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Study on Energy Consumption Optimization Scheduling for Internet of Things

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ABSTRACT In the complex working environment of the Internet of Things (IoT), there are many differences in the work between many devices, as well as complex associations and energy constraints. The entire task scheduling system needs to consume a large amount of energy for communication. In order to describe its relevance and constraint relationship, traditional scheduling modeling methods need to add a large number of constraints. In this paper, an energy loss optimization scheduling modeling method based on the multi-objective fuzzy algorithm is proposed. Based on the equipment scheduling energy cost and equipment scheduling time in the IoT environment, the multi-objective equipment scheduling optimization equation in the IoT environment is constructed, and the fuzzy algorithm is integrated into the single-target energy loss problem. The algorithm searches for the idle time of the device and optimizes the device scheduling energy consumption model to reduce the overall energy consumption of the device scheduling in the IoT environment. The experimental results show that based on the multi-objective fuzzy algorithm, the equipment scheduling modeling method in the IoT environment considering energy loss has the characteristics of high precision and energy saving.

INDEX TERMS Energy-saving scheduling, Internet of Things, energy consumption, resource-scheduling, energy loss optimization model.

I. INTRODUCTION

With the universal application of Internet of Things, the energy situation faced by the Internet of Things scheduling system is becoming more and more severe. In the equipment scheduling under the Internet of Things environment, how to establish an accurate equipment scheduling optimization model consider energy loss is a research hotspot in the industry. Aiming at the optimization of equipment scheduling model, there have been many excellent achievements in the academic world [1]. The equipment scheduling in the Internet of Things is establish by calculating the optimal relaxation coefficient of equipment scheduling in the IoT environment and reducing the frequency of the frequency when running different tasks model. The algorithm has high modeling accuracy, but it has a large limitation [2]. It proposes the integration of feedback control theory into equipment scheduling in the Internet of Things environment, and established a device schedule model in the Internet of Things environment.

The method is relatively simple, but the difference between the result and the actual degree of solving the equipment progress model established by the current algorithm is obvious, and there is a problem of large modeling error [3]. This paper focuses on the adaptive connection rate-based device scheduling modeling method in the IoT environment. This method dynamically adjusts the device scheduling utilization in the IoT environment and establishes a device scheduling model in the IoT environment. This method is adaptable, but there are computationally cumbersome and time consuming problems. In view of the competition problem of service computing resources in the IoT environment, the current research focus is on how to reduce resource consumption. Researchers have studied access protocol SOAP with low memory consumption and low communication overhead. Representative work includes eSOAP [4] and gSOAP [5]. Literature analyzes the advantages and disadvantages of two lightweight Web services based on SOAP and REST, and

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points out that it is an effective way to reduce resource consumption through lightweight service components [6]. Reference [7] uses the two lightweight service description methods of DPWS (Device Profile for Web Services) and RESTful Web services to service resource-constrained device functions. Literature [8] compares traditional Web services with RESTful-web services, pointing out that the latter is simpler on the interface, with good loose coupling and scalability. In addition, researchers have proposed to use lightweight service matching algorithms to reduce resource consumption in service discovery, thereby overcoming resource constraints. Reference [9] considers the limited availability of equipment service resources and only matches the input and output of services and QoS. Document [10] proposes a lightweight service discovery method that only matches the output of the service and the name of the service operation.

Most of the actual time series data obtained by the IoT energy loss-scheduling model tends to be highly nonlinear [11], that is, there are four characteristics: trend, time variation, cyclic fluctuation and irregular fluctuation. Traditional time series prediction has methods such as autoregressive moving average (ARMA), Kalman filtering [12], and neural network [13]. Among them, ARMA is simple to implement, but there are shortcomings such as low-order model with low prediction accuracy and high-order model parameters [14]. However, neural network method has shortcomings such as slow convergence rate, difficult selection of hidden layer nodes, and large training data [15]. Kalman filter real-time has good performance, but there are problems such as low prediction accuracy for complex nonlinear systems. Therefore, the accuracy of the method of traditional time-series data prediction is not high, and the above methods lack the uncertainty measure of the prediction result. Gaussian processes [16] (Gaussian processes) belong to the category of nonparametric modeling, and have advantages over parametric modeling or neural networks in nonlinear dynamic system identification [17]: Probability Gaussian processes can directly infer super-training from training data. The predictive output has a probability measure that characterizes uncertainty; a model with strong generalization ability can be obtained on small samples, and is suitable for big data processing in high-dimensional data space [18]. Based on the data processing framework of the Gaussian process, the Gaussian process is used to identify and describe the autoregressive model of dynamic system characteristics for non-stationary time series data collected by the Internet of Things [19]. It is an uncertainty of input data in multi-step prediction. Propagation is uncertainty measure of dynamic time series data, prediction method of culling missing values [20], [21].

Energy loss optimization scheduling modeling method is studied in our paper based on multi-objective fuzzy algorithm [22]. The method firstly uses the equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment as the basis, then construct the multi-objective equipment scheduling optimization equation in the Internet of Things environment with the constraint of interval scheduling efficiency, and incorporates the fuzzy algorithm to target multiple energy loss targets. The problem is transformed into a single-objective problem, and then the device scheduling energy consumption model in the IoT environment is established, and the idle time of the device is searched for by using the earliest start and end time of the task, and the latest allowed start and end times are taken as criteria for considering energy loss. This premise optimizes the established equipment scheduling energy consumption model and reduces the overall energy consumption of equipment scheduling in the IoT environment. The experimental results show that the equipment scheduling modeling method based on multi-objective fuzzy algorithm considering the energy loss of the Internet of Things has high modeling accuracy and ideal energy saving effect.

II. IoT BASED ON WIRELESS SENSOR NETWORKS RELATED WORK

A. WIRELESS SENSOR CONCEPT

A sensor network is a set of wired or wireless networks in which sensors are construct in an Ad Hoc manner [23]–[25]. The purpose is to perceive cooperatively, collect, and process information about perceived objects in a geographical area covered by the network and distribute it to the observer. Among them, sensors, sensing objects and observers are the three basic elements of sensor networks.

A wired or wireless network is a method of communication between sensors, between sensors and observers, and cooperatively sensing, collecting, processing, and distributing perceptual information is a fundamental function of a sensor network. A set of sensors with limited functions to perform large sensing tasks collaboratively is an important feature of sensor networks. Some or all of the nodes in the sensor network can be move. The topology of the sensor network changes due to the scheduling of the resource scheduling system. Nodes communicate in Ad Hoc mode, each node can act as a router, and each point has the ability to search, locate, and restore connections.

The sensor consists of the power supply, sensing components, embedded processor, memory, communication components, and software. The power supply provides the sensor with the energy it needs to function proper. Perceptual components are used to sense and acquire outside information, and then convert it to a digital signal. The processing component is responsible for coordinating the work of various parts of the node, such as performing necessary processing, saving, and controlling the working mode of the sensing component and the power supply. The communication component is responsible for communicating with other sensors or observers. The software provides the necessary software support for the sensors, such as embedded operating systems, embedded database systems, and more.

B. CHALLENGES OF WIRELESS SENSOR NETWORKS

In addition to the common features of Ad Hoc network mobility, disconnection, power supply limitations, etc., the sensor network has many other distinctive features. These characteristics have presented us with a series of challenging issues.:

(1) Capability of limited communication. The sensor network of the sensor network has a narrow communication bandwidth and often changes, and the communication coverage is only tens to hundreds of meters. The communication of the sensor is disconnect frequently, often resulting in communication failure. The sensor may leave the network for a long time and work offline. How to complete high-quality processing and transmission of sensory information with limited communication capabilities is one of our challenges.

(2) Power supply energy is limited. The power supply of the sensor is extremely limited. Sensors in the network often fail or become obsolete due to power source energy. Power supply constraints are a serious problem that hinders sensor network applications. Commercialized wireless transceiver power supplies are far from meeting the needs of sensor networks. Sensors transmit information more power than performing calculations. The power required to sense the transmission of 1-bit information is sufficient to perform 3,000 calculation instructions. How to save energy and maximize the life cycle of the network in the network work process is our challenge.

(3) Limited computing power. Sensors in sensor networks all have an embedded processor and memory. These sensors have the computing power to do some information processing. However, due to the limited capacity and capacity of embedded processors and memories, the ability to manage sensors is limited. How to use a large number of sensors with limited computing power for collaborative distributed information processing is also a challenge we face.

(4) The network is dynamic. The sensor network is highly dynamic. The three elements of the sensor, the perceived object, and the observer in the network may be mobile, and new nodes often join or existing nodes fail. Therefore, the topology of the network changes dynamically, and the path between the sensor, the perceived object, and the observer changes. Sensor networks must be reconfigurable and self-tuning.

(5) Large-scale distributed triggers. Many sensor networks require control over perceived objects, such as temperature control. In this way, many sensors have a control device and control software. We call the control device and control software a trigger. Thousands of dynamic trigger management is the problem of research

III. SCHEDULING MODELING PRINCIPLES OF IoT

A. SCHEDULING PRINCIPLE

For the complex Internet of Things, the internal variables and the associations between the variables are complex, so the case of the Internet of Things described by a sequence consisting of parameters that can reflect the important features of the Internet of Things. The scheduling principle is as follows: Assume that the state sequence in the ideal optimization state of the Internet of Things is the reference sequence, and the state sequence in the current state of the Internet of Things is the target sequence, which described as a mathematical model.

$$\hat{\mathbf{X}}^{(0)}(\boldsymbol{k}) = \left[\hat{\mathbf{X}}^{(0)}(1), \hat{\mathbf{X}}^{(0)}(2) \ldots, \hat{\mathbf{X}}^{(0)}(\boldsymbol{n})\right] \tag{1}$$

$$\boldsymbol{X}^{(0)}(\boldsymbol{k}) = \left[\boldsymbol{X}^{(0)}(1), \boldsymbol{X}^{(0)}(2) \ldots, \boldsymbol{X}^{(0)}(\boldsymbol{n})\right] \tag{2}$$

where x is variable and $\hat{\mathbf{X}}^{(0)}(\boldsymbol{k})$ is reference vectors sequence, and $\boldsymbol{X}^{(0)}(\boldsymbol{k})$ is a sequence of target vector.

For the sequence $\boldsymbol{X}^{(0)}(\boldsymbol{k})$, the correlation coefficient can describe as:

$$\eta(\mathrm{k}) = \frac{\eta_{\min\min}(k) + \rho\eta_{\max\max}(k)}{\hat{X}^{(0)}(k) - X^{(0)}(k) + \rho\eta_{\max\max}(k)} \tag{3}$$

where $\hat{\mathbf{X}}^{(0)}(\boldsymbol{k}) - \boldsymbol{X}^{(0)}(\boldsymbol{k})$ represents the absolute difference between the kth reference vector sequence and the target vector sequence; ρ represents the resolution, where $\rho \in (0, 1)$, usually take $\rho = 0.5$; $\eta_{\min\min}(k)$ and $\eta_{\max\max}(k)$ are used to represent the two-level minimum difference and the two-stage maximum difference, respectively.

$$\eta_{\min\min}(\mathbf{k}) = \min\min\left|\hat{\mathbf{X}}^{(0)}(\boldsymbol{k}) - \boldsymbol{X}^{(0)}(\boldsymbol{k})\right| \tag{4}$$

$$\eta_{\max\max}(\mathbf{k}) = \max\max\left|\hat{\mathbf{X}}^{(0)}(\boldsymbol{k}) - \boldsymbol{X}^{(0)}(\boldsymbol{k})\right| \tag{5}$$

The degree of association between $\hat{\mathbf{X}}^{(0)}(\boldsymbol{k})$ and $\boldsymbol{X}^{(0)}(\mathbf{k})$ can be regarded as the average of n correlation coefficients.

$$\mathrm{r} = \frac{1}{n}\sum_{k=1}^{n}\eta(k) \tag{6}$$

Specific steps of the task optimization-scheduling model:

(1) Randomly generate a set of particles, if they meet the constraints, assign their initial position and velocity.

(2) Set the reference vector sequence.

(3) Calculate the objective function based on the particles in the population, and compose the resulting results into a sequence of target vectors.

(4) Find the correlation degree between the target sequence and the reference sequence corresponding to each particle, and consider the correlation degree as the adaptive function of the particle swarm optimization algorithm.

(5) Update the particle position and velocity by formula (3) and formula (5).

(6) Repeat steps 1) - 5) until the conditions of the adaptation function are met

The flow chart is shown in Figure 1.

Due to the diversity of the Internet of Things and the limited resources, the system will be congested. The multi-task optimization-scheduling model in the Internet of Things based on the combination of particle swarm and correlation degree is not able to meet all task requests due to limited task computing resources. The task optimization scheduling is implemented. And this model does not consider the energy

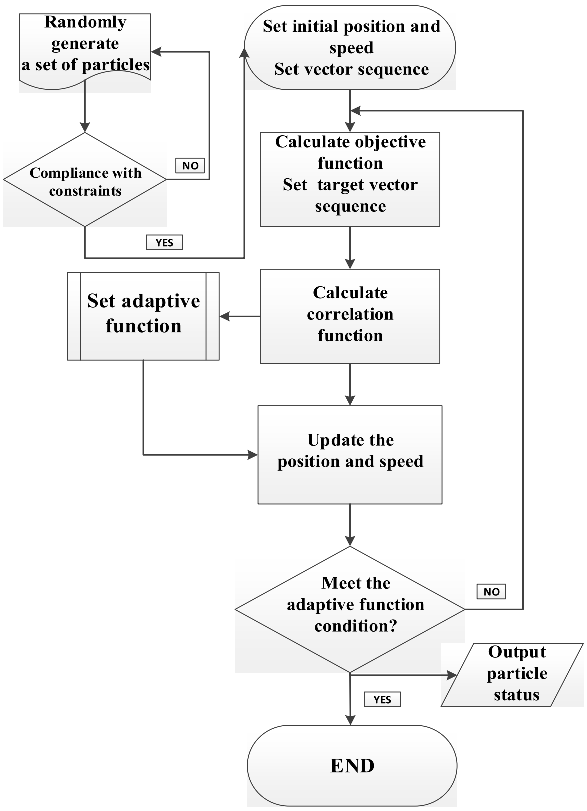

FIGURE 1. Process of optimization-scheduling.

consumption of the scheduling model, and the accuracy is low.

In an IoT environment with dynamic changes and limited resources, the computing resources of the service are limited, but the request for the service is unlimited, which easily leads to system congestion and the service resources are not rationally utilized. The service-scheduling model established by the resource scheduling mechanism and the service selection mechanism includes two modules: a service request scheduling module and a service personalized selection module.

(1) Extending the weighted round robin algorithm and establishing a corresponding queue scheduling model, so that the user request is scheduled according to certain rules;

(2) Establish an Internet of Things service QoS description model that describes the comprehensive characteristics of the service;

(3) Calculate the QoS composite value and use it as the best service selection method;

(4) Based on the extended queue scheduling model and optimal service selection method, the resource-oriented service-scheduling model is established.

B. EXTENDED WEIGHTED POLLING QUEUE SCHEDULING MODEL

In order to realize the optimal utilization of service resources, we introduce a weighted round-robin scheduling algorithm to solve the problem of resource competition through the scheduling mechanism. Although the weighted polling-scheduling algorithm can maintain the fairness of the service request and overcome the hunger problem of the traditional polling scheduling algorithm, it cannot solve the sudden problem of the service request. When a queue service request bursts, it will lead to high priority. The high latency of the service request queue affects the fairness of the high acquisition service of priority queue. In response to the above problems, this section will expand the following two aspects of the weighted round-robin scheduling model.

Set a buffer size for each request queue of priority service. When the queue capacity exceeds the buffer capacity, the new service request will no longer enter the queue, thereby avoiding the burst of a certain queue service request, thereby reducing the problem of delay characteristics of service request.

In the energy loss optimization scheduling modeling process, based on the equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment, the multi-objective equipment scheduling optimization equation in the IoT environment is constructed with the constraint of interval scheduling efficiency. Converting multiple target problems of energy loss into single-objective problems by fuzzy algorithm

A dynamic classifier is set before the service request arrives in the queue. All service requests need to be classified by the classifier before entering the corresponding priority queue to wait for scheduling of the scheduler. The classifier will dynamically adjust the number of queues and their weights. For example, when the number of service requests of a queue is scarce, the classifier will merge it into the adjacent priority queue, thereby reducing the number of queues; when a queue service request continues to exceed a certain threshold, the system dynamically adjusts its weight.

C. RESOURCE OPTIMIZATION ORIENTED SERVICE-SCHEDULING MODEL

Since the services in the IoT environment present some new features, the traditional QoS model has not adapted to its requirements. There has been a lot of research on the choice of Web services QoS attributes, but the points of interest vary. Other researchers have proposed multi-level and multi-dimensional QoS models, different levels, or latitudes to care about different attributes, so that Web services can be described from multiple perspectives. This paper chooses the QoS attributes of the service according to the characteristics of the service in the IoT environment. The Internet of Things service has two prominent features: the highly dynamic variability of services and the high degree of service computing resources. This article divides the selected QoS attributes into three categories, as show in Table 1.

The comprehensive extended queue-scheduling model and the optimal service selection method establish a resource-oriented service-scheduling model. The model is shown in the Figure 2.

The service-scheduling model includes two modules: service request scheduling and optimal service selection.

TABLE 1. Web services QoS description.

Attribute category	Attribute	Description
Attributes affected by service dynamics	Reliability	Demonstrate the ability to maintain a stable and reliable service quality
	Rate of success	Service success response percentage
Attributes affected by service resource constraints	Throughput	Number of requests processed per sec
	Response time	Average expected time from user making a request to the request to get a response
Service price and security	Security	Indicates the level of security of the method invocation process
	Price	The cost of the user when using the service

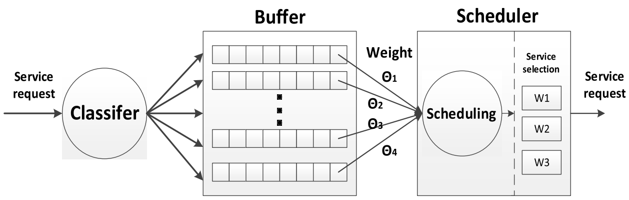

FIGURE 2. Scheduling model.

All service requests need to be scheduled by the scheduler before service selection can be performed.

When the service request passes through the classifier, it will be divided into several classes according to its priority, and then enter the corresponding queue buffer. At the same time, each queue will be given a weight according to its priority. The scheduling model sets a counter for each queue. The value is initialized to a weight. When the number of available services in the candidate service set is non-zero, the scheduler schedules the service requests in each queue in a polling manner. In addition, the counter is decremented by one per poll; when all counters are reset to weights, all counters are zero; when the number of service requests in the queue reaches the buffer capacity; subsequent service requests are no longer queued. After scheduling the service request, it will enter the service selection phase. The model sets a flag for each candidate service. The service request selects the best service that meets its requirements based on the service selection method in the previous section. When a candidate service is selected, its flag is set to an unavailable state, and its flag is set to be available at the end of the service.

Theoretical model [26]–[28]: In the energy loss optimization scheduling modeling process, based on the equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment, the multi-objective equipment scheduling optimization equation in the IoT environment constructed with the constraint of interval scheduling efficiency. The fuzzy algorithm converts multiple target problems of energy loss into single-objective problems. The specific steps are as follows. In the energy loss optimization scheduling process, there are three optimized targets, equipment scheduling energy cost in the IoT environment, equipment usage cost, and scheduling operation time of all devices in the IoT environment. Among them, the equipment scheduling energy cost and equipment usage cost in the Internet of Things environment used to describe the equipment scheduling cost in the Internet of Things environment.

The equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment are first According to the constraint of interval scheduling efficiency, the multi-objective equipment scheduling optimization equation in the IoT environment is constructed, and the fuzzy algorithm is used to convert multiple target problems of energy loss into single-objective problems, in order to realize the equipment in the IoT environment considering energy loss. Scheduling optimization modeling laid the foundation.

Assuming that $\boldsymbol{i}$ represent the total energy consumption of each device scheduling, it concludes that the energy consumption of each device scheduling is

$$\mathrm{E}_i = \sum_{q \in \mathrm{Q}_i} m_i(\alpha_i + \beta_i v_{iq} + \gamma_i v_{iq}^2) l_q r_i \tag{7}$$

To the above formula, the total energy consumption of all equipment scheduling in the IoT environment can obtain.

$$\mathrm{E} = \sum_{i \in I} \sum_{q \in Q_i} m_i(\alpha_i + \beta_i v_{iq} + \gamma_i v_{iq}^2) l_q r_i \tag{8}$$

where $\boldsymbol{m_i}$ represents the quality of device $\boldsymbol{i}$. In the process of energy loss optimization scheduling modeling, the sum of all equipment scheduling running times expressed as:

$$\mathrm{T} = \sum_{i \in I} (d_{i,\infty} - a_{i,o}) \tag{9}$$

The above-mentioned multi-objective equipment scheduling optimization equation's hybrid certificate planning problem expressed by the following formula.

$$\min F(x) = [F_1(x), F_2(x)]^T \tag{10}$$

Each objective function in the above equations can hardly reach their respective optimal solutions under the constraint conditions. It is necessary to integrate the fuzzy algorithm to convert multiple target problems of energy loss into single target problems. Expressed by the following formula

$$\max \mu + \varepsilon(N_1(x) + N_2(x))/2 \tag{11}$$

In summary, based on the equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment, the multi-objective under the IoT environment constructed with the constraint of interval scheduling efficiency. The equipment scheduling optimization equation integrated into the fuzzy algorithm to convert multiple target problems of energy loss into single-objective problems, which lays a foundation for realizing equipment scheduling optimization modeling in the IoT environment considering energy loss.

D. ENERGY LOSS OPTIMIZATION SCHEDULING MODELING

Establish the equipment scheduling energy consumption model in the IoT environment, and search for the idle time of the equipment based on the earliest start and end time of the task and the latest allowable start and end time to consider the energy. The premise of loss is to optimize the energy consumption model for equipment scheduling, and reduce the overall energy consumption of equipment scheduling in the IoT environment. The specific steps are as follows.

Considering that a task may execute repeatedly on different devices, the following formula can used to calculate the total energy consumed when all devices in the IoT are in operation.

$$EC_{busy} = pc_{busy} \sum_{j=1}^{m} \sum_{i=1}^{n} x_{ij} \cdot t_i \tag{12}$$

where EC_{busy} represents the total energy consumed by all equipment while it is in operation.

In the IoT environment considering energy loss, $L_{\max}$ represents the length of the scheduled task, that is, the completion time of the last task, which can be obtained by

$$L_{\max} = \max_{\mathrm{i}=1}^{\mathrm{n}} \max_{j=1}^{m} (f_{ij}) \tag{13}$$

In the IoT environment considering energy loss, each task and its relative predecessor tasks assigned to the same node, and the shortest device scheduling length obtained.

$$LACT(\mathrm{v}_i) = \begin{cases} ECT(v_i) \\ \min(LAST(v_i - c_{ij})) \end{cases} \tag{14}$$

In summary, the principle of energy loss optimization scheduling modeling method based on multi-objective fuzzy algorithm can explain, and the energy loss optimization's schedule model is established.

IV. EXPERIMENTAL RESULT

A. MODELING PRINCIPLE OF ENERGY LOSS SCHEDULING OF IoT

The scheduling relationship complexity between devices changes with time. Therefore, the space-time data of task scheduling in the IoT environment used to analyze the device scheduling and its tasks in real time. The relationship, forming a certain scheduling time series, and a detailed description of the scheduling time series, based on this to achieve dynamic modeling of equipment scheduling in the Internet of Things environment. The specific steps are as follows:

The objective function that calculates the minimum energy consumption of the equipment scheduling is expressed by the following formula:

$$\min_{\mathrm{u,p}} \sum_{t=1}^{T} \sum_{i=1}^{N} u_{it} f(p_{it}) + (1 - u_{i(t-1)}) u_{it} S_i \tag{15}$$

where T represents the overall running time of the device scheduling, N represents the number of devices, and $\boldsymbol{u_{it}}$ represents the operating state of device i during the t period. In the energy loss optimization scheduling modeling process, the time series of equipment scheduling is the core basis of equipment energy-saving scheduling, and the equipment scheduling model in the Internet of Things environment considering energy loss is established by using the following constraints.

$$\mathrm{u}_{it} \geq \mathrm{u}_{jt} \forall i, \quad j \in (0, N) \tag{16}$$

In the formula, $\boldsymbol{u_{it}}$ and $\boldsymbol{u_{jt}}$ respectively indicate the scheduling operation states of the devices i and j during the t period.

In summary, the principle of equipment scheduling modeling in the IoT environment considering energy loss can be explained, and the equipment-scheduling model in the Internet of Things environment considering energy loss is established.

Based on the multi-objective fuzzy algorithm, the equipment scheduling modeling method in the IoT environment considering energy loss is in the process of energy loss optimization scheduling modeling. Scheduling energy costs and equipment scheduling time based on equipment in the IoT environment. Then, the multi-objective equipment scheduling optimization equation is constructed in the Internet of Things environment, and the multi-objective problem of energy loss is transformed into a single-objective problem by combining the fuzzy scheduling algorithm with the interval scheduling efficiency as the constraint.

B. MODEL-BASED EXPERIMENT RESULTS

The experiment used the Matlab7.0 platform to establish an experimental environment. The experiment uses two real task sets, Robot and FPPPP. The number of tasks set in the Robot task set is 90, the average execution time is 29.6s, and the number of tasks in the FPPP task set is 343. The average execution time is 22.3s. The parameter settings is shown in Table 2.

TABLE 2. Attribute of different task sets.

Task Set	Number of tasks	Average execution time（ms）
Robot	90	29.6
FPPPP	343	22.3

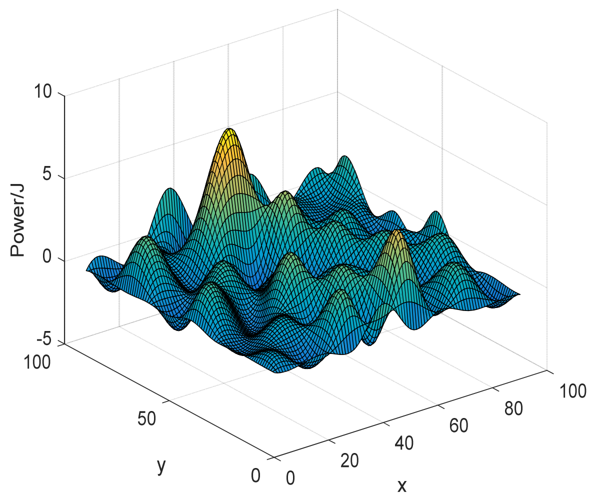

FIGURE 3. Energy consumption diagram of the IoT node.

Using the method 1 on the task set Robot and FPPPP respectively, the equipment's scheduling model in the Internet of Things environment established by calculating the optimal relaxation coefficient of the equipment in the IoT environment. It reduced the frequency of the frequency when running different tasks. The theory is integrated into the equipment scheduling's model in the Internet of Things environment; Method 3 is based on the multi-objective fuzzy algorithm for the equipment scheduling model in the IoT environment considering energy loss. The task set is simulated by the equipment scheduling's model in the IoT environment considering energy loss. The energy consumption diagram of the IoT node is shown in the Figure 3 and Figure 4.

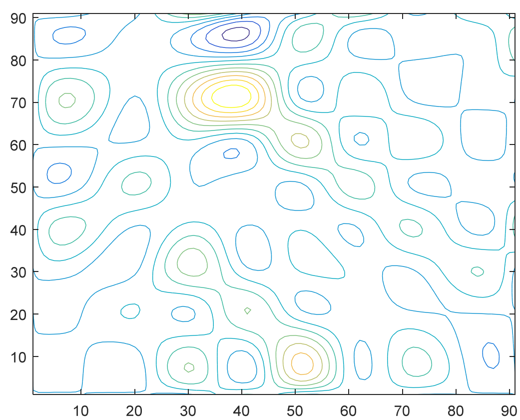

FIGURE 4. Energy consumption contour map of the IoT node.

Based on multi-objective fuzzy algorithm, the equipment scheduling modeling method in the IoT environment considering energy loss is in the energy loss optimization scheduling modeling process.

On different experimental task sets, the scheduling length and energy cost of the three algorithms under different experimental times compared to verify the effectiveness of the improved algorithm. The experimental results are shown in the Table 3∼6, and Figure 5∼8.

TABLE 3. Device scheduling length for task set Robot.

Number of experiment	Scheduling Lengths（S）		
	Improved Method	Method 1	Method 2
5	620	700	800
15	620	720	850
20	620	750	850
25	620	750	860
30	640	750	860
35	640	750	860
45	640	750	860
55	640	760	860

TABLE 4. Device scheduling length for task set FPPPP.

Number of experiment	Scheduling Lengths（S）		
	Improved Method	Method 1	Method 2
5	650	770	850
15	650	770	850
20	650	770	850
25	650	770	880
30	680	770	880
35	680	770	880
45	680	780	880
55	680	780	880

TABLE 5. Energy consumption for task set Robot.

Number of experiment	Energy Consumption(J)		
	Improved Method	Method 1	Method 2
5	40	300	500
15	40	300	500
20	40	300	500
25	40	300	500
30	50	320	520
35	50	320	520
45	50	320	520
55	50	320	520

Inevitably, due to the conflicting nature of multiple objectives, each target cannot be optimized at the same time. In this experiment, on the basis of reducing the delay by cooperation, the completion time is basically declining, but the processing cost is due to The increase in collaboration costs is on the rise.

To this end, the dispatcher needs to screen the resulting plan according to personal preferences, and achieve its stated goals in the case of other relatively good goals.

Production scheduling is the core module for enterprise-oriented production, adapting to internal and external

TABLE 6. Energy consumption for task set FPPPP.

Number of experiment	Energy Consumption(J)		
	Improved Method	Method 1	Method 2
5	43	350	540
15	43	350	540
20	43	350	540
25	43	350	540
30	55	380	560
35	55	380	560
45	55	380	560
55	55	380	560

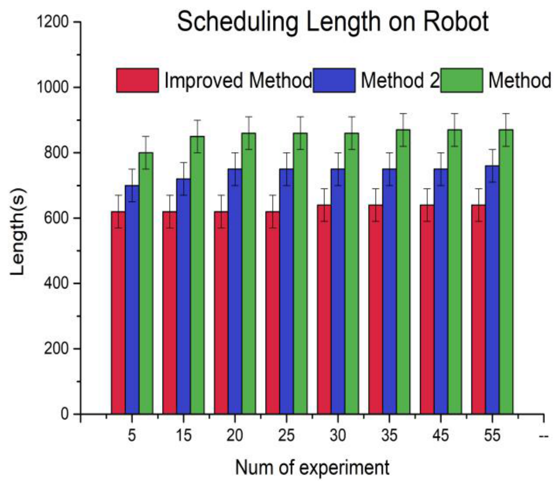

FIGURE 5. Scheduling Length on Robot.

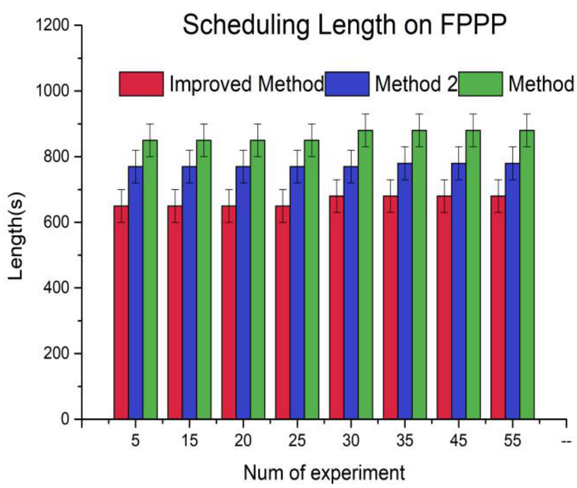

FIGURE 6. Scheduling Length on FPPP.

environmental changes, and external collaboration. The implementation of production scheduling requires planning guidance, the planning is the goal of scheduling, and the scheduling constrains the planning. Poor adaptability of production plans based on an idealized scheduling environment will directly affect the implementation of the scheduling.

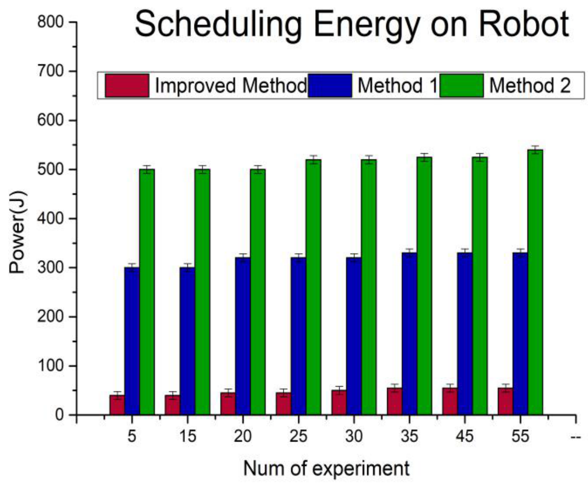

FIGURE 7. Scheduling Energy on Robot.

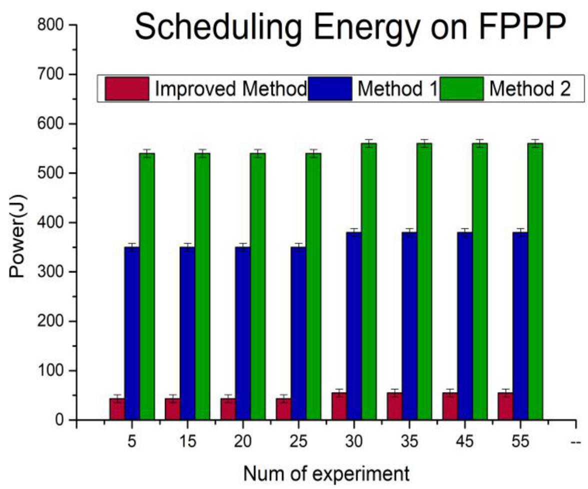

FIGURE 8. Scheduling Energy on FPPP.

Poor scheduling can lead to issues such as planned rescheduling, unbalanced load, and severe waste of resources. With the widespread use of supply chain management, in order to maximize the overall economic benefits of the supply chain, production planning has a broader meaning, including production coordination production planning.

From the results of Table 4, Table 5, and Table 6, it can be seen that the emergency demand changes with time. When the emergency response time is 25 minutes, the emergency resource demand changes. Therefore, the emergency resource scheduling plan must be adjusted to meet the emergency resource demand. Variability over time. Although the earliest emergency response time of the emergency dispatching scheme of the final scheme is longer than that of the initial scheme, it considers the emergency resource demand and the dynamic variability of the travel time and time, so it is closer to the actual situation.

From the above analysis, we can see that the meta-heuristic algorithm is mainly divided into two optimization models, one is based on a single solution algorithm, such as solid annealing algorithm, tabu search algorithm, etc.; the other is based on population strategy, such as genetic algorithm, ant colony algorithm, etc., whichever has its own advantages and disadvantages, need to choose the appropriate algorithm for different needs.

In summary, the principle of equipment scheduling modeling in the IoT environment considering energy loss can be explained, and the equipment-scheduling model in the Internet of Things environment considering energy loss is established.

Firstly, it based on the equipment scheduling energy consumption cost and equipment scheduling time in the IoT environment. Then construct multi-objective equipment scheduling optimization equations in the Internet of Things environment with the constraint of interval scheduling efficiency and incorporating fuzzy algorithm to convert multiple target problems of energy loss into single-objective problems.

Test the task completion time of the improved algorithm. It can see from the Figure 9 and Figure 10 that the task

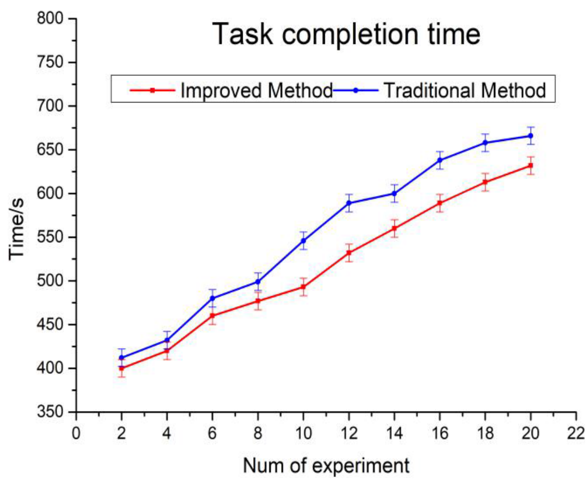

FIGURE 9. Task completion time comparison.

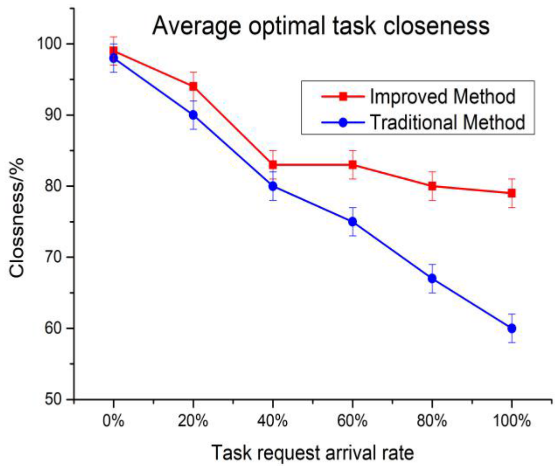

FIGURE 10. Average optimal task closeness comparison.

completion time of the scheduling model improved by the algorithm is significantly smaller than the traditional method.

When the task requests arrival rate increases, the average optimal task closeness of each task queue gradually decreases, but the average closeness of this model is slightly higher than the traditional method, as show in the figure.

It can see from Figure 5 to Figure 10 that the energy loss of the equipment scheduling's model in the IoT environment improved by the algorithm, and the scheduling length is smaller than other algorithms. This is mainly because the improved algorithm first uses the equipment in the Internet of Things environment. Based on the scheduling energy consumption cost and equipment scheduling time, the multi-objective equipment scheduling optimization equation in the IoT environment constructed with the constraint of interval scheduling efficiency. The fuzzy algorithm used to convert multiple target problems of energy loss into single-objective problems. Based on this, the equipment scheduling energy consumption model in the Internet of Things environment established, the idle time of the device searched for by the task's earliest start and end time, and the latest allowable start and end time taken as the premise to consider the energy loss. The energy consumption model is scheduling for optimization.

V. CONCLUSION

The equipment scheduling modeling method based on multi-objective fuzzy algorithm considering the energy loss of the Internet of Things has high modeling accuracy and good energy saving effect. The result of the device scheduling model established for the current algorithm is significantly different from the actual algorithm. An energy loss optimization scheduling model based on multi-objective fuzzy algorithm is established. The multi-objective equipment scheduling optimization equation in the IoT environment is composed of equipment scheduling energy consumption and interval scheduling efficiency in the IoT environment, and equipment scheduling energy consumption in the Internet of Things environment. The model is completed by task integration. The experimental results show that the equipment scheduling modeling method based on multi-objective fuzzy algorithm considering the energy loss of the Internet of Things has higher modeling accuracy and better energy saving effect.

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