A Machine Learning Based Smart Irrigation System with LoRa P2P Networks

Yu-Chuan Chang+, Ting-Wei Huang*, Nen-Fu Huang*,+

+Institute of Communications Engineering, National Tsing Hua University, Taiwan

* Department of Computer Science, National Tsing Hua University, Taiwan

{kkeevviinn840512@gmail.com, wei84914@gmail.com, nfhuang@cs.nthu.edu.tw}

Abstract*—In agriculture, the experiences of farmers are very valuable but difficult to replace and passing on. The lack of working power is also a serious problem for many agriculture countries. For planting organic crops, irrigation is one of the most critical steps but also a very labor intensive work. This paper provides a machine learning-based precise and smart irrigation system with LoRa P2P networks to automatically and seamlessly learn the irrigation experiences from expert farmers for greenhouse organic crops. The proposed system will firstly calculate the amount of water for each irrigation based on the trained irrigation model combined with the environment data, such as air temperature/humidity, soil temperate/humidity, light intensity, etc., and then irrigate the crops automatically via the long-distance and low-power wireless LoRa P2P network. The MAC protocol of standard LoRaWAN is Aloha based (random access) and may not be suitable for real-time automatically control. We implement the automatic irrigation system with LoRa P2P network which is a master-slave and TDM-based MAC protocol. Experimental results show that the proposed smart and precise irrigation system is very suitable for modern green house-based agriculture.

***Keywords*—Automation Irrigation System, LPWAN, LoRa P2P, Machine Learning, Precision Agriculture**

I. INTRODUCTION

Today, many young people wish to work in agriculture but they lack the relevant experiences. With the system proposed in this paper, it is easy to understand the experience of other farmers, making planting no longer difficult. By monitoring soil humidity, which is beneficial for crop production, water usage can be optimized. The processes involved in growing crops can be enhanced if soil humidity can successfully be predicted in any area. Knowledge about soil moisture content allows farmers to obtain information about the optimal times for sowing and cultivating crops and determine whether infiltration of the soil is appropriate. In addition to providing a system that automatically generates irrigating rules, a LoRa-based system for automatic irrigation is also provided. Since LoRa uses unlicensed wireless band, it is suitable for constructing a LoRa-based network for cost consideration. Therefore, we employ LoRa-based communication protocol for collecting data and controlling irrigation system. Nevertheless, for LoRaWAN (Aloha based MAC protocol), the latency of downlink communication from gateway to Class-A LoRa node (battery-based sensor) is relative long (needs to wait the transmission of a Class-A node). We therefore employ an alternative and more cost effective TDMA-based MAC protocol (LoRa P2P) to construct the smart irrigation system. The gateway converts the raw sensing data received from different devices into human-readable data and store them in a database. We provide a mobile application and a website to allow users to easily view the crop growing environment data. In addition, the users can trigger events according to the machine predicted-rules. There are two types of events, warning notifications and control events. Establishing control events helps achieve automatic control. We also integrated the controllers with the controlled devices. We established LoRa P2P communication between the gateway (master), sensor hubs (slaves), and controllers (slaves).

II. RELATED WORKS

A. LoRa and LoRaWAN

LoRa is a physical layer or wireless modulation technology that supports a long-range communication link. It is based on chirp spread spectrum modulation that not only has the same low-power characteristics as frequency-shift keying (FSK) modulation but also substantially increases the communication range. LoRaWAN [1] defines the MAC communication protocol (Aloha based random access) and system architecture (start topology) for the network based on LoRa physical layer communication link. To support different applications, the nodes of LoRaWAN are classified into three categories: Class-A node is battery-based sensor to save power consumption, Class-C is main-powered controller to continuously listen the commands from LoRaWAN gateway, and Class-B node is battery-based controller. For Class-A node, it will open two slots to receive the command or response from the gateway after it initiated a transmission to gateway. Thus, the gateway can communicate with a Class-A node only after the Class-A node transmitted a packet. Which means the communication time latency from gateway to Class-A node is unpredictable, and may not suitable for time-sensitive controllers.

B. Automation Control System

An IoT-based agriculture system has been proposed in [4] to provide automatic irrigation service. LoRa is very suitable for agriculture application due to its long-distance and low-power characteristics. Nevertheless, since LoRaWAN may cause transmission collisions (due to Aloha based MAC protocol) and long transmission latency from gateway to Class-A node, we employ an alternative and more cost effective TDMA-based MAC protocol (LoRa P2P) to construct the smart irrigation system.

III. System Design And Implementation

A. System Architecture

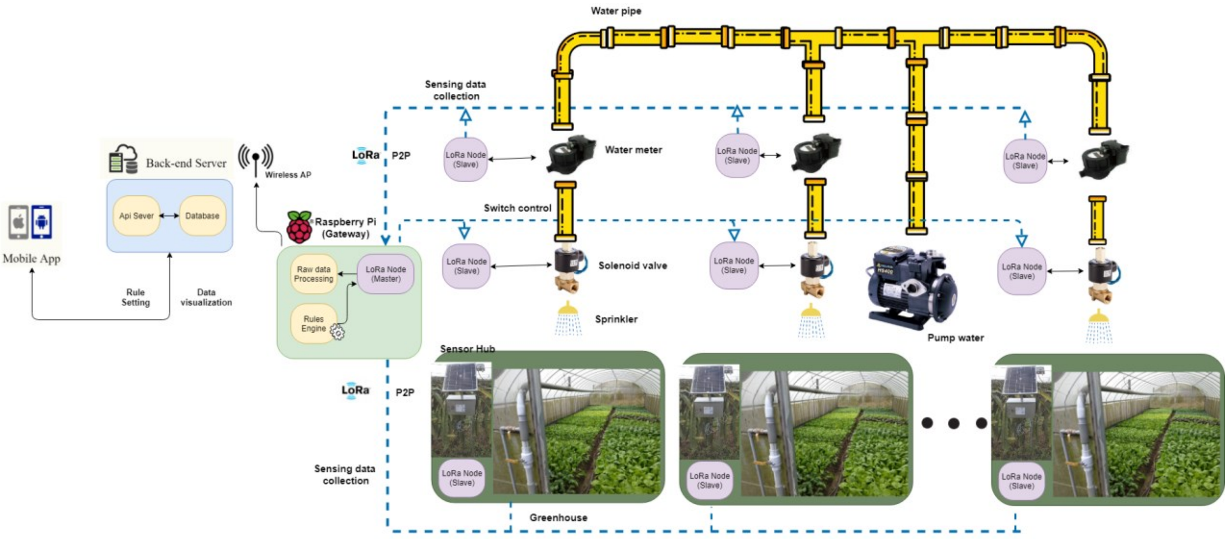

Fig. 1. Architecture of LoRa P2P network based smart irrigation system

Several automatic planting and irrigation mechanisms have been proposed for agricultural environment [5-6]. Machine learning approached are also applied for agriculture [7-8]. This article proposes a machine learning based mechanism to establish a model to learn the irrigation experiences from expert farmers. Then the model is used to calculate the amount of water required for each day according the collected environment data, such as light intensity, soil-temperature, soil-humidity, air-temperature, and air-humidity. And then automatically enable the irrigation system to irrigate that amount of water. Figure 1 illustrates the architecture of the proposed smart irrigation system based on LoRa P2P network; where we have sensor-hubs to collect the environment data, water meters to calculate the amount of water used, water solenoid valves to control the irrigation duration, and a gateway to receive data from sensors and send commands to controllers.

B. Sensor-Hub

Our sensor-hub supports LoRa communication and equipped with one solar-panel, one light intensity sensor, one air-temperature sensor, one air-humidity sensor, and four soil sensors with standard RS-485 interface. Sensor-hub acts as a slave node in the LoRa P2P network.

C. Gateway

The gateway acts as a master node in the LoRa P2P network which consists of two components: a data processing component and a rule engine. The data process component is used to process the data collected from slave sensor nodes, and the rule engine is the key component which employs multiple linear regression algorithm to determine the precise amount of water required for irrigation. Then the gateway will also issue a control command to the water controller to start automatic irrigation control.

D. Communication

In the LoRa P2P network, 32 time slots are designed in one cycle and each time slot is 0.5 second as shown in Figure 2. There are two types of time slots: reserved time slot and free time slot. For each cycle, there are 24 reserved slots and 8 free slots. A slave node can be assigned up to 3 reserved timeslots for each cycle, and a slave node can transmit a packet at each of the reserved slots. A free time slot can also be used for contention-based transmission. For example, as illustrated in Fig. 2, time slots 1-4 and 17-20 are free time slots. Device with ID1 can send packets to the gateway at 5 th, 8 th, and 13 th time slots; device with ID2 can send data to the gateway at 11th and 25th time slots..

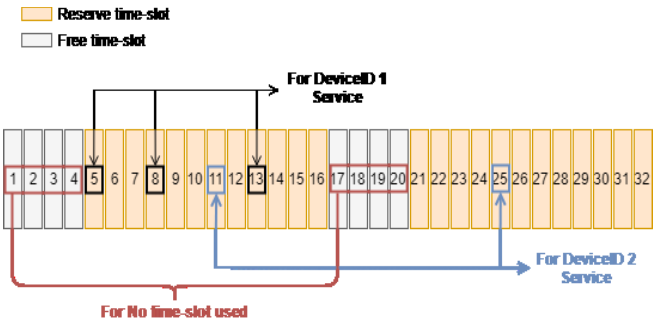

Fig. 2. Transmission structure of LoRa P2P Time-slot (TDMA)

The LoRa P2P network employs a master/slave architecture as presented in Figure. 3; where a master node can connect to multiple slave nodes. The LoRa gateway is designed as a master node and the sensor hubs, water meters, solenoid valves, are designed as slave nodes. Each node has a unique node address ranging from 0.0.0.0 to 255.255.255.255. The LoRa P2P communication module used in our system is Acsip EK-S76SXB.

Fig. 3. LoRa P2P Master-slave architecture with TDMA.

In the LoRa P2P network, we have eight radio channels for frequency hopping as illustrated in Figure 4. For each cycle, in the beginning, the master will send a *Ts* slot for synchronization. Then slave nodes send their packets based on the reserved slots or free slots (contention-based) accordingly. Then the master will use the *Tm* slot to send the commands or responses (such as ACKs for previous transmissions from slave nodes) to the slave nodes. If master node has multiple commands to slave nodes, then after a transmission on a *Tm* slot, the channel is then switched to next channel. This is for fitting the regulation that a node can not transmit on a channel longer than 0.4 second at a time.

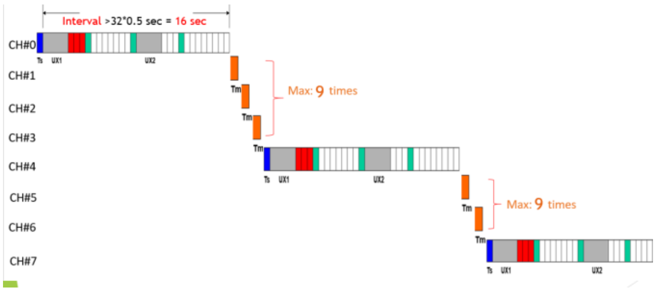

Fig. 4. LoRa P2P frequency hopping based transmission mechanism.

E. Controller

The controller is to control and switch on-off the solenoid valve for irrigation. It equipped with a LoRa communication module with LoRa P2P firmware module, and acts as a slave node in the LoRa P2P network.

IV. Experiment And Result

To evaluate the effectiveness of the proposed smart irrigation system, we designed and implemented the whole system in an organic vegetable farm located at Hsin-Chu county, Taiwan. For planting organic vegetable, the most critical process is precise irrigation. Usually, the farmer irrigates once or twice a day according to his/her experience based on the weather condition and soil condition. The experimental farm consists of 12 greenhouses, each of around $100m^2$. All hardware devices, including one LoRa Gateway, 5 sensor-hubs, 3 water meters, and 3 water solenoid valve installed in the farm are illustrated in Figure 5.

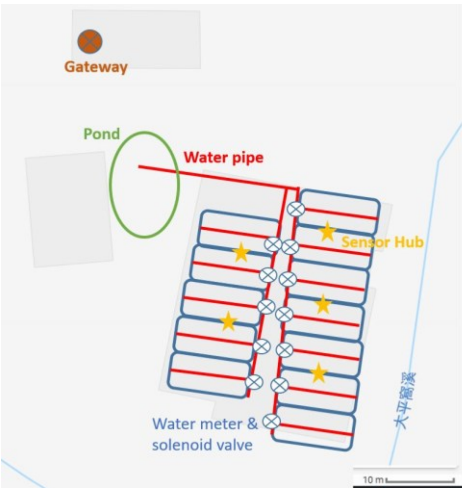

Fig. 5. System implemantation at an organic vegetable farm.

A. Hardware Devices

The designed sensor-hub is equipped with a solar panel, a LoRa P2P module, and several sensors, including four soil sensors, one air temperature/humidity sensor, and one light-insensity sensor (also shown in Figure 1). The sensor-hub is installed between two greenhiuses to collect environment data. The collected data are then delivered to the master (gateway) via the LoRa P2P communication protocol.

Figure 6 demonstrated the LoRa P2P water meter and LoRa P2P solenoid valve. Both of these devices are salve nodes in the LoRa P2P network. The LoRa P2P water meter is actually a smart water meter with a LoRa P2P communicaiton module. We can set the time interval or frequency for sending back the value of water meter. Currently, since the farmer only irrigates once a day, we set the water meter to send back the meter value each 12 hours.

Fig. 6. LoRa P2P-based water meter (up) and solenoid valve (down).

B. Automatic Rule Gegenation System

The main purpose of the system is to learn the irrigation experiences of farmers seamlessly and generate the irrigation rules automatically. Since planting period for organic vegetable is relative short and around 3-4 weeks, we can collect the data of each period very quickly. In this study, we collected the environment data for two months, which consists of two planting cycles. Then a linear regression model for these data is built. As presented in Table I, a correlation analysis is conducted which reveals that the farmer determines the amount of water each time is mainly related to air temperature and sunlight intensity. Therefore, these two parameters are employed in building the training model.

TABLE I. Correlation Analysis

	Soil humidity	Air Temp	Air humidity	Light	Water
Water	-0.6135	**0.4773**	-0.2287	**0.8533**	1.0000

Each time the farmer irrigates the vegetables according to his experience, our system collects the environmental data from the installed sensor-hubs accordingly as well as the amount of irrigated water via our LoRa water meter. Then all these data are combined into a dataset. Then, the dataset is divided into training data set (75%) and testing data set (25%). Of course, the data is also standardized and preprocessed. A multiple linear regression algorithm is employed to train the model with two highest correlation coefficient features: light intensity and soil humidity. The learning curve of *k*-fold cross-validation is presented in Figure.7; where the intercept is 81.2, the coefficient of x_1 is 0.0012, the coefficient of x_2 is -2.8, the MSE is 91, and R^2 is 0.74. The function is as follows:where $\hat{y}$: length of irrigating time (sec), x_1: the light intensity (lux), and x_2: the soil humidity (%).

$$\hat{y} = 81.2 + 0.0012x_1 - 2.8x_2 \tag{1}$$

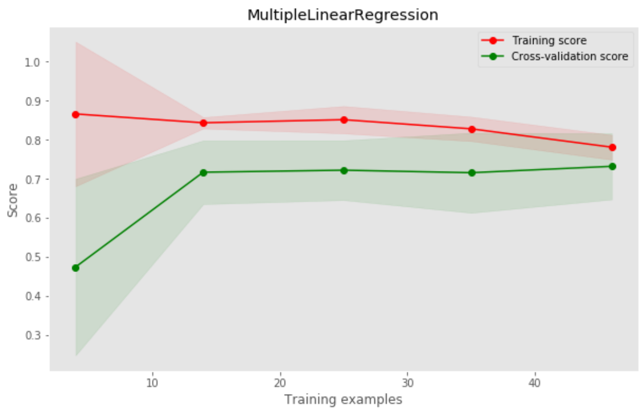

Fig. 7. Learning curve of *k*-fold cross-validation for multiple linear regression.

C. Automatic Irrigation System

To control the solenoid valve remotely, we combine the LoRa P2P module and a relay into the controller. The LoRa P2P solenoid valve is also illustrated in Fig. 6 inside the yellow circle. The command format for controlling the soleboid is presented in Figure 8. The maximum palyload size of a LoRa packet is 40 bytes (the spreading factor SF is set to 9). The command is divided into five equal parts, 8 bytes for each part, so that the master (gateway) can issue instructions to five different devices simultaneously. As illustrated in Fig. 8, the first 2 bytes are defined as irrigation equipment to be controlled, the next 2 bytes represent the status of the device, and the last 4 bytes indicate the control parameter, such as the duration of opening the solenoid valve. For example, “01010120” stands for opening a solenoid valve for 120 seconds, where the first “01” stands for a solenoid valve with ID = 01, the second “01” stands for “opening”, and “0120” stands for 120 seconds.

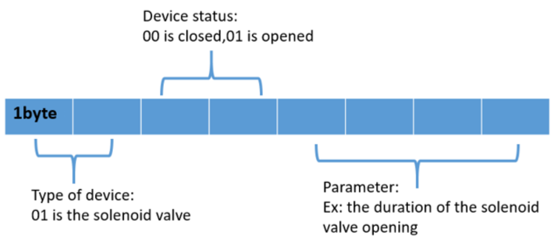

Fig. 8. Command format (8 bytes) for controlling solenoid valve.

V. Conclusion

In this paper, we proposed a machine learning-based smart irrigation system with LoRa P2P networks to automatically and seamlessly learn the irrigation experiences from expert farmers for greenhouse organic vegetable crops. The proposed system will firstly calculate the amount of water for each irrigation based on the trained irrigation model combined with the environment data, such as air temperature/humidity, soil temperate/humidity, light intensity, etc., and then irrigate the crops automatically via the long-distance and low-power wireless LoRa P2P network. The original MAC protocol of LoRaWAN is Aloha based (random access) and may not be suitable for real-time automatically control, especially for Class-A devices. We implemented the proposed AI-based automatic irrigation system with LoRa P2P network which is a master-slave and TDM-based MAC protocol. Experimental results show that combining the machine learning irrigation model with the proposed LoRa P2P network we are able to provide a very cost-effective, real-time, and two-way communications for green house precise and smart irrigation system.

Acknowledgment

This study is supported by the Ministry of Science and Technology (MOST) of Taiwan under grant MOST 107-2218E-007-004.

References

[1] “LoRaWAN”, http://www.lora-alliance.org/

[2] N. Hemageetha, "A survey on application of data mining techniques to analyze the soil for agricultural purpose," in *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 3112-3117, Mar 2016.

[3] S. Prakash, A. Sharma and S. S. Sahu, "Soil Moisture Prediction Using Machine Learning," in *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT),* pp. 1-6, Apr 2018.

[4] C. Yoon, M. Huh, S. Kang, J. Park and C. Lee, "Implement smart farm with IoT technology," in *2018 20th International Conference on Advanced Communication Technology (ICACT)*, pp. 749-752, Feb 2018.

[5] D. A. Pramuditya, A. N. Jati and F. Azmi, "Kufarm: A Modified Platform of Automation Planting System," in *2018 5th International Conference on Information Technology, Computer, and Electrical Engineering (ICITACEE)*, pp. 208-213, Sep 2018.

[6] R. Jauhari, A. N. Jati and F. Azmi, "Mechanical design of CNC for general farming automation," in *2017 5th International Conference on Instrumentation, Control, and Automation (ICA)*, pp. 47-50, Aug 2017.

[7] X. Fan, Y. Wang, C. Wu and H. Liu, "Research of Soil Moisture Content Forecast Model Based on Reference Evapotranspiration in Neighboring Periods," in *2018 7th International Conference on Agro-geoinformatics (Agro-geoinformatics)*, pp. 1-6, Aug 2018.

[8] H. Nie, L. Yang, X. Li, L. Ren, J. Xu and Y. Feng, "Spatial Prediction of Soil Moisture Content in Winter Wheat Based on Machine Learning Model," in *2018 26th International Conference on Geoinformatics*, pp. 1-6, June 2018.