Artificial Agent: The Fusion of Artificial Intelligence and a Mobile Agent for Energy-Efficient Traffic Control in Wireless Sensor Networks

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Abstract

As the range of applications for wireless sensor networks expands gradually, more and more people are involved in solving the limited factors of their development, among which energy consumption and latency are the most important. The main routes to solving these problems are effective traffic control and management. In this paper, we propose a traffic-control system based on deep reinforcement learning, which regards traffic control as a strategy-learning process, with the purpose of minimizing energy consumption. In this method an intelligent body uses deep neural network for learning, takes the state of the wireless sensor network as the input and outputs the optimal route path. We made simulation experiments to demonstrate that our method is an appropriate and feasible scheme to control the traffic in wireless sensor network and can reduce the consumed energy.

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1. Introduction

Nowadays, with the rapid development of the Internet of Things (IoTs) technology, wireless sensor networks (WSNs), as the core component of the IoT sensing layer, have been widely applied in a variety of field [1][2]. Sensor-network technology is able to integrate many technologies, such as computers, communications, and microelectronics [3], consisting of a set of unique or heterogeneous sensors distributed in different geographical regions. It concurrently monitors the physical or environmental conditions (such as temperature, pressure, motion and pollution) through the wireless channel, and transfers the data collected to the central server to form an autonomous network, realizing the dynamic intelligent collaborative perception of the physical world. At present, it has been widely used in intelligent furniture, logistics management, health supervision, flow monitoring and other fields.

Compared with a traditional wireless network, the sensor network is characterized by a large number of nodes, limited computing and storage capacity, limited power capacity, and limited communication capability [4]. Most data-collection sensor nodes are powered by batteries, which are usually deployed for life because of the poor working environment. Thus, the main challenge in the design of protocols for WSNs is energy efficiency [5][6], due to the limited amount of energy in the sensor nodes. One of the most important parts when we apply deep reinforcement learning to WSNs is the energy in the WSNs.

With the increase of the network flow, a large amount of heterogeneous data makes the network more complex, which increases the difficulty of realizing this goal. Meanwhile, it also poses challenges with respect to resource allocation/management and user-experience management. Most of the current research on WSNs, such as [7][8][9], are related to the features extracted by hand. The artificial features are shallow and unable to fully exert the characteristics of WSNs, thus the achieved progress is always limited. Therefore, there is an urgent need to introduce new technology in order to improve the performance of the WSNs.

The rapid development of deep learning technology based on big data has provided new ideas for the control and management of WSNs, among which the new idea of combining reinforcement learning [10], i.e., an independent decision-making ability with deep learning is in line with it. However, little research has been conducted to combine the two. If you are familiar with deep reinforcement learning, you may find the concept of mobile agent (MA) in WSNs is similar to the agent in deep reinforcement learning. In a MA-based WSN, the mobile agent moves between the sensor nodes to collect the data, and finally return to the sink node with the collected data. The reinforcement learning can force the MA to make a judgment and perform the best action based on the current situation, which enhances the intelligence of the MA [11] and improves the working efficiency [12][13][14]. In order to be able to intelligently realize the flow distribution in the WSNs so as to reduce the energy consumption and improve the efficiency, in this paper, a WSN flow-control system based on deep reinforcement learning is proposed, thus the intelligence, autonomy, and reliability are realized.

Our contributions are summarized as follows:

- 1). We Propose a deep reinforcement traffic-control system in MA-based WSN, which is the first one to apply deep reinforcement learning to MA-based WSN.
- 2). A simulation experiment is designed and compared with other algorithms in WSN to verify the efficiency of our system.

This paper is organized as follows: Section II includes an introduction to the MA in WSNs and up-to-date research about deep learning in WSNs. The architecture and design of the proposed intelligent agent used in WSNs are presented in Section III. A detailed description of our new traffic-control system is in Section IV, followed by the simulation experiment in Section V. Section VI summarizes the paper and makes three plans to deal with some exist problems.

2. Related Work

2.1. A Mobile Agent for WSNs

A WSN is the deployment of a large number of sensor nodes to monitor physical or environmental conditions such as temperature, humidity, and so on. The source nodes that generate the data, transmit this data to the sink. For the sink node, the influx of a massive amount of data will lead to traffic jams, a waste of communication bandwidth and the excess consumption of the battery's energy. The paper [15] proposed a mobile-agent pattern for data processing/fussion/transfer in WSNs. The paper [16] defined an itinerary as the route followed during mobile agent migration. Dynamic planning, where the mobile agent autonomously determines the source nodes to be visited and the route of migration according to the current network status. The paper [17] developed a distributed information fusion strategy for multi-agent networks. Compared with traditional distributed WSNs [18], the WSNs with MAs can effectively plan the dynamic network, improve the data-collection efficiency, reduce the communication energy consumption, and exhibit reliability. A WSN with single MA is shown in Figure 1.

A MA is a special kind of network module that moves unceasingly in a WSN and accesses the sensors in the network. It includes the four parts of identification, executive code, route path and data space. A MA can also employ advanced computation offloading mechanisms such as [19] to distribute its processing tasks to other cooperative MAs. Different MAs carry different information, so we need to give each MA a unique identification number. The executive code stores the information carried by the current mobile agent, and the route path is the core of the MA, used to indicate to a MA where to go in the next step, while the data space stores the data received from the sensor nodes. In this article, to simplify the model, we only discuss WSNs with a single MA.

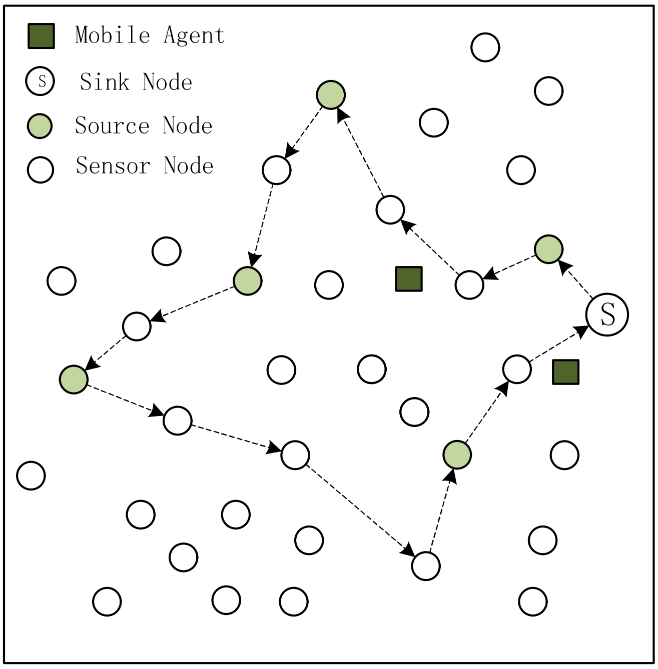

Figure 1: A single-mobile-agent-based WSN

2.2. Artificial Intelligence and Deep Learning for WSNs

With the rapid evolution of deep learning technology, more and more fields have made remarkable achievements by implementing its use [20][21]. As a result, WSN technology is at a turning point. The traditional way of deploying, operating and managing network systems cannot match the current requirements, and deep learning technology is considered as an effective means to solve these problems. The paper [22] proposed a method that can restore the communications when the infrastructure is damaged, for example, during a disaster or terrorist attack. In the case that the routing node's information is given, a three-layer neural network is used for learning in order to classify the degree of wireless nodes, and then create virtual routing using the Viterbi algorithm. Paper [23] took the flow mode of the edge node as the input and defined the router based on the GPU acceleration software that can realize large-scale parallel computing. A Deep Belief Architectures were trained to calculate the location of the next node. This method greatly improved the network flow control. Paper [24] proposed a real-time deep convolutional network to represent the considered Wireless Mesh Network backbone, and proved that this method can significantly reduce the average latency and packet loss rate compared with existing routing methods. The paper [25] proposed an artificial neural network model based on an energy-saving robust routing scheme. The artificial neural network is trained in a large number of data sets covering almost all scenarios, which can improve the reliability of the WSN and its adaptability to the environment, as well as greatly extending the life of the sensor nodes.

With the above information ,it is clearly that deep learning technology can improve the network in the field of WSN. At the same time, the above deep learning technology usually has a multi-layer network structure, rarely involving the reinforcement learning, not to mention the deep reinforcement learning. Therefore, it is a brand new idea to use the deep reinforcement learning to solve the wireless sensor flow-control problem.

3. Architecture and the Design of an Artificial Agent for WSNs

In the introduction of the agent-based WSN in Part A, Section II, it is easy to see that the functional principles of MAs and agents in deep reinforcement learning actually have a certain degree of intercommunication [26]. Therefore, we apply the deep reinforcement learning technology to WSNs in order to realize the route planning based on mobile agents.

Among the things that the MA knows, the locations of each node in the environment are the most important, and these are also set as the input for the intelligent agent. Assuming that there are n source nodes, then the input is formed as $\{x_1, x_2, x_3..., x_n\}, x_i \in R^2$, where x_i (usually a two-dimensional coordinate) represents the location of node i. The intelligent agent learns to make a decision, outputs the permutation of n nodes index permutation, e.g. $\{3, 5, 7, ..., n-1\}$, which indicates the path that the MA is going to take.

We adopted the network in [27][28] as the architecture of the intelligent agent, which is composed of an actor network and a critic network. The actor network works as policy gradient and the critic network is used to approximate function values. To be more exact, the actor chooses the best action according to the current state and the critic judges the goodness of each action. In our design, the structure of the two networks is similar, except that critic network has two more fully connected layers at the end of the network than the actor network, which outputs the expected reward for the input action. Figure 2 represents the architecture of the actor network.

In Figure 2, $x_1, x_2, x_3..., x_n$ are the locations of the input source nodes. Each x_i is mapped to a d-dimensional vector through linear transformation, and then fed into the encoder, which consists of Long Short-Term Memory (LSTM) cells [29]. The encoder is marked as E for short in Figure 2. At the initial stage of decoding, the decoder, which is also composed of the LSTM, reads a trainable vector V. The output of the decoder and the output of the encoder are taken as the inputs for the attention mechanism [30] (A in Figure 2) to obtain the token of the next source node. The decoder regards the output token a_i' as the

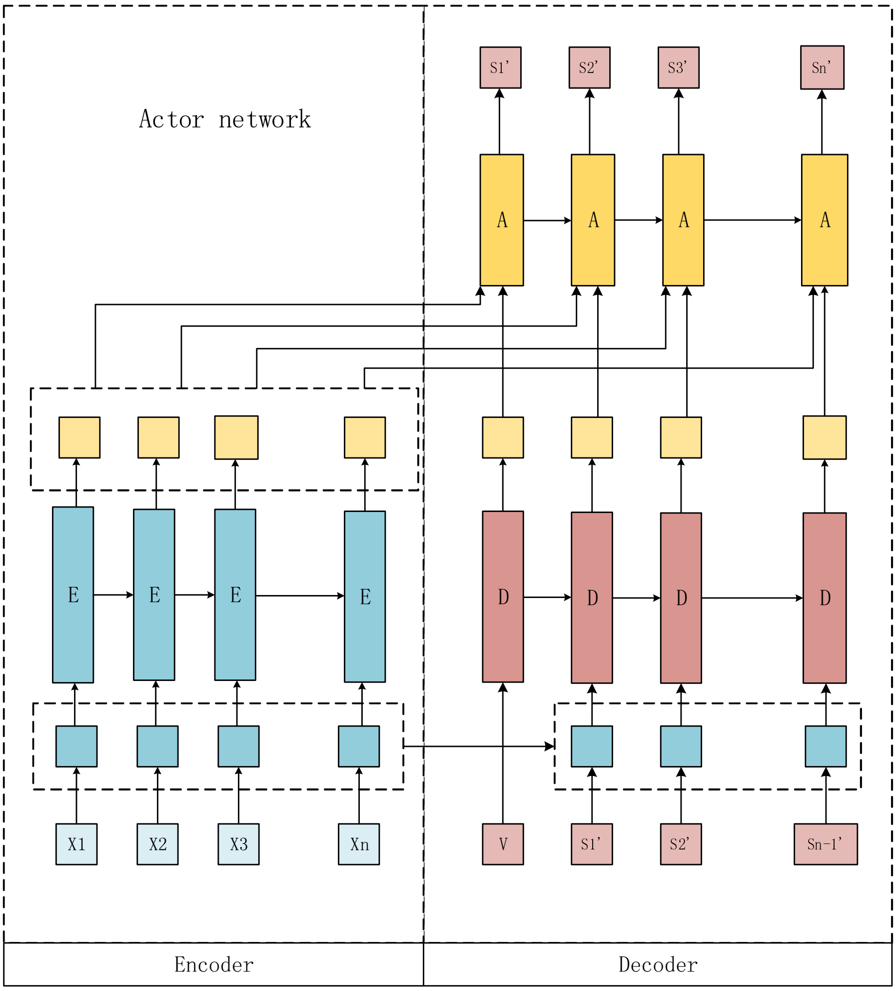

Figure 2: Architecture of the actor network

index to find the corresponding embedded input and uses it to obtain the next a'_{i+1}, and so on. Finally, a permutation of source-node tokens $\{a'_1, a'_2, a'_3, ..., a'_n\}$ is generated. At the training stage, the a_i is from the dataset instead of the decoder output. The training process of the Actor-Critic is shown in Algorithm 1.

Algorithm 1 Actor-Critic Training

Initialize actor network $P(a|x, \theta)$
Initialize critic network $Q(r|x, a, \phi)$
for step = 1,2,...,M **do**
    Sample input sequence X=$\{x_1, x_2, ..., x_n\}$
    Sample output tokens A=$\{a_1, a_2, ..., a_n\}$
    Predict output $A' = P(a|X, \theta)$
    Get reward R of A' from the environment
    for substep = 1,..,k **do**
        $R' \leftarrow Q(X, A')$
        $L_c \leftarrow \|R - R'\|_2^2$
        $\phi \leftarrow$ ADAM$(\phi, \bigtriangledown_\phi L_c)$
    end for
    $R' \leftarrow Q(X, A)$
    g $\leftarrow (R - R') \bigtriangledown_\theta \log P(X)$
    $\theta \leftarrow$ ADAM(θ, g)
end for

In training process, the critic network is updated by the output of the actor network using Adam optimizer. After several steps, the critic network is assumed to be more stable, and then its output is used to train the actor network. The actor network is updated by the results of the critic network.

4. Artificial Agent Energy-Efficient Traffic Control in WSNs

In this section we will describe the energy consumed in WSNs and then design it as reward to combine with the deep reinforcement learning. The goal of the deep reinforcement learning is to maximize the total rewards obtained by the MA [31]. For WSNs, an important indicator to measure the performance of an algorithm is the energy consumption. Let M_{ma}^{i} denote the size of MA when it arrives at the ith source node, in which M_{ma}^{0} indicates that MA is at the sink node. Let M_{data}^{i} denote the size of data generated by the ith source node. The decay rate of the ith node is r_i. The fusion rate of the ith node is p_i, where the data collection for the first time is without the fusion rate. The size of the MA increases as it travels around the WSN. When it reaches the kth source node, its size is:

$$M_{ma}^{k} = M_{ma}^{0} + M_{data}^{i} * r_1 + \sum_{i=2}^{k} M_{data}^{i} * r_i * p_i \tag{1}$$

We assume that a sensor node consumes e_{out} when sending out one bit of data, and consumes e_{in} when receiving one bit of data. The transmitter amplifier's energy is $e_{amp} * d^k$, where d means the distance and k is the propagation loss exponent. We use M_{in}^{i} to mean the packet size received by the node i, use M_{out}^{i} to mean the packet size of the sent data. Then the total energy consumption of the sensor node is:

$$E(M_{in}^{i}, M_{out}^{i}) = e_{in} * M_{in}^{i} + (e_{out} + e_{amp} * d^k) * M_{out}^{i} \tag{2}$$

Therefore, the energy consumption of the mobile agent moving from the $k-1$th sensor node to the kth node is:

$$\begin{aligned} E_{k-1}^{k} = E(0, M_{ma}^{k-1}) + H_{k-1}^{k} * E(M_{ma}^{k-1}, M_{ma}^{k-1}) \\ + E(M_{ma}^{k}, 0) + e_p * M_{data}^{k-1} \end{aligned} \tag{3}$$

Here, H_{k-1}^{k} means the estimated hop count of the multi-hop with the help of other sensor nodes in the process of jumping from the $(k-1)$th node to the kth node. The last item is the data-processing energy of node $k-1$, and e_p is the unit energy consumption of the data processing.

In order to calculate the total energy consumption cost E, we decompose the action of the MA into three steps: from the sink node to the first sensor node,

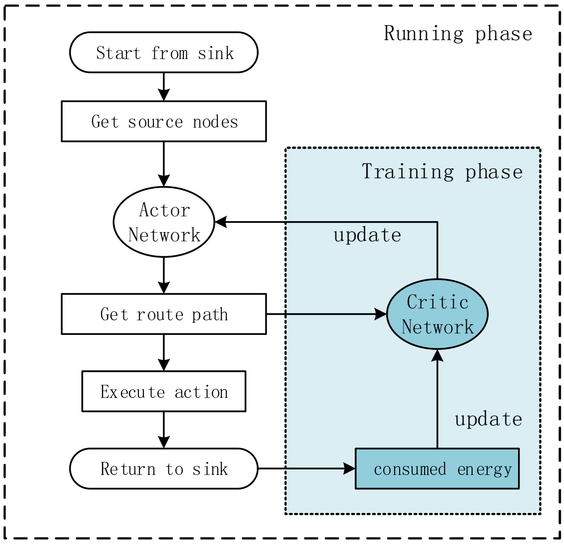

Figure 3: The traffic-control system in WSNs

from the first sensor node to the last sensor node, and from the last sensor node back to the sink node. The total energy consumption is:

$$E = E_{begin} + \sum_{i=2}^{n} E_{i-1}^{i} + E_{end} \tag{4}$$

After the energy consumption is determined, we take the negative of the consumed energy as the reward for the reinforcement learning, the coordinates of the source nodes as the state, and a permutation of the node tokens as the action. Figure 3 shows how the agent controls the traffic in WSNs.

A MA starts from the sink, obtains the route path from the actor network, and executes it in the WSN. When it returns to the sink node, the reward (consumed energy) is calculated to update the critic network, which updates the actor network in return. When the training comes to a stable phase, the training part can be removed.

Table 1: Environment description

Parameters	**Value**
Simulation Area	100 × 100m
Coordinate of Sink Node	(101, 50)
Number of Sensor Nodes	200
Number of Source Nodes	20
Channel Type	Wireless Channel
Energy Model	battery
Transmission Energy	50nJ/bit
Receiving Energy	50nJ/bit
Transmitter Amplifier Efs	$10pJ/bit/m^2$
Transmitter Amplifier Emp	$0.0013pJ/bit/m^4$
Data Process Energy	5nJ/bit
Data Compression Ratio	0.45

5. Experiments and Performance Evaluation

To evaluate the performance of the proposed method, we conducted a simulation experiment in the WSN. For the sake of simplifying, a few assumptions were made, as follows: the initial energy of each node is the same; the source nodes are unchanged in the simulation process; the amount of data sent by each node is fixed; and the energy of the sink node and the mobile agent is unlimited.

In all the simulation cases the sensor nodes are randomly distributed in a square area. The MA starts from the sink node, collects data from the source node in a multi-hop way, and finally returns to the sink node. The initial size of the mobile agent is 500 bits. Each source sensor generates 4000 bits of data. The details of the simulation environment are shown in Table 1.

As mentioned in [32] , local closest first (LCF) [33] ,global closest first (GCF) [33] and MA-based directed diffusion (MADD) [34] are three traditional efficient method for single-MA-based WSN. In the LCF, the source node which is closest

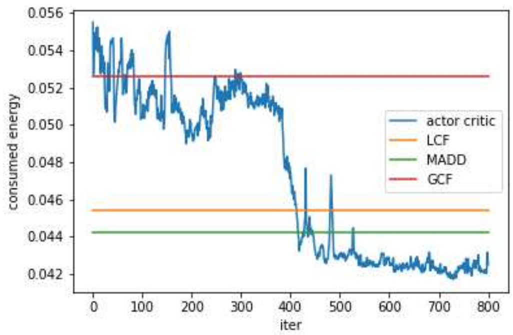

Figure 4: Energy consumption during actor-critic training Process

to the current source node is selected every time. While in the GCF, the MA chooses the source node which is closest to the sink node. MADD is similar to LCF but differs in which MA selects the farthest node from the sink node in the first step.

We set these three methods as comparisons and use the energy consumed by mobile agents as the basis for the judgement. Figure 4 shows the consumed energy during the training process. The y-axis values of LCF, GCF and MADD in the figure are the mean value because they do not need to learn. It is clear that our proposed method was originally at a disadvantage and gradually surpassed the others, which proves that deep reinforcement learning can work effectively for wireless sensor problems.

We also analyzed the actual routing situation of the four methods, which is shown in Figure 5.

Through an analysis of these two graphs, we can see that LCF, GCF and MADD have major shortcomings. They choose path without considering the energy consumption for the energy consumed in the WSN until the MA returns to the sink node. The Actor-Critic can estimate the energy consumption and make decision. Through the behavior of the agents in Actor-critic, we can also deeply analyze the WSN traffic information. For example, in order to reduce the energy consumption, with an increase of the mobile agent volume, it is

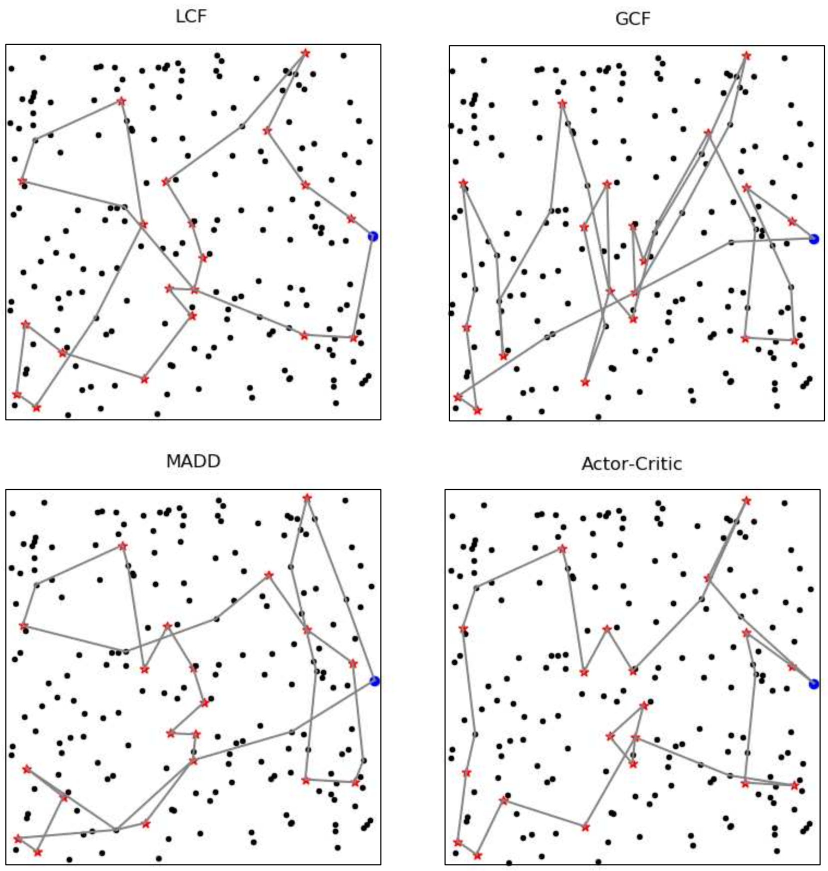

Figure 5: Route of four methods

more advantageous for MAs to traverse the distant nodes at the beginning and traverse the nearest points at the end of collecting the information, which the other three have no ability to learn.

6. Conclusion

In this paper we first analyzed the current difficulties faced by a WSN, and then investigated the application of deep learning in the WSN. After that, we proposed the system in which deep reinforcement learning is used for WSN's flow control. Before introducing the system, we popularized the basic knowledge of the WSN and the deep reinforcement learning, and then introduced the WSN flow-control system based on deep reinforcement learning.

Although the above research can improve the efficiency of the WSN flow control, there are still some deficiencies. For this, we propose three future plans: (1) Though our method performs well compared to other methods, single MA itinerary has many drawbacks, for example, the increase in size of MA packet will cost higher energy. Thus, we plan to investigate into multi-MA itinerary planning based on our results [35]. (2) In this paper, we assume that the nodes of the WSN do not move, but in fact, they move slowly. Therefore, we will consider adjusting the network structure dynamically to accommodate the node changes [36]. (3) Security and privacy are unavoidable aspects in wireless network. In the future, we will improve the security of data transmission while ensuring lower energy consumption [37].

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