Design of a Decentralized AI IoT System Based on Back Propagation Neural Network Model

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***Abstract*—In the Internet of Things (IoT) era, when user needs are continually evolving, the coupling of AI and IoT technologies is unavoidable. Fog devices are introduced into the IoT system and given the function of hidden layer neurons of Back Propagation neural network, and Docker containers are combined to realize the mapping of devices and neurons in order to improve the quality of service of IoT devices. This study proposes the design of a decentralized AI IoT system based on Back Propagation neural network model. The testing data revealed that, at various data transfer intervals, the average transmission rate between the fog device and the sensing device was 8.265Mbps, and that the device's transmission rate could satisfy user demand. When the data transmission interval was 20s, the network data transmission rate was greater than 8.5Mbps and did not vary much when the number of data transmissions rose. The research demonstrates that the decentralized AI IoT system's network performance, which is based on a back propagation neural network model, can match user usage requirements and has good stability.**

Keywords*—*BP neural networks; artificial intelligence; IoT systems; fog devices; Docker containers

I. Introduction

Artificial intelligence (AI) is a method for enhancing and extending human intelligence. It is a subfield of computer science that primarily focuses on the concepts of computer intelligence, human brain intelligent computers, etc. in order to advance computer applications [1]. The development of artificial intelligence (AI) can be aided by the mutual integration of mathematics and AI because AI is not confined to logical thinking but also requires the consideration of figurative and inspirational thinking [2]. The Massachusetts Institute of Technology was the first to suggest the idea of the Internet of Things (IoT), and the foundation of early IoT was radio frequency identification technology [3]. IoT applications now particularly encompass information interchange, sensing, and acquisition amongst objects. The seamless access to wireless networks has further broadened the field of IoT applications as a result of ongoing technological advancements [4]. The integration of IoT technology with computers, the Internet, and wireless communication technologies is the primary study area in the field of information technology today. IoT technology has become a popular field of technology because to its strong potential. IoT edge intelligence technologies and platform-based technologies for vertical applications are two examples of related technologies that have evolved as a result of the IoT technology boom [5]. The Internet of Things system is connected to sensors, actuators, and intelligent devices with huge amounts of data. Usually, actuators only need data from local devices to respond, rather than all devices. All data is transmitted to the cloud, transmitting a large amount of inefficient data, resulting in a waste of network bandwidth. Sending sensor data to the cloud may introduce security vulnerabilities and privacy issues. The communication path from the terminal to the cloud is long and there are many nodes, making it susceptible to network attacks. The study recommends the Back Propagation Neural Networks (BPNN) model for decentralized AI IoT of Systems (IoTS) architecture in order to further improve the level of service offered by IoT devices. The study is broken down into four sections: a summary of current BPNN and IoT technologies; the design of decentralized AIIoTS based on the BPNN model; an analysis of decentralized AIIoTS applications based on the BPNN model; and a summary of the entire article.

II. Related Works

A multilayer feed forward network trained using the error back propagation algorithm; the BPNN is one of the most well-known neural network models. The results demonstrated that the particle swarm algorithm may increase the effectiveness of fault diagnosis. Xiao's scientific research team proposes a fault diagnosis system based on particle swarm optimization BP neural network for gearbox fault diagnosis. The particle swarm algorithm is used to optimize the weights and thresholds. The results show that the algorithm can improve the accuracy of fault diagnosis by up to 85% [6]. Yang in order to train the BPNN for the issue of information fusion state estimation of multi-sensor systems, the research team presented particle swarm and additional momentum approach. The simulation results prove that the method is effective [7]. In order to enhance the effectiveness of human shape prediction, Cheng used principal component analysis to reduce the dimensionality of pertinent variables. The experimental results show that the accuracy of this method is 12% higher than the K-means prediction model [8]. For the problem of enterprise asset valuation, Xie's group proposed a BPNN-based valuation model for technology enterprises. The model included financial and non-financial performance indicators related to intellectual property, and the results indicated that the inclusion of these indicators could enhance the model training effect [9]. Shi proposed a BPNN-based short-term load forecasting model for smart grids, in which various types of data are fed into the model and its output is represented as conforming to the forecast results. Experiments show that the method is able to clearly display the distribution of load demand at various time periods [10].

The IoTS architecture can be divided into a sensing layer, a network layer, and an application layer. It uses communication technologies like local networks or the Internet to connect sensors, controllers, machines, and people in novel ways to create intelligent networks that connect people to things and things to people. Using a near real-time approach to data streams and big data-based pattern analysis of stakeholder needs, Luckner and his team propose an IoT architecture that is data-centric for urban services and applications, and test results show that the approach is effective at lowering latency in smart city IoT [11]. In order to ease further analysis of human health, Chandrakar's research team presented a smart device for healthcare system based on IoT architecture employing smart sensors for human tracking. The study's findings show that the technique can support IoT architecture for healthcare [12]. The research group of Shapsough suggested a general IoT architecture for context-aware learning. To enable on-the-fly scene learning, a variant of the architecture is constructed utilizing IoT edge devices, and testing findings demonstrate that the architecture is resource-efficient while limiting application protocols [13]. In order to meet the demands of the IoT ecosystem, the Sarrigiannis scientific group built a 5G platform using virtual network capabilities for lifecycle management of heterogeneous architectures in conjunction with multi-access edge computing. Experiments reveal that the method can allocate edge and core resources in real time to maximize the number of service users [14]. In order to connect travel paths, Cheng and his team proposed a new carrier-based sensor deployment algorithm that matches redundant sensors with uncovered areas. Experimental data shows that under different parameter settings, this algorithm can reduce the path length of rows by 20% -30% [15].

In conclusion, BPNN and IoTS structures have been the subject of several studies and designs by numerous research teams, but more work has to be done to increase their stability. The study recommends a decentralized AIIoTS design built upon the BPNN model in order to boost the data transmission rate.

III. DECENTRALISED AIIOTS DESIGN BASED ON BPNN MODEL

The design of the AIIoTS in this chapter makes use of BPNN. The architecture of the system based on the BPNN model is covered in the first half of this chapter, and the implementation of the decentralized AIIoTS capability is covered in the second section. To implement the mapping of BPNN and IoTS, Fog Devices (FD) and Docker Containers (DC) are introduced.

A. System Design based on the BPNN Model

BPNN is one of the widely used and more successful neural networks [16]. When the signal is propagated forward, the data flows from the input layer (IL) to the hidden layer (HL), and the error is back-propagated by comparing the actual value with the expected value in the output layer [17]. Fig. 1 depicts the BPNN's construction.

The IL, output layer and HL form the BPNN, and the forward propagation of the BPNN algorithm is calculated as shown in Eq. (1).

$$\begin{cases} net_{ij} = W_{(i-1)kj} * \sum_{k=1}^{N_{i-1}} O_{(i-1)k} \\ O_{ij} = \dfrac{1}{1-\exp[net_{ij}+\theta_{ij}]} = f_s(net_{ij}) \end{cases} \tag{1}$$

In Eq. (1), the total input, output and threshold of the j th neuron in layer i are net_{ij}, O_{ij} and θ_{ij} respectively, the number of neuron nodes in layer i is N_i, and the connection weight of the j th neuron in layer i to the k th neuron in layer $i+1$ is W_{ijk}. The error in the backoff algorithm is defined as shown in Eq. (2).

$$e_j = d_j - y_j \tag{2}$$

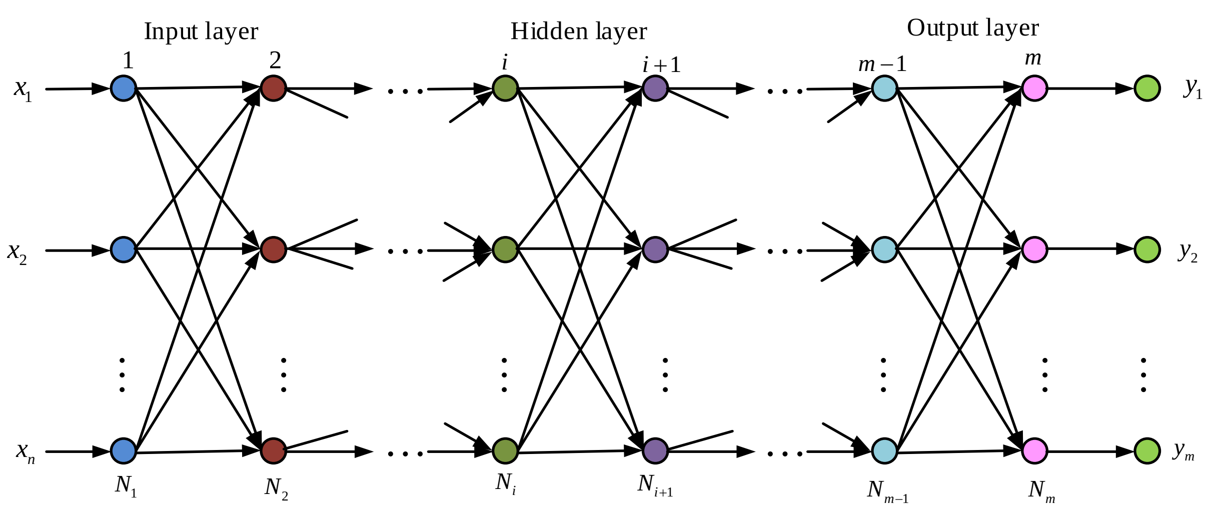


Fig. 1. BP neural network structure.

In Eq. (2), the back propagation error is e_j, the desired output is d_j, and the actual output of the neural network is y_j. The network objective function is shown in Eq. (3).

$$E = \frac{1}{2}\sum_j (d_j - y_j)^2 \tag{3}$$

In Eq. (3), the network objective function is E, and the weights are calculated as shown in Eq. (4) with the correction value along the direction of the gradient of the objective function falling.

$$\Delta W_{ijk} = -\eta \frac{\partial E}{\partial w_{ijk}} \tag{4}$$

In Eq. (4), the gradient descent value is ΔW_{ijk} and the learning efficiency is η, which takes values in the range of [0,1]. The recursive relationship between the gradient descent value and the neuron output is shown in Eq. (5).

$$\Delta W_{ijk} = -\eta \frac{\partial E}{\partial w_{ijk}} = -\eta \frac{\partial W}{\partial net_{(i+1)k}} * \frac{\partial net_{(i+1)k}}{\partial w_{ijk}} = \eta \delta_{ik} \frac{\partial net_{(i+1)k}}{\partial w_{ijk}} \tag{5}$$

In Eq. (5), the whole is denoted by δ_{ik} in terms of $-\frac{\partial E}{\partial net_{(i+1)k}}$. The common principles of BPNN design are the selection of the input quantity that will be able to meet the feature reflection requirements; the output quantity is the target that the system needs to reach; the training set samples can meet the generalization ability of the test metrics; the initial weight setting needs to meet the initial net input of the nodes as close to zero as possible; the number of HL neurons is calculated is shown in Eq. (6).

$$\begin{cases} m = \sqrt{n+l} + \alpha \\ m = \sqrt{nl} \end{cases} \tag{6}$$

In Eq. (6), m stands for the number of HL neurons, l for the output neurons, n for the input neurons, and α for the regulatory constant, which has a range of values from [1,10]. The study uses the BPNN structure as a model to construct the decentralised AIIoTS, and the whole system is divided into the cloud computer layer, and the decentralised AIIoTS architecture is shown in Fig. 2.

The edge of the IoT is the end device layer, containing IoT-aware devices and execution devices, mapped to the IL and output layers of the BPNN respectively, with one device corresponding to one neuron. The IoT-aware devices send the collected data information to the fog processing layer. The middle layer of the cloud hybrid architecture is the fog processing layer. The cloud computing layer, which makes up the top layer of the entire architecture, principally consists of cloud servers in charge of storing data, training neural networks, and distributing devices. The decentralised AIIoTS architecture works in both decentralised and centralised ways. Decentralized working involves the absence of the cloud computing layer, the deployment of the BPNN's input devices as sensing devices, the HL deployment of the fog processing layer, and the output devices as execution devices. The cloud computing layer is required for centralised work and its function is to train the neural network, which is a component of the BPNN algorithm deployment. The study uses a three-layer BPNN as a model, with HL neuron inputs as shown in Eq. (7).

$$net_j = \sum_i W_{ij} O_i \tag{7}$$

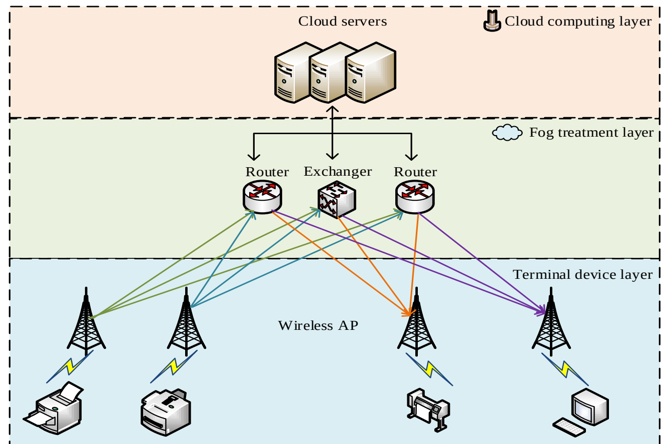


Fig. 2. Decentralized Artificial intelligence of things architecture.

In Eq. (7), the input of the j th neuron of HL is net_j, the weight of the i th neuron of IL and the j th neuron of HL is W_{ij}, and the output of the i th neuron of IL is O_j. The output of the HL neuron is shown in Eq. (8).

$$\begin{cases} O_j = g(net_j) \\ g(x) = \dfrac{1}{1+e^{-(x+\theta)}} \end{cases} \tag{8}$$

In Eq. (8), the output of the j th neuron of HL is O_j and the threshold is θ. the IL and HL neuron weights change as shown in Eq. (9).

$$\Delta W_{ij} = \eta O_j (1 - O_j) \sum_k \delta_k W_{kj} O_i \tag{9}$$

In Eq. (9), the weight change of the i th neuron of IL and the j th neuron of HL is ΔW_{ij}, the output of the k th neuron of HL is W_{kj}, the residual of the k neuron of the output layer is δ_k, and the learning efficiency is η. The threshold change of the HL neuron is shown in Eq. (10).

$$\Delta \theta_j = \eta O_j (1 - O_j) \sum_k \delta_k W_{kj} \tag{10}$$

In Eq. (10), the threshold change for the j h neuron of HL is $\Delta\theta_j$, and the output layer neuron input is calculated as shown in Eq. (11).

$$net_k = \sum_j W_{kj} O_j \tag{11}$$

In Eq. (11), the input of the k th neuron in the output layer is net_k, and the output of the neuron in the output layer is calculated as shown in Eq. (12).

$$O_k = g(net_k) \tag{12}$$

In Eq. (12), the output of the k th neuron in the output layer is O_k, and the weights between the output layer and HL neurons change as shown in Eq. (13).

$$\Delta W_{kj} = \eta(t_k - O_k)O_k(1-O_k)O_j \tag{13}$$

In Eq. (13), the weight of the k th neuron in the output layer is changed to ΔW_{kj} with the j th neuron in HL, and the residuals of the neurons in the output layer are shown in Eq. (14).

$$\delta_k = (t_k - O_k)O_k(1-O_k) \tag{14}$$

In Eq. (14), the residual of the k th neuron in the output layer is δ_k, the expected output of the k th neuron in HL is t_k, and the threshold of the neuron in the output layer changes as shown in Eq. (15).

$$\Delta\theta_k = \eta(t_k - O_k)O_k(1-O_k) \tag{15}$$

In Eq. (15), the threshold change for the k th neuron of the output layer is $\Delta\theta_k$. The FD layer is given the function of an HL neuron, and forward and backward calculations are required during training.

A. Decentralised AIIoTS Functional Implementation

Once the system based on the BPNN model is constructed, it needs to be implemented in conjunction with the appropriate tools and devices. The study uses the Python programming language and deploys DCs on FD and execution devices. The Python programming language is simple, easy to learn and implement, and is a free and open source software with source code that can be read and modified [18]. Python is a high-level language that is programmed without the need to consider low-level details when programming, and has the advantages of portability, interpretability and extensibility [19]. Docker's object is server-side and belongs to a Linux container technology, Docker can be installed on most Linux systems [20]. The first step in the study to install DC on FD and execution devices is to check the kernel version. 64-bit computers are required to install and run Docker, so the Linux system kernel version needs to be greater than 3.0, and the kernel needs to be upgraded if it is not up to standard [21]. The second step is to update the advanced packaging tool source, and the third step is to install the DC according to the command. The Docker image is the basis for the DC build, and the study builds the image using a Dockerfile file. The mapping of the IoT nodes to the BPNN, the code written in the DC, gives the FD and the execution device the function of hiding neurons and output neurons, respectively. Fig. 3 displays the decentralized AIIoTS capabilities based on the BPNN model.

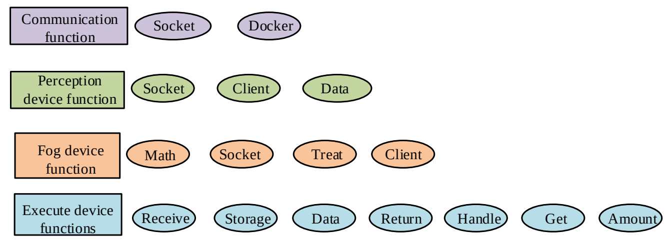


Fig. 3. Functions of decentralized Artificial intelligence of things system based on BP neural network model.

Communication between DCs needs to be implemented using sockets, also called sockets, which support the TCP/IP network communication protocol and are the endpoints for bidirectional communication between different hosts [22]. There are three types of sockets. Streaming sockets use the TCP protocol, which provides a reliable connection-oriented bi-directional data transfer service that guarantees error-free data transfer and is suitable for high-volume and data transfer demanding communication situations. Datagram sockets use the UDP protocol, which provides a connectionless service that does not guarantee reliable and sequential data transfer and requires programmatic processing to be used. Raw sockets use the underlying protocol and are suitable for network protocol analysis and verification [23]. Socket communication requires the availability of a server and a client, and the connection process consists of server listening, client request and connection confirmation. The role of the client is to connect to the server and send data to the server side.

The study uses the socket server module to simplify the web application, which contains a framework of service classes and request processing classes. The first step in the creation of the service is the creation of the service class, which uses the TCP protocol to enable asynchronous processing [24]. The second step is the creation of the request processing class, along with the overriding of the processing functions. The third step is the instantiation of the service object, for which the service address and request processing class are passed. The fourth step is the invocation of the service class object function and the server is kept running after the function is started.

The inverse device is used to acquire data, which is then sent to the fog processing layer, which contains the hardware software study of the sensing device [25]. This study only simulates the function of the device; it does not create a functional implementation. Instead, it uses the Client function, which is the Client function of the upper level, to send data. The function of FD is to process, store and send the data, and its DC is distributed in the server side and the client side, IL and Output layer client request and processing is completed through the server side, FD function implementation flow is shown in Fig. 4.

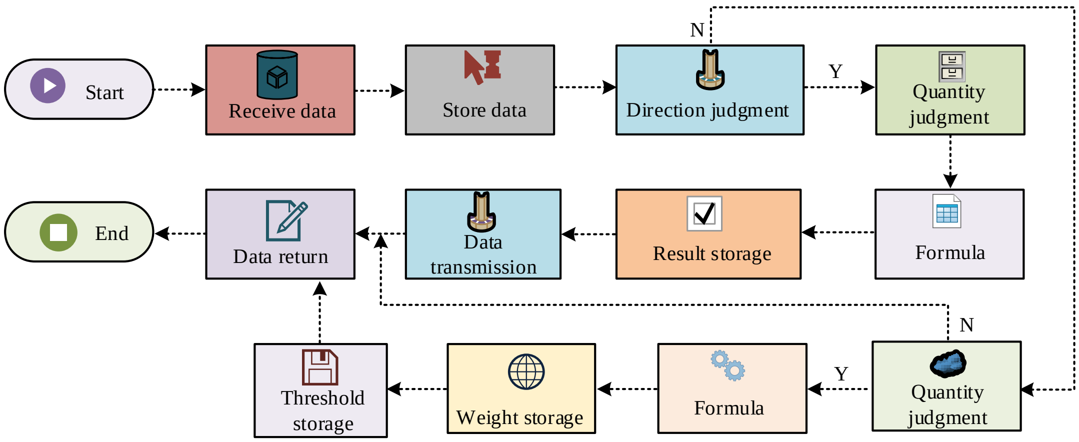


Fig. 4. Implementation process of fog equipment functions.

FUNCTIONS USED TO IMPLEMENT DEVICE FUNCTIONS

Function Name	Parameter	Return Value	Function
Client	Host, port, senddata	/	Connect to the server of the hidden layer and send data
Tansform	Filename, number	Data_list	Convert the relevant data in the file into a list
Error_term	D, output	Output_e	Calculate the residual of a single output layer neuron
Th_updata	Output_e, efficiency, th	Updatated_th	Update threshold
Save_data	Data, number	/	Store data in the appropriate location
Get_Data	Filename, number	Data	Obtain data with corresponding numbers from files containing storage numbers
Handle	Self	/	Please handle hidden layer clients Request, process received data
Freedforward	F_input, w, th	Output	Forward calculation of output layer
Weight_update	Output_e, efficiency, f_input, w	Updatated_weight	Update the weights of output layer neurons to corresponding hidden layer neurons
Save	Filename, data	/	Store data
Get_number	Data	Number	Obtain storage number
Amount	Data, number	Data_number	Obtain the number of stored data corresponding to the current storage number

The first step in the implementation of the FD function is the reception and storage of data, which comes from the sensing and execution devices. The format of the data storage is JSON, which is a lightweight data exchange format. The second is to process the data, firstly to determine the type of data, forward data from the sensing device and backward data from the executing device. Returning the data to the connected client is the third stage, and whether data processing is done or not has no bearing on the client obtaining the returned data. The functions used to implement the functions of the execution device are shown in Table I.

The main function of the execution device is also data processing, storage and sending, its DC is distributed in the client and server side, the source of processing data is FD, the format of data storage is still JSON format, the storage file is f_input.json, data processing before also to determine whether to meet the requirements, the number of data and the number of hidden neurons equal to the judgment criteria, after receiving data are returned a data to the client.

IV. ANALYSIS OF DECENTRALISED AIIOTS APPLICATIONS BASED ON THE BPNN MODEL

This chapter addresses the application and analysis of decentralised AIIoTS based on the BPNN model. The first section of this chapter is a simulation analysis of the performance of decentralised AIIoTS, and the second section of this chapter is an analysis of the practical application of decentralised AIIoTS.

A. *Performance Simulation Analysis of Decentralized AIIoTS based on BPNN Model*

Two laptops were used to simulate the FD and IoT sensing devices, with Laptop 1 simulating the FD and Laptop 2 simulating the sensing device. The operating system of both computers is Ubiquitous 20.10, and the network connection of laptop 2 is provided by the hotspot of laptop 1. The DCs are deployed at the corresponding locations of laptops 1 and 2, and the FD transmission rate is shown in Fig. 5.

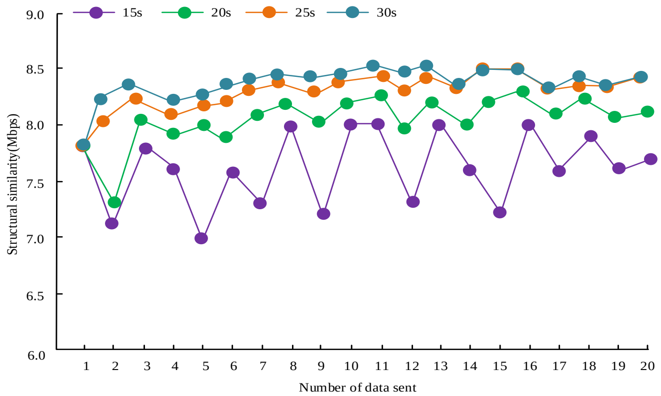


Fig. 5. Transmission rate of fog equipment.

In Fig. 5, laptop #2 sends data to laptop #2 at 15s, 20s, 25s and 30s intervals, and 20 times at different time intervals. It can be seen that the transmission rate between FD and sensing device is distributed in the interval [7.0,8.5] Mbps, with an average transmission rate of 8.265 Mbps, and the transmission rate increases when the data transmission interval increases. The results show that the transmission rate of the device under the decentralized AIIoTS based on the BPNN model proposed in the study can meet the user requirements. To further analyse the communication link bandwidth (marked as BP) under the decentralised AIIoTS based on the BPNN model, the experiments used the communication link bandwidth between the common sensor and the cloud server (marked as S), the Unified Storage Network architecture link communication bandwidth (marked as U), and the machine-to-machine architecture link communication bandwidth (marked as M) as comparisons, and the bandwidth comparison results are shown in Fig. 6.

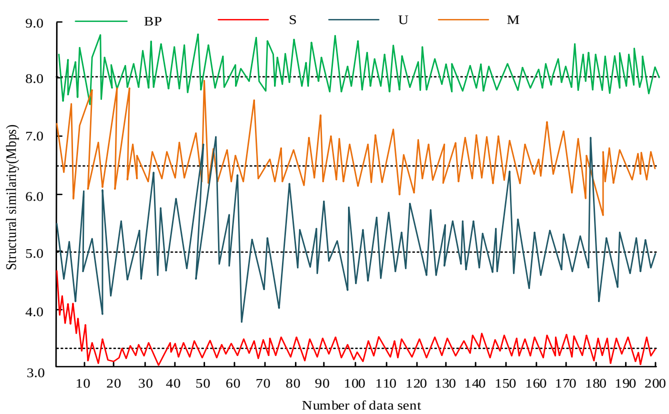


Fig. 6. Bandwidth comparison results.

In Fig. 6, the data is sent at an interval of 10s and a total of 200 times. It can be seen that the average communication link bandwidth between ordinary sensors and cloud servers is 3.2Mbps, the average link communication bandwidth of the Unified Storage Network architecture is 5.0Mbps, the average link communication bandwidth of the machine-to-machine architecture is 6.43Mbps, and the average communication link bandwidth under the decentralised AIIoTS based on the BPNN model is 8.01Mbps. The outcomes demonstrated that the study's decentralized AIIoTS may offer greater communication bandwidth, faster data transmission rates, and higher stability. A comparison of the data transmission delay under decentralised AIIoTS and the delay of sensor data sent to the cloud is shown in Fig. 7.

In Fig. 7, a total of six sensing devices are set for data transmission. When the number of sensing devices is 1 and 2, the difference in latency between the data sent by the sensing devices to the FD and the cloud is small, and the difference in latency gradually increases, the latency of sending data to the cloud is 1.80s, the latency of sending data under decentralized AIIoTS is 0.83s, and the latency is reduced by 0.97 s, and the latency of sensor data sent to the cloud is 1.74s, with a latency reduction of 0.06s. The results show that the latency reduction of data sent under the decentralized AIIoTS based on the BPNN model proposed in the study is greater. To further validate the correct data delivery rate under the decentralised AIIoTS (labelled as BP), the study uses the Unified Storage Network architecture (labelled as U) and the machine-to-machine architecture (labelled as M) as comparisons, and the correct data delivery rates of the different architectures at different data delivery intervals are shown in Fig. 8.

In Fig. 8, three data transmission intervals are set to 20s, 15s and 10s, respectively. It can be seen that the correct data transmission rate for decentralised AIIoTS and with a data transmission interval of 20s is 1.00, and the correct data transmission rate cannot be maintained at 1.00 under the Unified Storage Network architecture and machine-to-machine architecture. The experimental results show that the data processing and transmission are better under the decentralized AIIoTS based on the BPNN model proposed in the study, and the data sending interval can be set to 20s if there is no special requirement.

B. *Analysis of Decentralised AIIoTS Applications based on the BPNN Model*

To verify the effectiveness of the practical application of decentralised AIIoTS based on the BPNN model, six users were experimentally recruited to analyse the network performance under the system, setting the data transmission interval to 20s and the user network data transmission rate as shown in Fig. 9.

As shown in Fig. 9, none of the users' network data transmission rates are less than 8.5Mbps, and even as the volume of data transmissions rises, these rates remain stable in the [8.4,8.7] Mbps range, which can accommodate users' typical usage requirements. When the data transmission interval is set to 10s, the user network data transmission error is shown in Fig. 10.

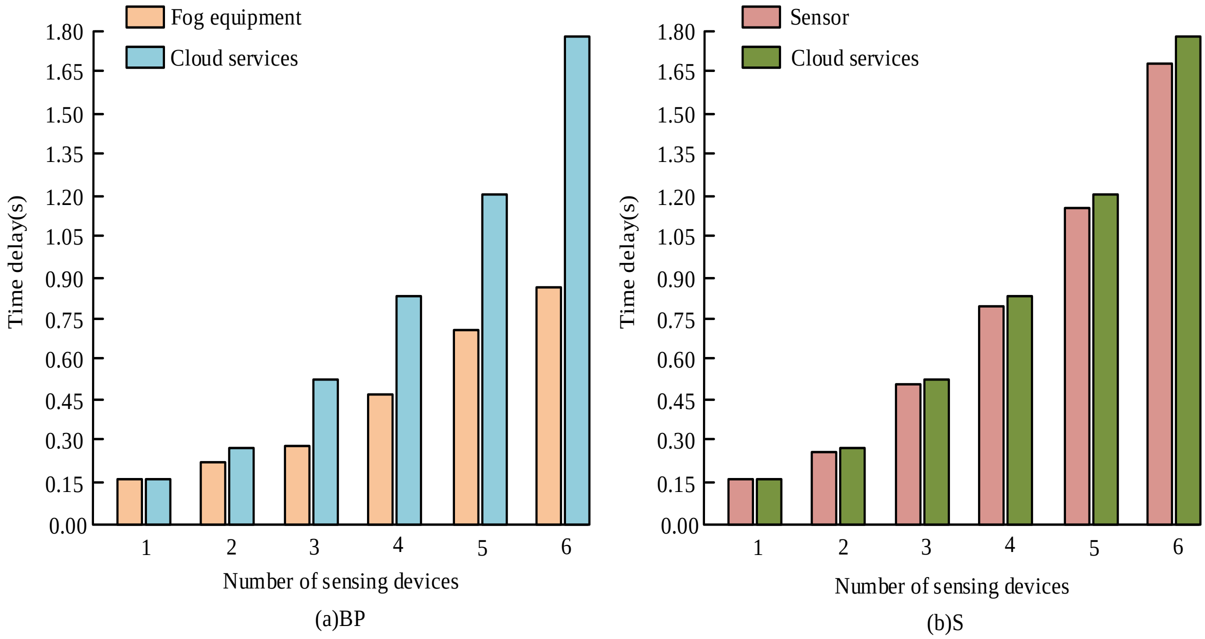


Fig. 7. Comparison of data transmission delay.

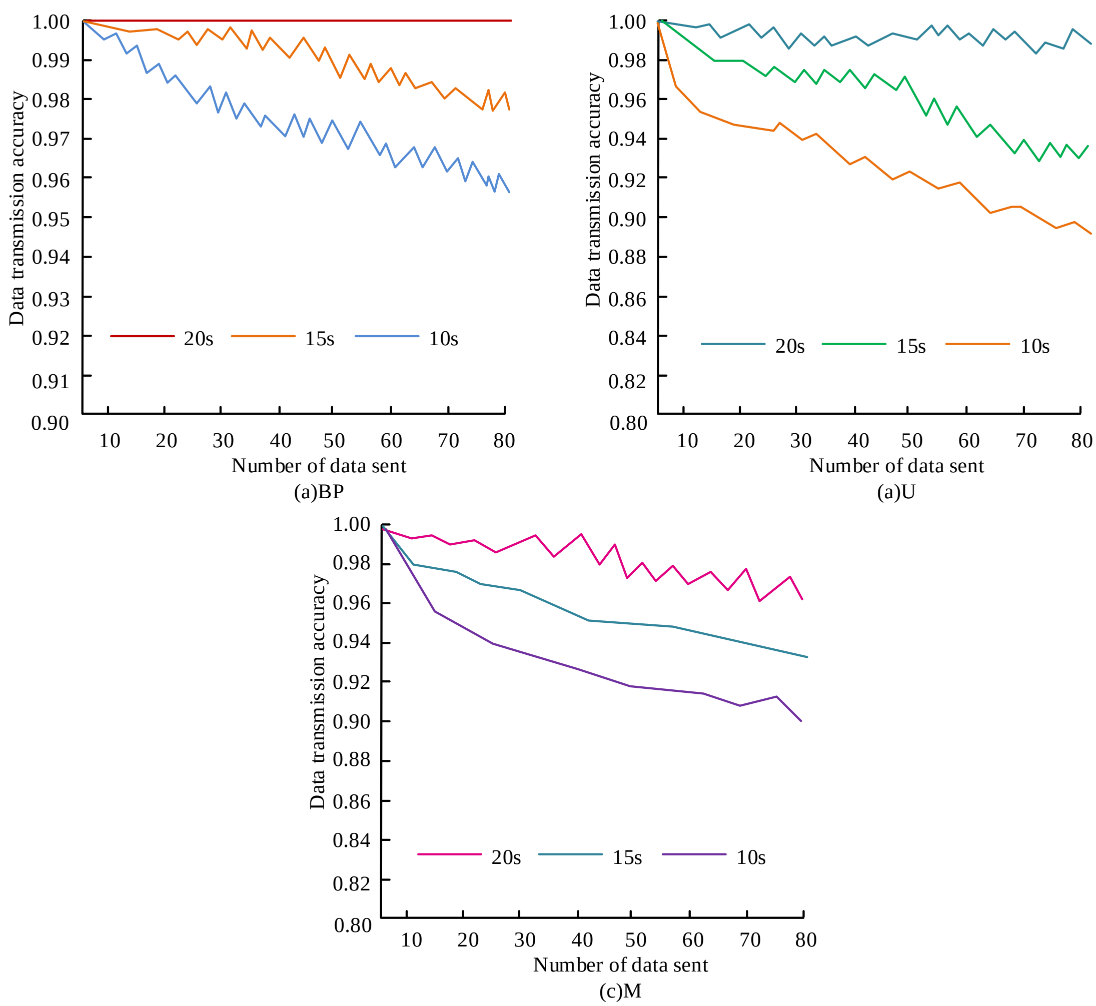


Fig. 8. Data transmission accuracy of different architectures at different data transmission time intervals.

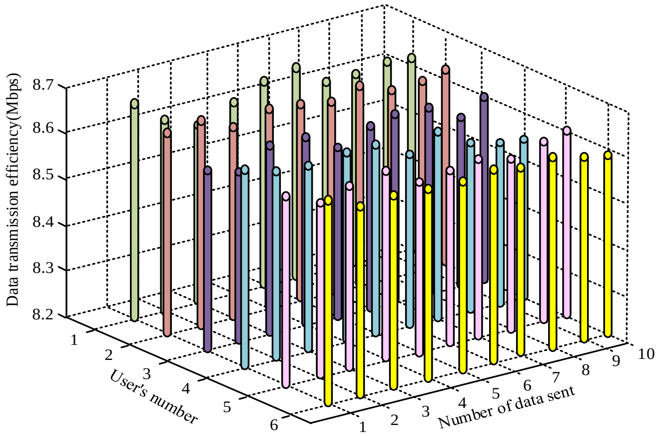


Fig. 9. User network data transmission rate.

Fig. 10 illustrates how the network data transmission error increases gradually as the number of users rises, although the error is still less than 0.07. Analysis of the experimental data shows that the correct rate of network transmission at this time is higher than 0.93. The accuracy of user data transmission can be guaranteed when there are no special requirements for user data transmission accuracy. To verify the security of the network transmission under the decentralised AIIoTS based on the BPNN model, the experiments were verified using an attack test, and the results of the attack test are shown in Fig. 11.

In Fig. 11, the network is able to identify 85% of threat attacks when the data transmission interval is 10s, 95% of threat attacks when the data transmission interval is 15s, and 100% of threat attacks when the data transmission interval is 20s. The experimental data shows that the security of network data transmission under the decentralised AIIoTS based on the BPNN model is high and can meet users' needs.

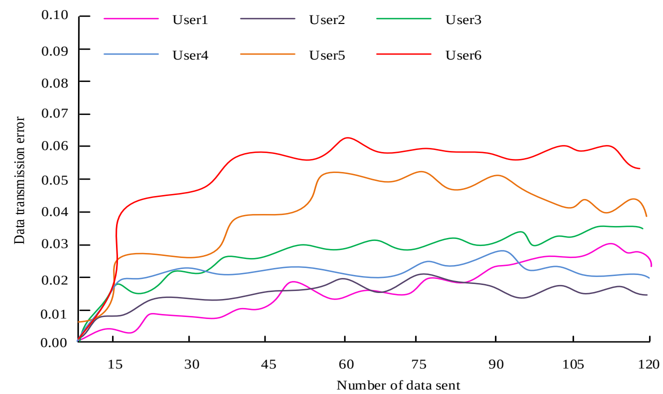
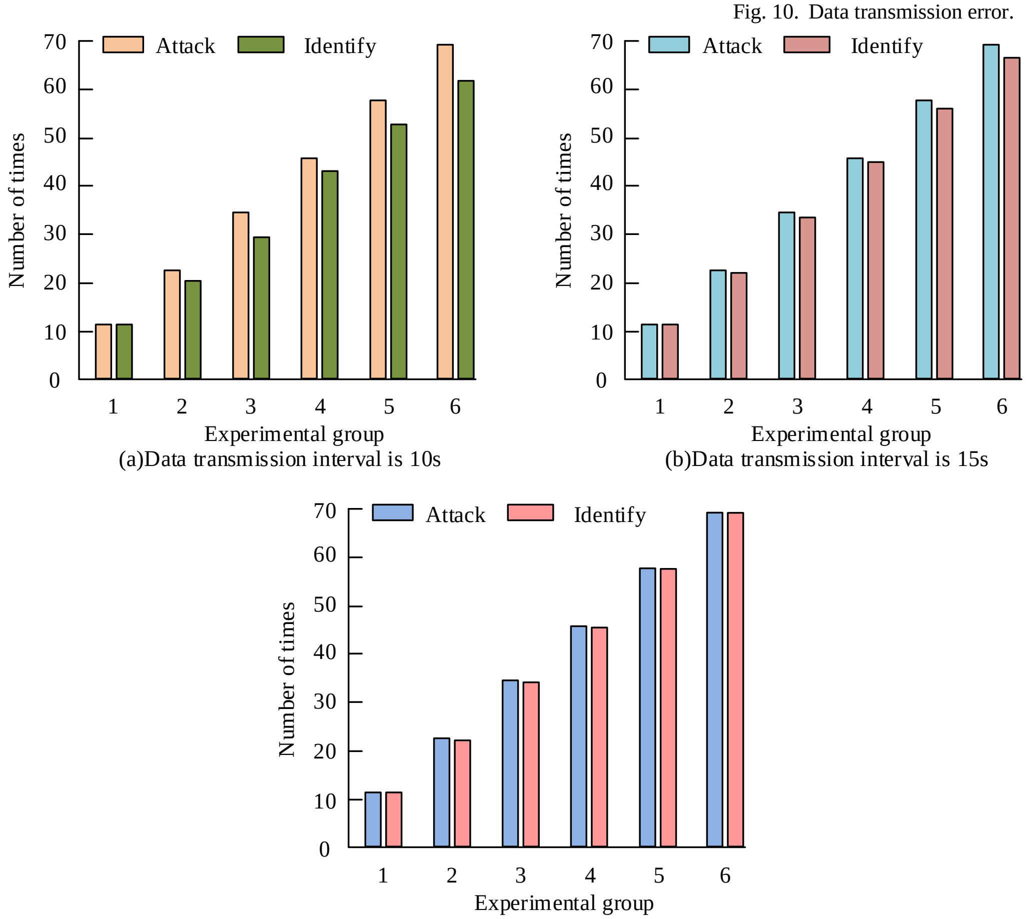


Fig. 10. Data transmission error.



(a)Data transmission interval is 10s

(b)Data transmission interval is 15s

(c)Data transmission interval is 20s

Fig. 11. Attack test results.

V. CONCLUSION

IoT's future development trajectory is to merge with AI as both IoT and AI technology advance. The study suggests a decentralized AIIoTS design based on the BPNN model to enhance the quality of service of IoT devices by leveraging the concept of cloud-fog combination to develop the functionalities of the devices and causing the DC to be in the system to realize the mapping of BPNN and IoTS. The experimental data revealed an average transmission rate of 8.265 Mbps between the sensing device and the FD, which was sufficient to satisfy customer demand. The average communication connection bandwidth between a typical sensor and a cloud server was 3.2 Mbps, whereas the decentralized AIIoTS based on the BPNN model had an average communication link bandwidth of 8.01 Mbps, which increased data transmission efficiency by 4.81 Mbps and increased stability. Users' network data transmission rates were more than 8.5Mbps when the data transmission interval was set to 20s, and as data transmission increased, these rates did not vary substantially and could accommodate users' usage needs. The network data transmission error increased gradually as the number of users increased, but all mistakes were less than 0.07, and the proper network transmission rate was higher than 0.93 at that point, guaranteeing the correctness of user data transfer. When the data transmission interval was 20s, the network was able to recognize 100% of threat attacks, showing that the decentralized AIIoTS based on the BPNN model had stronger data transmission security and better network device service quality. The decentralized artificial intelligence IoT system proposed in the study currently only achieves basic functions, and further improvement is needed to make the system more fully functional. In terms of system stability, the studied system uses network edge devices, and the stability of the system may be relatively poor. For example, if the sensing device, fog device, or execution device may be damaged, how should the system continue to operate correctly? Future research can develop towards the direction of intelligent systems, upgrading devices in the system to intelligent agents, achieving automatic redeployment in the event of system failures, and further developing and intelligentising Docker containers.

REFERENCES

[1] Li X, Wu J. Node-oriented secure data transmission algorithm based on IoT system in social networks. IEEE Communications Letters, 2020, 24(12): 2898-2902.

[2] Meng A, Gao X, Zhao Y, Yang Z. Three-dimensional trajectory optimization for energy-constrained UAV-enabled IoT system in probabilistic LoS channel. IEEE Internet of Things Journal, 2021, 9(2): 1109-1121.

[3] Yugank H K, Sharma R, Gupta S H. An approach to analyse energy consumption of an IoT system. International Journal of Information Technology, 2022, 14(5): 2549-2558.

[4] Ioannou I, Vassiliou V, Christophorou C, Pitsillides A. Distributed artificial intelligence solution for D2D communication in 5G networks. IEEE Systems Journal, 2020, 14(3): 4232-4241.

[5] Zhao X. Implementation of English ICAI MOOC system based on BP neural network. Journal of Ambient Intelligence and Humanized Computing, 2023, 14(4): 3177-3186.

[6] Xiao M, Wen K, Yang G, Lu X. Research on gearbox fault diagnosis system based on BP neural network optimized by particle swarm optimization. Journal of Computational Methods in Sciences and Engineering, 2020, 20(1): 53-64.

[7] Yang Y H, Shi Y. Application of improved BP neural network in information fusion Kalman filter. Circuits, Systems, and Signal Processing, 2020, 39(10): 4890-4902.

[8] Cheng P, Chen D, Wang J. Clustering of the body shape of the adult male by using principal component analysis and genetic algorithm–BP neural network. Soft Computing, 2020, 24(17): 13219-13237.

[9] Xie X T. Technology enterprise value assessment based on BP neural network. International Journal of Computing Science and Mathematics, 2020, 12(2): 192-203.

[10] Shi J, Chengchao S, Lei H, Mengxi X. Smart grid short-term load estimation model based on BP neural network. International Journal of Computing Science and Mathematics, 2020, 11(2): 123-136.

[11] Deng S, Zhao H, Fang W, Yin J, Dustdar S, Zomaya A Y. Edge intelligence: The confluence of edge computing and artificial intelligence. IEEE Internet of Things Journal, 2020, 7(8): 7457-7469.

[12] Chandrakar M, Patle V K. Security issue in iot based architecture for health care system. Research Journal of Engineering and Technology, 2020, 11(2): 89-97.

[13] Shapsough S Y, Zualkernan I A. A generic IoT architecture for ubiquitous context-aware learning. IEEE Transactions on Learning Technologies, 2020, 13(3): 449-464.

[14] Sarrigiannis I, Ramantas K, Kartsakli E, Mekikis P V, Antonopoulos A, Verikoukis C. Online VNF lifecycle management in an MEC-enabled 5G IoT architecture. IEEE Internet of Things Journal, 2019, 7(5): 4183-4194.

[15] Cheng C F, Chen Y C, Lin C W. A Carrier-Based Sensor Deployment Algorithm for Perception Layer in the IoT Architecture.IEEE Sensors Journal, 2020, 20(17): 10295-10305.

[16] Sun G, Zeng G, Hu C, Jiang T. Starch-based aerogel prepared by freeze-drying: establishing a BP neural network prediction model. Iranian Polymer Journal, 2023, 32(1): 37-44.

[17] Zhou W, Li M, Li L, Yeh K. Prediction of SET on SRAM Based on WOA-BP Neural Network. Journal of Internet Technology, 2023, 24(2): 267-273.

[18] Li T, Deng J, Ren J. Security and Energy Efficiency: Breaking the Barriers of High Peak-to-Average Power Ratio and Disguised Jamming in NextG IoT System Design. IEEE Internet of Things Journal, 2022, 10(3): 2658-2666.

[19] Qi P, Zhou X, Ding Y, Zhang Z, Zheng S, Li Z. Fedbkd: Heterogenous federated learning via bidirectional knowledge distillation for modulation classification in iot-edge system. IEEE Journal of Selected Topics in Signal Processing, 2022, 17(1): 189-204.

[20] Bashar D A. Survey on evolving deep learning neural network architectures. Journal of Artificial Intelligence and Capsule Networks, 2019, 1(2): 73-82.

[21] Wang X, Cheng M, Eaton J, Hsieh C J, Wu S F. Fake node attacks on graph convolutional networks. Journal of Computational and Cognitive Engineering, 2022, 1(4): 165-173.

[22] Nimrah S, Saifullah S. Context-Free Word Importance Scores for Attacking Neural Networks. Journal of Computational and Cognitive Engineering, 2022, 1(4): 187-192.

[23] Chen Z. Research on internet security situation awareness prediction technology based on improved RBF neural network algorithm. Journal of Computational and Cognitive Engineering, 2022, 1(3): 103-108.

[24] Andavan M T, Vairaperumal N. Cloud computing based deduplication using high-performance grade byte check and fuzzy search technique. Journal of Intelligent & Fuzzy Systems, 2023, 44(2): 1-15.

[25] Mohanaprakash T A, Nirmalrani D V. Exploration of various viewpoints in cloud computing security threats. Journal of Theoretical and Applied Information Technology, 2021, 99(5): 1172-1183.