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Evolutionary Algorithm of Optimization Technology in IoT Data Management Communication Based on Artificial Intelligence and Edge Computing

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Abstract: *Nowadays, the development level of the Internet of Things (IoT) and related technologies is getting higher and higher, and the development speed is getting faster and faster, and its data management is becoming more and more important. How to optimize the calculation in its communication data will be a technical problem that needs to be broken through urgently. Artificial intelligence (AI) is a high-tech that has developed rapidly in recent years. It can simulate the human brain to perform some complicated tasks, and can also combine various recognition technologies to identify various items. Using AI can make IoT communication more efficient. Edge computing (EC) is a more efficient algorithm developed on the basis of cloud computing (CC), which can effectively reduce the computing process of the device, thereby reducing the power consumption of the device and improving the computing speed. This paper aims to study the management of IoT data by combining AI and EC technology, so as to further improve the efficiency of personnel communication in communication, improve the speed of logistics, and ensure the safety of logistics. This paper proposes a CNN neural network model, which combines EC to optimize the data management of IoT communication technology, and conducts simulation tests from the aspects of power consumption, queue average and overall performance. The final results show that the overall power consumption of the optimization algorithm in this paper is about 15W lower than that of CC, and about 18W lower than that of traditional EC, and the average queue value is the smallest. And the evolutionary EC proposed in this study has the best optimization effect, and its final objective function value is about 70 lower than CC and about 30 lower than traditional EC. Finally, the algorithm proposed in this study has advantages in queue value and power consumption, and the overall performance is also significantly improved.*

Keywords: *Artificial Intelligence, Edge Computing, IoT Data, Communication Optimization*

1. Introduction

As the IoT rapidly develops, increasingly number of resource-constrained machines and devices are connected to ultra-dense networks, posing huge challenges to wireless networks. In the 5G cellular network currently under rapid construction, there can be hundreds or thousands of machines connected to the network at the same time, which brings unprecedented challenges to the connectivity of the network. Unlike traditional cellular communications, most services in MTC systems are above-line dominated, with relatively small data sizes and critical latency requirements. As an important part of the data acquisition terminal, its requirements are getting higher and higher. For the IoT acquisition terminal in the WAN environment, battery power supply is a common power supply method, and an important criterion for evaluating the performance of a battery power supply system is the battery operating time. Therefore, power consumption has become an important indicator to measure the performance of the terminal. Reducing power consumption can focus on two aspects: hardware low power consumption and software low power consumption. At present, the development of hardware low-power technology related to the wide area IoT is becoming more and more mature. With its technical advantages such as wide coverage, large number of connections, and low cost and power consumption, the NB-IOT technology that has been put into commercial use can be applied to IoT scenarios where communication methods are applicable.

The prevalence of the IoT also brings many problems such as coexistence management with traditional human communication and the large amount of data generated by IOT devices, which increases the pressure on communication network traffic. The current computing solutions are difficult to meet the high requirements for real-time data processing results in typical MTC scenarios such as smart factories.

AI combined with a variety of technologies can help people realize intelligent voice, fingerprint, face recognition, etc., which can improve logistics efficiency and ensure logistics security. Combining AI and EC to optimize Internet data management is a practical and urgent technical problem that needs to be broken through. The breakthrough of this technology will greatly improve the data management efficiency of the IoT, and is more conducive to serving the society and the people.

The innovations of this paper are as follows: (1) It proposes an optimization algorithm combining AI and EC. (2) It solves the problem of high power consumption of the data acquisition terminal. (3) The data comparison with the traditional data management optimization algorithm can better reflect the advantages of this algorithm.

2. Related Work

The world of AI is taking shape, and the LOT revolution is helping companies change the way they do business, work smarter, and achieve better results. Mckeithan P's research shows that processors can harness the power of digitization to more safely and efficiently produce products, goods or services due to the rapid increase in device availability, combined applications and always-on opportunities. For years, the industrial processing sector has lagged the consumer market in cutting-EC technology. But this is all changing as personal life expectations collide with the workplace, and there are multiple ways to change outdated, dry modes of operation [1]. Wan S proposed a three-layer online data processing network based on MEC technology and an online edge processing scheduling algorithm based on Lyapunov optimization. At the same time, the hovering UAV base station provides a large and flexible service coverage, leading to path planning problems. Wan S also considered this problem and applied deep reinforcement learning to develop online route planning algorithms. Through simulation, Wan S verified its effectiveness in improving service coverage, and this result will have an important role in the future big data processing of the IoT [2]. Ubiquitous big data, IoT and smart devices are revolutionizing society. Today personal lives are tracked and digitized by gamification. Sung S H said that in gamification, information is relevant for all income levels, genders and families, and society needs to embrace and exploit this phenomenon to improve safety and productivity. Managing and then unlocking massive amounts of unstructured data in an IoT society requires the use of the latest tools and methods. Sung S H shows that gamification can be more convenient, and like personal smart devices, these technologies promise to significantly improve operator feedback, tracking, and performance management at a lower cost [3]. Sean describes two strategies for managing IoT data replication and consistency in Fog infrastructure. Sean's strategy is to choose an appropriate number of replicas and their locations for each piece of data to reduce data access latency and replica synchronization costs. This is done while respecting the required level of integrity. Sean also proposed an evaluation platform based on the simulator iFogSim, allowing users to implement and test their own IoT data replication and integrity management strategies. According to Sean's experiments, using Sean's strategy, compared with iFogStor, the service latency of small Fog infrastructure can be reduced by 30%, and the service latency of large Fog infrastructure can be reduced by 13% [4]. Naas MI introduces an energy management system (EMS) for smart homes. In this system, each home device interfaces with a data acquisition module, which is an IoT object with a unique IP address, enabling a large mesh wireless network of devices [5]. IoT security is more of a need than a technical issue, as it requires a common set of governance and fail-safe systems. Therefore, the Al-Ali AR research proposes efficient key management to make IoT data reliable in CC. Compared with existing sensor network key distribution centers, the cloud proxy key server federated key management proposed by Al-Ali AR allows to recover and update active keys instead of a central management point. The key management proposed by Al-Ali AR is not a pre-determined private key method, but a method to share key information for cloud proxy key servers in autonomous clouds, reducing key generation and space complexity. In addition, Al-Ali AR compares with previous IoT key research conducted, cloud proxy key server federated key provides the ability to extract meaningful information when moving data [6].

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3. IoT Communication Data Management Method Based on AI and EC

3.1 AI Technology

After Turing, it was the early semiotics school that sought the concept of intelligence, and it was also the sub-school computer software school (or logic school), the early school of AI research. The Semiotics view AI as the science and engineering of creating intelligent machines, especially intelligent computer programs. Accordingly, the task of using computers to learn as much as possible about human intelligence is not limited to trying out methods observed in biology. The current explanation holds that AI is a science and technology that develops and studies the knowledge, technology, theories, and methods used to simulate and expand human beings [7].

At present, the core technologies of AI mainly include pattern recognition, intelligent algorithms, data mining, and machine learning. Pattern recognition mainly includes fingerprint recognition, face recognition, speech recognition, etc.; intelligent algorithms currently include various neural network algorithms, such as RNN, CNN, BP, etc.; the main methods of data mining include classification, valuation, clustering, etc. Machine learning methods can be divided into many categories according to learning strategies, means, methods and goals, and their algorithms include EM algorithms, deep learning algorithms, etc., as shown in Figure 1 [8].

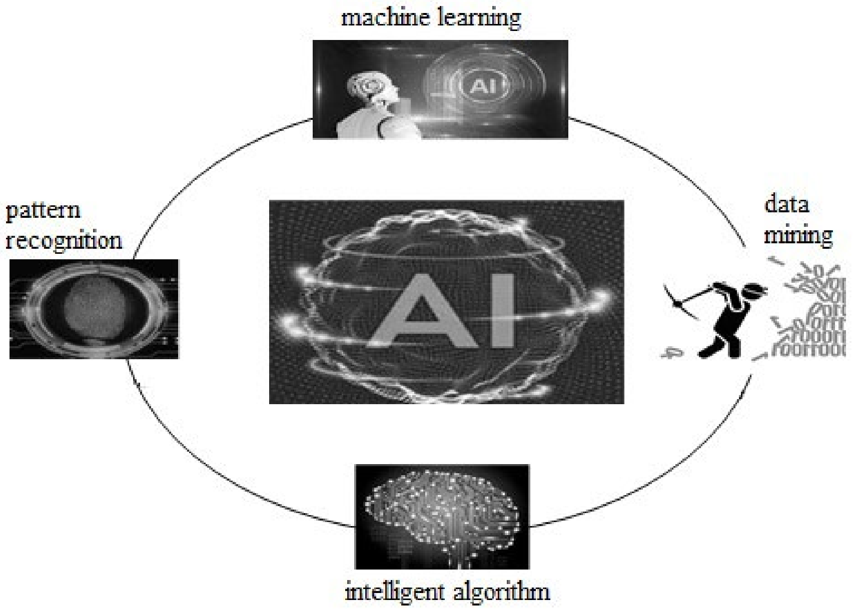

Figure 1. AI core technology

3.2 EC

If CC is the human brain, then EC is the nerve endings of human beings, which can receive data faster and more directly. EC has evolved over 18 years since Akamai's partnership with IBM in 2003. Data consumers can obtain data faster through EC, and data producers can also serve data more conveniently through EC. In this way, the amount of data through CC is relatively reduced, and the pressure of CC is naturally reduced [9].

3.3 IoT Communication Data Management

(1) Concept: IoT, that is, the Internet of things connected with things. Although the IoT has the same functions as the Internet and sensor networks, it has its own unique characteristics. The IoT basically combines two networks, that is, information can be collected and then transmitted to the system network, and the system network will make corresponding responses according to the collected information. According to the characteristics of the IoT, the whole system can be divided into perception layer, network layer and application layer. The perception layer is to perceive the information of the surrounding environment, and obtaining the information needed by the system is the main task of the perception layer. In the perception layer, some perception terminal devices are used to

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obtain information, such as sensor nodes, two-dimensional codes, RFID, digital cameras, etc. The network layer is also called the transport layer. Its task is to transmit and exchange the information perceived by the perception layer, playing the role of a transporter. The application layer, also known as the processing layer, mainly processes the information transmitted by the network layer, and then can respond accordingly, or obtain the information required by the user through the application layer. IoT requires the automatic collection, processing and analysis of data about the environment and things in real time 24 hours a day. On this basis, a service platform is built to make social life and production decisions more intelligent, and provide information through various application systems. Ultimately, it connects people to different devices to form the IoT, providing different types of services when and where. The basic IoT organization, which is mainly composed of various networks, gateways, data collectors, data processing centers, and client terminals [10].

(2) Features: One of the most important purposes of IoT devices is to obtain data from the surrounding material world. IoT data has the characteristics of multi-source heterogeneity, massiveness, spatiotemporal correlation and real-time. In the wireless sensor network, a wide variety of sensors such as temperature and sound are all data sources, and their data content and format are different due to different types and performances. In the RFID system, the varieties of tags and readers are also very diverse. These complex and diverse sources of data come in numerous formats, including objects, text, images, audio and video, and more. The different architectures of the various subsystems of the IoT cause the polymorphism and heterogeneity of this data. With the development of technology and the increase of interconnected devices, the multi-source heterogeneity of its data is more prominent [11-12].

Aiming at the difficulties of IoT data processing, the current research still has many limitations, mainly the intelligent identification of a single sensor in the IoT, the compressed sensing technology in the sensor network, or the new network interconnection. Focus on the network layer of the technology, or the hardware layer, such as Qualcomm servers [13].

3.4 Communication Data Management Optimization Algorithm

Denoting r as the proximity distance from the user to the base station, and P denotes the probability density function of r. Using the random geometry method of setting up the base station in the network, we can obtain:

$$P[r > R] = e^{-\lambda\pi R^2} \tag{1}$$

In the formula, λ is the density parameter, and R is the interference distance of other base stations.

From this, the cumulative distribution function f_r can be obtained as:

$$f_r = \frac{dF_r(r)}{dr} = e^{-\lambda\pi r^2} 2\pi\lambda r \tag{2}$$

When the proximity distance changes, the cumulative distribution function can be calculated as:

$$f(r_n) = \frac{2(\pi\lambda_\alpha)^n}{(n-1)!} {r_n}^{2n-1} e^{-\pi\lambda_\alpha {r_n}^2} \tag{3}$$

Where α represents the loss coefficient of the channel. Then the density function of the first n adjacent distances is:

$$f(r_1, r_2, \dots, r_n) = e^{-\lambda\pi {r_n}^2} (2\lambda\pi)^n r_1, \dots, r_n dr_1, \dots, dr_n \tag{4}$$

The channel spectrum is represented by p_c, then:

$$p_c(T, \lambda, \alpha) \triangleq P[SINR > T] \tag{5}$$

In the formula, SINR represents the signal-to-interference plus noise ratio, that is, the "signal-to-noise ratio", and T is a limited range. And there are:

$$\mathrm{SINR} = \frac{h{r_1}^{-\alpha}}{\sigma^2 + I_{r_1}} \tag{6}$$

$$I_r = \sum_{n\in\Phi} g_n {R_n}^{-\alpha} \tag{7}$$

In the formula, h represents the enhancement parameter of the signal, σ^2 represents the signal variance, I represents the transmit power, and g_n represents the interference channel.

According to the above formula, we can continue to derive:

$$p_c(T,\lambda,\alpha)=E_{r_1}\left[P[SINR>T|r_1]\right]=\int_{r_1>0}e^{-\lambda\pi r_1{}^2}P\left[h_1>Tr_1{}^{\alpha}(\sigma^2+I_{r_1})|r_1\right]2\pi\lambda r_1dr_1 \tag{8}$$

According to formula (1), it can be known that:

$$P\left[h_1>Tr_1{}^{\alpha}(\sigma^2+I_{r_1})|r_1\right]=\mathrm{E}_{\mathrm{I}_{r_1}}\left[\exp(-\mu\mathrm{Tr}_1{}^{\alpha}(\sigma^2+\mathrm{I}_{r_1}))|r_1\right]=\mathrm{e}^{-\mu\mathrm{Tr}_1{}^{\alpha}\sigma^2}\mathcal{L}_{\mathrm{I}_{r_1}}(\mu\mathrm{Tr}_1{}^{\alpha}) \tag{9}$$

According to Laplace's transformation, it can be known that:

$$\mathcal{L}_{\mathrm{I}_{r_1}}(\mathrm{s})=\exp(-2\pi\lambda\int_{r_1}^{\infty}(1-\mathrm{E_g}[\exp(-\mathrm{sgv}^{-\alpha})])\mathrm{vdv}) \tag{10}$$

By substituting $s=\mu\mathrm{Tr}_1{}^{\alpha}$ into:

$$\mathcal{L}_{\mathrm{I}_{r_1}}(\mu\mathrm{Tr}_1{}^{\alpha})=\exp(-2\pi\lambda\int_0^{\infty}\int_{r_1}^{\infty}(1-\mathrm{e}^{-\mu\mathrm{Tr}_1{}^{\alpha}\mathrm{v}-\alpha\mathrm{g}})\mathrm{vdv})\mathrm{f(g)dg}) \tag{11}$$

Assuming that the channel gain function is a Rayleigh distribution, then we can obtain from the above:

$$\mathcal{L}_{\mathrm{I}_{r_1}}(\mu\mathrm{Tr}_1{}^{\alpha})=\exp\left(-2\pi\lambda\int_{\mathrm{r}}^{\infty}(1-\frac{1}{1+\mu\mathrm{T}(\frac{\mathrm{r}}{\mathrm{v}})^{\alpha}})\mathrm{vdv}\right) \tag{12}$$

The final signal frequency is:

$$p_c(\mathrm{T},\lambda,\alpha)=\int_{\mathrm{r}>0}2\pi\lambda\mathrm{r}\mathrm{e}^{-\lambda\pi\mathrm{r}^2}\mathrm{e}^{-\mu\mathrm{Tr}_1{}^{\alpha}\sigma^2}\exp\left(-2\pi\lambda\int_{\mathrm{r}}^{\infty}(1-\frac{1}{1+\mu\mathrm{T}(\frac{\mathrm{r}}{\mathrm{v}})^{\alpha}})\mathrm{vdv}\right)\mathrm{dr} \tag{13}$$

Using the improved gradient algorithm, let the gradient function be f, k represents the number of iterative calculations, and g represents any iterative value, where the iteration method is:

$$\mathrm{x}^{(\mathrm{k}+1)}=\mathrm{x}^{\mathrm{k}}-\alpha\mathrm{g}^{\mathrm{k}} \tag{14}$$

Setting the minimum gradient function to get the optimized model:

$$\mathrm{f}_{\mathrm{bcst}}^{(\mathrm{k})}=\min\left\{\mathrm{f}(\mathrm{x}^1),..,\mathrm{f}(\mathrm{x}^{\mathrm{k}})\right\} \tag{15}$$

C is expressed as a set of convex functions of gradient, and the gradient projection method can be expressed as:

$$x^{(k+1)}=P(x^k-\alpha g^k) \tag{16}$$

Where P is the projection, and g is an arbitrary iterative value.

Then the distance from point x to C can be expressed as:

$$\mathrm{dist}(\mathrm{x}_0,\mathrm{C})=\inf\{\|\mathrm{x}_0-\mathrm{x}\||\mathrm{x}\in\mathrm{C}\} \tag{17}$$

The value of the projection function P in the set C and the closest point x_0 can be expressed as:

$$\mathrm{P_C}(\mathrm{x}_0)=\mathrm{argmin}\{\|\mathrm{x}_0-\mathrm{P_C}(\mathrm{x}_0)\||\mathrm{x}\in\mathrm{C}\} \tag{18}$$

The C set is represented as a set of linear sets, namely:

$$\mathrm{Ax}=\mathrm{b},\quad \mathrm{f_i}(\mathrm{x})\le\mathrm{o},\mathrm{i}=1,\dots\mathrm{m} \tag{19}$$

The expression of the solution parameter x is obtained, and any optimal solution is the projection of x to the set C.

$$\min\mathrm{imize}\|\mathrm{x}_0-\mathrm{x}\|_2^2 \tag{20}$$

4. Algorithm Testing Based on AI and EC

In the IoT smart factory scenario, each task has its own edge server, and the intelligent data collection terminal uploads the collected images, videos and other data to the queue of its corresponding edge server through wireless transmission. Different from the offloading of traditional computing tasks, this paper studies the design of offloading schemes based on the particularity of convolutional neural network computing tasks. The neural network model is shown in Figure 2. Figure 2 (a) is the three-dimensional model of the neural network, and Figure 2 (b) is the computational model of the CNN neural network.

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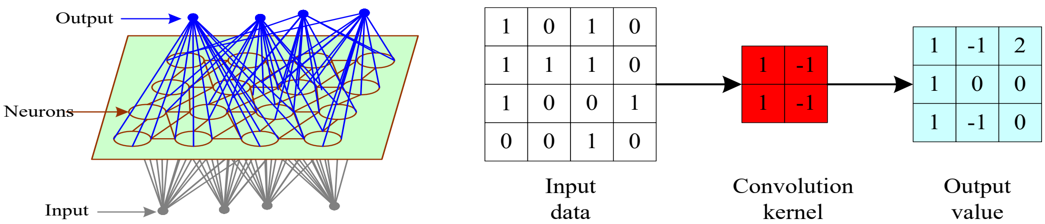


(a) 3D model of neural network (b) CNN calculation model

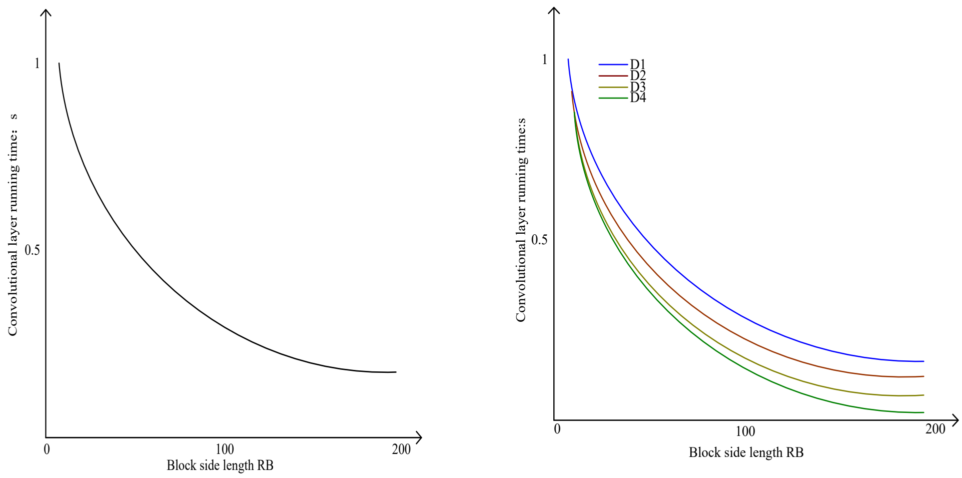
Figure 2. CNN model

The CNN neural network calculation method is to perform the so-called convolution process through the convolution kernel calculation according to the data of the queue or matrix, so as to reduce the amount of operation data and reduce power consumption.

Table1.The main parameter settings of the simulation test

System parameters	Take value
The power of the base station to transmit energy	5W
Frame length	10ms
Energy conversion efficiency	0.5
Noise variance	10^{-6}

This article will test and analyze it through simulation and actual IoT terminals. The main parameters of the simulation process are shown in Table 1. The simulation mainly analyzes the validity of the established time model, and analyzes how each parameter affects the running time of the convolution layer. The actual test of the IoT terminal is to run the target detection algorithm on the IoT terminal with certain resources to achieve target detection, and analyze the actual effect of the convolution parallel parameters and ordinary parameters obtained by the established time model running on the IoT terminal. Figure 3 shows the relationship between CNN block and running time, in which Figure 3 (b) shows the relationship curves under different parallelisms, and there are parallelisms D1<D2<D3<D4. The larger the convolutional layer block, the shorter the CNN operation time, the higher the parallelism, and the shorter the operation time.



(a) (b)

Figure 3. The relationship between CNN block and runtime for different degrees of parallelism

Figure 4 shows a flow chart of the task computation data in the transmission slot. The data is first sent to the edge server queue by the video image acquisition device, and the pre-task computing unit of the edge server is in a time slot according to the CPU computing frequency set by itself. According to the CNN level index, the source data is calculated to calculate the intermediate data of the first several layers of the CNN, and the intermediate data output by the calculation is sent to the data transmission buffer of the edge server. The data transmission buffer is based on the transmission power set by itself. Intermediate data is transferred to the cloud server queue. The cloud server allocates the CPU computing frequency to the second half of the task through the post-task computing unit, and finally outputs the calculation results.

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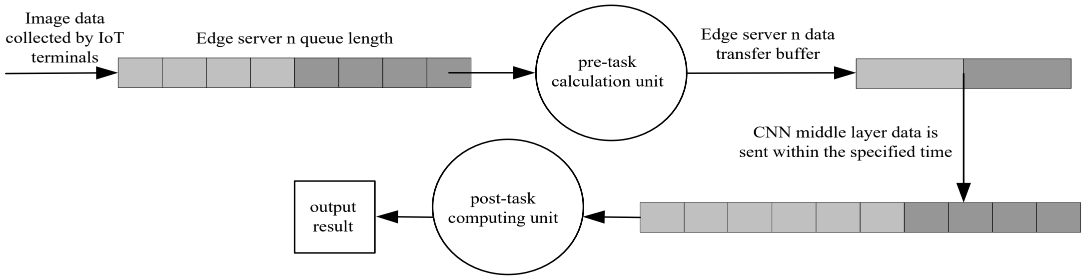

Figure 4. Computer data flow diagram

Allocating the number of layers of CNN neural network and the CPU frequency of edge servers to tasks also affects the queue status of edge servers, and even the queue status of cloud servers. Likewise, the CPU frequency allocation for each task on the edge server also affects the data in the queue. Therefore, according to the mathematical model of the optimization problem established in the previous algorithm section, the tasks on the edge server are allocated to the number of convolutional neural network layers, the CPU frequency of each task and the edge server to reduce the total power consumption of the system. Figure 5 is a comparison of the network throughput of traditional communication technology, CC, and the optimized communication technology improved in this paper. The throughput of the more popular CC methods continues to increase when the amount of data continues to increase from Figure 5. Although the computing speed is not traditionally fast, its data throughput even exceeds that of traditional algorithms. The CNN optimization communication technology algorithm studied in this paper has the least network throughput, and the throughput is about 1/2 of the traditional algorithm and about 1/3 of the CC.

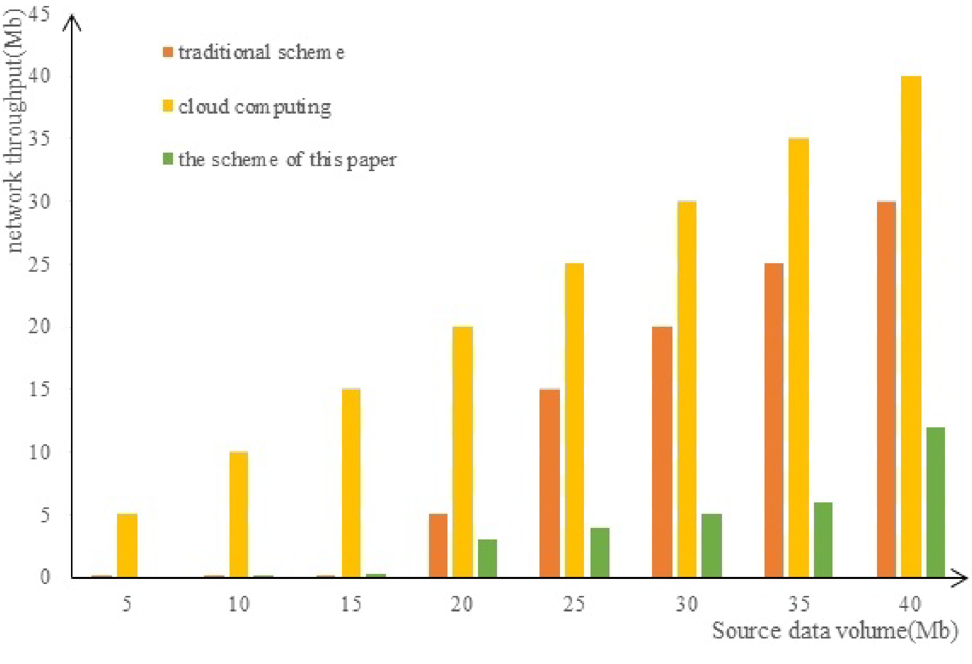

Figure 5. Network throughput comparison of the three schemes

In order to prove the effectiveness of the algorithm and unloading scheme proposed in this chapter, the simulation work shown in Figure 6 to Figure 7 is carried out in this paper, and Table 2 is the simulation test parameter setting of the loss function in Figure 6. Figure 6 shows the loss function values during training for two different online neural networks in the optimization algorithm. During the learning process of the neural network of reinforcement learning, the loss value and reward value of the neural network fluctuate due to the leap of each input state. In order to reduce the volatility, the simulation process of Figure 6 limits the change of the input state to a small amount. Therefore, under the acceptable fluctuation interference, the loss value of the two online neural networks shows a downward trend as a whole, which also proves the correctness of the optimization algorithm.

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Table 2. Simulation parameter settings for the loss function

System parameters	Take value
Maximum transmission power	1W
Battery capacity	10Ah
Channel bandwidth	15KHz
Time slot length	1ms

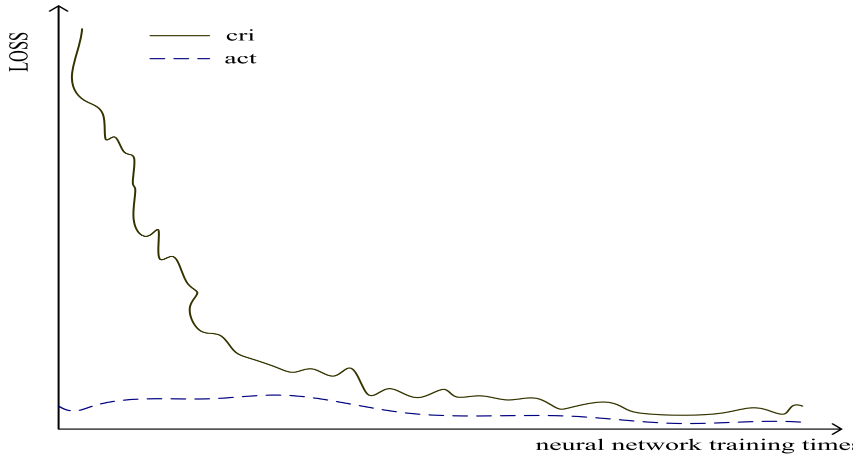

Figure 6. Comparison of loss functions for two online neural networks

In addition, this paper compares the power consumption and queue mean of the three schemes, and focuses on the analysis of the unloading performance of the calculation scheme. Table 3 shows the parameter settings of the simulation. Figure 7 (a) shows the simulation results of CC, traditional offloading scheme and the scheme proposed in this research point in terms of power consumption. The results compare the power consumption results of data at various stages of computing, which are the power consumption of local computing on the edge server, the sending power consumption when transmitting to the cloud, the computing power consumption of the cloud server, and the total power consumption of the three. According to Figure 7 (a), in terms of local computing power consumption, the CC solution is directly uploaded to the cloud for computing, so the local computing power consumption of this solution is zero. Compared with traditional EC, the solution proposed in this study has a small power consumption, but the gap is not large. In terms of transmission power consumption, it is obvious that the solution proposed in this paper is the least, followed by the traditional edge solution, and the overall power consumption of the optimization algorithm in this paper is about 15W lower than that of CC and about 18W lower than that of traditional EC.

Table 3. Simulation parameter settings for the offload performance

System parameters	Take value
Maximum cache capacity	1KB
Frame length	10Kbit
Channel bandwidth	15KHz
Noise variance	10^{-6}
Battery capacity	10Ah

In this paper, the queue mean of the server equipment is used as the comparison index to obtain the queue status of the three calculation schemes. The network queue mean in Figure 7 (b) is the sum of the edge server queue mean and the cloud server queue mean. When the queue state value at a certain moment and the amount of data arriving in the queue at that moment are determined, the main frequency of the server CPU, that is, the computing power of the server, has an obvious impact on the amount of data in the queue. From Figure 7 (b), compared with the traditional computing offloading scheme, whether it is the mean value of the edge server queue, the mean value of the cloud server queue and the sum of the two, the corresponding queue mean value of the scheme proposed in this study is relatively small. Compared with the CC scheme, the traditional computing offloading scheme has obvious advantages in the mean value of the cloud service queue, but it is limited by the computing power of the edge server, resulting in a larger mean value of the edge server queue, thus losing the overall advantage.

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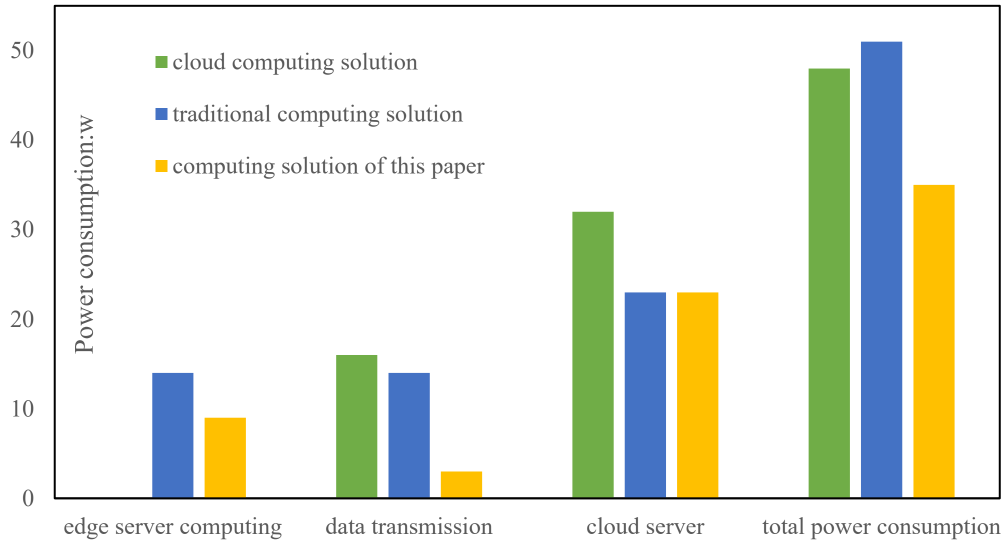
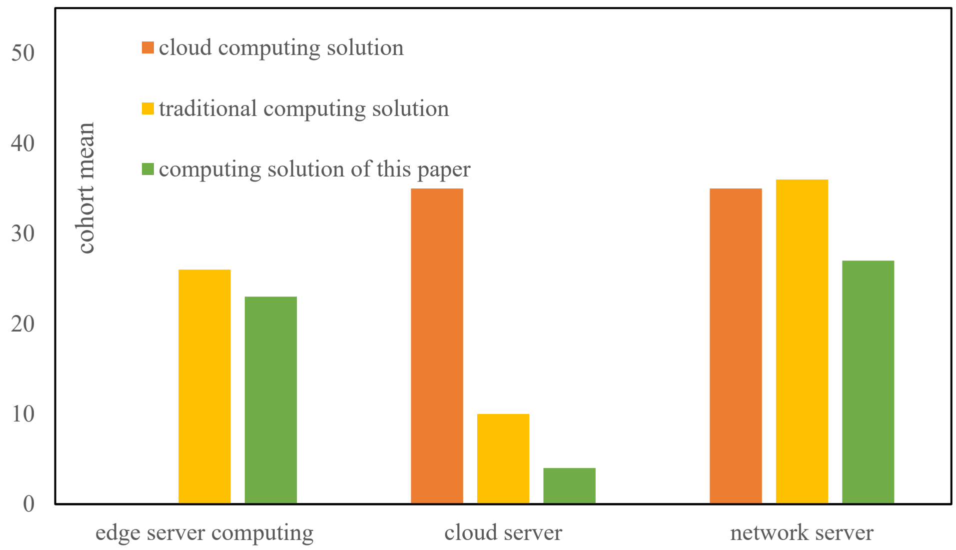


(a) Power consumption comparison



(b) Cohort mean comparison

Figure 7. Performance comparison of the three schemes

Table 4. Simulation parameter settings for overall performance

System parameters	Take value
Maximum cache capacity	2KB
Frame length	15Kbit
Channel bandwidth	20KHz
Noise variance	10^{-6}
Battery capacity	15Ah
Time slot length	1ms
The power of the base station to transmit energy	5W
Energy conversion efficiency	0.5

Finally, in order to obtain the overall performance of the EC in this paper, this paper compares the minimum values of the objective functions of the three schemes for the previous calculation methods. Table 4 shows the settings of the simulation parameters. Figure 8 shows the simulation results of the optimal function values of the three schemes under different source data input conditions. With the increasing amount of source data from Figure 8, the optimal utility function values of the three schemes increase in turn, but the result value of the CC scheme is always the largest among the three schemes. The new EC offloading scheme proposed in this study has the best computing effect, and its final objective function value is about 70% lower than that of CC and about 30% lower than that of traditional EC. Finally, the unloading scheme proposed in this study has advantages in terms of queue

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value and power consumption. Therefore, in the utility function that comprehensively considers the queue value and power consumption value, the simulation results of this research scheme are bound to be better than the other two schemes.

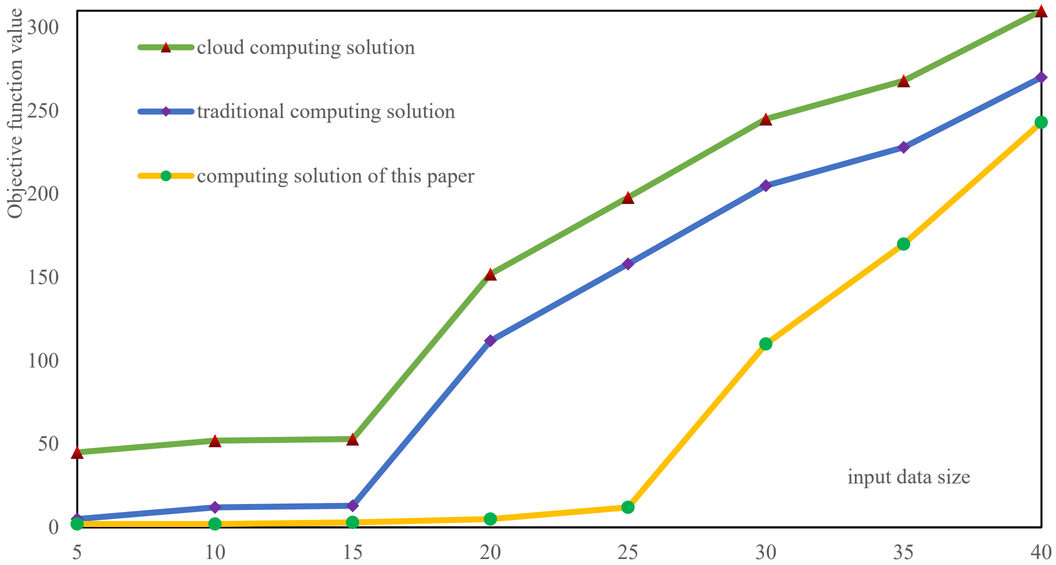

Figure 8. Comparison of objective functions of the three schemes

5. Discussion

IoT data communication is the foundation of the Internet of everything in the future. From the research status of this paper, it is necessary to design a practical and efficient IoT data management system to improve the versatility, security, reliability, autonomous interaction and other characteristics of the IoT system. To accelerate the value mining of IoT data, a lot of key technology research work is still needed. This paper studies the data management and application of the IoT based on AI and EC. The security of the scheme and the results of simulation experiments have achieved some results. However, there are still some problems in this paper that need further research.

Since it is impossible for the index structure to be optimal in every aspect, each structure has only some of its advantages, and each index structure has a major problem that affects its performance, that is, the overlapping phenomenon. Therefore, this paper also needs to improve the feature extraction algorithm to analyze the data: the clustering algorithm in the field of data mining can realize the storage of objects with close spatial distance in the same area or adjacent areas. Through the clustering algorithm, the objects located within the same node have greater aggregation, while the similarity of objects between different nodes is low, so that the overlapping area of the rectangular space of the intermediate nodes is reduced, thereby improving the retrieval efficiency. In addition, due to the movement characteristics of IoT devices and the time characteristics of data, it is also necessary to optimize the dynamic resource retrieval process with time constraints.

6. Conclusions

In the theoretical research part, this paper first introduces AI technology and edge algorithms, including their sources, functions and core technologies. Then this paper introduces the concept, characteristics and optimization algorithm of IoT communication data management, and explains it with the help of charts.

Finally, in the algorithm design of optimization and upgrading, it is mentioned that the CNN neural network in AI is used for optimization and upgrading. After simulation tests of multiple performance parameters, the results obtained are compared with traditional EC and CC, and the advantages of the scheme proposed in this paper are obtained.

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