Joint Optimization of PAoI and Queue Backlog with Energy Constraints in LoRa Gateway Systems

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Abstract. Peak Age of Information(PAoI), as a performance indicator representing the freshness of information, has attracted the attention of researchers in recent years. The data packet transmission rate in the LoRa network determines the information freshness level for system packets. In order to study the optimal scheduling of data packets, we try to use the PAoI to describe the real-time level of the end devices(*EDs*) and reduce it. We use edge servers to process monitoring data packets at the edge of the network to improve the efficiency of *EDs* and the information freshness level of data. Since packet transmission will be constrained by *EDs* battery queue energy and gateway queue backlog, we propose an optimization problem that aims to minimize the long-term average PAoI of *EDs* while ensuring network stability. With the Lyapunov optimization framework, the long-term stochastic optimization problem is transformed into a single-slot optimization problem. Furthermore, to avoid the problem of too large search space, we propose a dynamic strategy space reduction algorithm (SSDR) to shrink the strategy space. The simulation experiments show that our SSDR algorithm can optimize the PAoI index of *EDs* in various situations and satisfy the constraints of long-term optimization.

Keywords: PAoI · LoRa · Lyapunov optimization · scheduling algorithms

1 Introduction

In monitoring scenarios such as outdoor fire warning and dam water level monitoring, the traditional wireless communication network deployed by existing base stations is greatly limited. Moreover, whether the monitoring data can be processed by the server in time is also one of the key factors. LoRa is a self-deployed

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wireless network that does not rely on existing base stations. *EDs* can be self-charged by solar energy and other means without connecting to the power grid, which can adapt well to special scenarios where base stations are scarce and power grid coverage is not comprehensive [1]. LoRa technology modulates the baseband signal using a Chirp Spreading Spectrum, based on carrier frequency (CF), spreading factor (SF), bandwidth (BW) and coding rate (CR) [2,3]. Due to the orthogonality of the transmission sub-bands and quasi-orthogonality of the spreading factors, gateway can simultaneously receive signals from multiple end devices.

The Age of Information (AoI) is an emerging data freshness metric in wireless networks. It is defined as the time elapsed since the last data packet was generated at the source and received at the destination [4,5]. Another age-related metric is the Peak Age of Information (PAoI), which characterizes the staleness of the last received packet at the time of updating the AoI value, i.e., when a transmitter sends a data packet to the receiver [6]. PAoI focuses more on the worst-case scenario during the scheduling process, which can be used to monitor scheduling events that occur less frequently but have a severe impact on the real-time performance of the system [7,8]. With the help of PAoI indicators, the occurrence of special events can be better monitored and reduced, thereby improving the response speed of the system.

Deploying edge servers at the network edge allows monitoring devices to send data to the edge server through a gateway, instead of sending data packets to the cloud center, which can accelerate the decision-making and processing of monitoring information [9,10]. The generation of data packets from end devices and battery queue charging process are random. The traditional LoRa monitoring network has in-depth research on the energy consumption of *EDs*, but there is insufficient research on the timeliness of data packet transmission. Using AoI/PAoI can better evaluate the data freshness level of *EDs*, and design an appropriate data packet scheduling strategy based on the backlog of buffer queues of the gateway and the energy consumption of *EDs*. Based on the AoI buffer queue model of *EDs*, we derive the peak AoI of the *EDs* and attempt to minimize the expected long-term PAoI to improve the data freshness level performance of the wireless network system. In summary, the main contributions are summarized as follows:

1) According to the characteristics of LoRa wireless network, the PAoI performance index of end device is derived, and the long-term PAoI optimization problem of end device is given under the condition of queue backlog constraint and battery queue energy constraint.
2) Using the Lyapunov optimization framework, we have localized the solution to stochastic optimization problems, previously evaluated over the long term, to each time slot. To address the impact of a large search space on algorithm efficiency, we introduce the SSDR algorithm, which dynamically reduces the strategy space. This enables fast identification of the optimal scheduling strategy.

3) The simulation experiments conducted under various parameter settings validated the reliability of the SSDR algorithm and included comparative experiments with three other commonly used scheduling algorithms. The simulation results demonstrate that our SSDR algorithm reduces the PAoI for end devices while ensuring overall system stability, and outperforms the compared algorithms in terms of performance.

The rest of the paper is organized as follows: In Sect. 2, we introduce the related work. In Sect. 3, we introduce the system model of LoRa wireless dispatching network, and give our optimization problems. In Sect. 4, we use the Lyapunov optimization framework to transform the problem into a single-time-slot optimization problem. In Sect. 5, we design a strategy space dynamic reduction algorithm to search for the optimal scheduling strategy in the strategy space as soon as possible. We present the simulation results and analysis in Sect. 6. Finally, in Sect. 7, we summarize this paper.

2 Related Work

In recent years, many literature has considered the use of AoI and PAoI indicators to improve data freshness and improve the real-time level of the system when integrating different scenarios. In [6], the author derived the distribution of PAoI for systems in series, including M/M/1 and M/D/1 systems, and analyzed the possible optimization of these two systems, which may be a complex operation that needs to be performed in real-time. In [11], the author investigated the age-optimal scheduling in a multiple access channel with stability constraints, where two heterogeneous source nodes transmit to a common receiver. In [12], the author utilized a probabilistic scheduling method to minimize the AoI metric for the entire wireless transmission system.

As an alternative to cloud computing, edge computing has been studied to improve the real-time level of data by using edge servers deployed at the edge of the network to provide computing resources. In [13], Tang et al. analyzed the AoI performance metrics of a multi-user mobile edge computing (MEC) system, where the base station generates and sends compute-intensive packets to the user device for computation. The processing of real-time information is critical for many applications. In [14], Lv et al. used edge computing resources to reduce AoI levels and devised a pricing mechanism to determine the allocation decisions of real-time computing tasks. In [15], Liu et al. consider a unicast network scenario where the sender periodically sends data to the receiver over a multihop network. AoI/PAoI indicators have also been studied in the Internet of Things, and in [16], Hu et al. studied the optimal arrival rate of packets under AoI and PAoI constraints. Based on the violation probability of AoI and PAoI, the optimal arrival rate of receiver status update is analyzed from the perspective of asymptotic optimality. In [17], Wang et al. investigated the design of an optimal strategy to minimize the long-term mean information age in a cognitive radio-based IoT monitoring system.

In real-time status update systems, energy consumption is an important factor that cannot be ignored in packet transmission scheduling. In [18], the authors performed an analysis of AoI based on queuing theory, in which transmitter nodes powered by energy harvesting systems frequently send status update packets to destinations. The SHS method was used to derive MGF closed expressions for AoI under several queuing rules of transmitters, including non-preemption (LCFS-NP) and service/waiting preemption (LCFS-PS/LCFS-PW) strategies, and similar related work was done [19,20]. In order to save energy consumption, in [21], the authors designed a trade-off between sensor transmission data and energy consumption, and after the service is completed, the sensor can go into a sleep state, thus saving energy. In [22], the authors examine the energy-saving scheduling problem for AoI minimization in opportunistic NOMA/OMA downlink broadcast wireless networks, where user devices operate with different QoS requirements. The Lyapunov framework is used to convert the original long-term time mean into a single-slot multi-objective optimization problem. Zhou et al. [23] investigated how to optimize the freshness of real-time data from energy-harvesting (EH)-based networked embedded systems in energy-constrained situations. The proposed solution can reduce the average AoI by an average of 47.2% and 69.1% with a low harvest rate. In [24], Fang et al. studied the Age of Peak Information (PAoI) in underwater wireless sensor networks (UWSN), as well as the energy cost of transmitting packets. Active and idle modes are designed to reduce energy consumption. The closed expressions of average PAoI and energy cost under AQM and non-AQM strategies are derived, and the results are verified by simulation experiments. In general, the work on AoI and PAoI focuses on ensuring the real-time level of the entire system, while considering constraints such as throughput, energy consumption, transmit power, etc. or joint optimization.

As a long-distance low-power radio communication technology, LoRa wireless network has good anti-interference and sensitivity, and has a wide range of application scenarios in wireless monitoring and power supply, and has many related papers [2,25–27]. In [28], the authors investigated resource management in a LoRa wireless network based on instantaneous channel coefficient and energy availability when LDs are powered by energy harvesting sources. They developed an optimal SF allocation, device scheduling, and power allocation algorithm that maximizes the number of scheduled LDs. In [29], two offline scheduling algorithms for LoRa-based data transmission were proposed. The algorithms allocate time slots and assign SF to nodes to minimize the overall data collection time. In [9], Liu et al. propose a new design of a LoRa system that uses edge computing on a LoRa gateway. This design enables some of the time-computing tasks of latency-sensitive applications to be processed in a timely manner. In [30], the authors assumed that in a house, all smart appliances are connected to a smart meter with edge devices and LoRa nodes. An energy-efficient smart metering system using remote edge computing is proposed to solve the problem of latency and energy consumption.

3 System Model

In this section, we introduce the system model, as shown in Fig. 1. In the LoRa network, *EDs* are deployed in an energy-constrained environment and need to obtain energy from the environment for self-charging. When *EDs* transmit data to the gateway, their AoI decreases. If the gateway receives too much data, the queue backlog will increase. Therefore, it is necessary to design a suitable scheduling algorithm. Our goal is to minimize the information age of *EDs* while ensuring energy constraints and gateway backlog constraints. Next, we will sequentially introduce the network and energy models, the peak information age formula, and the derivation of the gateway queue backlog model.

3.1 LoRa Network Model and Battery Status

In a single-server monitoring network,consider $\mathbb{N} = \{1, 2, ..., N\}$ as *EDs*. When there are no packets on the *EDs*, it monitor the nearby environmental conditions and generate packets based on a random process. If the packet already exists on the *EDs*, the packet is no longer obtained according to the random process. The packet is time-stamped to record the current age of information(AoI) changes. AoI is an indicator for expressing the freshness of information, which will be explained in detail in Sects. 3.2. We discretize time into intervals of the same length.

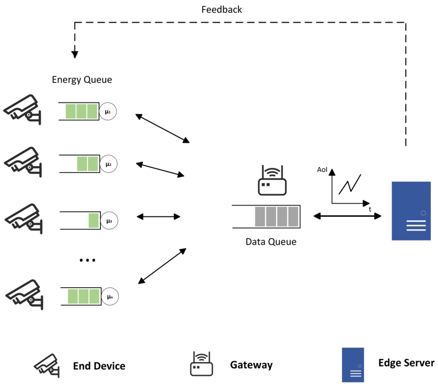

Fig. 1. Lora Network Organization

Suppose that the unit energy consumption for transmitting a data packet is E^{trans}. Assuming that the charging process follows the Bernoulli process with probability λ, the charging probability of each device follows $\lambda \in (0, 1)$. $E(t)$ represents the battery status of the end device. Battery status can be expressed as

$$E_i(t+1) = \min\{E_i(t) - \mu_i(t) \cdot (E_c + E^{trans}) + \lambda(t) \cdot E, E_{max}\}, \tag{1}$$

where E_{max} indicates the maximum capacity of the battery queue, E_c represents a fixed energy consumed by the circuit, E represents the unit of energy for charging, and the greater the probability of charging $\lambda_i(t)$, the more energy the battery charges. $\mu_i(t)$ indicates whether end device i successfully transmits packets in time slot t, $\mu_i(t) = 1$ when it is successfully transmitted to the gateway, otherwise $\mu_i(t) = 0$. The battery queue status of all *EDs* at t time slot is represented by the set $E(t) = \{E_0(t), E_1(t), ..., E_i(t), ..., E_N(t)\}, i \in \mathbb{N}$.

The gateway maintains an AoI cache queue and does not discard any data packets transmitted by *EDs*. The gateway can connect to the power grid, so energy is not a concern. The *EDs* are guided by a scheduling controller that considers the current network status. This controller provides a strategy π to determine if *EDs* should send data packets in the next time slot. The controller is deployed in the edge server. After the gateway receives packets from the *EDs* at time slot t, these packets are stored in the gateway's cache queue and processed sequentially according to the gateway's packet service rate. The packet transmission process is shown in Fig. 2 below.

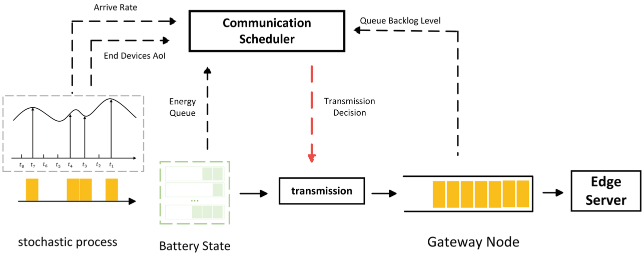

Fig. 2. *EDs* rely on AoI and Queue Backlog Level scheduling strategy

The queue backlog for a gateway represents the total number of packets in the cache queue at a given time. The PAoI of the end device is derived from the average age of information change of the packet over time, which we will describe in Sect. 3.3.

3.2 Peak Age of Information

For packets that have been generated and temporarily stored in the end device, the age of the information will increase when it is not their turn to transmit the time slot. When it is the turn of the appropriate transmission time slot, the packet is transmitted to the gateway and the information age drops to 1. Its packets are cached in the gateway's AoI cache queue along with packets transmitted by other *EDs*. When it is the appropriate transmission time slot, packets are in turn transmitted to the Edge Server for processing, with a service rate μ_{gw} affected by the hardware performance of the gateway. The status update process of information age is shown in Fig. 3, where the information age corresponds to the change of the data packets information age of ED_i

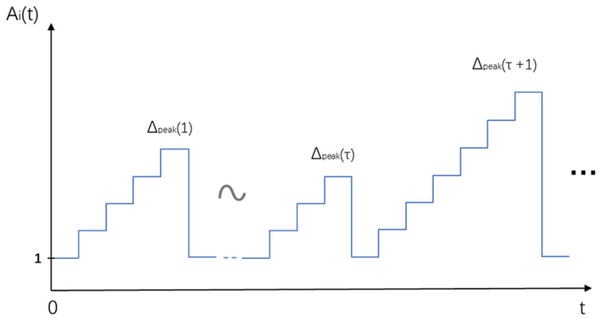

Fig. 3. AoI status update process

As we can see from the figure above, the AoI of the data packet decreases after transmission to the Edge Server. At the time slot t, the AoI of the *EDs* is defined as the difference between the current time t and the timestamp $\triangle t$ of the outgoing packet [4]. Then the AoI of the *EDs* at the time slot t is defined as

$$A(t) = t - \triangle t. \tag{2}$$

Suppose that in each discrete time slot, AoI takes an integer value, i.e.,$A(t) \in \{1, 2, 3, ...\}$. We suppose that the *EDs* sending a packet can be completed before the end of the previous time slot. In this paper, the AoI of all data packets on all *EDs* is constructed into a set $\mathbb{A}(t) = \{A_0(t), A_1(t), ..., A_i(t), ..., A_N(t)\}, i \in \mathbb{N}$, and $\mathbb{A}(t)$ represents the AoI of all *EDs* under t time slot. $\mu_i(t)$ indicates whether to transmit data packets in the current time slot. Then the AoI variation formula for two consecutive time slots can be updated to

$$A_i(t+1) = A_i(t) + 1 - \mu_i(t)A_i(t). \tag{3}$$

It can be seen from the AoI change plot that when $\mu_i(t) = 1$, the AoI of the t time slot is the PAoI. Average PAoI is defined as

$$\overline{A_i^{peak}} = \lim_{t \to +\infty} \frac{\mathbb{E}[\sum_{\tau=0}^{t-1} \mu_i(\tau)A_i(\tau)]}{\mathbb{E}[\sum_{\tau=0}^{t-1} \mu_i(\tau)]}. \tag{4}$$

Our goal is to optimize the PAoI of the *EDs*. However, reducing the PAoI may have a certain impact on the queue backlog of gateway, so we propose a queue backlog model of gateway below to analyze the impact of packet transmission on gateway.

3.3 Gateway Queue Backlog Model

The gateway's queue backlog depends on data packets arrival rate and gateway service rate. In time slot t, the service rate of the i-th end device can be expressed as $\mu_i(t)$, the queue backlog of gateway is represented by the symbol $S_{gw}(t)$. The queue backlog model in $t+1$ at the next moment, we have

$$S_{gw}(t+1) = max[S_{gw}(t) - \mu_{gw}(t), 0] + \sum_{i=0}^{N} \mu_i(t), \tag{5}$$

where $\mu_{gw}(t)$ is the service rate of the gateway at time t, and $\sum_{i=0}^{N} \mu_i(t)$ is the sum of all packets transmitted to the gateway by all *EDs* at time slot t.

Since queue models are affected by stochastic processes, we need to consider the long-term stability of the queue.When the time t tends to infinity, the total number of packets enqueued should be less than or equal to the total number of packets out of the queue, i.e., $\lim_{t\to+\infty} \frac{1}{T} \sum_{\tau=0}^{t-1} \mathbb{E}[\sum_{i=0}^{N} \mu_i(\tau) - \mu_{gw}(\tau)] \leq 0$.We convert the queue model into an inequality constraint, we have

$$S_{gw}(t+1) \geq S_{gw}(t) + \sum_{i=0}^{N} \mu_i(t) - \mu_{gw}(t). \tag{6}$$

The inequality transformation yields $\sum_{i=0}^{N} \mu_i(t) - \mu_{gw}(t) \leq S_{gw}(t) - S_{gw}(t+1)$. When $S_{gw}(0) = 0$, combining the first *EDs* time slots to the above equation-accumulate transformation, we have

$$\sum_{\tau=0}^{t-1}[\sum_{i=0}^{N} \mu_i(\tau) - \mu_{gw}(\tau)] \leq S_{gw}(t) - S_{gw}(0) = S_{gw}(t) - 0 = S_{gw}(t). \tag{7}$$

Then we expect both sides of the inequality to be at the same time, we have

$$\frac{1}{t}\sum_{\tau=0}^{t-1} \mathbb{E}[\sum_{i=0}^{N} \mu_i(t) - \mu_{gw}(t)] \leq \frac{\mathbb{E}[S_{gw}(t)]}{t}. \tag{8}$$

Observing the above equation, in order to meet the stability constraint of the left equation, we can ensure that the queue achieves long-term stability through $\lim_{t\to\infty} \frac{\mathbb{E}[S_{gw}(t)]}{t} = 0$, i.e., the queue can achieve mean rate stable. Based on the above considerations, the optimization problems of this article are given below.

3.4 Problem Formulation

The optimization goal of this paper is to select a suitable scheduling strategy for each time slot that helps to keep the gateway's queue stable while minimizing the average PAoI.

Firstly, we provide the definition of packet arrival probability. The data arrival probability refers to the probability that the *EDs* obtains the monitoring data in the random process, and different data arrival probabilities will affect the data packet generation rate of *EDs*. We define the data arrival probability as θ, and $\theta \in (0,1)$.

We define the scheduling strategy π as a row vector composed of the dequeue rates of all *EDs* at a certain moment. It is expressed as $\pi = (\mu_0, \mu_1, ..., \mu_i, ..., \mu_N), i \in \mathbb{N}$, where μ_i represents whether the i-th end device transmits data packets to the gateway. Define scheduling strategy space: $\mathit{\Pi} = (\pi_0^T(t), \pi_1^T(t), ..., \pi_m^T(t), ...)$, where $\pi_m^T(t)$ represents the scheduling strategy for all *EDs* in the time slot t. Our goal is to find the best scheduling strategy to minimize average system PAoI. *EDs* energy and gateway queue backlog serve as optimization constraints. The optimization problem in this article is defined as

$$\text{P1}: \quad \min_{\pi \in \mathit{\Pi}} \mathbb{E}[\overline{A_i^{peak}}] \tag{9}$$

$$\text{s.t.} \quad \lim_{t \to \infty} \frac{\mathbb{E}[S_{gw}(t)]}{t} = 0 \tag{9a}$$

$$\overline{A_i^{peak}} = \lim_{t \to +\infty} \frac{\mathbb{E}[\sum_{\tau=0}^{t-1} \mu_i(\tau) A_i(t)]}{\mathbb{E}[\sum_{\tau=0}^{t-1} \mu_i(\tau)]} \tag{9b}$$

$$\mu_i \in (0,1), \quad \forall i \in \mathbb{N}, \tag{9c}$$

$$E_i \le E_{max}, \quad \forall i \in \mathbb{N}, \tag{9d}$$

$$\lambda \in (0,1), \tag{9e}$$

$$\theta \in (0,1). \tag{9f}$$

This optimization problem is a stochastic optimization problem. A random number of packets are generated in each time slice. The objective function will be influenced by random events and the chosen scheduling strategy. Long-term averaging involving objective functions and constraints cannot be directly solved by traditional optimization techniques. This paper adopts the Lyapunov optimization framework. It convert a stochastic optimization problem measured from a long-term perspective into a single time slice.

4 PAoI-Queue-Aware Scheduling Using Lyapunov Framework

For the above optimization problem, our goal is to transform the long-term optimization problem into single-slot online optimization, and find the appropriate scheduling strategy from the scheduling strategy space $\mathit{\Pi}$. Suppose that the network state at time t is $\mathit{\Omega}(t) = [S_{gw}(t), \mathbb{A}(t), E(t)]$. We define the quadratic Lyapunov function $L(t) = \frac{S_{gw}^2(t)}{2}$ [23,31]. The Lyapunov drift $\triangle L(t)$ is defined as

$$\triangle L(t) = L(t+1) - L(t). \tag{10}$$

For the objective function, we use a penalty function $p = P(\mathit{\Omega}(t), \pi_m^T(t))$ to represent the impact of the current AoI and the scheduling decision taken on the objective function. We define a non-negative weight coefficient V as the balance factor between the penalty function and Lyapunov drift. We aim to continuously solve for the minimum of the Lyapunov drift combined with the penalty function in each time slot. Then our optimization problem **P1** can be rewritten as

$$\begin{aligned} \text{P2}:\quad & \min_{\pi \in \Pi} \mathbb{E}[\triangle L(t) + Vp(t)], && (11)\\ \text{s.t.}\quad & (9c), (9d), (9e), (9f), \\ & \triangle L(t) = L(t+1) - L(t), && (11\text{a})\\ & p = P(\Omega(t), \pi_m^T(t)). && (11\text{b}) \end{aligned}$$

Optimization problem **P2** converts the original long-term optimization function into the optimization objective function in a single time slot. But the Lyapunov drift here is by definition known to know $L(t+1)$ in the next time slice. It goes against our goal of single-slot online optimization. In order to solve this problem, $\triangle L(t) + Vp(t)$ can be scaled to a certain extent [32]. $\triangle L(t)$ has an upper bound, i.e. $\triangle L(t) \leq B + S_{gw}(t)\sum_{i=0}^{N}\mu_i(t)$, where B is a normal number. Because both the arrival rate and service rate of the gateway cache queue are bounded, therefore there must be a bounded constant $B > 0$ that ensures $\mathbb{E}[B(t) \mid \Omega(t)] \leq B$ in each time slot, i.e. $\triangle L(t) \leq B + S_{gw}(t)\sum_{i=0}^{N}\mu_i(t)$.

In a single time slot, observe the cache queue status of the gateway and give a Drift-Plus-Penalty function about PAoI, we have

$$\triangle L(t) + Vp(t) \leq B + S_{gw}(t)\sum_{i=0}^{N}\mu_i(t) + Vp(t), \tag{12}$$

where $p(t)$ is the penalty function associated with the PAoI state, battery queue state and action strategy of the *EDs*. We can solve the optimization problem **P2** by solving the minimum value to the right of the above inequality. At this point, the optimization problem **P2** can be transformed into problem P3

$$\begin{aligned} \text{P3}:\quad & \min_{\pi \in \Pi} \mathbb{E}[B + S_{gw}(t)\sum_{i=0}^{N}\mu_i(t) + Vp(t)] && (13)\\ \text{s.t.}\quad & (9c), (9d), (9e), (9f), (11a), (11b), \\ & B > 0. && (13\text{a}) \end{aligned}$$

Based on the optimization problem **P3**, we can finally give a single-slot optimization algorithm, as shown in Algorithm 1.

Algorithm 1. DPP Algorithm for PAoI and Queue Backlog

```
Initialization:$S_{gw}(0) \leftarrow 0, \mathbb{A}(0) \leftarrow 0, E(0) \leftarrow 0, p_i(t) = 14dBm$. Select $BW, \alpha_i(t), PL, H, DE, CR$ according to the LoRa network architecture. Choose appropriate $V$ and $E_{max}$. Set $t = 1$.
Under the t time slot, observe the network state $\Omega(t) = [S_{gw}(t), A(t), E(t)]$ and select the appropriate scheduling strategy $\pi \in \Pi$ so that it satisfies the Lyapunov drift-plus-penalty function:
    $$\min_{\pi \in \Pi} \mathbb{E}[B + S_{gw}(t) \sum_{i=0}^{N} \mu_i(t) + Vp(t)]$$
    where the Lyapunov drift-plus-penalty function satisfies the following constraints: (9c),(9d),(9e), (9f), (11a),(11b).
Update the LoRa network architecture:
    $$E_i(t+1) = \min\{E_i(t) - \mu_i(t) \cdot (E_c + E_i^{trans}(t)) + \lambda_i(t) \cdot E, E_{max})\},$$
    $$A_i(t+1) = A_i(t) + 1 - \gamma_i(t) B_i(t) A_i(t),$$
    $$S_{gw}(t+1) = max[S_{gw}(t) - \mu_{gw}(t), 0] + \sum_{i=0}^{N} \mu_i(t).$$
In the next time slot t + 1, repeat the previous steps.
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5 Strategy Space Dynamic Reduction Algorithm

In LoRa network, the LoRa gateway can support a large number of *EDs*. The increase in the number of *EDs* will cause the strategy space to increase exponentially. It is obviously inappropriate to traverse the entire strategy space to obtain the optimal solution for the Lyapunov drift-plus-penalty function in a single time slot. In order to solve this problem, this paper proposes a Strategy Space Dynamic Reduction (SSDR) algorithm. It reduces the dimension of the action strategy space through further analysis of the LoRa network structure. It finds an approximate optimal solution that satisfies the constraints of the optimization problem in the strategy space more quickly.

5.1 Battery Queue State and AoI Constraints

As can be seen from the LoRa network system model, the battery queue status in the end device will determine whether the packet can be successfully transmitted to the gateway. If at one moment, the end device does not acquire enough energy to store in the battery queue, the decision to transmit packets at the next moment will be invalidated. Assuming that there are N end devices in the current LoRa network, the action strategy space Π_1 is represented as

$$\Pi_1 = \begin{bmatrix} \mu_{0,0} & \mu_{0,1} & \cdots & \mu_{0,2^N} \\ \mu_{1,0} & \mu_{1,1} & \cdots & \mu_{1,2^N} \\ \vdots & \vdots & & \vdots \\ \mu_{N,0} & \mu_{N,1} & \cdots & \mu_{N,2^N} \end{bmatrix}. \tag{14}$$

It can be seen that the size of the current strategy space is $N \times 2^N$, and the increase in the number of *EDs* represents that the strategy space rises according to the exponential trend. It is not appropriate to take an exhaustive method to traverse the entire search space. We base constraints on the battery queue status of the *EDs* when the battery status of the device does not meet the constraints, we have

$$E_i(t) \geq E_c + E_i^{trans}(t). \tag{15}$$

Assuming that the number of *EDs* that do not meet the above constraints is β_1, remove these *EDs* from the strategy space and rebuild the strategy space Π_2

$$\Pi_2 = \begin{bmatrix} \mu_{0,0} & \mu_{0,1} & \cdots & \mu_{0,2^{N-\beta_1}} \\ \mu_{1,0} & \mu_{1,1} & \cdots & \mu_{1,2^{N-\beta_1}} \\ \vdots & \vdots & & \vdots \\ \mu_{N-\beta_1,0} & \mu_{N-\beta_1,1} & \cdots & \mu_{N-\beta_1,2^{N-\beta_1}} \end{bmatrix}. \tag{16}$$

At this point, the size of the strategy space Π_2 is $(N - \beta_1) \times 2^{(N-\beta_1)}$ and the dimension drops to $N - \beta_1$.

Observing the strategy space, it is not difficult to find that when the packet AoI of the end device is 1, it means that the packet has been successfully transmitted to the gateway, or no packet is generated or store in the end device at the current moment. We remove the *EDs* with an AoI of 1 from the strategy space because the transmission decision will be meaningless when there is no packet in the end device. Assuming that the number of *EDs* with AoI=1 is β_2, rebuild the strategy space Π_3

$$\Pi_3 = \begin{bmatrix} \mu_{0,0} & \mu_{0,1} & \cdots & \mu_{0,2^{N-\beta_1-\beta_2}} \\ \mu_{1,0} & \mu_{1,1} & \cdots & \mu_{1,2^{N-\beta_1-\beta_2}} \\ \vdots & \vdots & & \vdots \\ \mu_{N-\beta_1-\beta_2,0} & \mu_{N-\beta_1-\beta_2,1} & \cdots & \mu_{N-\beta_1-\beta_2,2^{N-\beta_1-\beta_2}} \end{bmatrix}. \tag{17}$$

After analyzing the battery status and the AoI state of the *EDs*, the strategy space size at this time is reduced to $(N - \beta_1 - \beta_2) \times 2^{(N-\beta_1-\beta_2)}$ and the dimension is $N - \beta_1 - \beta_2$.

5.2 Further Analysis of AoI

Through the above analysis, the dimension of the strategy space has been reduced to a certain extent. We further analyze that the AoI of each end device and the queue backlog of the gateway will determine whether to transmit packets. All *EDs* with the same AoI are essentially the same in our transmission decisions. Therefore, the action behavior of these end devices with the same AoI is somewhat repeated in the strategy space.

Suppose that the number of *EDs* with the same AoI is η. For example, when $\eta = 5$, we number the five *EDs* as 1, 2, 3, 4, 5. Through the permutation analysis, we can obtain a total of 32 possibilities for the transmission decision of 5 end devices. There are six effective decisions in these decisions. So when $\eta = 5$, the original 32 strategies can be reduced to 6. That is, the original 2^N action decisions now only need $\eta + 1$ decisions. We set up a hash table, when there are η end devices with the same AoI, store $\eta + 1$ decisions in this table. When the decision scheduling of a specific number of *EDs* is searched, the specific action decision can be taken out from the hash table.

Based on the above analysis, for a certain time, when there are β_1 end devices with insufficient battery energy and β_2 end devices with 0 AoI in the LoRa network, and the number of end devices with the same AoI (excluding 1) is η, our SSDR algorithm can reduce the total number of policies from 2^N to $(\eta + 1) \times 2^{(N-\beta_1-\beta_2-\eta)}$. If more than one AoI indicator is the same, that is, there are $\phi = (\eta_0, \eta_1, \cdots, \eta_\kappa)$ duplicates, then the total number of strategies that can be implemented by the SSDR algorithm is $(\eta_0 + 1)(\eta_1 + 1) \cdots (\eta_\kappa + 1) \times 2^{(N-\beta_1-\beta_2-\eta_0-\eta_1-\cdots-\eta_\kappa)}$. The specific SSDR algorithm is shown below.

Algorithm 2. SSDR Algorithm

```
Input: Initialize the parameter environment of the LoRa wireless network: Select
    $BW, \alpha_i(t), PL, H, DE, CR$ according to the LoRa network architecture. Choose
    appropriate $V$, LoopTime and $E_{max}$. Set $t = 1$.
$S_{gw}(0) = 0, \mathbb{A}(0) = 0, E(0) = 0, p_i(t) = 14dBm$.
for each $i \in Looptime$ do
    Update the AoI of all end devices.
    Update the battery queue for all end devices.
    if $E_i(t) < E_c + E_i^{trans}(t)$ then
        Remove devices that do not meet energy constraints from the scheduling strategy.
    else
        Add end devices to the scheduling strategy space.
    end if
    if Traverse to the end device that has duplicate AoI then
        Store the duplicate AoI end device in a hash table.
    end if
    Execute the DPP algorithm, search the dynamically reduced strategy space, and
    find the most suitable scheduling strategy $\pi$.
    According to the obtained scheduling strategy, update the AoI index, gateway
    backlog level, and battery queue energy level of the end device.
end for
```

6 Simulation Results

In this section, we evaluated the performance of the SSDR algorithm through simulation experiments and conducted controlled experiments using other commonly used algorithms for comparison to compare the average PAoI performance under different algorithm strategies. Our simulation experiment results are shown below.

6.1 Parametric Analysis Under SSDR Algorithm

The calculation of the preamble and payload duration can be obtained through the LoRa chip calculation tool officially provided by Semtech [3]. Suppose that the initial network environment is: data arrival probability is $\theta = 0.4$, the number of *EDs* is $N = 10$, and the spreading factor is $SF = 8$. By setting different energy arrival probabilities, the simulation results obtained are shown in Fig. 4. As the energy arrival probability increases, the energy in the battery queue of *EDs* is no longer in a state of shortage. Moreover, due to the long-term scheduling of SSDR, the overall stability of the system is improved. So the energy state of the battery will maintain at a steady level after a period of time.

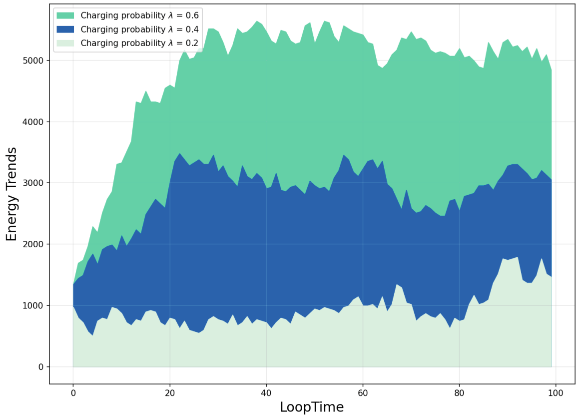

Fig. 4. Trend of Battery Energy with Varying Charging Probabilities.

In order to better observe the trend of queue backlog status and the average PAoI variation under the SSDR algorithm, we set the energy arrival probability to $\lambda = 0.4$ based on the above parameter environment. The queue backlog status of the gateway and the average PAoI change trend of the system are shown in Fig. 5 and Fig. 6.

As shown in Fig. 5, it can be seen that the queue backlog of the gateway has a significant initial decrease, followed by fluctuations at a lower level. It indicating that our SSDR algorithm does not fully sacrifice the queue backlog

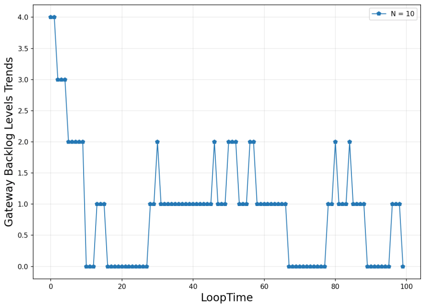

Fig. 5. Gateway Backlog.

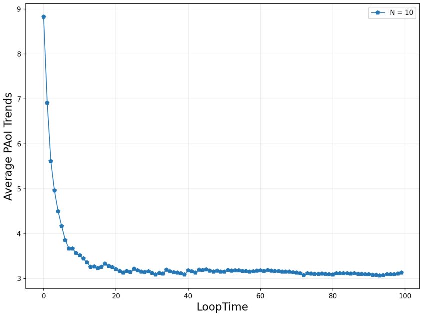

Fig. 6. Average PAoI Level.

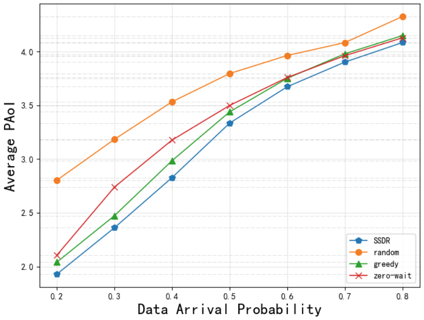

Fig. 7. Different Data Arrival Probabilities.

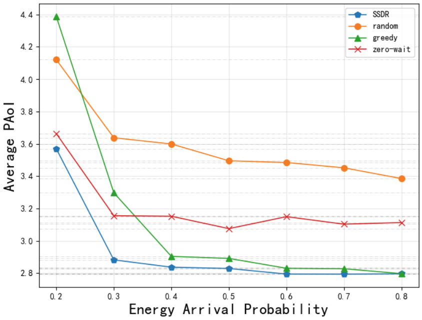

Fig. 8. Different Battery Energy Arrival Probabilities.

of the gateway to minimize the system average PAoI. Figure 6 shows that the system's average PAoI can rapidly decrease at the initial stage under the SSDR algorithm, and then stabilize at a very low level. It is in line with our expectations for the LoRa wireless monitoring network.

6.2 Compare with Other Algorithms

We have chosen three common wireless network scheduling algorithms to compare the performance of the SSDR algorithm. The random scheduling algorithm randomly selects a specific number of *EDs* for transmission in each time slot while satisfying the queue backlog constraint. The greedy scheduling algorithm searches for the *EDs* with the highest AoI in each time slot and selects a specific number of *EDs* for data transmission. The zero-wait scheduling strategy is a common AoI scheduling strategy that maximizes system resource utilization to avoid any task waiting or suspension. In each time slot, once a qualifying data packet is generated, it is immediately transmitted, thereby reducing the PAoI level of *EDs*.

In Fig. 7, we initially set the probability of battery queue energy reaching $\lambda = 0.4$, the number of end devices $N = 10$, and the spread factor $SF = 8$. While the probability of data arrival increases on the *EDs*, the AoI of the *EDs* will gradually increase, and eventually tend to a roughly stable level. This is because the faster the packet is generated, the efficiency of transmission to the gateway is affected by the backlog of the gateway queue, the energy consumption constraint of the battery queue, etc., the transmission efficiency decreases, resulting in the PAoI level of the end device rising.

In Fig. 8, we set different battery queue energy arrival probabilities, and it can be seen that the average effect of the random scheduling algorithm is poor, the greedy scheduling algorithm converges quickly and eventually tends to the effect of our SSDR algorithm, while the zero-wait strategy decreases moderately. This is because when the probability of energy reaching increases, the battery of the end device has a greater possibility to ensure the normal transmission of packets, thereby reducing the PAoI level of the end device.

7 Conclusion

We have conducted research on the optimal packet scheduling problem in LoRa wireless networks. By utilizing edge servers at the network edge, we obtained processing results for monitoring data and provided network status feedback to end devices. We formulated optimization problems tailored to specific model scenarios. Using the Lyapunov optimization framework, we transformed the long-term optimization problem into a single time slot optimization problem for selecting the best scheduling strategy. To address the challenge of a large search space, we introduced the SSDR algorithm, which dynamically reduces the strategy space to quickly identify the optimal scheduling strategy. Through simulation experiments, we analyzed the performance of the SSDR algorithm under varying network conditions and compared it with three other commonly used scheduling algorithms. The simulation results demonstrate that our SSDR algorithm consistently achieves favorable optimization outcomes across different parameter settings, significantly reducing the age of information for *EDs*.

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