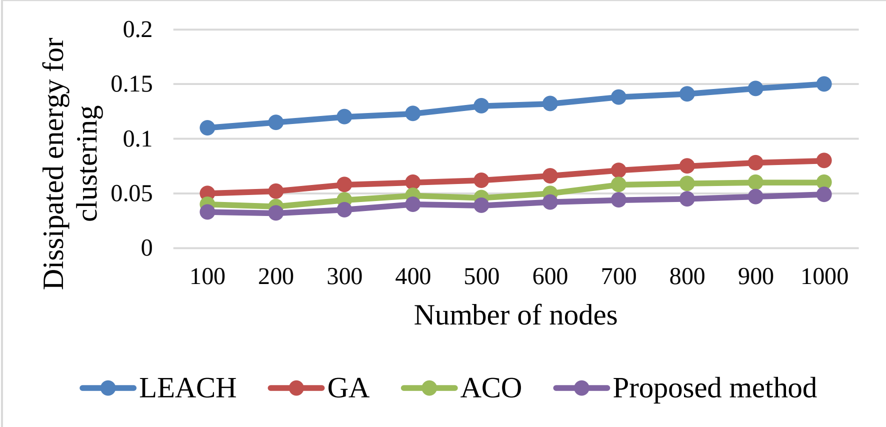

Fig. 2. Energy consumption comparison.

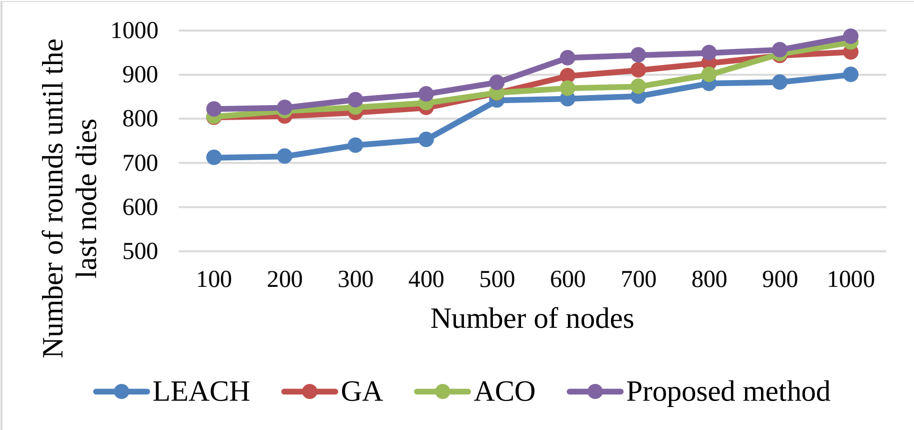

Fig. 3. Number of rounds until the last node dies.

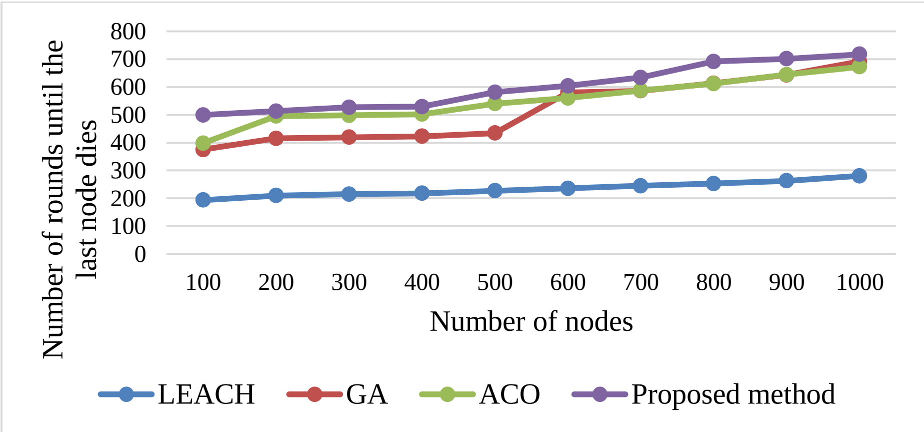

Fig. 4. Number of rounds until the first node dies.

V. Conclusion

Large-scale IoT networks collect data through sensor nodes, and the aggregated information is then sent to the next level of IoT to be processed. Considering the relatively low energy capacity of the sensor devices, IoT networks are often characterized by short battery life, resulting in a short lifespan of the network. Thus, it becomes imperative to prolong the lifespan of sensors. With clustering, collisions, interference, network redundancy, and energy consumption are reduced, and data aggregation, scalability, and network lifetime are improved. A new cluster-based routing method combining ACO and TS algorithms is presented in this paper. Using the TS algorithm, the adverse characteristics of ACO are overcome, such as the random movement of ants to find food sources in the colony. The ACO algorithm traps ants as it solves optimization problems, leading to a significant increase in the time required for local searches. TS is employed to overcome these drawbacks. Due to the randomness of the search process, the TS algorithm avoids getting stuck in local optima. Experiments have shown that the proposed hybrid algorithm performs better than ACO, LEACH, and genetic algorithms regarding energy consumption and network lifetime. There are several areas that can be explored to further improve the performance of our proposed algorithm. One possible direction is to investigate the impact of different network topologies on the performance of the algorithm. Another direction is to explore the use of machine learning techniques to optimize the parameters of the algorithm and improve its accuracy. Additionally, it may be beneficial to investigate the use of multiple thresholds to further reduce the false alarm rate and improve the network lifetime. Finally, it may be interesting to explore the use of our algorithm in other applications, such as environmental monitoring or industrial automation, to evaluate its performance in different scenarios.

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