Research Article

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Greenhouse monitoring system integrating NB-IOT technology and a cloud service framework

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Abstract: The strong support for the rural revitalization strategy has gradually made greenhouse monitoring systems an important component of modern agriculture and the planting industry in China. To efficiently and intelligently monitor and regulate the greenhouse environment, a greenhouse monitoring system based on narrowband Internet of Things and a cloud service framework was proposed. The experiment introduced particle swarm optimization and genetic algorithms to improve the parameter optimization of this system, ultimately achieving intelligent regulation of the greenhouse environment. When the system iterated to the 49th and 78th iterations on the training and testing sets, respectively, the constructed method had the optimal fitness value, with values as high as 97.58 and 96.27. Comparing the packet loss rates, the communication success rate of the monitoring system was over 99% when the constructed method was running. Upon comparing the relative errors, under the operation of the constructed method, the average relative measurement errors of particulate matter, hydrogen sulfide, and ammonia were ±2.58 $\mu g/m^3$, $\pm 0.216 \times 10^{-6}$, and $\pm 0.175 \times 10^{-6}$, respectively, all within a reasonable range. In addition, the constructed method was closer to the actual control values for temperature, humidity, light, and carbon dioxide. In summary, the greenhouse monitoring system constructed by this method has lower energy consumption and can reduce manual intervention, providing new ideas for achieving precision agriculture and sustainable development.

Keywords: NB-IoT technology, cloud services, greenhouse monitoring, genetic algorithm, PID control, intelligent agriculture

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1 Introduction

In recent years, China has continued to promote the revitalization strategy of rural agriculture, trying to promote the deep integration of rural production, university, and research through the rise of modern agriculture and planting projects, drive the rapid development of small-scale peasant economies and national economies, and finally realize the grand blueprint of rural revitalization [1]. However, in this process, although traditional agricultural facilities such as plastic film and brick-concrete greenhouses are popular due to their low cost and easy construction, their simple structure and technical defects are increasingly becoming prominent, which makes it difficult to meet the precise requirements of temperature and humidity for plant growth, resulting in low production efficiency [2,3]. Moreover, the majority of extant greenhouse monitoring systems remain in the fundamental monitoring stage, unable to achieve real-time, demand-oriented, and scientifically accurate management. This significantly constrains further advancement of facility agriculture [4]. Faced with this challenge, the deepening of international technical exchanges and cooperation provides a valuable opportunity for the introduction of an intelligent technology. In particular, the rise of narrowband Internet of Things (NB-IoT) technology, with its low power consumption, low cost, and excellent penetration capability, has laid a solid communication foundation for the construction of efficient and stable greenhouse sensor networks [5]. At the same time, as an emerging computing model, the cloud service framework opens up a new path for the construction of intelligent greenhouse monitoring systems with its powerful data processing, flexible resource scheduling, and convenient remote access characteristics. In this context, an innovative greenhouse monitoring method based on NB-IoT and a cloud service framework is proposed to achieve intelligent, accurate, and efficient management of the greenhouse environment.

In the existing research, intelligent agriculture and greenhouse automation control has become a hot topic. The igrow system proposed by Cao *et al.* realized the autonomy of greenhouse control by integrating artificial intelligence algorithms. However, it focused more on algorithm optimization and less on the deep integration of communication technology and a cloud service framework [6]. Farooqui *et al.* used the Internet of Things (IoT) technology and machine learning methods to build an automated greenhouse system. Although there was a breakthrough in intelligent control, the flexibility and scalability of the overall system architecture still need to be improved [7]. Soheli *et al.*'s research focused on the application of IoT and artificial intelligence in greenhouse monitoring. However, there was a lack of in-depth discussion on how to effectively reduce the energy consumption and cost of the system and improve the stability of data transmission [8]. In addition, although the IoT-based intelligent greenhouse framework proposed by Farooq *et al.* emphasized the importance of control strategies, it lacked adaptability to complex environmental changes in practical applications and is difficult to ensure long-term stable monitoring effects [9]. Laktionov *et al.* attempted to use fuzzy logic to comprehensively monitor and control the greenhouse microclimate. Although innovative in theory, the applicability and maintainability of large greenhouses in practice still need to be verified [10]. Ahmad *et al.* realized intelligent greenhouse monitoring using a Raspberry PI microcontroller and evaluated tomato crop production. However, there is still much room for improvement in system intelligence and depth of data analysis [11].

In summary, although existing research has made some progress in the field of intelligent greenhouse monitoring, there are still obvious limitations in terms of system integration, cost control, environmental adaptability, and data analysis capability. The research proposes a novel greenhouse monitoring method based on NB-IoT and a cloud service framework. This method integrates advanced communication technology and a cloud computing platform, as well as particle swarm optimization and intelligent algorithms. The latter are employed to optimize the control parameters in the greenhouse monitoring system, thereby facilitating more efficient and accurate greenhouse environmental management. The research aims to provide more powerful technical support for agricultural production, promote the intelligent and efficient development of facility agriculture, and further advance the implementation of the rural revitalization strategy through the deep integration of big data analysis and machine learning technology.

This article mainly consists of three parts. First, research methods are employed to construct an intelligent greenhouse monitoring method using the IoT platform. Next is the research results, mainly analyzing the performance and application effects of the greenhouse monitoring method constructed. Finally, the conclusion mainly summarizes the content of the entire article and proposes suggestions for future development.

2 Greenhouse monitoring system based on improved NB-IoT and intelligent algorithms

The first step of this section is to build a remote monitoring and intelligent regulation system using NB-IoT and a cloud service platform. Second, fuzzy Proportional integral derivative (PID) control and genetic algorithm (GA) are introduced to improve the nonlinearity of this greenhouse system, ultimately resulting in a complete greenhouse control system.

2.1 Greenhouse monitoring method based on NB-IoT technology and a cloud service framework

To improve the monitoring system of facility greenhouses, a greenhouse monitoring system based on NB-IoT and a cloud service framework is proposed. This system consists of four parts: perception, network, platform, and application layers to achieve remote monitoring and intelligent regulation of large-scale intensive greenhouse environments [12,13]. Figure 1 shows the overall system design.

In the overall system design shown in Figure 1, the greenhouse monitoring system is clearly divided into four main parts: perception layer, network layer, platform layer, and application layer. The sensing layer is responsible for collecting environmental data and video information in the greenhouse. The network layer realizes stable data transmission through NB-IoT technology. The platform layer uses the cloud service platform for data processing and analysis and optimizes control parameters. The application layer provides a user-friendly monitoring and control interface. This layered design ensures that the system is modular and scalable for easy maintenance and upgrade. The perception layer in this system framework mainly includes a module for collecting environmental data and a video monitoring module. The environmental data collection module mainly uses an ST microelectronics 32-bit microcontroller (STM32) as the core to read information from the environment. Subsequently, this information is verified and stored through sensors before being sent to the NB-IoT communication module. The video monitoring module is obtained by

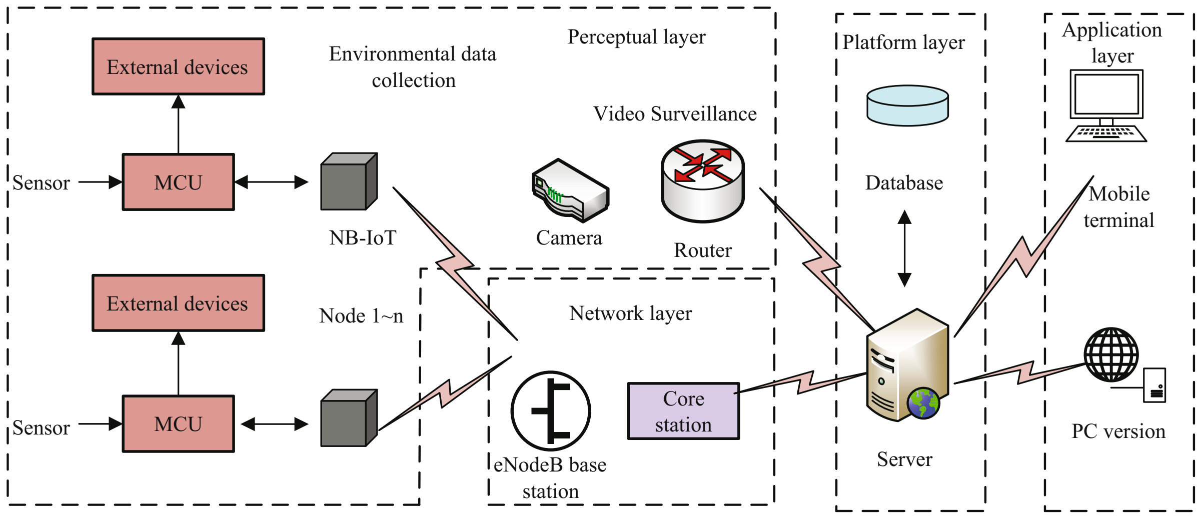

Figure 1: Overall architecture of the facility greenhouse system.

using cameras to capture images of the internal environment of the greenhouse, which can transmit information to the platform layer through wireless networks [14,15]. The network layer utilizes NB-IoT communication technology and a core network to achieve data exchange between the platform layer, base station, and perception layer. Then, the base station is provided and maintained by the operator, and the core network provides and transmits services to the cloud and terminals. Figure 2 shows the overall architecture of network transmission.

The NB-IoT network transport layer has optimized and enhanced IoT business functions, allowing users to select corresponding transmission paths according to their actual needs. In the overall architecture of the network, it mainly includes the user terminal (UE), Evolved Universal Terrestrial Radio Access Network Node B (eNodeB), mobility management entity (MME), Home Subscriber Server (HSS), Service Creation Environment Facility (SCEF), and service gateway (SGW), Packet Data Network Gateway (PGW), and application server (AS). The application layer includes monitoring interfaces for both mobile and PV ends. Managers can monitor and regulate environmental data, greenhouse real-time images, and historical data in real-time through applications or portable mobile devices. The acquisition of data is achieved through sensor networks, which can arrange the sensors inside the greenhouse and place each sensor node inside the greenhouse. How to reduce the consumption of network nodes is the key point for the deployment of NB-IoT networks and cloud services. There are many factors that affect the energy consumption of IoT operation, such as sending and receiving power, sending and receiving data frequency, *etc.* [16,17]. In the entire IoT system, there is a

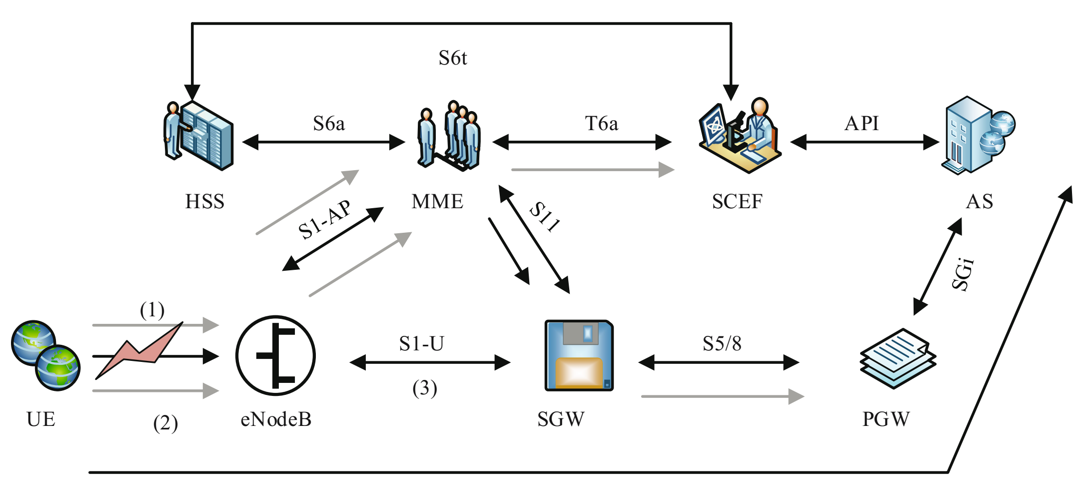

Figure 2: Overall framework of network transmission.

significant issue of uneven energy consumption, for example, aggregation nodes often generate high energy consumption due to their responsibility for local data exchange. The calculation corresponding to individual energy consumption is represented by Eq. (1)

$$E_a = P_{TX} \times t_{tx} + P_{RX} \times t_{rx} + P_c t_c. \tag{1}$$

In Eq. (1), E_a refers to the overall energy of the system, P_{TX} is the transmission power, t_{tx} refers to the time of sending data, P_{RX} is the received power, t_{rx} is the time when data is received, P_c refers to the switching power of the state, and t_c refers to the time spent in switching states. Based on the above problems, the experiment aimed at the current greenhouse control modeling. The greenhouse model is built according to humidity, temperature, light, and carbon dioxide. The greenhouse can be regarded as a closed system, and the model is built through reasonable assumptions and the above mechanism, and then the model is updated in real time according to the collected data of the sensor network. The planting greenhouse is regarded as an independent system. The principle of energy conservation, that is, the energy change of the greenhouse is equal to the synthesis of all the energy it receives. The energy change ΔQ, the humidity model ΔW in the greenhouse, the carbon dioxide balance model ΔC in the greenhouse, and the light intensity model in the greenhouse can be obtained. Assuming that the greenhouse temperature is x_1, the humidity is x_2, the carbon dioxide concentration is x_3, and the light intensity is x_4, the calculation model of the above four parameters can be expressed by Eq. (2)

$$\begin{cases} \Delta Q = Q_g + Q_{t1} + Q_c - Q_{t2} - Q_j - Q_z \\ \Delta W = W_z - W_y - W_l + W_{t1} - W_{t2} \\ \Delta C = C_h - C_g - C_t + C_f \\ \Delta R = \eta_r (R_r - R_s). \end{cases} \tag{2}$$

In Eq. (2), Q_{t1} and Q_c refer to the energy of sunlight received by the greenhouse and the energy transmitted by soil and air, respectively, Q_{t2} refers to the energy exchanged with the outside world, Q_j refers to the energy exchange between the greenhouse and the outside world through walls, *etc.*, Q_z refers to the energy consumed by plant transpiration, W_z refers to the plant transpiration rate, W_y refers to the efficiency of condensate droplets on the blade surface, W_l refers to the efficiency of condensation between air and the outside world, W_{t1} refers to the efficiency of soil evaporation, W_{t2} refers to the reduced humidity rate during ventilation, η_r refers to the efficiency of artificial shading, and R_r refers to the artificial regulation of plant growth in the greenhouse. Based on the above equations, the energy model of greenhouse in Figure 3 is obtained.

As shown in Figure 3, in the actual plant growth, the energy consumed by transpiration is far greater than the energy changes produced by plant respiration and photosynthesis. Therefore, the energy of photosynthesis and respiration is usually ignored, and only the energy calculation of transpiration is retained.

2.2 Greenhouse parameter decision-making model based on genetic algorithm–particle swarm optimization (GA–PSO) optimized PID control

The greenhouse control system is a classical nonlinear system. In plant growth, indoor temperature, humidity, light, carbon dioxide, and other environmental factors will have a direct impact on plant growth. Therefore, it is difficult to establish an accurate greenhouse control model.

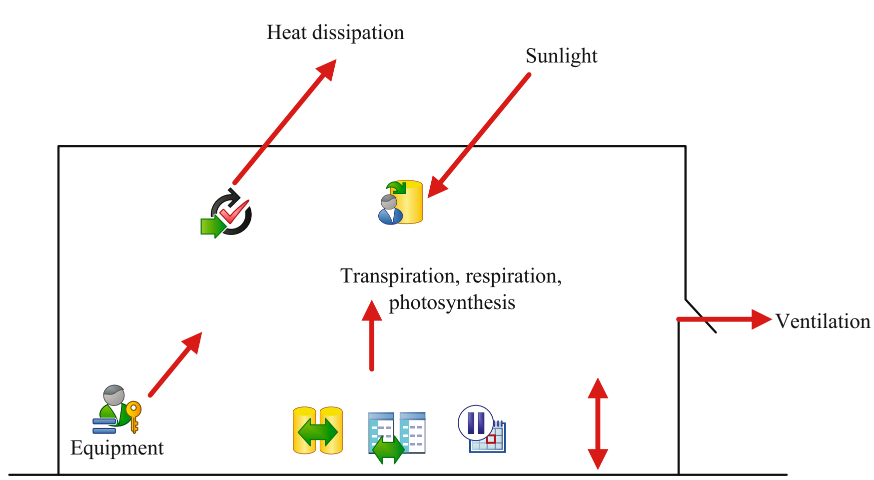

Figure 3: Energy model of a facility greenhouse.

To solve this problem, fuzzy control is introduced into the greenhouse monitoring system design based on NB-IoT and a cloud service framework, and the parameter decision of the greenhouse system is optimized. Figure 4 shows the composition of the fuzzy decision model.

As shown in Figure 4, the fuzzy controller mainly includes four parts: fuzzification, fuzzy reasoning, clarity, and database. The soil moisture deviation E_H and air temperature deviation E_T are used as input variables of this model. The input variables are composed of three actuators: heating equipment, drip irrigation controller, and side window. The humidity deviation variable is expressed by Eq. (3)

$$E_H = H - H_0. \tag{3}$$

In Eq. (3), H represents the actual value of soil moisture uploaded by the on-site electrical equipment and H_0 refers to the appropriate value given by the management personnel according to expert experience at different growth stages of species of plants. Similarly, the air temperature deviation variable can be obtained, which is expressed by Eq. (4)

$$E_T = T - T_0. \tag{4}$$

For the electrical equipment in reality, the control value should be determined before the equipment can be driven. However, the output of the fuzzy decision model is a membership function of the controlled variable. The process of converting this function to a specific value is actually an anti-fuzzification. The center of gravity method is used to realize anti-fuzzification, which is represented by Eq. (5)

$$u = \frac{\int x\mu_N(x)d_x}{\int \mu_N(x)d_x}. \tag{5}$$

After the data obtained through the greenhouse detection and the desired target data, the experiment needs to give the greenhouse control parameters. According to this control method, the greenhouse is controlled to enable the parameters of the greenhouse reach the target value. In the experiment, GA was used for iterative updating to optimize the control parameters of greenhouse [18]. The roulette selection method was used to select operators, and the fitness was compared. The proportion of individuals in the overall population was used as the basis for selection. Assuming that there is a population size N and f_i represents the fitness of individual i, the probability of i being selected can be obtained, which is expressed by Eq. (6)

$$P_i = \frac{f_i}{\sum_{j=1}^{N} f_i}, \quad i = 1, \ 2, \ \ldots, \ N. \tag{6}$$

This also means that the probability of an individual being selected is positively correlated with his fitness value. The model control method is also needed to monitor the greenhouse. In industrial control, the PID control algorithm has the obvious advantages of simple structure and strong robustness, especially suitable for the establishment of a deterministic control system. However, the parameters of the traditional PID controller are often easy to be set improperly, which have poor adaptability in the implementation [19]. To avoid this situation, the experiment uses the PSO intelligent algorithm to optimize the traditional PID control. To realize the anti-fuzzification control decision after the system fuzzy decision, the control of greenhouse environmental parameters is taken as the goal. Figure 5 shows the operation of the PID controller.

As shown in Figure 5, $r(t)$ represents the given value and $y(t)$ refers to the actual value of the controller, so its input $e(t)$ is obtained by the difference between the given value $r(t)$ and the actual value $y(t)$, which is expressed by Eq. (7)

$$e(t) = y(t) - r(t). \tag{7}$$

Then, $u(t)$ is set as the output of the PID controller and the input of the control target, expressed by Eq. (8)

$$u(t) = K_p\left[e(t) + \frac{1}{T_i}\int_0^t e(t)\mathrm{d}t + T_d\frac{\mathrm{d}e(t)}{\mathrm{d}t}\right]. \tag{8}$$

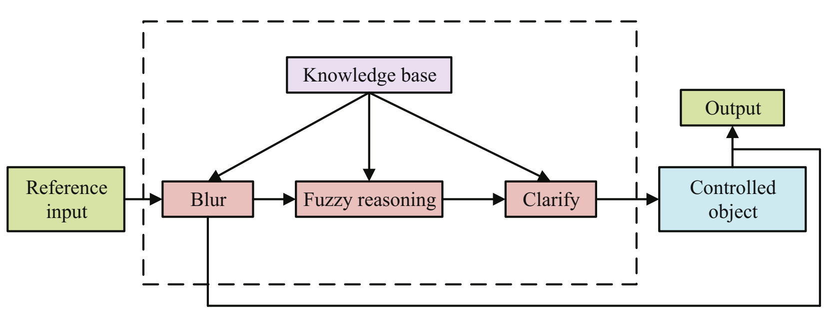

Figure 4: Fuzzy control system architecture.

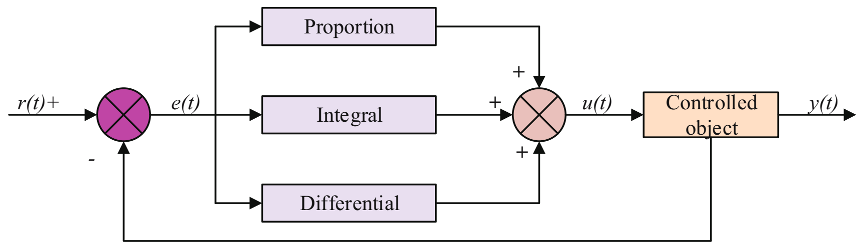

Figure 5: Operation of the PID controller.

In Eq. (8), K_p is a proportional function, T_i is an integral coefficient, and T_d is a differential coefficient. Based on the above equation, the integral function and differential function can be obtained, which are expressed by Eq. (9)

$$\begin{cases} K_i = \dfrac{K_p}{T_i}\displaystyle\int_0^t e(t)\mathrm{d}t \\ K_d = K_p \times T_d \dfrac{\mathrm{d}e(t)}{\mathrm{d}t}. \end{cases} \tag{9}$$

To facilitate the calculation, the triangular membership function is selected to formulate the input parameters. According to the fuzzy rules, the correction calculation of the three PID parameters can be expressed by Eq. (10)

$$\begin{cases} K_p = K_{p0} + \Delta K_p \\ K_i = K_{i0} + \Delta K_i \\ K_d = K_{d0} + \Delta K_d. \end{cases} \tag{10}$$

In Eq. (10), K_{p0}, K_{i0}, and K_{d0} are the initial parameters and K_p, K_i, and K_d refer to the corresponding parameters after optimization. A back-propagation neural network (BPNN) is used to optimize the fuzzy PID control. BPNN realizes the real-time tuning of PID control parameters based on a certain control rule or set value to achieve better control effect. The non-negative sigmoid function is selected as the activation function of the neurons in the output layer, which is expressed by Eq. (11)

$$g(x) = \frac{1}{2}(1 + \tanh(x)) = \frac{e^x}{e^x + e^{-x}}. \tag{11}$$

In Eq. (11), $g(x)$ represents an activation function. BPNN has significant advantages in PID regulation, but it also has some disadvantages, such as slow convergence speed, long response time, and easy to fall into local optimum. PSO corresponds to these shortcomings, so this experiment uses PSO to jointly optimize the operation of the PID controller. First, the connection weight and threshold in PSO are initialized, and then the fitness function of particles is calculated, which is expressed by Eq. (12)

$$f(x_i) = \frac{1}{n_j}\sum_{t=1}^{n_j}(\theta_{it} - O_{it})^2. \tag{12}$$

In Eq. (12), n_j represents the number of training samples, x_i refers to the position of the ith particle in PSO, and θ_{it} means the output value of training sample t of i in n_j. After determining the fitness, because the neuron and particle correspond one-to-one, the particle can update the two extreme values according to the fitness function. The connection weights and thresholds on the network in the process are updated. Figure 6 shows the operation of the PSO optimized neuron PID controller.

As shown in Figure 6, because the connection weight and threshold directly affect the optimization of NN model, this experiment uses PSO to optimize the connection weight and threshold of NN control to increase its self-adaptability.

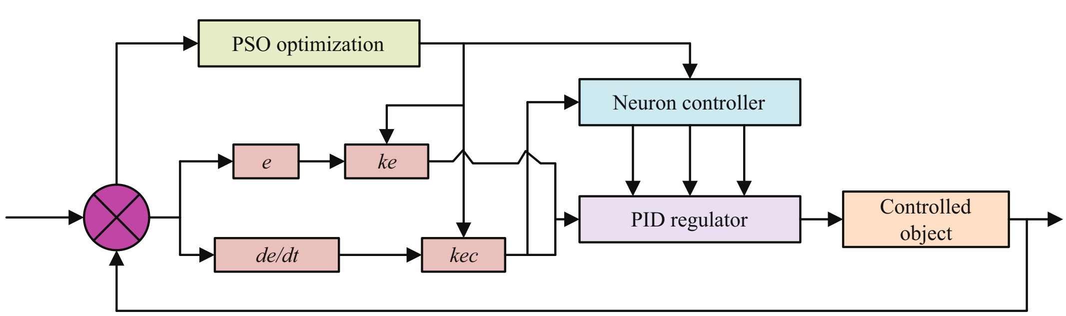

Figure 6: PSO optimized neuron PID controller operation process.

3 Performance testing and application effects of an improved greenhouse monitoring system

To intuitively prove that the designed improved narrow-band internet of things (INB-IOT) is better than the conventional BPNN in PID control effect, MATLAB simulation and comparative analysis were made. Meanwhile, three other algorithms were selected to compare with INB-IOT.

3.1 Performance testing comparison

To verify the actual performance of INB-IOT, wireless sensors and fuzzy PID controller (WSN-PID), wireless sensors and IoT platform (WSN-IoT), IoT and dedicated simulators (IoT-DS), and INB-IOT were selected to compare different performance indicators [20–22]. In the formal experiment, it is inevitable to be affected by some external factors, which will lead to the deviation of the actual performance of different algorithms. To reduce the experimental error as much as possible, the environmental parameters of the simulation experiment were unified before the experiment. Table 1 shows the settings of simulation environment parameters.

Table 1: Settings of related parameters

Project	Choice
Graphics card	NVIDIA RTX 2080 Ti
Operating system	Ubuntu18.04
Network architecture	PyTorch v1.2.0
Programming software	VS Code2017 Anaconda3
CUDA	CUDA 11.0 with cuDNN
Optimizer	Adam
Graphics card memory	64G

The monitoring data of an intelligent greenhouse in the United States were selected as the task data set. Approximately 8,000 pieces of monitoring data were randomly selected, and the data with low authenticity and redundancy were eliminated, leaving 6,485 pieces of data. Then, 5,000 pieces of data were randomly selected, 50% as the training set and 50% as the test set. First, the convergence rates of the four algorithms on two datasets were compared. Figure 7 shows the transformation of the relevant fitness values.

Figure 7(a) shows the change of fitness value in the training set. With the increase of system iteration, the fitness values of the selected algorithms begin to decrease. However, when the system started running, the fitness value of INB-IOT changed little. When iterating to the 49th time, the fitness value of INB-IOT had the maximum value and then remained stable, up to 97.58. When the fitness values of WSN-IoT, WSN-PID, and IoT-DS reached stability, the system iterations were greater than 100 times, and the corresponding maximum fitness values were 80.25, 72.61, and 71.06, respectively. Figure 7(b) shows the change of fitness value on the test set. Until the 78th training, the INB-IOT began to achieve the optimal fitness value, which was as high as 96.27 and remained stable from then on. At this time, the fitness values of the other three algorithms were still in a downward trend and were always less than the fitness values of INB-IOT. These results confirmed that INB-IOT had a large fitness and reached the state of convergence in a short time, which proved that it had a high computing speed. Then, ten nodes were randomly selected to analyze the data packet loss rate of intelligent

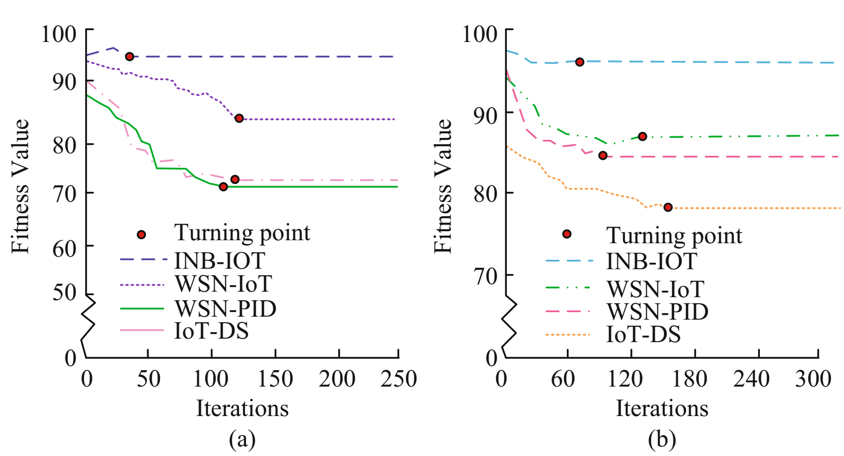

Figure 7: Comparison of fitness values on the two data sets. (a) Training set. (b) Test set.

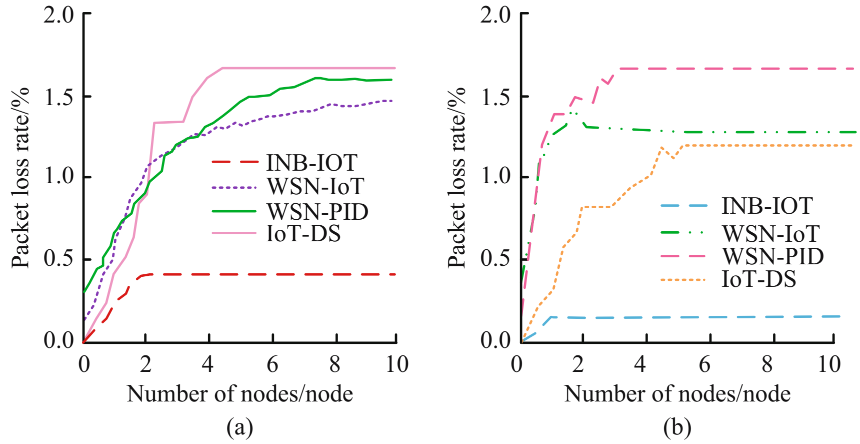

Figure 8: Communication monitoring packet loss rate under different algorithm operations. (a) Training set. (b) Test set.

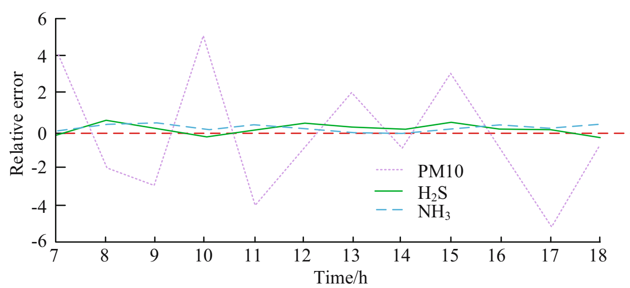

Figure 9: Comparison of measurement results of the two algorithms.

greenhouse monitoring under the operation of four algorithms in Figure 8.

Figure 8(a) shows the packet loss rate of the four algorithms on the training set. With the increase of nodes, the packet loss rate of the four algorithms increased. When the second node appeared, the packet loss rate of INB-IOT communication monitoring was stable at 0.404%. At this time, the packet loss rate of the remaining three algorithms increased and significantly greater than 1.5%. Figure 8(b) shows the packet loss rate of different algorithms on the test set. When the first node appeared, the INB-IOT had a stable packet loss rate, which was only 0.147%. These results showed that under the operation of INB-IOT, the communication stability of the greenhouse monitoring system was good, the packet loss rate of the selected node was 0.404%, the success rate of monitoring communication was more than 99%, and the performance was superior.

3.2 Application effect analysis

Different environments had a direct impact on the growth of plants in the greenhouse. Therefore, the experiment

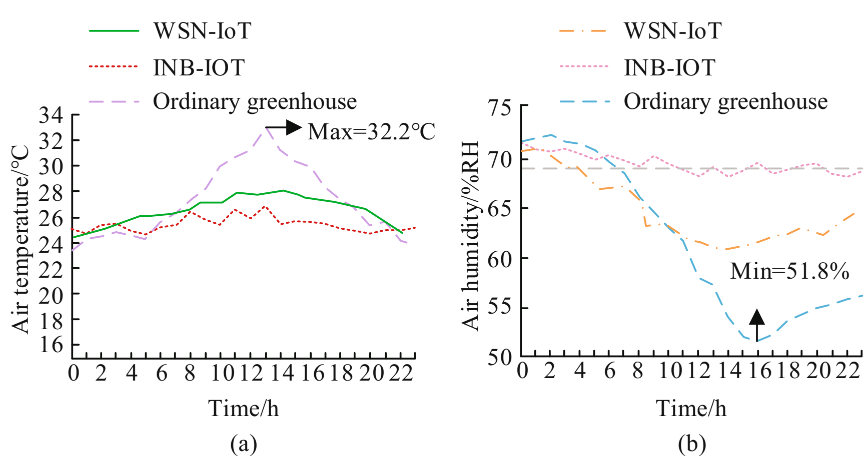

Figure 10: Comparison results of temperature and humidity. (a) Temperature comparison. (b) Humidity comparison.

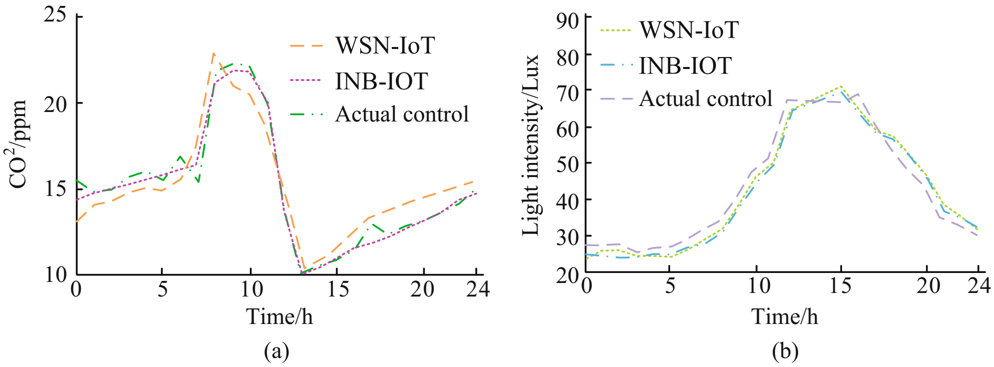

Figure 11: Comparison of carbon dioxide and light intensity. (a) Comparison of target CO_2. (b) Comparison of target light intensity.

time selected from 7:00 a.m. to 18:00 p.m. was the main observation time. The relative error between INB-IOT and the data actually collected on site was analyzed. The error between the measurement results is compared in Figure 9.

As shown in Figure 9, the average relative measurement errors of PM10, H_2S, and NH_3 were ±2.58 μg/m^3, ±0.216 × 10^{-6}, and ±0.175 × 10^{-6}, respectively, which were within a reasonable range, indicating that INB-IOT had high data accuracy. In addition, a suitable environment was conducive to the growth of plants. Therefore, WSN-IoT and INB-IOT with good performance were used to automatically regulate the greenhouse. Three planting greenhouses with basically the same environment were selected, and one greenhouse was regulated and monitored by WSN-IoT. A greenhouse used INB-IOT for regulation and monitoring. Another was a greenhouse with ordinary facilities. Figure 10 shows the comparison results of temperature and humidity within 24 h.

Figure 10(a) shows a comparison of greenhouse temperature changes. The temperature change of the ordinary greenhouse showed a trend of first increasing and then decreasing, and the highest temperature was 32.2°C at 14 o'clock. The greenhouse temperature regulated by INB-IOT was maintained at about 25°C. The temperature change trend of greenhouse under the control of WSN-IoT was consistent with that of ordinary greenhouse, and the temperature was higher than 25°C. Figure 10(b) shows the comparison of greenhouse humidity changes. The humidity of ordinary greenhouse decreased with the increase of temperature, and the lowest humidity was 51.8% at 16 o'clock, which was in the state of high temperature and low humidity for a long time. However, the greenhouse humidity regulated by INB-IOT fluctuated around 69% and retained a small fluctuation. The humidity of the greenhouse under the control of WSN-IoT also showed a downward trend, and there was a minimum humidity at 14 o'clock. INB-IOT better maintained the suitable environment for the healthy growth of plants and achieved the best intelligent regulation. Then, taking the target carbon dioxide concentration and target light intensity of greenhouse as an example, the comparison results of carbon dioxide and light intensity within 24 h were analyzed (Figure 11).

Figure 11(a) and (b) shows the gap between target carbon dioxide and target light intensity and actual control, respectively. The gap between WSN-IoT regulation and actual control was significant. However, the difference

Table 2: Comparison of INB-IOT system performance in different data sets

Data set name	Sample size	Number of iterations	Optimal fitness value	Average communication success rate (%)	Mean relative error (range)
United States smart greenhouse dataset	6,485	49	97.58	99.60	PM10: ±2.58 μg/m^3 H_2S: ±0.216 × 10^{-6} NH_3: ±0.175 × 10^{-6}
European Agricultural Research Centre data set	9,870	65	96.82	99.45	PM10: ±2.34 μg/m^3 H_2S: ±0.198 × 10^{-6} NH_3: ±0.158 × 10^{-6}
Greenhouse data set in northern China	7,320	57	97.25	99.55	PM10: ±2.72 μg/m^3 H_2S: ±0.225 × 10^{-6} NH_3: ±0.185 × 10^{-6}

between the target carbon dioxide concentration and the target light intensity obtained under the INB-IOT operation and the actual control curve was small, which regulated the system more stably. This further verified that INB-IOT monitored and controlled the parameters of greenhouse more effectively. To further analyze the generality of the proposed system, the research applied it to the intelligent greenhouse data set of the United States, the European Agricultural Research Center data set, and the greenhouse data set of Northern China. Then, the study selected fitness values, average communication success rate, and average relative error indicators for analysis. The specific results are shown in Table 2.

Table 2 shows that the INB-IOT system performs well on different data sets. The optimal fitness values were close to 97%, indicating that the optimization effect of the system was remarkable. The average communication success rate was more than 99%, which proved the communication stability and reliability. Although the sample size and number of iterations were different, the system could quickly converge to the optimal solution on different data sets. The average relative error was kept at a very low level, indicating that the measurement accuracy of the system was high. In summary, the INB-IOT system showed strong versatility and adaptability, which was suitable for data monitoring and control in a variety of greenhouse environments.

4 Conclusions

For greenhouse monitoring, an intelligent monitoring and control system combining IoT and artificial intelligence algorithm was proposed. First, a sensor network framework based on IoT was designed, and the cloud service framework was introduced to analyze a large number of data. Artificial intelligence algorithms such as PSO were introduced to optimize the greenhouse monitoring environmental parameters. These data confirmed that when four different algorithms were applied to the training set, the maximum fitness value of INB-IOT was 97.58 when iterating to the 49th time. The appropriate stability stress values of WSN-IoT, WSN-PID, and IoT-DS were 80.25, 72.61, and 71.06, respectively, with more than 100 iterations. When applied to the test set, the fitness value of INB-IOT was as high as 96.27 at the 78th iteration. In the comparison of temperature and humidity, the greenhouse temperature regulated by INB-IOT was maintained at about 25℃. The greenhouse humidity regulated by INB-IOT fluctuated around 69% and kept a small fluctuation. The difference between the curve of target carbon dioxide concentration and target light intensity and the curve of actual control was small. These results confirmed that INB-IOT had faster convergence speed and better maintained the suitable environment for the healthy growth of plants to achieve the best intelligent regulation. Although the proposed INB-IOT system showed excellent performance in greenhouse monitoring, there are still some potential drawbacks. For example, the system is highly dependent on the accuracy and reliability of the sensor, and if the sensor fails, the data may be distorted, which affects the control effect. In addition, the energy consumption and cost of the system need to be further considered. Future studies can explore more environmental factors, such as soil moisture, light direction, *etc.*, to optimize the greenhouse environment more comprehensively. Concurrently, an investigation into the means of reducing the energy consumption and expenditure of the system, while enhancing its practicality and economic viability, can be undertaken. More advanced artificial intelligence algorithms can also be considered to further improve the intelligence level and control the accuracy of the system.

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