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Optimization of Time and Power Resources Allocation in Communication Systems Under the Industrial Internet of Things

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ABSTRACT In the Industrial Internet of Things (IIoT), it is an urgent task to reduce power loss and enhance energy efficient through reasonable allocation of resources. Inspired by time slot channel frequency hopping, this paper puts forward a dynamic allocation model for time and power resources. Based on the proposed model, a dynamic resource allocation algorithm was designed to reduce energy consumption. In addition, a power and time allocation algorithm was developed to maximize the energy efficiency of the system. The workflows of the two algorithms were introduced in details. Simulation results show that both dynamic resource allocation algorithm could reduce the energy loss of the communication system, while ensuring the stability of the data queue. The research findings help to promote the performance of communication systems in different scenarios of the IIoT.

INDEX TERMS Dynamic resource optimal allocation, Industrial Internet of Things, slot frequency hopping technology, dynamic resource allocation algorithm.

I. INTRODUCTION

In recent years, with the continuous development and innovation of related technologies of Internet of things, the production mode of traditional industries and people's life style have changed dramatically. One typical example is the industrial Internet of things. Through various communication systems, many devices are interconnected, thus a system that can monitor, collect, exchange, analyze and transmit valuable information is formed.

With the continuous development of the Industrial Internet of things, the security and reliability of the system become more and more important. The key factor for solving the security problem is to ensure the stability of communication between nodes. So what kind of scheduling mechanism or technology is used to ensure the reliability of transmission has been a hot research topic. However, due to the limited power resources available to the nodes themselves, how to allocate the resources reasonably to reduce the power loss and improve the energy efficiency of the system is an urgent problem.

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With the increasing number of industrial devices such as wireless sensors, the amount of data needed to be processed by the system is also increasing rapidly, it leads to a large increase in the demand for computing resources and communication resources. However, in reality, due to the limitation of available time, bandwidth, energy and other resources, how to reduce the delay, reduce the communication overhead and improve the energy utilization of the rapidly growing data service under the limited resources is also facing great challenges.

This paper mainly focuses on the application of time slot channel frequency hopping (TSCH) in Industrial Internet of Things, and based on this technology, how to meet the energy cost, energy efficiency and delay requirements of the system through dynamic power resource and time resource allocation mechanism is studied.

II. RELATED WORKS

For Industrial Internet of Things, reliable information exchange is an effective way to maintain system security. IEEE 802.15.4 standard defines the standards of medium access control in physical layer and data link layer to realize low rate, low overhead and low power wireless network. However, IEEE802.15.4 standard (transmission rate of 250kbps at 2.4GHz) has defects in reliability, scalability and delay constraints. Therefore, IEEE published IEEE 802.15.4e TSCH standard [1], which can optimize the current physical layer and media access layer to improve the stability of the system. The core of TSCH technology is the integration of channel hopping and time synchronization technology to complete the scheduling of time slot and frequency [2]. Voulgaris *et al.* [3] pointed out that TSCH technology can guarantee 99% end-to-end communication stability under the premise of 1% radio duty cycle.

In IEEE 802.15.4 standard, there is no specific description of TSCH to provide the establishment and maintenance mechanism of scheduling. But many scheduling solutions are proposed. These scheduling schemes can be divided into centralized scheduling, distributed scheduling and automatic scheduling. Considering the maximum minimum fair scheduling principle, Ojo *et al.* [4] proposed a polynomial time algorithm to maximize the throughput of the system based on the centralized scheduling mechanism of TSCH mode. Javan *et al.* [5] proposed an actual energy loss model based on TSCH. Hwang and Nam [6] proposed an energy loss model and analyzed the energy loss, throughput and delay performance of TSCH mechanism. Kim *et al.* [7] found that based on the TSCH minimum scheduling mode, the biggest cause of energy loss is idle monitoring in the monitoring time, so they analyze how to control the monitoring time to maximize the energy efficiency of the system under the single hop network and the multi hop network respectively. Soua *et al.* [8] proposed an adaptive static scheduling algorithm to improve the energy efficiency of the TSCH network by giving the state of time slot allocation between the communication nodes in the topology network.

In Industrial Internet of Things, nodes are usually limited by energy, that is to say, the total energy that nodes can use is limited. Therefore, most of researches focus on how to reduce the cost of energy, and how to improve the energy efficiency of the system. However, the actual channel state changes with time, it means that the algorithms mentioned in the above literatures can not be applied to the actual system simply. n addition, the amount of data arriving at the node is mostly uncertain, that is to say, the data may arrive at the node at any time to request service, but the existing algorithms don't take the arrival of random data into account, so it may cause data loss, overflow, large delay and other situations. Therefore, in this paper we will consider the random arrival of time-varying channel and data, and minimize the energy consumption and maximize the energy efficiency of the system through dynamic allocation of time and power resources, so as to improve the system performance in different scenarios of Industrial Internet of Things.

III. A DYNAMIC RESOURCE ALLOCATION ALGORITHM FOR POWER CONSUMPTION OPTIMIZATION

A. TSCH NETWORK SCHEDULING MODEL

In TSCH network, nodes must form a TSCH network in MAC layer to exchange data packets with higher layer for communication. In the formed TSCH network, time is divided into several time slots, and the combination of several time slots will form time slot frame. In the process of system operation, the time slot frame will be repeated continuously. In this case, the number of time slots in a time slot frame will determine the cycle speed of the time slot frame, that is, the maximum rate at which nodes can communicate and send information is determined by the number of time slots in a time slot frame. Each time slot must be long enough to accommodate the transmission of a frame and its corresponding reply signal. According to the scheduling of the coordinator, there may be two states in each slot, sleep state and active state. When a node is in a sleep slot, the node will shut down its radio interaction and perform radio task cycle, when a node is in an active slot, the node will perform information transmission or information reception. At the same time, the time slot will be allocated a channel offset and a time offset by the coordinator. The time offset determines the position of the time slot in a time slot frame, while the channel offset is used to determine the channel used by the node in communication. The channel offset can be calculated as follows:

$$CH_{offset} = V[\left(N_{AS} + Time_{offset}\right) Mod V_L] \tag{1}$$

where V is a vector, it contains channels available to nodes in the TSCH network, N_{AS} represents absolute slot number, $Time_{offset}$ represents time offset, V_L represents the length of vector V.

In TSCH network, the coordinator allocates time slots and channels according to the maximum capacity of all nodes in a certain time slot and a certain channel [9], [10]. After allocating time slots to nodes, because the channel condition is not very good, and information transmission is not necessary at this time, in this case, nodes can choose not to transmit information, and then carry out information transmission when the channel condition is good, so as to prolong the service life of nodes. In TSCH network scheduling model, considering the frequency and time allocation of a node based on the coordinator in the TSCH network, the node can decide whether to carry out data transmission by observing its own data queue length and current channel status information.

The transmission power of a node in the TSCH network is set to p_k, the transmission time of the node in k time slot is $t_k = \{0, 1\}$, when the channel gain between communication nodes is g_k, according to Shannon formula, the maximum amount of data transmitted in k slot is defined as follows:

$$B_k = t_k \cdot \log_2 (1+\frac{p_k g_k^2}{W\sigma^2}) \tag{2}$$

where σ^2 represents noise power spectral density, W is channel bandwidth. And in k time slot, the energy loss of the node is defined as follows:

$$R_k = p_k + r_c \cdot t_k \tag{3}$$

where r_c represents constant circuit loss of nodes.

Through introducing circuit loss [11], we can make our model more practical. Suppose there is a data queue in a node, the length of the data queue is L_k in k slot. Assume that the amount of data arriving at the node in k slot is D_k, the amount of data transmitted by the node is S_k. Then the dynamic data queue length change of the node can be expressed as:

$$L_{k+1} = [L_k - S_k]^+ + D_k \tag{4}$$

The data queue is stable only when it is constrained by the average queue backlog. Therefore, we can describe the queue delay and the stability of the queue by the length of the data queue. If a data queue can remain stable, it needs to meet

$$\frac{1}{K} \lim_{K<\infty} \sum\nolimits_{k=1}^{K} L_k < \infty \tag{5}$$

According to the above analysis and related literatures [12]–[14], some empirical values can be given. In order to minimize the time average power consumption of the system, we can describe the problem as the following optimization problem:

$$\min \bar{P} = \frac{1}{K} \sum_{k=1}^{K} R_k \tag{6}$$

s.t.

$$t_k = \{0, 1\}, \quad \forall k \neq 0 \tag{7}$$

$$0 \leq p_k + r_c \leq p_{max}, \quad \forall k \neq 0 \tag{8}$$

$$\frac{1}{K} \lim_{K<\infty} \sum\nolimits_{k=1}^{K} L_k < \infty \tag{9}$$

where Eq. (7) is the time resource allocation constraint, which ensure that the node can only transmit or not transmit in the allocated time slot. Eq. (8) is power constraint, which ensure that the maximum transmission power of the node cannot exceed the maximum transmission power it can provide. Eq. (9) is data queue constraint, which ensure the stability of the data queue of the node, so as to ensure the stability of the system.

B. DYNAMIC RESOURCE ALLOCATION ALGORITHM FOR REDUCING ENERGY CONSUMPTION

The stochastic optimization problem defined in Eq. (6) can be transformed into a series of continuous deterministic optimization problems through Lyapunov optimization theory [15], [16]. In each time slot, the standard convex optimization method is used to solve these problems.

Lyapunov function is defined as follows:

$$L(X_k) = \frac{1}{2}(L_k)^2 \tag{10}$$

where $X_k = \{L_k : k = 1, 2, \ldots, K\}$.

In addition to Lyapunov function, Lyapunov offset [17], [18] is another key factor to solve stochastic optimization problems. According to the dynamic change of queue given in Eq. (4), the first order condition Lyapunov offset is defined as

$$\begin{aligned}
\Delta X_k &= E\{L(X_{k+1}) - L(X_k) \mid X_k\} \\
&= E\left\{\frac{1}{2}\left((L_{k+1})^2 - (L_k)^2\right) \mid X_k\right\} \\
&\leq E\left\{\frac{1}{2}(S_k)^2 + \frac{1}{2}(D_k)^2 - L_k(S_k - D_k) \mid X_k\right\} \\
&= \frac{1}{2}E\left\{(S_k)^2 + (D_k)^2 \mid X_k\right\} - EL_k(S_k - D_k)|X_k
\end{aligned} \tag{11}$$

where $E\{\cdot\}$ represents mathematical expectation.

In a real system, S_k always has an upper bound S_{max}. Similarly, there must be an upper bound D_{max} for the amount of data D_k arriving at the node. Then,

$$c_{max} = \frac{1}{2}((S_k)^2 + (D_k)^2) \tag{12}$$

Therefore, combining Eq. (10) and Eq. (11), Eq. (12) can be obtained:

$$\Delta X_k \leq c_{max} - L_k E\{S_k \mid X_k\} + L_k E\{D_k \mid X_k\} \tag{13}$$

Since D_k is assumed to be the amount of data arriving at the node at the end of slot k, D_k is independent of queue length L_k and X_k at slot k. Therefor, $E\{D_k \mid X_k\}$ is constant and it is independent of the power distribution p_k and time distribution t_k at this time. Then the following formula can be obtained:

$$\Delta X_k \leq C_{max} - L_k E\{S_k \mid X_k\} \tag{14}$$

where $C_{max} = c_{max} + L_k D_k < \infty$.

Thus, the stability of the queue can be guaranteed by minimizing the offset factor. However, in this case, because the objective function of minimizing stochastic optimization problem is not taken into account, it may cause huge power loss. In order to solve the stochastic optimization problem thoroughly, we can turn to Lyapunov penalty function:

$$\Delta X_k + \alpha E\{R_k \mid X_k\} \leq C_{max} + E\{\alpha R_k - L_k S_k | X_k\} \tag{15}$$

where α is a system control parameter, $E\{R_k \mid X_k\}$ is penalty function, and it's also the objective function in the stochastic optimization problem.

The system control parameter α in Eq. (15) can be regarded as the node's emphasis on the minimization of power consumption, and it can be used as an important parameter to adjust the relationship between energy loss and delay performance. In order to solve the stochastic optimization problem, we only need to minimize the right side of the inequality sign of Eq. (15). According to the above analysis, the stochastic optimization problem can be transformed as follows:

$$\max L_k S_k - \alpha R_k \tag{16}$$

s.t.

$$t_k = \{0, 1\}, \quad \forall k \neq 0 \tag{17}$$

$$0 \leq p_k + r_c \leq p_{max}, \quad \forall k \neq 0 \tag{18}$$

Based on the above analysis, a power and time allocation algorithm to minimize the power consumption of the system is proposed. The specific step of the proposed algorithm is defined as follows:

Step 1: Input parameters p_{max}, σ^2, α and W.

Step 2: At the beginning of each slot k, the status information and channel status of data queue $Q_k^D(t)$ is observed.

Step 3: The optimization problem defined in Eq. (16) is solved, and the optimal power and time allocation strategy is obtained.

Step 4: Update data queue length according to Eq. (4).

Step 5: Repeat Step 2 to Step 4 for each slot.

In the algorithm, repeat steps 2-4 in each slot, then according to different channel state information and data queue information in each slot, time and power resources can be allocated dynamically in each slot. The proposed algorithm does not need the prior information of channel distribution and data arrival distribution. Therefore, the algorithm is a typical online algorithm, and can be easily applied to Industrial Internet of Things.

C. SIMULATION RESULTS AND ANALYSIS

In this section, the correctness of the proposed algorithm is proved through simulation experiment. In the simulation, multiple time slots whose time interval is 0.01 s is used to transmit data from one node to another node, and the distance between nodes is set to 40m in the TSCH network. In addition, both path loss and small-scale Rayleigh fading are considered in the simulation, and the path loss index is assumed to be 2.1. The available channel bandwidth of the node is 2MHz, the noise power spectral density of the channel is -168d BM/Hz, the maximum transmitting power of the node is 0.5 watt, the circuit loss power remains constant at 0.1 Watt, and there will be circuit loss only when it is transmitted.

Figure 1 shows the trend of average power consumption with control parameter α.

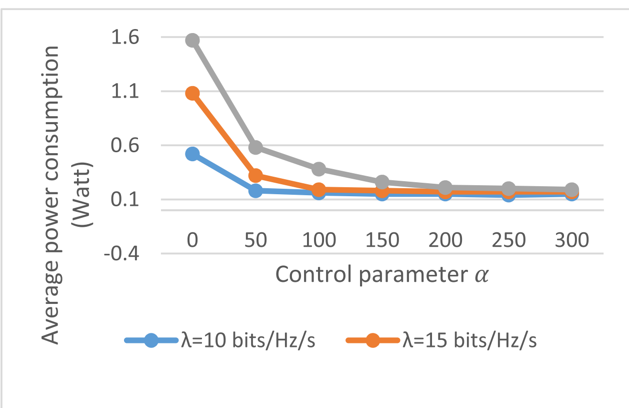

FIGURE 1. Average power consumption varies with control parameters α.

For any given data arrival rate λ, when α increases, the average power consumption decreases at the rate of O($1/\alpha$). Generally speaking, with the increase of data arrival rate λ, the system needs more transmission energy to transmit data so as to ensure the stability of the queue. Therefore, it can be found that in Figure 1, the average power consumption increases with the increase of data arrival rate.

Figure 2 shows the trend of the average queue length with control parameter α.

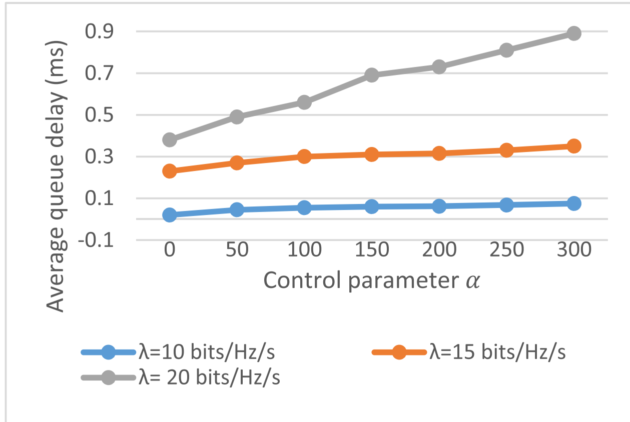

FIGURE 2. Average queue length varies with control parameters α.

As can be seen from Figure 2, when α increases, the average queue length increases at the rate of O(α). And when the data arrival rate λ increases, the average queue length will also increase.

From Figure 1 and Figure 2, it can be seen that we can balance the performance between the average power consumption and the average queue delay by adjusting the control parameter α. If we want lower power consumption and ignore the delay, we can choose a larger α value. Otherwise, if we want smaller delay and ignore the power consumption, we can choose a smaller α value. In addition, we can also find that the data arrival rate λ will affect the power consumption and data transmission delay of the system. The larger λ, the greater the power consumption of the system, and the greater the data delay.

IV. A DYNAMIC RESOURCE ALLOCATION ALGORITHM FOR ENERGY EFFICIENCY OPTIMIZATION

A. DYNAMIC RESOURCE ALLOCATION ALGORITHM FOR IMPROVING ENERGY EFFICIENCY

With the rapid growth of the amount of processed data in Industrial Internet of Things system, the energy needed to process the data is also increasing dramatically. It is very important to be able to reasonably use limited resources for data transmission. In this section, based on the proposed model in Section 3, an index (energy efficiency) [19] that can evaluate the resource utilization rate of nodes is adopted to propose a dynamic resource allocation algorithm, which can allocate dynamic resources to nodes in a long time, and then improve the energy efficiency of Industrial Internet of Things system.

The energy efficiency e_p of the system [20] is defined as the ratio of the accumulated transmission data per unit bandwidth over a long period of time to its corresponding energy consumption, it can be defined as follows:

$$e_p = \lim_{k\to\infty} \frac{\sum_{k=1}^{K} E\{S_k(t_k, p_k)\}}{\sum_{k=1}^{K} E\{R_k(t_k, p_k)\}} = \frac{\bar{S}}{\bar{R}} \tag{19}$$

where S_k and R_k represents node transmission rate and node transmission energy consumption at k time slot.

Combined with Section 3 and the above analysis, on the premise of ensuring the stability of the queue, how to maximize the energy efficiency of the system through dynamic resource allocation can be expressed as the following stochastic optimization problem:

$$\max e_p = \frac{\bar{S}}{\bar{R}} \tag{20}$$

s.t.

$$t_k = \{0, 1\}, \quad \forall k \neq 0 \tag{21}$$

$$0 \leq p_k + r_c \leq p_{max}, \quad \forall k \neq 0 \tag{22}$$

$$\frac{1}{K} \lim_{k\to\infty} \sum_{k=1}^{K} L_k < \infty \tag{23}$$

The above constraints are the same as those in Section 3, so we can use the similar method in Section 3 to solve the stochastic optimization problem in this section.

Because the objective function and constraints are non-convex, the stochastic optimization problem is a non-convex optimization problem [21]. However, it can be found that the objective function is a fractional form, so we can first use the properties of fractional programming to transform the objective function in the stochastic optimization problem.

If $\varphi(\varphi \neq \emptyset)$ represents feasible solution set of the stochastic optimization problem, then there must be an optimal time allocation $t^* = \{t_1^*, t_2^*, \ldots, t_K^*\}$ and power allocation $p^* = \{p_1^*, p_2^*, \ldots, p_K^*\}$ satisfying the stochastic optimization problem. When e_p in Eq. (19) is maximized, the optimal value of energy efficiency satisfies:

$$e_p^* = \frac{\bar{S}(t^*, p^*)}{\bar{R}(t^*, p^*)} = \max_{(t,p)\in\varphi} \frac{\overline{S(t, p)}}{\bar{R}(t, p)} \tag{24}$$

According to the properties of fractional programming, we can know that e_p^* in Eq. (24) can be obtained if and only if the following formula is satisfied.

$$\max \bar{S}(t, p) - e_p^* \bar{R}(t, p) = 0 \tag{25}$$

Although through the properties of fractional programming [22] and Lyapunov optimization theory, the initial stochastic optimization problem is transformed into a continuous static deterministic optimization problem. However, due to the existence of non-convex constraints in the transformed problem, it is still unable to use the standard convex optimization methods to solve it. In order to use standard convex optimization methods, we need to relax the constraints in the transformed problem. The optimization problem will be transformed as follows:

$$\max (\alpha + L_k)\, t_k \log_2\left(1 + \frac{p_k t_k h_k^2}{t_k W \sigma^2}\right) - \alpha e_p (p_k t_k + r_c t_k) \tag{26}$$

s.t.

$$t_k = \{0, 1\}, \quad \forall k \neq 0 \tag{27}$$

$$p_k t_k + r_c t_k - p_{max} t_k \leq 0, \quad \forall k > 0 \tag{28}$$

Based on the above analysis, a power and time allocation algorithm to maximize the energy efficiency of the system is proposed. The specific step of the proposed algorithm is defined as follows:

Step 1: Input parameters p_{max}, σ^2, α and W.

Step 2: At the beginning of each slot k, the status information and channel status of data queue $Q_k^D(t)$ is observed.

Step 3: The optimization problem defined in Eq. (26) is solved, and the optimal power and time allocation strategy is obtained.

Step 4: Update data queue length and energy efficiency of the system at k slot according to Eq. (4) and Eq. (24).

Step 5: Repeat Step 2 to Step 4 for each slot.

In the proposed algorithm, repeat steps 2-4 in each slot, then according to different channel state information and data queue information in each slot, time and power resources can be allocated dynamically in each slot. The proposed algorithm does not need the prior information of channel distribution and data arrival distribution. Therefore, the algorithm is a typical online algorithm, it aims to improve the energy efficiency of the system, and transmit as much data as possible under the limited energy conditions.

B. SIMULATION RESULTS AND ANALYSIS

In the experiment in this section, the used simulation settings are the same as those in Section 3.

Figure 3 shows the trend of energy efficiency with control parameter α. As we expected, for any given data arrival rate λ, when α increases, the energy efficiency e_p increases at the rate of $O(\alpha)$. Generally speaking, with the increase

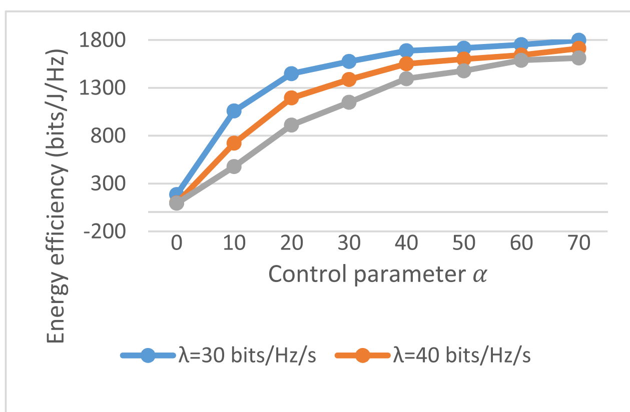

FIGURE 3. **Energy efficiency varies with control parameters α.**

of data arrival rate λ, the system needs more transmission energy to transmit data to ensure the stability of the queue. However, the increase of transmission energy is not directly proportional to the increase of transmission rate, it is caused by the property of logarithmic function corresponding to rate power. Therefore, we can find that in Figure 3, the energy efficiency decreases with the increase of data arrival rate.

Figure 4 shows the trend of the average queue length with control parameter α.

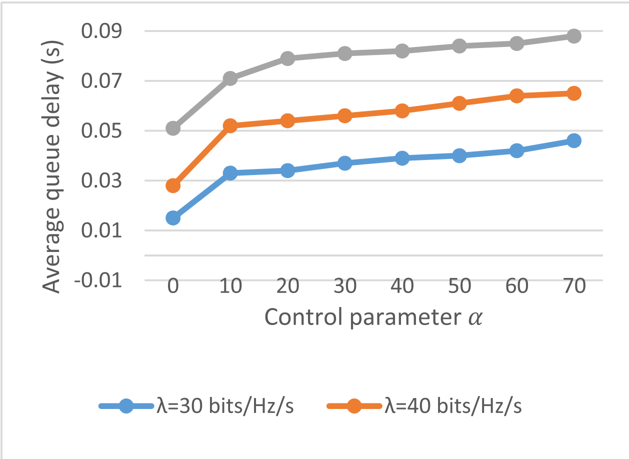

FIGURE 4. **Average queue length varies with control parameters α.**

As can be seen from Figure 4, when α increases, the average queue length increases at the rate of O(α). And when the data arrival rate λ increases, the average queue length also increases. That is, the average queue length is proportional to the data arrival rate λ.

From Figure 3 and Figure 4, it can be seen that we can balance the performance between energy efficiency and time delay by adjusting the control parameter α. if we want higher energy efficiency and ignore the time delay, we can choose a larger α value. Otherwise, if we want a smaller time delay and ignore the energy efficiency, we can choose a smaller α value. In addition, we can also find that the data arrival rate λ will affect the energy efficiency and data transmission delay of the system. The larger λ, the lower the energy efficiency of the system, and the greater the data delay.

V. CONCLUSIONS

In this paper, the industrial Internet of things as the background, through the use of time slot frequency hopping technology to ensure the stability of data transmission, thus ensuring the stability of the system. Through the dynamic time resource allocation and power allocation of nodes, the power consumption of the system is reduced, the energy efficiency of the system is improved, and the service life of the network is improved. According to the channel state and the queue length of the node, by dynamically allocating the time and power resources of a single node, the power consumption of the system is minimized and the energy efficiency of the system is improved under the premise of ensuring the stability of the data queue of the node. By introducing a control parameter α, the performance relationship between power consumption and average queue delay can be controlled and adjusted according to the delay requirements of nodes for different services. And then two corresponding dynamic resource allocation algorithms are proposed.

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