DESIGNING AN INTELLIGENT IRRIGATION SYSTEM BY USING BACKPROPAGATION NEURAL NETWORK TO PREDICT WATER DEMAND
/
基于需水量预测的智能灌溉系统设计

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ABSTRACT
To realize the real-time remote monitoring of the jujube orchard environment and the prediction of irrigation amount, an intelligent irrigation system was designed in this study by using sensors, Internet of Things (IoT), and backpropagation (BP) neural network. In this system, the jujube tree is taken as the test object, the meteorological data are used as the model feature input vector, the BP neural network prediction model is used to predict the water demand of the crop, and data visualization monitoring and remote control of the irrigation switch are realized using the IoT platform and mobile terminal platform.

摘要
为实现枣树园环境的实时远程监测和灌溉量的预测，设计了基于传感器技术、物联网技术及人工智能技术相结合的智能灌溉系统。该系统以枣树为试验对象，以气象数据作为模型特征输入向量，运用 BP 神经网络预测模型预测作物当前需水量，并通过物联网平台与移动端平台实现数据可视化监测和灌水开关远程控制。

INTRODUCTION
As a traditional agricultural country, China’s agricultural water consumption accounts for approximately 70% of China’s water consumption. Moreover, China faces severe water shortage, with per capita water resources being only one-fourth of the world level. Currently, traditional artificial irrigation is still used in most areas of China, which is inefficient and wastes a lot of water resources. Therefore, how to save agricultural water efficiently has become an important topic of current social development. Recently, advanced technologies such as the Internet of Things (IoT) have been applied to agricultural production to promote the transformation of traditional agriculture to modern agriculture (*Wang et al., 2016*). For intelligent irrigation, the STC89C52 microcontroller has been employed as the core controller, and an intelligent irrigation system has been designed and developed (*Yang et al., 2020*); the system is divided into manual mode and intelligent mode to control the relay pump.

The AT89S52 microcontroller has been used to control the flow of the pump, and temperature and humidity sensors have been used to collect data and compare the set data for detection and control (*Peng et al., 2017*). Furthermore, the Arduino microcontroller has been used as the core controller for achieving intelligent irrigation (*Fu et al., 2019*). However, due to the limited computing power of single-chip microcomputers, the aforementioned intelligent irrigation systems do not involve intelligent algorithms and are not sufficiently intelligent.

Currently, Raspberry Pi is widely used in intelligent irrigation systems because its high computing power and extensive open-source codebase are highly suitable for realizing intelligent algorithms. For example, Raspberry Pi has been used as the core controller, supplemented by sensors for monitoring the parameters of the crop growth environment, and the intelligent monitoring of changes in the crop growth environment has been realized through a mobile phone application (*Huang et al., 2021*). Moreover, an intelligent cloud irrigation system has been developed using Raspberry Pi that can collect information such as air temperature, humidity, and soil moisture in real time and output the appropriate amount of irrigation through the fuzzy computing controller (*He et al., 2017*).

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In terms of software control, a series of intelligent algorithms such as fuzzy control, expert systems, and neural networks have been applied to irrigation systems (*Liu et al., 2021; Xu et al., 2020; Yu et al., 2019; Du et al., 2020; Zhao et al., 2017; Umair et al., 2010，Ding et al., 2011*).

To sum up, in this study, Raspberry Pi was used to develop a low-cost, easy-to-operate intelligent irrigation system, and the backpropagation (BP) neural network prediction model was used to predict the irrigation amount of the crops from the meteorological data to provide data support for the intelligent irrigation system.

MATERIALS AND METHODS

System architecture

In this study, farmland data acquisition, data transmission, intelligent prediction, real-time monitoring, and irrigation control were achieved using a combination of sensor technology, embedded technology, IoT technology, and artificial intelligence technology. The structure of the designed system is shown in Fig. 1. The system first collects the required environmental data by using various environmental sensors and then transmits the data to the central processor of Raspberry Pi through the 485 communication Modbus protocol. The forecasting model predicts the crop water demand based on the meteorological data and then uploads it to the cloud IoT platform through Raspberry Pi's wireless communication module, and the data are stored in the cloud database. Commands can be sent to Raspberry Pi through the MQTT protocol to control the level of the GPIO port of Raspberry Pi to achieve remote control of the irrigation system. The physical appearance of the system is shown in Fig. 2.

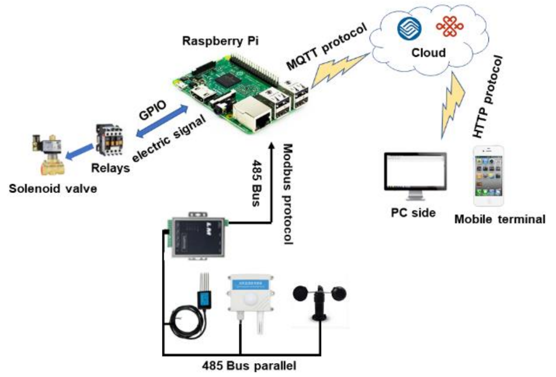


Fig. 1 - Structure of the system

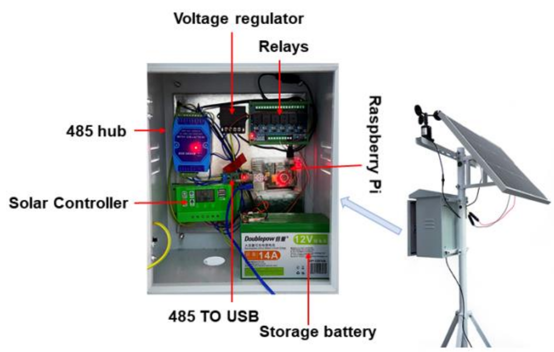


Fig. 2 - Physical appearance of the system

Core control module

The system uses Raspberry Pi as the central processing unit. Raspberry Pi is a Linux-based microcomputer. Compared with single-chip microcomputers, it has more powerful data processing functions, can perform multi-threaded tasks smoothly, and has rich interfaces with the basic functions of a PC (*Liu et al., 2021*). Moreover, Raspberry Pi comes with its own wireless network and wired network ports and does not require additional network communication modules, making it more convenient to use. Its structure is shown in Fig. 3.

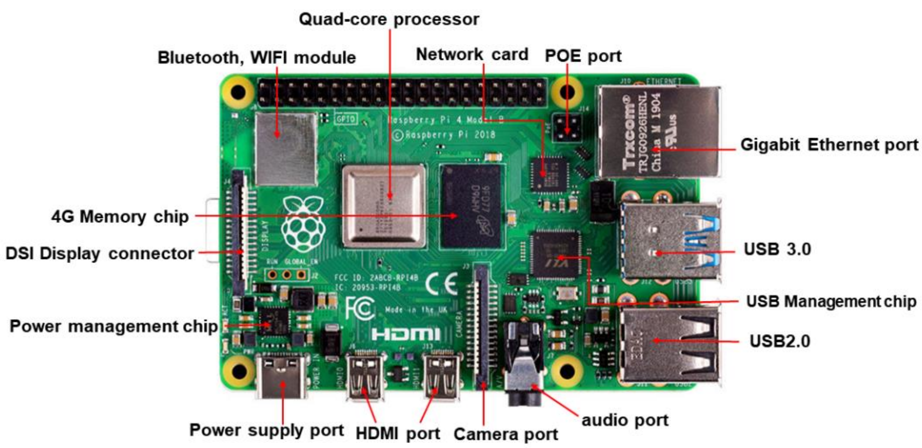


Fig. 3 - Structure of Raspberry Pi

Raspberry Pi can be connected to devices such as a mouse, keyboard, and screen, and programs can be directly written in it. However, for the convenience of programming and modification, the code can be written on a PC with the Windows operating system and then transplanted to Raspberry Pi to run. The network cable is used to connect Raspberry Pi to the computer, and the same IP address is set; then, Raspberry Pi can be accessed using the VNC Viewer software. VNC Viewer has a file transfer function that can realize file transfer between Raspberry Pi and a Windows PC. The written code file can be transplanted to Raspberry Pi and run in the command window of the Raspberry Pi terminal.

BP neural network model construction

BP neural network has good self-learning, self-adaptation, and generalization ability; moreover, it systematically solves the problem of learning the connection weights of hidden units in multilayer networks. The learning process of the BP neural network includes two stages: forward and reverse propagation. In the forward propagation process, the input information is passed according to the order of the hidden layers. Each time the information is passed to a layer, it affects the next layer without affecting the information transfer to the upper layer. The BP network can perform error inversion during the training process. When the obtained output result does not meet the error requirement, the output is back-propagated according to the original channel, and the model is retrained until the output meets the error requirement. Fig. 5 shows the structure of the BP neural network model developed in this study. The input layers are X_1–X_4, which are the average temperature, wind speed, air relative humidity, and light intensity, and *Y* is the output vector, which is the water demand of jujube trees.

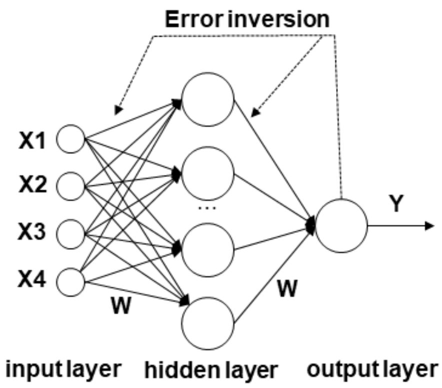


Fig. 5 - Structure of the BP neural network

The mean square error (*MSE*) function was employed as the loss function in the model because the curve of the MSE function is smooth, continuous, and differentiable everywhere, which is suitable for gradient descent algorithms (*Li et al., 2018*). According to the characteristics of the test data and model structure, the specific construction parameters of the BP neural network prediction model are presented in Table 1.

Table 1

Prediction model parameter settings

model parameter	parameter name	parameter value
epoch	Iteration times	1000
Batch_size	Training capacity per batch	128
validation_split	training validation set	0.2
Lr	learning rate	0.01

After the model was trained, 40 groups of data were randomly selected from the validation sample data for prediction, and linear regression analysis was performed on the prediction results. As shown in Fig. 6, the regression coefficient R^2 is 0.983, indicating that the model has high accuracy. The residual distribution diagram displayed in Fig. 7 shows that the residuals of the 40 groups of prediction data are stable with values between −0.5 and 0.5, which proves that the BP prediction model meets the accuracy requirements.

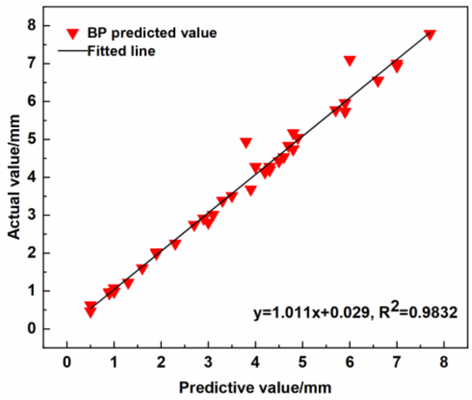


Fig. 6 - Model fitting results

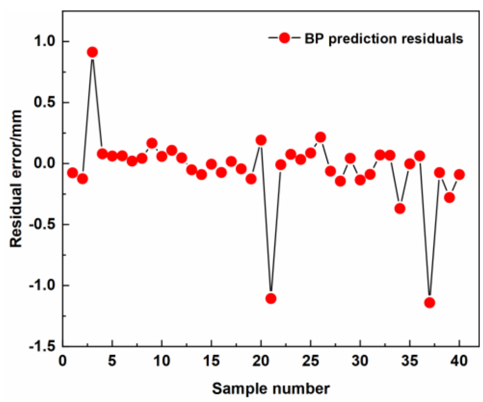


Fig. 7 - Model residuals

After the model is trained, the BP.h5 file is generated. To facilitate the practical application of the model, an infer.py script needs to be written, which can directly call the trained model. The generated model file is then transplanted to Raspberry Pi and run in its terminal.

System irrigation strategy

The irrigation process is illustrated in Fig. 8.

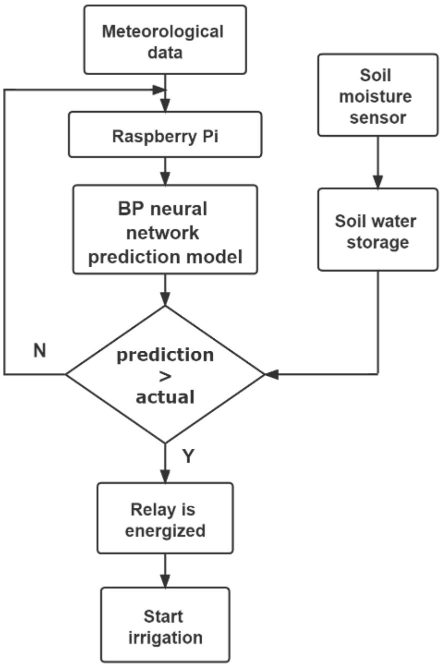


Fig. 8 - Irrigation strategy flowchart

First, the BP neural network prediction model predicts the current crop water demand according to the meteorological data collected by the sensors. The prediction model then compares it with the soil water storage in the field determined from the soil moisture data collected by the soil moisture sensor. When the predicted value is greater than the soil water storage, the GPIO port of Raspberry Pi changes from low level to high level, the electromagnetic relay is energized, the electromagnetic valve gets activated, and the system irrigates. In contrast, when the soil water storage detected by the sensor is more than the predicted value, the GPIO port of Raspberry Pi changes from high level to low level, the electromagnetic relay is powered off, and the irrigation task is completed. If the water demand predicted by the meteorological data is less than the current soil water storage, the system will not perform the irrigation task.

The calculation formula of field water storage is as follows (*Yan et al., 2008*):

$$Q = d \cdot h \cdot c \tag{1}$$

where Q is the field water requirement [mm], d is the soil heat flux [g/cm^3],
h is the soil layer thickness [mm], and c is the water content by weight [%].

In the experiment performed in this study, because the soil moisture sensor is buried at a depth of 30 cm, *h* was taken as 300 mm, and the soil bulk density *d* was taken as 1.43 g/cm^3 according to a previous study (*Zhou et al., 2020*). The mass moisture content was then obtained by multiplying the soil bulk density by the volumetric moisture content measured by the soil moisture sensor.

IoT platform development and design

To achieve remote monitoring and real-time control of the environment and to provide agricultural operators with convenient and fast irrigation operations, in this study, the IoT platform developed using Alibaba Cloud's web visualization tool was used as the application client. The connection between the intelligent irrigation system and the IoT cloud platform was completed. Web interface design and development includes the following two aspects:

(1) Remote irrigation switch control: As shown in Fig. 9, by using the button on the irrigation control page, the user can realize the remote control of the field solenoid valve switch.

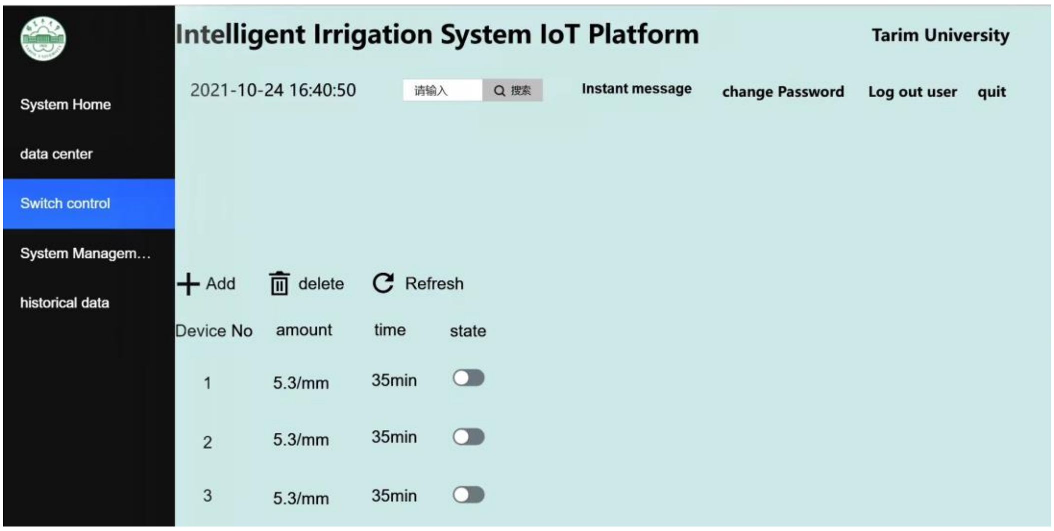
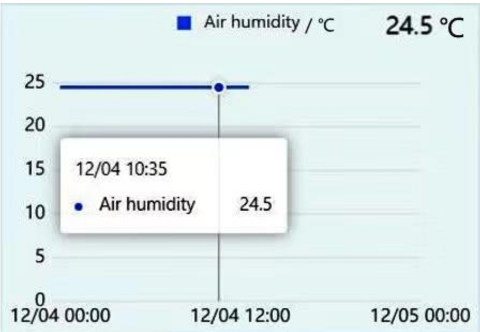
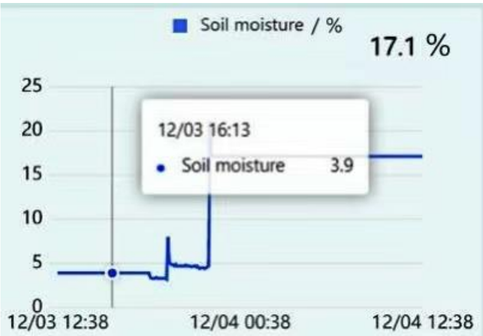


Fig. 9 - IoT platform remote control

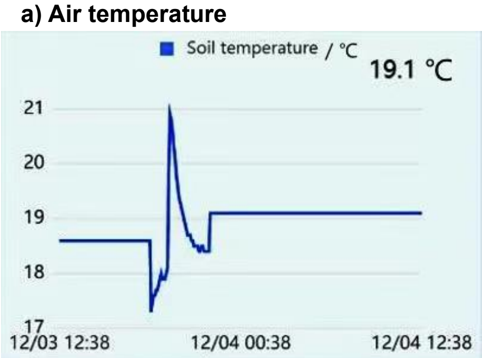
(2) Real-time environmental data display: The data center of the IoT cloud platform can display the real-time environmental data of jujube orchards. The air temperature, soil moisture, soil temperature, and light intensity data are shown in Fig. 10 a–d, respectively.



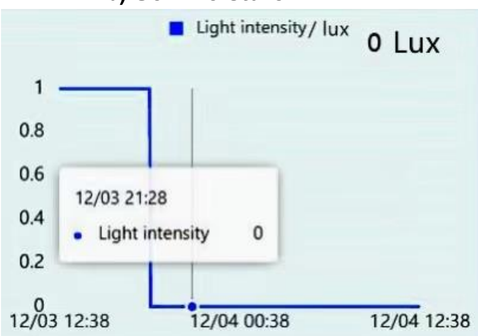
a) Air temperature



b) Soil moisture



c) Soil temperature



d) Light intensity

Fig. 10 - Real-time monitoring of IoT platform environment

Mobile IoT Platform

To facilitate usage among mobile users, the system not only has a PC-side IoT platform but also has a mobile-side platform. The mobile terminal was developed in Alibaba Cloud web visualization tool. The mobile terminal offers the real-time monitoring of data and control of the switch of the solenoid valve. The mobile interface is shown in Fig. 11 and includes various meteorological data detected by the system sensors and the display of the current water demand of crops; switches 1–3 are solenoid valve manual control switches.

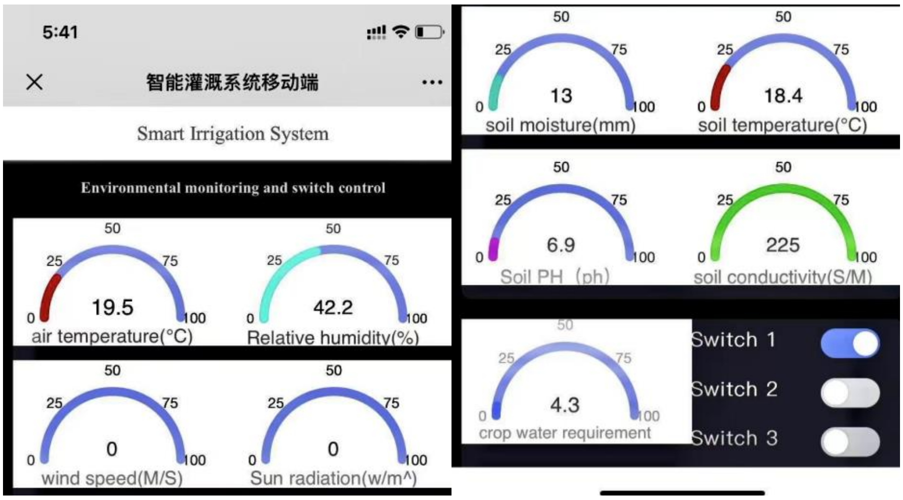


Fig. 11 - IoT platform mobile interface

RESULTS

Water demand prediction test

The accuracy of the water demand prediction model was tested. Moreover, the meteorological data collected by the sensor in the field was used to calculate the water demand of jujube trees, and the calculation results were compared with the model prediction results, as shown in Table 2.

Table 2

Model prediction comparison test

Air temp [℃]	Wind speed [m/s]	light intensity [lux]	Relative humidity [%]	Predictive value [mm/d]	Calculated value [mm/d]	absolute error [%]
3.5	1.1	125.9	39	2.54	2.6	2.3
5.5	2.2	80.1	38	3.62	3.5	3.4
6.2	3.5	96.3	43	5.38	5.3	1.5
3.4	0.9	109.2	45	2.59	2.7	4.1
7.4	1.1	67.6	46	4.36	4.2	3.8

From Table 2, it can be seen that the absolute errors of the models in the experimental group predicting the water demand of jujube trees are below 5%, and the average absolute error is 3.02%; thus, indicating that the model has high accuracy and can meet the system requirements.

Irrigation test

In terms of irrigation decision-making, four irrigation experiments were conducted; the test results are presented in Table 3.

Table 3

Irrigation Test Results

number of tests	Model predictions[mm]	soil water storage[mm]	Solenoid switch
1	4.3	5.3	close
2	7.6	6.4	open
3	4.7	3.6	open
4	3.5	4.8	close

Results presented in Table 3 reveal that the system can work as required. When the predicted value is greater than the soil water storage capacity, the solenoid is turned on, and the system starts performing the irrigation task. Otherwise, the solenoid valve is turned off and the system does not irrigate.

CONCLUSIONS

IoT technology plays a crucial role in modern agriculture. An intelligent irrigation system based on the BP crop water demand prediction model was designed and implemented in this study. Based on predetermined properties of air humidity, temperature, wind speed, light intensity, and water demand, the BP neural network prediction model was established, and the fitting analysis and residual analysis of the prediction model were performed. The results showed that the model fitting coefficient is 0.983, and the model prediction value residual is stable at around 0.5, indicating that the model exhibits superior performance and high prediction accuracy. In terms of hardware, each module can function independently, and the IoT platform and mobile terminal designed and developed in this study meet the stipulated requirements. Furthermore, the water demand prediction test and irrigation experiment were conducted. The results revealed that the average absolute error between the predicted value and the calculated value is 3.02%; thus, the error is within acceptable limits. In the irrigation experiment, the irrigation task was completed as designed. In future studies, the system needs to be tested in the field for a long time for further improvement.

ACKNOWLEDGEMENT

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REFERENCES

[1] Du, T., Zou, J., Sun, S., Qian, C., Liu, D., (2020). Design of Intelligent Irrigation Control System for Facility Vegetables (设施蔬菜智能灌溉控制系统的设计). *Water Saving Irrigation*, Vol.02, pp.92-95, Wuhan / China;

[2] Ding S, Su C, Yu J. (2011). An optimizing BP neural network algorithm based on genetic algorithm[J]. *Artificial Intelligence Review*, 36(2): 153-162;

[3] Fu, N., Liu, H., Tang, Y., Gao, Y., (2019). Design of intelligent irrigation system based on Arduino microcontroller (基于 Arduino 单片机的智能灌溉系统设计). *Information and Computers* (Theory Edition), Vol.8, pp.76-77, Beijing/China

[4] Huang, J., Kui, Y., Kou, Y., Gao, Y., (2021). Design of Intelligent Cloud Irrigation System Based on Raspberry Pi (基于树莓派的智能云灌溉系统设计). *Shanxi Electronic Technology*, Vol.3, pp.19-21, Shanxi / China;

[5] He, J., (2017). An intelligent cloud irrigation system (一种智能云灌溉系统). *Water Saving Irrigation*, Vol.3, pp.97-99, Hubei / China;

[6] Li, H., Yang, G., Xin, J., (2018). Corrosion prediction of atmospheric tower top oil and gas system based on neural network and genetic algorithm (基于神经网络与遗传算法的常压塔顶油气系统腐蚀预测). *Petrochemical corrosion and protection*, Vol.35, pp.34-37. Henan / China;

[7] Liu, X., (2021). Optimal Design of Intelligent Irrigation Expert System Based on SQL (基于 sql 的智能灌溉专家系统优化设计). *Agricultural Mechanization Research*, Vol.44, pp.235-238+243, Heilongjiang / China;

[8] Liu, W., Li, S., (2021). The Application of Raspberry Pi in the Teaching of Internet of Things (树莓派在物联网专业教学中的应用). *Fujian Computer*, Vol.37, pp.139-141, Fujian / China;

[9] Liu, J., Liu, X., Wu, H., Zheng, H., Li, Z., (2021). Application of Support Vector Machine Model Based on GA Optimization in Prediction of Green Pepper Crop Water Requirement (基于 GA 优化的支持向量机模型在青椒作物需水量预测中的应用). *Water Saving Irrigation*, Vol.1, pp.70-76, Hubei / China;

[10] Peng, H., Wang, Y., Han, G., Zhang, J., (2017). Design of Intelligent Irrigation System Based on Single Chip Microcomputer (基于单片机的智能灌溉系统设计). *Software engineering*, Vol.2, pp.40-43, Liaoning / China;

[11] Umair S M, Usman R. (2010). Automation of irrigation system using ANN based controller [J]. *International Journal of Electrical & Computer Sciences* IJECS-IJENS, 10(02): 41-47.

[12] Wang, C., Chen, X., Zhang, A., (2016). The Application and Prospect of the Internet of Things in Agriculture (物联网在农业中的应用前景及展望). *Journal of Agronomy*, Vol.6, pp.96-98, Beijing / China;

[13] Xu, J., Wang, L., Tan, X., Wang, Y., Zhao, Z., Shao, M., (2020). Research on Intelligent Irrigation Control Strategy Based on SOA Optimizing PID Control Parameters (基于 SOA 优化 PID 控制参数的智能灌溉控制策略研究). *Journal of Agricultural Machinery*, Vol.51, pp.261-267, Beijing / China;

[14] Yang, Q., Zhai, J., Zhang, T., (2020). Smart Bluetooth Irrigation System Based on Single Chip Computer (基于单片机的智能蓝牙灌溉系统). *Software*, Vol.41, pp.110-112+184, Beijing/China;

[15] Yu, X., Zhang, L., (2019). Design and Realization of Fuzzy Intelligent Irrigation System (模糊智能灌溉系统的设计与实现). *Microcomputer application*, Vol.35, pp.73-76, Shanghai / China;

[16] Yan, Y., Li, F., Yan, L., (2008). Dynamic change law of soil water storage in the source regions of the Yangtze and Yellow Rivers (长江、黄河源区土壤储水量动态变化规律). *Agricultural Research in Dry Areas*, Vol.04, pp.23-27, Shanxi / China;

[17] Zhao, Y., Ji, J., Cui, H., Yan, S., Wang, X., Sun, Z., (2017). Design of Intelligent Irrigation System for New Sliding Cover Greenhouse Based on Crop Evapotranspiration Model (基于作物蒸散量模型的新型滑盖温室智能灌溉系统设计). *Water Saving Irrigation*, Vol.08, pp.83-87+91. Wuhan / China;

[18] Zhou, S., (2020). Effects of dual control of water in root zone canopy of jujube in southern Xinjiang on root zone evaporation, fruit set rate and quality (南疆枣树根区冠层水分双控对根区蒸发、坐果率及品质的影响). Master dissertation, Tarim University, Xinjiang / China;