IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 6, 2020, accepted September 17, 2020, date of publication September 21, 2020,
date of current version October 1, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3025590

An Intelligent Irrigation Scheduling System Using Low-Cost Wireless Sensor Network Toward Sustainable and Precision Agriculture

CHAOWANAN JAMROEN[1,2], (Member, IEEE), PREECHA KOMKUM[1], CHANON FONGKERD[1], AND WIPA KRONGPHA[1]

[1]Division of Instrumentation and Automation Engineering Technology, Faculty of Engineering and Technology, King Mongkut's University of Technology North Bangkok, Bangkok 10800, Thailand

[2]Plasma and Automatic Electric Technology Research Group, King Mongkut's University of Technology North Bangkok, Rayong Campus, Bangkok 10800, Thailand

Corresponding author: Chaowanan Jamroen (chaowanan.j@eat.kmutnb.ac.th)

This work was supported by the King Mongkut's University of Technology North Bangkok under Contract KMUTNB-63-DRIVE-15.

ABSTRACT Agricultural irrigation developments have gained attention to improve crop yields and reduce water use. However, traditional irrigation requires excessive amounts of water and consumes high electrical energy to schedule irrigations. This paper proposes a fuzzy-based intelligent irrigation scheduling system using a low-cost wireless sensor network (WSN). The fuzzy logic system takes crop and soil water variabilities into account to adaptively schedule irrigations. The theoretical crop water stress index (CWSI) is calculated to indicate plant water status using canopy temperature, solar irradiation, and vapor pressure deficit. Furthermore, the soil moisture content obtained by a capacitive soil moisture sensor is used as a determination of water status in soil. These two variables are thus incorporated to improve the precision of the irrigation scheduling system. In the experiment, the proposed irrigation scheduling system is validated and compared with existing conventional irrigation systems to explore its performance. Implementation of this system leads to a decrease in water use by 59.61% and electrical energy consumption by 67.35%, while the crop yield increases by 22.58%. The experimental results reveal that the proposed irrigation scheduling system is effective in terms of precision irrigation scheduling and efficient regarding water use and energy consumption. Finally, the cost analysis is performed to confirm the economic benefit of the proposed irrigation scheduling system.

INDEX TERMS Crop water stress index (CWSI), fuzzy logic system, irrigation scheduling, wireless sensor network (WSN), soil moisture content.

I. INTRODUCTION

Agricultural irrigation always receives attention as an important application for the purpose of crop cultivation and production. A reliable and suitable irrigation water supply can significantly raise vast improvements in agricultural productivity and water savings. Clearly, traditional irrigation consumes not only bulk amounts of water, but electrical energy may also be required greatly, depending on the geographical location. The traditional irrigation practice involves applying water as uniformly as possible over every part of the field without taking the variability of soil and crop water needs into account. Consequently, some parts of the field are over-irrigated, meanwhile, other parts of the field are under-irrigated [1]. In addition, variable rate irrigation (VRI) provides the flexibility to manage spatial and temporal variabilities within different zones of a production field. However, the adoption of VRI is very limited, and it does not always guarantee the best irrigation [2]. Presently, water demands are continuously increasing, whereas water resources are unfortunately limited. With water scarcity, precision irrigation (PI) systems have been focused and enabled by the advancement of sensor technologies and the internet of things (IoT). Currently, the new paradigm of massive measurements is represented in terms of wireless sensor networks (WSN). As the rapid growth of IoT, low-power and low-complexity communications are one of the greatest challenges faced by practitioners today. In [3],

The associate editor coordinating the review of this manuscript and approving it for publication was Zhenzhou Tang.

backscatter communication was proposed based on a bistatic semi-passive scatter radio principle for a long-range WSN. However, the backscatter communication has several major limitations, such as short transmission range, low data rate, and unidirectional information transmission [4]. Hence, due to the development of network-based information technology, a WSN plays a significant role in the variety of agriculture applications. It becomes essential to integrate sensor technology and WSN to stimulate and perform precision irrigation. To date, along with those developments, the sensor-based automatic irrigation system has considerably been innovated and applied in widespread agriculture instead of the traditional irrigation, leading to smart and sustainable agriculture. In general, irrigation scheduling systems can be categorized into three approaches [5], i.e. (i) soil-based approach, (ii) weather-based approach, and (iii) plant-based approach.

In the literature, automatic irrigation and monitoring systems are typically based on a soil approach. They can be achieved by using soil moisture content and climatic data. The soil moisture content is used to describe the water status in the uppermost part of a field soil [6]. The determination of soil moisture status has been considered regarding plant-water relations [7], while the climatic data are considered to perform a model-based real-time decision support system for irrigation systems together with the soil moisture status, such as air temperature, air humidity, solar radiation, and wind speed [8]. Furthermore, the smart watering system was developed for irrigation scheduling based on Block-chain and fuzzy logic approach by employing economical sensor devices [9]. The decision-support system of this system mainly relied on five variables such as change rate of temperature, change rate of humidity, intensity of light, and change rate of moisture and type of plant. Similarly, the urban irrigation systems were introduced in [10] aiming at saving water and maintaining crop yields; nevertheless, the system was simply based on a soil moisture set-point to make a decision for irrigation. The web-based application was designed and implemented to manipulate details of crop data and field information using soil moisture sensors. Subsequently, the data were analyzed for the watering process and notifying to users via mobile application [11]. The smart irrigation system based on IoT was developed and implemented using a low-cost soil moisture sensor. The system was applied by the Neuron network for irrigation decisions, while the environment information can be monitored via the web-page [12]. Also, the IoT-based smart irrigation system was developed driven by a fuzzy logic system. The system could schedule irrigation employing soil moisture content, temperature, and humidity. This system could provide acknowledgment messages of the job's statuses via mobile phone [13]. Although numerous researches have presented the irrigation scheduling based on a soil-based approach, the irrigation scheduling using solely soil-based approach may fail to deliver enough amounts of water to plants as reported in [14], resulting in severe water stress of the plant.

Besides, the weather-based approach has been developed using environment variables and forecast methods. In [15], the environment parameters were monitored and controlled through WSN, including temperature sensor, humidity sensor, and illumination sensor, to provide optimal crop conditions. However, the above system only employed the pre-defined threshold value of those parameters to control irrigations. An automated greenhouse system was proposed using an affordable weather sensor network for cultivation in India [16]. Nevertheless, this automated greenhouse system only employed constant thresholds for environment variables to control the dynamic behavior of greenhouse micro-climate. In [17], an innovative irrigation scheduling was developed combining earth observation data, weather forecasts, and numerical simulations to plan more precisely water allocation in space and time in the irrigated agriculture. The different types of weather forecasts were taken into account for irrigation scheduling [18]. Furthermore, a new methodology based on the use of weather forecast data was proposed to determine irrigation scheduling [19]. The results showed that there was only a minor difference between the proposed weather forecast and the measured weather data. It should be noted that there are two issues surrounding the use of available climate prediction and weather forecast for irrigation scheduling: forecast reliability and the dissemination of the forecast information to farmers.

For the plant-based approach, crop water stress index (CWSI) is widely used as an estimator for quantifying plant water status (water deficit of crops) at any local point based on measurements of plant temperatures [20]–[22]. Basically, canopy temperature and temperature baselines are required to calculate an empirical CWSI. The temperature baselines can be obtained by artificial crop reference surfaces, while the canopy temperature can be measured directly by an infrared temperature sensor. To avoid the artificial crop reference surfaces, a temperature baseline prediction has been modeled and developed for the CWSI calculation [23]. Based on the empirical method, the average CWSI was used for irrigation scheduling of bermudagrass in the Mediterranean region [24]. CWSI in this technique was calculated based on the empirical method adapted for practical convenience and used to create the seasonal CWSI as a criterion for irrigation. In [24], the effect of water stress on crop yield was also evaluated. Furthermore, various physiological parameters were investigated including crop water stress index for drip and furrow irrigated processing for red pepper in Turkey [25]. A threshold of CWSI was utilized by prior defining constant values with day-to-day changes for drip and furrow irrigation. In addition, a dynamic threshold of crop water stress index was employed to an automatic irrigation scheduling for apple trees. These thresholds were evaluated associated with stem water potential and canopy-air temperature difference during midday [14], [26]. In [26], seven irrigation scheduling algorithms were also evaluated and discussed for more accurate improvement of water use efficiency. The authors reported that the plant-based irrigation system was able to deliver enough irrigation water to the plant and avoid water stress. Moreover, CWSI could be used to measure crop water status and to improve irrigation scheduling for broccoli. The research indicated that the CWSI of about 0.51 before irrigation was able to produce the maximum yield and water-saving irrigation [27]. CWSI could reliably be used in irrigation scheduling for seed pumpkin plants. The lower limit baseline was determined by the data of 2015 and 2016 [28]. The aforementioned researches mainly relied on predefined CWSI thresholds to schedule irrigations; however, this could result in improper irrigations due to the lack of farmers' knowledge for the threshold setting. Recently, the sensitivity analysis was applied for CWSI to explore the most influential factors of ambient environment uncertainties to the output variance of the index. The research reported that CWSI was not recommended to use under shaded conditions [29].

According to the review of the current literature, the authors have found the opportunities and challenges to bridge the gap of design and implementation of an intelligent irrigation scheduling system using a low-cost WSN. Particularly, most of the research has utilized merely soil water status or crop water variability for irrigation. Moreover, the limitations of soil moisture status or crop water stress have been addressed by [14], [26], [29], [30]. Therefore, the proposed irrigation scheduling system simultaneously considers soil water variability obtained by soil moisture content and crop water variability obtained by CWSI. These two variabilities used by the proposed irrigation scheduling system, which give both soil and plant water status information, can improve the precision of irrigation. However, the implementation of precision irrigation systems, which may require a high financial investment, is very limited, especially farmers who have a tight budget. Thus, the development of a precision irrigation system using commercially inexpensive WSN is taken into account in this research. The proposed irrigation scheduling system is divided into 3 main parts, consisting of sensor aggregator, central controller unit, and irrigation unit. The sensor aggregator employs the availability of low-cost environment sensors, i.e. soil moisture content, canopy temperature, air temperature, humidity, and light. The soil moisture and climatic data are collected by the aggregator and transmitted to the central controller unit via a WSN. In the central controller unit, the solar irradiation is measured in addition to the measured data from the sensor aggregator. The received data are processed for noise elimination and data averaging. Afterward, the processed data are used to calculate the CWSI and soil moisture content. By taking the plant and soil variabilities into account, the fuzzy system receives the CWSI and soil moisture content to make irrigation decisions and releases the control signal to the pump in the irrigation unit, according to the designed fuzzy system. In the experiment, the measurements are connected to measure water use and electrical energy consumed by the proposed system. The experimental results are evaluated to explore the effectiveness and efficiency of the proposed system compared with the existing systems. Furthermore, the cost analysis is performed to evaluate the cost-effectiveness of the proposed system. Therefore, the main contributions of this paper, that reduce the knowledge gap between low-cost commercial available and system designs, are listed as follows.

1) A fuzzy-based intelligent irrigation scheduling system is designed and implemented using a low-cost WSN.
2) Crop water stress index (CWSI) and soil moisture content are simultaneously considered as variables for irrigation scheduling strategy.
3) The prototype of the proposed system is constructed and validated to gather data on the performance and functionality of the design.
4) The proposed irrigation scheduling system is experimentally tested to evaluate its effectiveness.
5) The comparative study is performed to explore the efficiencies of the proposed irrigation scheduling system in terms of water use and energy consumption.
6) The cost analysis is performed to assess the economic viability of an investment.

The remainder of this paper is organized into five main sections. In Section II, the materials and methods are primarily described. The intelligent irrigation scheduling system is proposed in Section III. The experimental setup is performed, and the experimental results and cost analysis are provided in Section IV. Finally, the conclusions and discussions are summarized in Section V.

II. MATERIALS AND METHODS

A. CROP WATER STRESS INDEX (CWSI)

Crop water stress index (CWSI) was first introduced and widely used to measure the stress of plants regarding water [20], [21]. CWSI can be divided into two main categories, i.e. empirical CWSI and theoretical CWSI. The empirical CWSI employs the difference between the actual canopy temperature and the non-water stressed baseline normalized by the difference between the water-stressed baseline and the non-water stressed baseline as calculated in Eq. (1).

$$\mathrm{CWSI_E} = \frac{T_c - T_{\mathrm{nws}}}{T_{\mathrm{dry}} - T_{\mathrm{nws}}} \tag{1}$$

where $\mathrm{CWSI_E}$ is the empirical CWSI. T_c is the actual plant canopy temperature in degree Celsius (°C). T_{nws} is the non-water stressed baseline obtained by the canopy temperature of a well-watered crop transpiring at maximum rate in degree Celsius (°C), while T_{dry} is the water stressed baseline obtained by the canopy temperature of a non-transpiring in degree Celsius (°C). Nevertheless, T_{nws} and T_{dry} require additional artificial wet and dry reference surfaces, resulting in limitations of potential use of CWSI in practical implementations.

Accordingly, the theoretical CWSI was developed and proposed based on the prediction of temperature baselines instead of the artificial surfaces. The theoretical CWSI can be expressed as follows [14].

$$\mathrm{CWSI_T} = \frac{\Delta T_m - \Delta T_l}{\Delta T_u - \Delta T_l} \tag{2}$$

where $CWSI_T$ is the theoretical CWSI. ΔT_m is the temperature difference between the canopy temperature and air temperature ($T_c - T_a$). ΔT_l is the temperature difference between the canopy temperature and the well-watered plant canopy temperature, as expressed in Eqs. (3) to (6). ΔT_u is the temperature difference between the canopy temperature and the non-transpiring plant canopy temperature. ΔT_u can be calculated by assuming closed stomata for a non-transpiring canopy and replacing g_v with zero as provided in Eq. (7).

$$\Delta T_l = R_n \frac{1}{\gamma + \frac{\Delta}{P_a}} - \mathrm{VPD} \frac{1}{P_a(\gamma + \frac{\Delta}{P_a})} \tag{3}$$

$$R_n = 0.25\Big(\alpha_S S_r + \alpha_S \tau S_r + 4(\alpha_L - 1) L_a\Big) \tag{4}$$

$$\gamma = \frac{2 g_H C_P - (3\alpha_L - 4)\varepsilon_a \sigma \boldsymbol{T}_a^3}{\alpha g_v} \tag{5}$$

$$g_H = 0.189\sqrt{\frac{u}{d}} \tag{6}$$

$$\Delta T_u = \frac{R_n}{2 g_H C_P - (3\alpha_L - 4)\varepsilon_a \sigma \boldsymbol{T}_a^3} \tag{7}$$

where R_n is the net radiation ($\mathrm{Wm^{-2}}$). γ is the psychrometric constant (Pa $^\circ\mathrm{C}^{-1}$). Δ is the slope of the relationship between saturation vapor pressure and air temperature (Pa $^\circ\mathrm{C}^{-1}$), while P_a is the atmospheric pressure (Pa). VPD is the vapor pressure deficit (Pa). α_S and α_L are the absorptivity in the short and absorptivity in the thermal waveband (-), respectively. g_H is the air boundary layer conductance to heat ($\mathrm{ms^{-1}}$). C_P is the heat capacity of air ($\mathrm{J\,mol^{-1}\,C^{-1}}$). ε_a is the emissivity of the sky (-). σ is the Stefan-Boltzmann constant ($\mathrm{J\,K^{-1}}$). $\boldsymbol{T}_a$ is the air temperature in Kelvin (K). q_v is the vapor conductance ($\mathrm{mol\,m^{-2}\,s^{-1}}$). S_r is the global solar irradiance ($\mathrm{Wm^{-2}}$). τ is the green leaf transmittance (-). L_a is the atmosphere long-wave flux density computed using the Stefan–Boltzmann equation ($\mathrm{Wm^{-2}}$). u is the wind speed ($\mathrm{ms^{-1}}$). d is the characteristic dimension defined as 0.72 times the leaf width (-).

As given in Eq. (1) and (2), the CWSI value ranges between 0 to 1, where CWSI of 0 indicates a well-watered condition, while CWSI of 1 indicates a water-stressed condition. Therefore, the CWSI can be used to quantify a crop water status as a simple indicator for irrigation scheduling.

B. SOIL MOISTURE CONTENT

Soil moisture content (θ) is a critical variable in irrigation management. Soil moisture content can be used for the estimation of water in soils. Generally, soil moisture content can be determined by a gravimetric method. However, the gravimetric method is based on a direct measure of soil water content, which is destructive and laborious [31]. Hence, the gravimetric method is not able to use for real-time measurement and application. In the past few decades, indirect methods have been proposed and applied, relying on various measurement techniques. Essentially, capacitance and frequency techniques are adopted to develop a soil moisture sensor, this type of sensor is called by a capacitive soil moisture sensor. A capacitive soil moisture sensor uses soil dielectric properties to determine soil moisture content. The soil permittivity measured by a capacitive soil moisture sensor can be obtained by inserting its electrodes into the soil. The measured soil permittivity is then converted into volumetric soil moisture content. The volumetric soil water content is expressed by the volume of water in $\mathrm{cm^3}$ per unit volume of soil in $\mathrm{cm^3}$. Hence, the volumetric soil moisture content (θ) ranges between 0 to 100 in $\mathrm{cm^3\,cm^{-3}}$ or %.

Based on the capacitance and frequency techniques, a capacitive soil moisture sensor offers various advantages over other instruments, i.e., lower cost, continuous monitoring, and data logging capabilities. Due to those advantages, the capacitive soil moisture sensor is widely used for many applications in agriculture.

C. NOISE FILTERING TECHNIQUE

Normally, measured data contain noises associated with the capability of measurement devices. Prior to using the data, the measured data should be processed to eliminate noises. The simplest technique used for time-series data is based on a simple moving average (SMA) to eliminate noises. However, SMA normally creates significant issues, particularly lags. To reduce lags created by SMA, exponential moving average (EMA) has been developed by adding exponentially weights on historical data [32]. The EMA definition can be provided by the following equations.

$$\bar{y}(k) = \alpha y(k) + (1 - \alpha)\bar{y}(k-1) \tag{8}$$

$$\alpha = \frac{2}{n+1} \tag{9}$$

where $\bar{y}(k-1)$ is the EMA of the observed data over specific data points in a series at a previous time instant $k-1$. α is the smoothing coefficient, which is between 0 and 1. n is also the number of data points used in EMA.

In practice, the number of data points (n) is varied based on the type of measured data. The high fluctuating data are smoothed with a higher number of data points, in contrast, a small value of the number of data points is defined for the low fluctuating data. Moreover, the smoothing technique can compensate for missing data in case of a temporary sensor failure or a temporary electrical system failure. Commonly, the climatic data are defined as the high fluctuating data, while the soil moisture content data are defined as the low fluctuating data. In this paper, the climatic data obtained by environment sensors are thus filtered by defining a higher number of data points than soil moisture data.

D. STRUCTURE OF WSN

WSNs have contributed significantly to various agriculture applications. Particularly, a WSN has applied in order to form precision and sustainable irrigation systems. A WSN is conceptually constituted by a number of small sensing nodes that work in a cooperative way to sense and control the environment surrounding them [33], [34]. The structure of WSN is commonly composed of three components, i.e. sensor

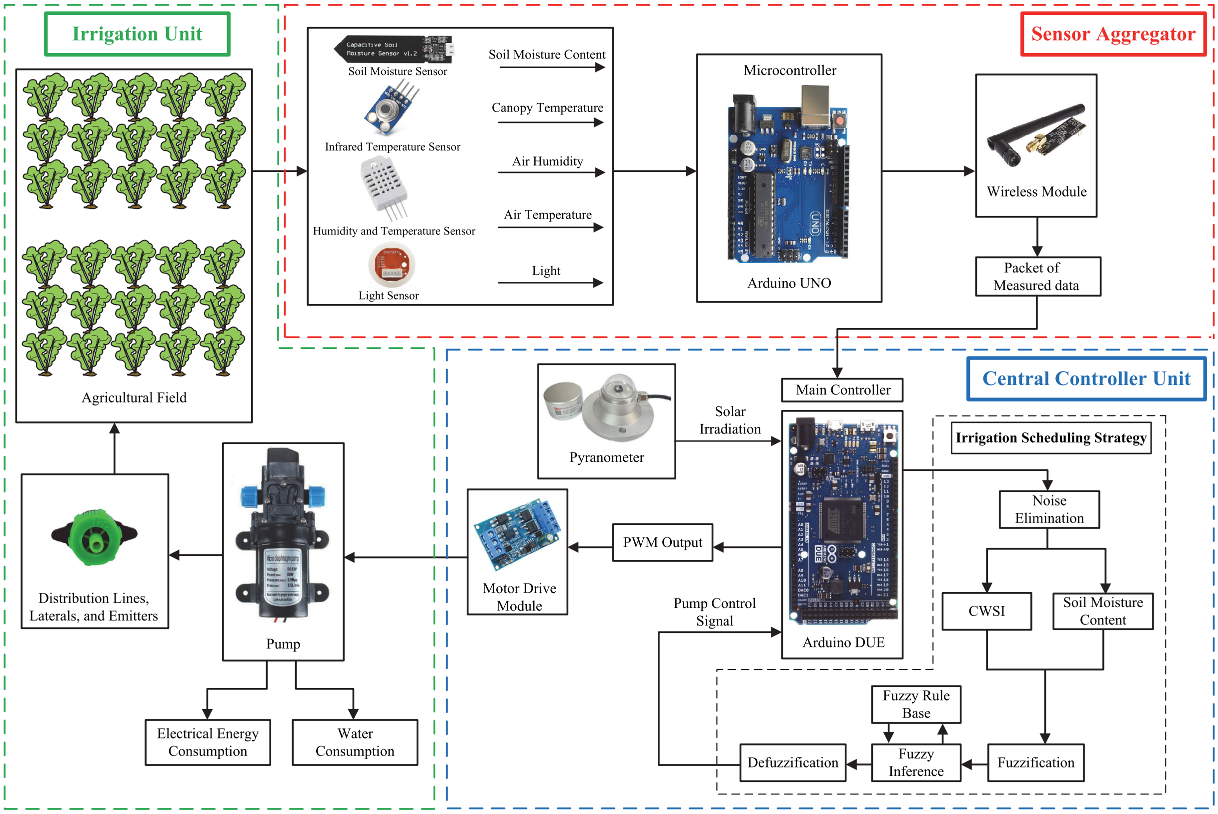

FIGURE 1. The structure of the proposed intelligent irrigation scheduling system.

nodes, coordinator node (gateway), and external node [33]. Sensor nodes are responsible for sensing, data collection, and data forwarder through wireless communication. Also, sensor nodes should work cooperatively to form a centralized network system. Afterward, the relevant data collected by sensor nodes will be transmitted to a coordinator node. A coordinator node allows data communications among the network and field devices. In a gateway, those data will be handled and processed. Finally, the processed data will be utilized by an external node or system. Furthermore, a coordinator node can communicate with a cloud server for remote applications.

III. PROPOSED IRRIGATION SCHEDULING SYSTEM

A. DESIGN

According to the literature review in Section I, and materials and methods provided in Section II, the preliminary design of the intelligent irrigation scheduling system is presented in Fig. 1. The proposed irrigation scheduling system consists of 3 main parts, i.e. sensor aggregator, central controller unit, and irrigation unit. Each part can be explained hereinafter.

1) SENSOR AGGREGATOR

In the sensor aggregator, it is responsible as a sensor node in WSN. Environment sensors are embedded with the aggregator including soil moisture sensor, air temperature sensor, relative humidity sensor, light sensor, and infrared temperature sensor. The soil moisture content is determined using a soil moisture sensor SKU:SEN0193. The ambient air temperature and relative humidity are determined using a temperature/relative humidity sensor DHT22, while a GY-906 (MLX90614ESF) infrared temperature sensor is employed to measure the crop canopy temperature. The calibrations of the sensors used in this aggregator are provided as follows: soil moisture sensor [35], temperature/relative humidity sensor [36], and infrared temperature sensor [37]. The Arduino UNO R3 board is employed as the main micro-controller to aggregate the relevant data measured by the sensors. Furthermore, the sensor aggregator is contained within a water-proof plastic container for weather protection. This irrigation scheduling system also adopts the availability of a WSN to enhance the implementation in practice. In practical implementation, single measurement data cannot accurately describe the average variation of actual field data, as reported in [38]. To deal with this issue, this paper employs two sensor aggregators accordingly. The sensor aggregators are able to send the measured data obtained by the sensors to the central controller unit using the NRF24L01 transceiver module for a suite of communication protocols. The NRF24L01 transceiver module is used because of its ultra-low power (ULP) consumption, simpler and less expensive. It integrates a complete 2.4GHz RF transceiver, RF synthesizer, and baseband logic including the Enhanced ShockBurst hardware protocol accelerator supporting a high-speed ubiquitous SPI (Serial Peripheral Interface) for the application controller. However, the NRF24L01 can only transmit data less than 100 m. In this work, the NRF24L01 with Power Amplifier/Low Noise Amplifier (PA/LNA) is thus selected to boost the power of the signal being transmitted from the NRF24L01 module (up to 1000 m.). The star topology based WSN is utilized and implemented for this irrigation scheduling system, as illustrated in Fig. 2. In order to save electric power consumed by the sensor aggregator, a light lux sensor BH1750FVI is used to automatically turn-on during the daytime and turn-off during the nighttime. In addition, this can prevent damaging injuries to plants. Normally, most transpiration activity (the loss of water from foliage) occurs during the day. Any irrigation cannot be expelled by stomata at night. Subsequently, moisture remains on the plant for pathogen infiltration, causing rot and other damaging injuries to the foliage.

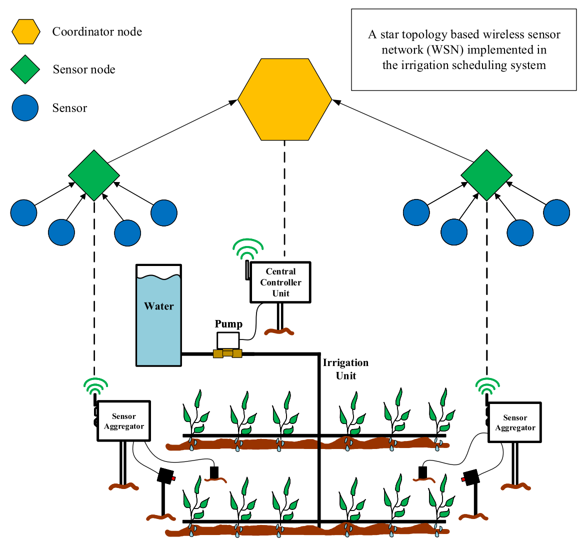

FIGURE 2. The star topology used in the proposed intelligent irrigation scheduling system.

2) CENTRAL CONTROLLER UNIT

In the central controller unit, it is responsible as both a coordinator node in WSN for receiving and transmitting data from the sensor nodes and an irrigation (external) system for irrigation scheduling. For the role in WSN, the central controller unit receives the time series data obtained by the aggregators as described in the previous mention. On the other hand, the central controller unit acted as a coordinator node will forward the data to an irrigation scheduling system (external system). For the role of the irrigation scheduling system, the forwarded data will proceed in the intelligent irrigation scheduling system as described hereinafter. According to the challenges and opportunities in Section I, the proposed irrigation scheduling system is designed based on both soil and plant-based irrigation approaches. Therefore, the proposed intelligent irrigation scheduling system employs soil moisture content and CWSI as input variables of the fuzzy logic system as shown in Fig. 1. The soil moisture content is used to indicate soil water variability, which can be measured by a soil moisture sensor. On the other hand, the CWSI calculation traditionally requires temperature baselines obtained by artificial plant surfaces. Nevertheless, artificial plant surfaces lead to limit the use of CWSI in practical application. As a consequence, this paper uses the theoretical CWSI developed by [14]. By adopting the theoretical CWSI, the plant water status can be obtained. To do this, air temperature, relative humidity, plant canopy temperature, and solar irradiation are required for the calculation of the theoretical CWSI in Eq. 2. These measurements are provided by the sensor aggregator except solar irradiation. Thus, in addition to the sensors embedded in the sensor aggregator, a pyranometer BGT-JYZ2 is installed at the central controller unit to measure solar irradiation. The pyranometer was calibrated based on the procedure in [39]. Due to solar irradiation varies depending on the sun and the weather, this paper thus installs only one pyranometer at the central controller unit. Also, the investment cost can be reduced. Prior to proceeding the data to any calculations, the measured data will be processed to eliminate noises contained in the data using an exponential moving average (EMA) technique in Eq. (8) and (9). The number of data points for the EMA technique is defined based on the characteristic of the measurement data. Since there are two sensor aggregators, the processed measurement data will be calculated to obtain the average value. Afterward, the processed measurement data are used to calculate the CWSI. The calculated CWSI and soil moisture content will be used as the input variables of the fuzzy logic system. The fuzzy logic system will be described in Section III-C. The fuzzy logic system will release the irrigation decision based on the knowledge-based design. The irrigation decision will drive the pump in the irrigation unit accordingly.

3) IRRIGATION UNIT

In this paper, the irrigation unit uses surface drip irrigation. The irrigation unit is comprised of water supply, pump, valves, distribution lines, laterals, and emitters. The pump can be changed its speed to adjust water pressure by pulse-width modulation (PWM)-based pump drive, according to the irrigation decision released by the central controller unit. This paper also takes the water-energy efficiencies into account. To measure water use, the water flow sensor is thus installed. Also, the energy consumption is calculated by integrating electric power consumed by the motor operation over time for each irrigation strategy. Hence, the voltage and current measurements are installed to obtain voltage and current data of the motor. The voltage and current data are then used to calculate the motor's electric power. Subsequently, the resulting power is used to calculate the energy. The work-flow of the proposed irrigation scheduling system is provided in Fig. 3.

B. IMPLEMENTATION

According to the proposed irrigation scheduling system design, the irrigation scheduling system design consists of sensor aggregator, central controller unit, and irrigation unit. The prototype of the proposed irrigation scheduling system is shown in Fig. 4. The central controller unit is shown in number 1 of Fig. 4. The sensor aggregators are shown in

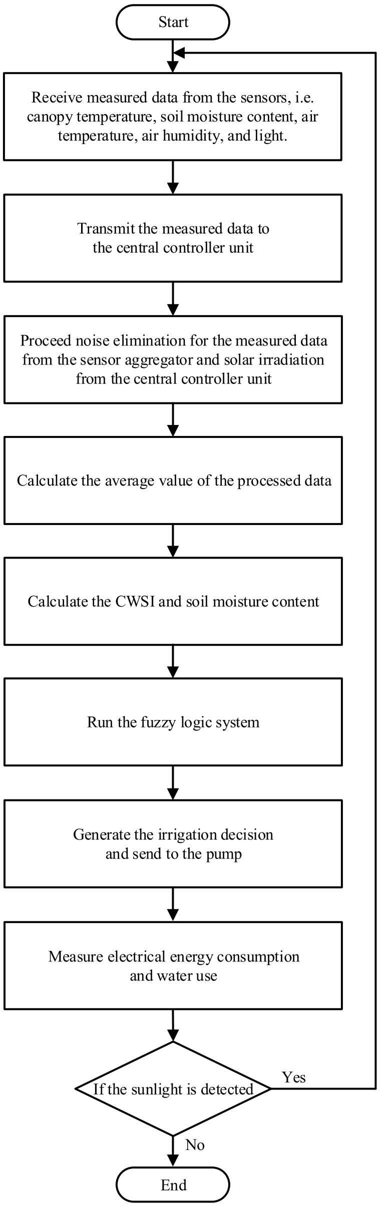

FIGURE 3. The work-flow of the proposed intelligent irrigation scheduling system.

number 2 of Fig. 4, while the irrigation unit is shown in number 3 of Fig. 4. In the sensor aggregator, the dielectric-based capacitance soil moisture sensor is used because of its capability as described in Section II, as shown in number 4 of Fig. 4. To calculate CWSI, the infrared temperature sensor is used and embedded in the water-proof plastic container as shown in number 5 of Fig. 4. Furthermore, the air temperature and humidity sensor are necessarily used to calculate CWSI, as installed in number 6 of Fig. 4. The light sensor is also used to detect the sunlight and used to automatically turn off during the nighttime, as shown in number 7 of Fig. 4. The wireless module is installed to send the measurement data to the central controller unit, as shown in number 8 of Fig. 4. In the central controller unit, the pyranometer is installed to measure the solar irradiation, as shown in number 9 of Fig. 4. The structure of the central controller unit is made as shown in number 10 of Fig. 4.

C. FUZZY IRRIGATION SCHEDULING STRATEGY

This paper applies the discrete affine Takagi-Sugeno (TS) fuzzy logic system to the proposed irrigation scheduling system. Basically, the fuzzy logic system consists of three main processes, i.e. fuzzification, fuzzy inference, and defuzzification [40]. The overview of the fuzzy logic system is illustrated in Fig. 1. In the fuzzification process, the CWSI and soil moisture content are converted to fuzzy logic according to the membership functions in the fuzzification process. This paper employs a set of symmetric triangular membership functions. Hence, the membership functions of CWSI and soil moisture content are provided in Fig. 5. Based on the previous section, the CWSI value ranges between 0 to 1, thus the membership function of CWSI is classified into five types, namely, very low (VL), low (L), medium (M), high (H), and very high (VH), as shown in Fig. 5(a). Furthermore, The soil moisture content value also ranges between 0 to 100%, thus the membership function of soil moisture content is classified into five types as well, namely, very low (VL), low (L), medium (M), high (H), and very high (VH), as shown in Fig. 5(b). The fuzzy inference is designed using the knowledge base to evaluate the fuzzy rules and produce an output for each rule. The rule base is designed based on the two inputs as provided in Table 1. The 25 rules have been defined for the output variable.

Subsequently, in the defuzzification, the multiple input outputs are transformed into a crisp output, in accordance with the rule base and the output membership function. The fuzzy system output is designed for generating a control signal to the pump in the irrigation unit. The fuzzy system output is converted to the crisp using a center-average method. The fuzzy output membership function employs a singleton output membership function, hence, the output membership function is classified into five types, namely, zero (Z), low (L), medium (M), high (H), and very high (VH) as shown in Fig. 5(c). Some interpretations of the rules are provided as follows: if CWSI is high (H) and soil moisture content is low (L), the pump is operated at 75% in high (H). If CWSI is high (H) and soil moisture content is very high (VH), the pump is operated at 0% in zero (Z).

In the discrete multiple input single output (MISO) of the TS fuzzy model, the fuzzy implication (R) can be represented by the following set of rules [41].

$$\begin{aligned} R: &\text{ If } x_1(k) \text{ is } A_1 \text{ and } \ldots \text{ and } x_n(k) \text{ is } A_n \\ &\text{Then } q = g(x_1, \ldots, x_n) \end{aligned} \tag{10}$$

where x is the input crisp. A fuzzy sets in the antecedent. n is the number of data. y is the output crisp. q is the consequent. $g(\cdot)$ is the function of output calculation. Furthermore, the output crisp (y) can be expressed using a center-average

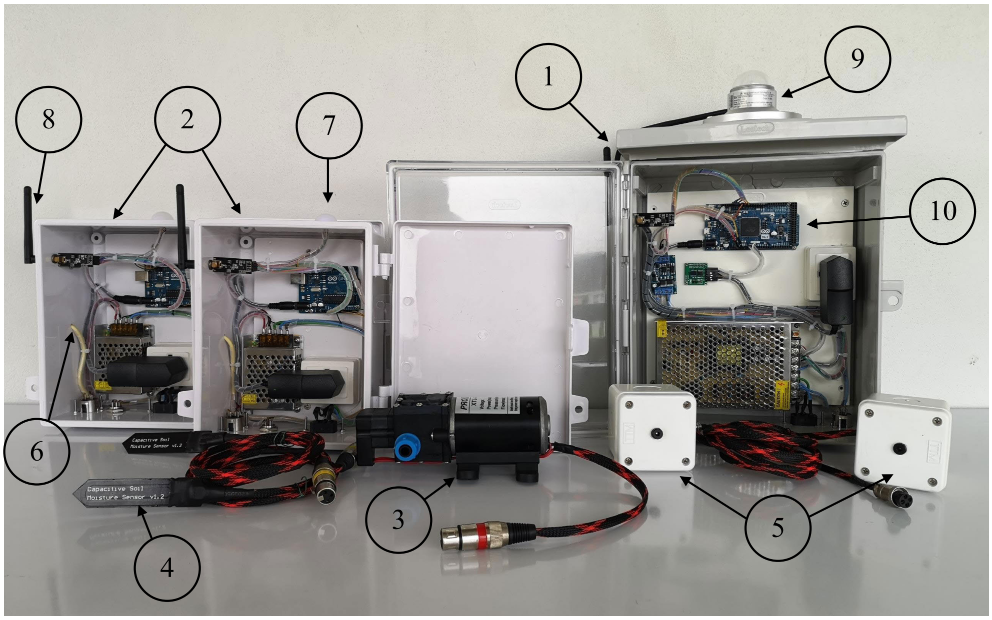

FIGURE 4. The prototype of the proposed intelligent irrigation scheduling system.

TABLE 1. Fuzzy rules base.

CWSI	Soil moisture content				
	VL	L	M	H	VH
VL	H	M	L	Z	Z
L	H	M	L	Z	Z
M	H	H	M	Z	Z
H	VH	H	H	Z	Z
VH	VH	VH	M	L	Z

method as provided in the following equation.

$$y(k+1) = \frac{\sum_{n=1}^{m} q \cdot \mu(k)}{\sum_{n=1}^{m} \mu(k)} \tag{11}$$

where y is the crisp output. μ is the premise membership function of the rule.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL SET-UP

The field experiments were conducted in a small sample field of 2×3 m^2 in Rayong province, Thailand. The location obtained by the global positioning system is thus 12.824342, 101.216274 (latitude, longitude), elevation above sea level of 7 meters. The two sensor nodes were adopted in the experiment as described in the previous section. The experimental testing focused on the verification of the proposed irrigation scheduling system. In addition to the verification, a comparative study was performed to obtain the performance of the proposed irrigation scheduling system, compared with the traditional irrigation system and conventional drip irrigation system. In the experiment, the manual irrigation was used for the traditional irrigation system, while the conventional drip irrigation system was based on pre-defined time-based irrigation. This paper chose a Southern Giant Curled mustard (Brassica juncea) due to its appropriation related to the locations and its growing duration. The root depth was approximately between 10-15 cm; therefore, the selected soil moisture sensor was suitable for covering the root depth [38]. The photograph of the configuration of the proposed irrigation scheduling system is provided in Fig. 6. The experiment was tested for ten days in April 2020 (6 to 15 April 2020), during the summer period in Thailand. All measurements were collected every 1-minute interval throughout the experiment.

B. SYSTEM EVALUATION

According to the experiment setup, the experimental results are provided in the following explanations. The relevant measured and calculated data are shown in Fig. 7 for the ten days during the experiment. As seen in Fig. 7(a), the soil moisture content increased during the daytime due to the operation of the proposed irrigation scheduling system, whereas it gradually decreased during the nighttime. On the other hand, the relative humidity varied in the opposite direction of the soil moisture content, as shown in Fig. 7(b). Since the experiment was performed in the summer period; hence, the air temperature variation was above 30°C during the daytime, as shown in Fig. 7(c). Also, the canopy temperature varied related to the air temperature variation, as shown in Fig. 7(d). Furthermore, solar irradiation variation is provided in Fig. 7(e). It can be observed that the solar irradiation reached 1,000 Wm^{-2} in the sunny days. Finally, the CWSI and pump control signal are respectively given in Fig. 7(f) and Fig. 7(g).

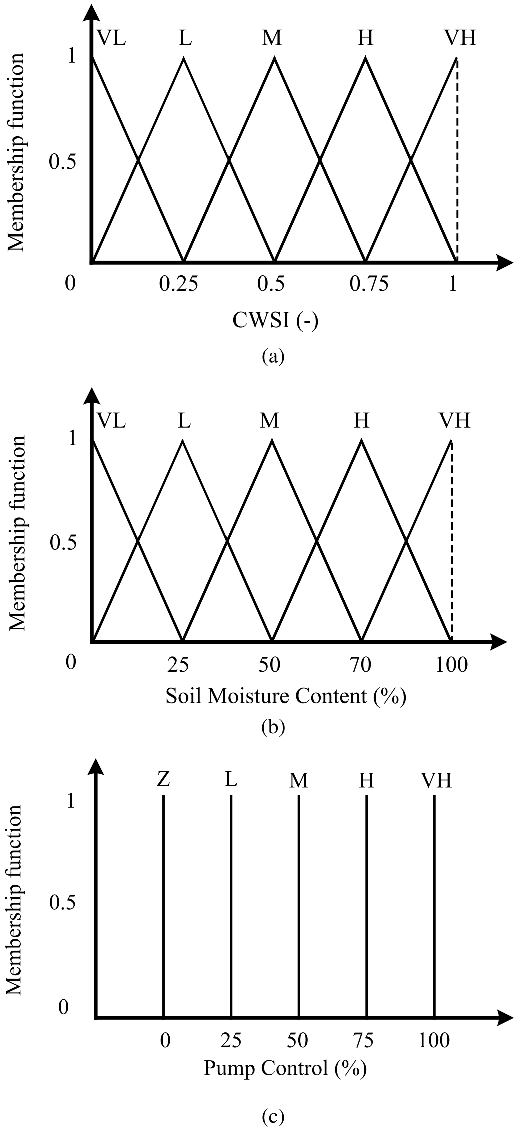

FIGURE 5. **The designed fuzzy system. (a) input membership functions of CWSI; (b) input membership functions of soil moisture content; (c) output membership functions of pump control.**

FIGURE 6. **The experimental configuration of the proposed irrigation scheduling system.**

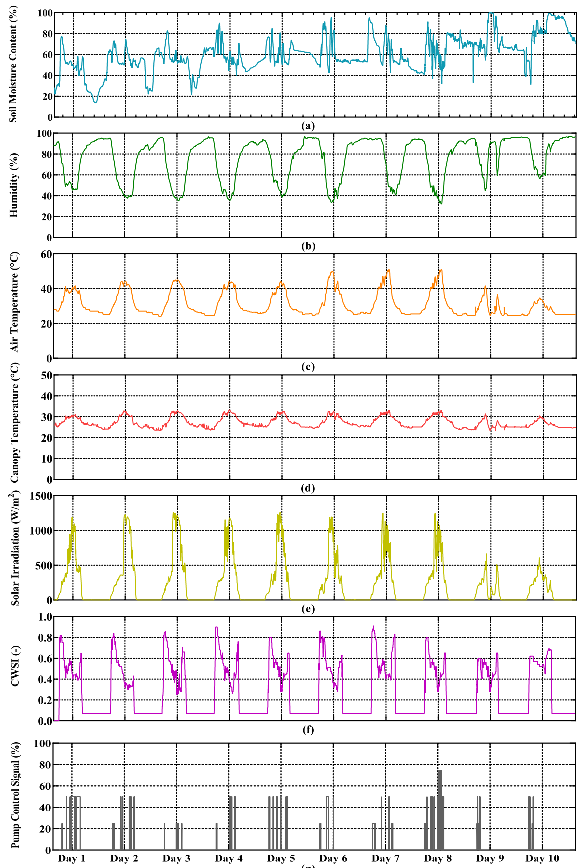

FIGURE 7. **Measured and calculated data used by the proposed irrigation scheduling system for 10 days. (a) soil moisture content; (b) relative humidity; (c) air temperature; (d) canopy temperature; (e) irradiation (f) CWSI; (g) pump control signal.**

In this study, the proposed irrigation scheduling system was compared with the time-based irrigation system to evaluate its performance. The input and output data of the fuzzy logic system on 13 April 2020 (Day 8) was selected as shown in Fig. 8. The soil moisture content and CWSI are respectively depicted in Fig. 8(a) and Fig. 8(b) for the input variables of the fuzzy logic system, while the pump control signal is shown in Fig. 8(c) for the output variable of the fuzzy logic system. Besides, the variations of CWSI, soil moisture content, and pump control signal on Day 8 are also illustrated in Fig 9 for the time-based irrigation system. As can be seen in the shaded area of Fig. 9, the time-based irrigation system applied irrigation water 2 times a day at 07.00 am and 16.00 pm for 2 hours.

In the morning, the soil moisture content was higher than 75% as indicated in area A of Fig. 8(a) under the proposed irrigation scheduling system, that refers to the water in the soil is between high (H) and very high (VH) in the input membership function of soil moisture content in Fig. 5(b). Meanwhile, in area A of Fig. 8(b), CWSI was higher than 0.75 due to the increase in solar irradiation, which is between high (H) and very high (VH) in the input membership function of CWSI in Fig. 5(a). Accordingly, the output signal of the fuzzy

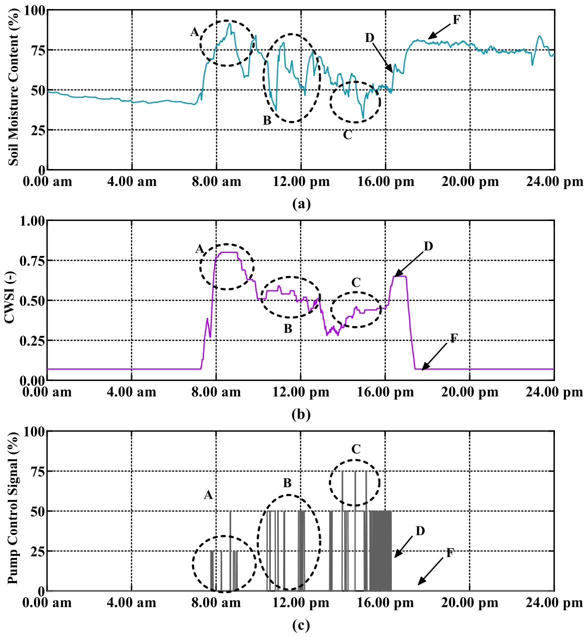

FIGURE 8. Input and output data used in fuzzy logic system for 13 April 2020 (Day8). (a) soil moisture; (b) CWSI; (c) pump control signal.

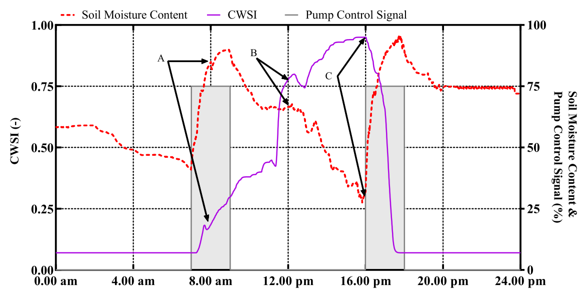

FIGURE 9. Variations of CWSI, soil moisture content, and pump control signal for time-based irrigation.

logic system was between 0% and 25%, according to the rule base and the output membership function in Fig. 5(c). After the irrigations, the soil moisture content gradually increased, meanwhile the value of CWSI decreased. As irrigations were applied, the crop stress was reduced after area A of Fig. 8(b). In this period, the time-based irrigation system started to irrigate for 2 hours at 07.00 am. The soil moisture rapidly increased; however, CWSI was quite lower than the proposed irrigation scheduling system as illustrated at point A in Fig. 9. It can be observed that the time-based irrigation system could prevent the stress of crops during this period of the day as a result of a large amount of applied irrigation water.

In area B of Fig. 8, CWSI was around 0.50 under the proposed irrigation scheduling system, which is medium (M) in the input membership function of CWSI. At the same time, the soil moisture content tended to be decreased at midday and varied around 25% to 75%, which is between in large (L), medium (M), and high (H) in the input membership function of soil moisture content. The output signal was hence between medium (M) and zero (Z), according to the rule base as illustrated in Fig. 8(c). As a result of the successive irrigation events, the crops could be prevented from water stress conditions. However, in this period, the irrigation did not schedule under the time-based irrigation system. As can be seen at point B in Fig. 9, the soil moisture content continuously decreased, while CWSI increased significantly due to high solar irradiation. Hence, the crops were more severe to the water stress condition at midday under the time-based irrigation system.

The crops maintained relatively high solar irradiation over the noon as indicated in area C of Fig. 8(a). The soil moisture content was quite low in L of the membership function, while CWSI was nearly 0.50 in medium (M) of the membership function of CWSI as shown in Fig. 8(b). Therefore, the output was 75% in high (H) of the membership function as shown in Fig. 8(c), according to the rule base. Hence, the pump was activated to schedule irrigations. After the successive irrigation events, the soil moisture content increased while CWSI decreased, avoiding water stress of crop. Nevertheless, for the time-based irrigation system, the highest variability in CWSI was observed with low soil water availability at point C in Fig. 9. In this situation, it can be interpreted that the crops were under water stress conditions. This supports that the use of the proposed irrigation scheduling system can precisely irrigation to crop, preventing crop water stress conditions during midday.

Finally, at point D in Fig. 8(a), the soil moisture content was between 50% and 75%, which is between medium (M) and high (H) in the input membership function of soil moisture content. CWSI was also between 50% and 75%, which is between medium (M) and high (H) in the input membership function of CWSI. Thus, the output signal was 50% in medium (M) of the output membership function. As seen at point D in Fig. 8(c), the pump was activated continuously until the reach of point D. In consequence, the soil moisture content increased to point F of Fig. 8(a). In contrast, CWSI dropped to nearly 0 at point F of Fig. 8(b). Hence, the pump control signal was deactivated (0%) as indicated in point F of Fig. 8(c). At 16.00 pm, the time-based irrigation system started to applied irrigation water for 2 hours. There was no significant difference in the tendency for soil moisture content and CWSI for the proposed irrigation system and the time-based irrigation system.

Although the frequency of applied irrigations for the proposed irrigation system was higher compared to the time-based irrigation system, the amount of irrigation water applied by the proposed irrigation system was significantly less than the time-based irrigation system as shown in Fig. 10(a). Moreover, the daily electrical energy consumption is provided in Fig. 10(b) for the ten days in the experiment. It can be noticed that the proposed irrigation scheduling system consumed less electrical energy consumption and water use, compared with the manual irrigation system and the time-based irrigation system. Total electrical energy consumption and water use are illustrated in Fig. 11. By using the manual irrigation system as the base case scenario, the time-based irrigation system can reduce electrical

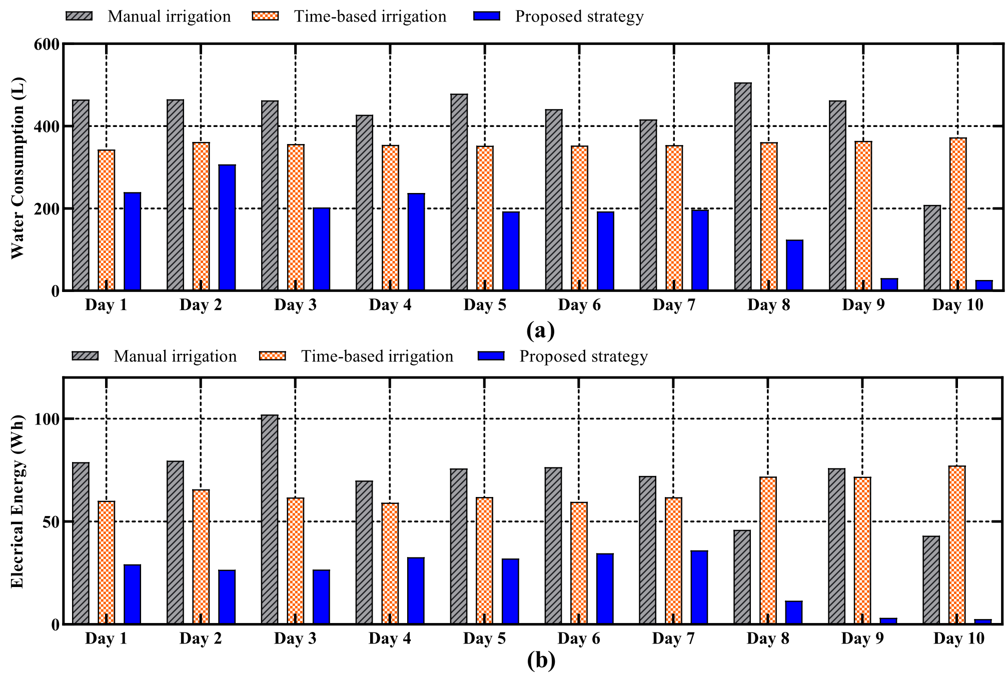

FIGURE 10. Comparative results for electrical energy and water consumption. (a) water use; (b) electrical energy.

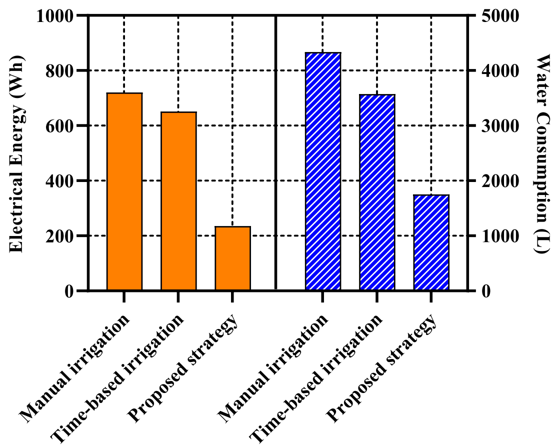

FIGURE 11. Total electrical energy and water consumption.

energy consumption and water use by 9.58% and 17.57%, respectively. The proposed irrigation scheduling system can significantly decrease electrical energy consumption and water consumption by 67.35% and 59.61%, respectively.

In this study, the crop yield was determined by manually picking and weighing after the end of the experiment, verifying the agricultural output. The crop yield of 25,333 kg ha^{-1} was obtained under the proposed irrigation system, which was higher than the manual irrigation (20,666 kg ha^{-1}) by 22.58%. The crop yield was 21,833 kg ha^{-1} for the time-based irrigation system, while an increase in crop yield was 5.64 %.

Based on these experimental results, the proposed irrigation scheduling system can schedule irrigation precisely according to the soil moisture content and CWSI variability. The soil water status can be improved; simultaneously, the crop water stress can be reduced by using the proposed irrigation scheduling system. It can be concluded that the proposed irrigation scheduling system was the most effective irrigation strategy. The efficiencies in terms of water use and electrical energy consumption were improved significantly by adopting the proposed irrigation scheduling system. Furthermore, the crop yield was increased by the proposed irrigation scheduling system compared with the others.

C. COST ANALYSIS

According to the design in Section III-A, the intelligent irrigation scheduling system was implemented and validated as shown in the previous section. The adding components for the proposed system are provided in Table 2. It can be observed that the total cost of the complete prototype (one central controller and two sensor aggregators) was about \$288.98, i.e., \$196.56 for one central controller and \$46.21 for each sensor aggregator. The comparisons of existing WSNs used by irrigation systems are provided in Table 3. It is shown that it cost \$84.10 for the sensor node proposed by [7], while the cost of the sensor aggregator (node) was \$46.21 for the proposed irrigation scheduling system. Considering the whole WSN system, the cost of the proposed irrigation system was relatively low compared with the other systems.

Moreover, the revenue from the proposed system investment was evaluated by using the time-based drip irrigation system as the base case scenario. From the previous analysis, the proposed irrigation scheduling system used the average amount of water of 175.03 liters/day, while the time-based drip irrigation system consumed the average water of 357.25 liters/day. For the electrical energy consumption, the proposed irrigation scheduling system consumed the average electrical energy of 23.51 Wh/day, while

TABLE 2. The list of the adding components.

No.	Item Description	Quantity	Price/Unit ($)	Total Price ($)
1	Arduino Uno R3 board	2	7.65	15.30
2	Arduino DUE board	1	21.87	21.87
3	Capacitive soil moisture sensor SKU:SEN0193	2	2.5	5.00
4	Air temperature and humidity sensor DHT22	2	5.62	11.24
5	Infrared temperature sensor GY-906 (MLX90614ESF)	2	11.72	23.44
6	Light sensor BH1750FVI	2	2.5	5.00
7	Pyranometer BGT-JYZ2	1	147	147
8	Current to voltage converter module	1	13.12	13.12
9	Switching power supply	2	4.68	9.36
10	Power adapter	3	2.5	7.50
11	Transceiver module NRF24L01+PA/LNA	3	3.44	10.32
12	Connector	3	3	9.00
13	Plastic container size 11.5×13.0×6.0 inc.	1	5.63	5.63
14	Plastic container size 8.5×9.5×5.0 inc.	2	2.60	5.20
	Total			288.98

TABLE 3. Comparisons of existing WSNs for irrigation system.

No.	Description	System Component	Monitor	Cost ($)	Ref.
1	A low-cost microcontroller-based system to monitor crop temperature and water status.	sensor node	soil moisture content, soil temperature, air temperature, and canopy temperature	84.10	[7]
2	Precision irrigation based on wireless sensor network.	base station, container node, weather node, and soil node.	soil moisture content, soil temperature, air temperature, light, humidity	388.95	[42]
3	A wireless design of low-cost irrigation system using ZigBee technology.	portable controller, wireless actuator node, wireless sensor node, and weather station.	air temperature, air humidity, and meteorological information	400	[43]
4	IoT based low cost and intelligent module for smart irrigation system.	sensor information unit, unified sensor pole, irrigation unit, and remoter user	air temperature, air humidity, soil moisture content	800-1,000	[12]
5	Automated irrigation system using a wireless sensor network and GPRS module.	wireless sensor unit, wireless information unit, irrigation unit	soil moisture content, soil temperature	1,900	[44]

the time-based drip irrigation system consumed the average electrical energy of 65.11 Wh/day. This paper assumes that the average water tariff rate is \$0.00425/liter, and the average electricity price is \$0.2/kWh. By summing the costs created by water use and electrical energy consumption, the proposed irrigation scheduling system spent approximately \$0.7486/day, meanwhile, the time-based drip irrigation system spent approximately \$1.5313/day. Comparing to these two systems, the difference in daily cost is \$0.7827/day. It can observe that the proposed irrigation scheduling system can save the daily cost created by water use and electrical energy consumption by 51.11%. Finally, considering the difference in the daily cost of \$0.7827/day, it shows that the proposed system can return its extra cost after approximately 374 days.

V. CONCLUSION

This paper mainly presented the design and implementation of an intelligent irrigation scheduling system using a potential low-cost wireless sensor network (WSN). The proposed irrigation scheduling system considered the two variabilities of soil moisture content and crop water stress simultaneously rather than only one variability consideration, while the use of low-cost WSN can enable the potential implementation in practical agricultural applications. As the experimental results, the proposed irrigation scheduling system yielded significant improvement in reliability and precision irrigation, improving the soil water and plant water status within the proper levels. The proposed irrigation scheduling system can precisely apply amounts of water for irrigation. Additionally, it can prevent crop water stress conditions. Hence, it can be concluded that the proposed irrigation scheduling system is effective in terms of the improvement of precision irrigation. Moreover, the experimental results confirmed that water use and energy consumption were dramatically reduced when the proposed irrigation scheduling system was adopted. Therefore, it can be concluded that water use and energy efficiencies can be improved simultaneously, moving toward sustainable agriculture. The cost analysis also offered a good agreement that the proposed irrigation scheduling system can be considered as an affordable and low-cost option for farmers and can be implemented on a large-scale agricultural farm with lower investment.

In the current study, we mainly focused on developing an intelligent adaptive irrigation scheduling strategy considering soil and plant water variabilities. However, an error associated with measurements used in the WSN should be taken into account to explore the impact on irrigation scheduling performance for future research works. The worst-case error scenario should be carefully analyzed. Furthermore, in order to improve WSN capability, next-generation communication networks should be considered to provide a longer range of data transmission.

ACKNOWLEDGMENT

The author would like to thank Mr. Chakkrit Chantawong for his assistance in collecting the data used in this study and for the installation and maintenance of field equipment and sensors. Furthermore, the authors would also like to express special thanks for the constructive comments from the editor and reviewers, leading significant and substantial improvements to the manuscript.

REFERENCES

[1] A. Daccache, J. W. Knox, E. K. Weatherhead, A. Daneshkhah, and T. M. Hess, ''Implementing precision irrigation in a humid climate–recent experiences and on-going challenges,'' *Agricult. Water Manage.*, vol. 147, pp. 135–143, Jan. 2015, doi: 10.1016/j.agwat.2014.05.018.

[2] V. Sharma and S. Irmak, ''Economic comparisons of variable rate irrigation and fertigation with fixed (uniform) rate irrigation and fertigation and pre-plant fertilizer management for maize in three soils,'' *Agricult. Water Manage.*, vol. 240, Oct. 2020, Art. no. 106307, doi: 10.1016/j.agwat.2020.106307.

[3] E. Kampianakis, J. Kimionis, K. Tountas, C. Konstantopoulos, E. Koutroulis, and A. Bletsas, ''Backscatter sensor network for extended ranges and low cost with frequency modulators: Application on wireless humidity sensing,'' in *Proc. IEEE SENSORS*, Nov. 2013, pp. 1–4, doi: 10.1109/icsens.2013.6688469.

[4] W. Liu, K. Huang, X. Zhou, and S. Durrani, ''Next generation backscatter communication: Systems, techniques, and applications,'' *EURASIP J. Wireless Commun. Netw.*, vol. 2019, no. 1, p. 69, Mar. 2019, doi: 10.1186/s13638-019-1391-7.

[5] Q. Zhang and F. J. Pierce, *Agricultural Automation: Fundamentals and Practices*. Boca Raton, FL, USA: CRC Press, Apr. 2016, doi: 10.1201/b13962-2.

[6] N. Romano, ''Soil moisture at local scale: Measurements and simulations,'' *J. Hydrol.*, vol. 516, pp. 6–20, Aug. 2014, doi: 10.1016/j.jhydrol.2014.01.026.

[7] D. K. Fisher and H. Kebede, ''A low-cost microcontroller-based system to monitor crop temperature and water status,'' *Comput. Electron. Agricult.*, vol. 74, no. 1, pp. 168–173, Oct. 2010, doi: 10.1016/j.compag.2010.07.006.

[8] Chen, Qi, Gui, Gu, Ma, Zeng, Li, and Sima, ''A model-based real-time decision support system for irrigation scheduling to improve water productivity,'' *Agronomy*, vol. 9, no. 11, p. 686, Oct. 2019, doi: 10.3390/agronomy9110686.

[9] M. S. Munir, I. S. Bajwa, and S. M. Cheema, ''An intelligent and secure smart watering system using fuzzy logic and blockchain,'' *Comput. Electr. Eng.*, vol. 77, pp. 109–119, Jul. 2019, doi: 10.1016/j.compeleceng.2019.05.006.

[10] B. Mason, M. Rufí-Salís, F. Parada, X. Gabarrell, and C. Gruden, ''Intelligent urban irrigation systems: Saving water and maintaining crop yields,'' *Agricult. Water Manage.*, vol. 226, Dec. 2019, Art. no. 105812, doi: 10.1016/j.agwat.2019.105812.

[11] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, ''IoT and agriculture data analysis for smart farm,'' *Comput. Electron. Agricult.*, vol. 156, pp. 467–474, Jan. 2019, doi: 10.1016/j.compag.2018.12.011.

[12] N. K. Nawandar and V. R. Satpute, ''IoT based low cost and intelligent module for smart irrigation system,'' *Comput. Electron. Agricult.*, vol. 162, pp. 979–990, Jul. 2019, doi: 10.1016/j.compag.2019.05.027.

[13] R. S. Krishnan, E. G. Julie, Y. H. Robinson, S. Raja, R. Kumar, P. H. Thong, and L. H. Son, ''Fuzzy logic based smart irrigation system using Internet of Things,'' *J. Cleaner Prod.*, vol. 252, Apr. 2020, Art. no. 119902, doi: 10.1016/j.jclepro.2019.119902.

[14] Y. Osroosh, R. Troy Peters, C. S. Campbell, and Q. Zhang, ''Automatic irrigation scheduling of apple trees using theoretical crop water stress index with an innovative dynamic threshold,'' *Comput. Electron. Agricult.*, vol. 118, pp. 193–203, Oct. 2015, doi: 10.1016/j.compag.2015.09.006.

[15] M. Srbinovska, C. Gavrovski, V. Dimcev, A. Krkoleva, and V. Borozan, ''Environmental parameters monitoring in precision agriculture using wireless sensor networks,'' *J. Cleaner Prod.*, vol. 88, pp. 297–307, Feb. 2015, doi: 10.1016/j.jclepro.2014.04.036.

[16] N. P. Mohanty, D. Singh, A. Hota, and S. Kumar, ''Cultivation of cash crops under automated greenhouse using Internet of Things (IoT),'' in *Proc. Int. Conf. Commun. Signal Process. (ICCSP)*, Apr. 2019, pp. 0235–0239, doi: 10.1109/iccsp.2019.8697930.

[17] Z. Chitu, F. Tomei, G. Villani, A. Di Felice, G. Zampelli, I. C. Paltineanu, I. Visinescu, A. Dumitrescu, M. Bularda, D. Neagu, R. Costache, and E. Luca, ''Improving irrigation scheduling using MOSES short-term irrigation forecasts and *in situ* water resources measurements on alluvial soils of lower danube floodplain, Romania,'' *Water*, vol. 12, no. 2, p. 520, Feb. 2020, doi: 10.3390/w12020520.

[18] D. Wang and X. Cai, ''Irrigation scheduling—Role of weather forecasting and farmers' behavior,'' *J. Water Resour. Planning Manage.*, vol. 135, no. 5, pp. 364–372, Sep. 2009, doi: 10.1061/(asce)0733-9496(2009)135:5(364).

[19] I. J. Lorite, J. M. Ramírez-Cuesta, M. Cruz-Blanco, and C. Santos, ''Using weather forecast data for irrigation scheduling under semi-arid conditions,'' *Irrigation Sci.*, vol. 33, no. 6, pp. 411–427, Oct. 2015, doi: 10.1007/s00271-015-0478-0.

[20] S. Idso, R. Jackson, P. Pinter, R. Reginato, and J. Hatfield, ''Normalizing the stress-degree-day parameter for environmental variability,'' *Agricult. Meteorol.*, vol. 24, pp. 45–55, Jan. 1981. [Online]. Available: https://doi.org/10.1016/0002-1571(81)90032-7

[21] R. D. Jackson, S. B. Idso, R. J. Reginato, and P. J. Pinter, ''Canopy temperature as a crop water stress indicator,'' *Water Resour. Res.*, vol. 17, no. 4, pp. 1133–1138, Aug. 1981, doi: 10.1029/wr017i004p01133.

[22] V. Gonzalez-Dugo, P. J. Zarco-Tejada, and E. Fereres, ''Applicability and limitations of using the crop water stress index as an indicator of water deficits in citrus orchards,'' *Agricult. Forest Meteorol.*, vols. 198–199, pp. 94–104, Nov. 2014, doi: 10.1016/j.agrformet.2014.08.003.

[23] O. Adeyemi, I. Grove, S. Peets, Y. Domun, and T. Norton, ''Dynamic modelling of the baseline temperatures for computation of the crop water stress index (CWSI) of a greenhouse cultivated lettuce crop,'' *Comput. Electron. Agricult.*, vol. 153, pp. 102–114, Oct. 2018, doi: 10.1016/j.compag.2018.08.009.

[24] Y. Emekli, R. Bastug, D. Buyuktas, and N. Y. Emekli, ''Evaluation of a crop water stress index for irrigation scheduling of bermudagrass,'' *Agricult. Water Manage.*, vol. 90, no. 3, pp. 205–212, Jun. 2007, doi: 10.1016/j.agwat.2007.03.008.

[25] S. M. Sezen, A. Yazar, Y. Daşgan, S. Yucel, A. Akyıldız, S. Tekin, and Y. Akhoundnejad, ''Evaluation of crop water stress index (CWSI) for red pepper with drip and furrow irrigation under varying irrigation regimes,'' *Agricult. Water Manage.*, vol. 143, pp. 59–70, Sep. 2014, doi: 10.1016/j.agwat.2014.06.008.
[26] Y. Osroosh, R. T. Peters, C. S. Campbell, and Q. Zhang, ''Comparison of irrigation automation algorithms for drip-irrigated apple trees,'' *Comput. Electron. Agricult.*, vol. 128, pp. 87–99, Oct. 2016, doi: 10.1016/j.compag.2016.08.013.
[27] Y. Erdem, L. Arin, T. Erdem, S. Polat, M. Deveci, H. Okursoy, and H. T. Gültaş, ''Crop water stress index for assessing irrigation scheduling of drip irrigated broccoli (Brassica Oleracea l. Var. Italica),'' *Agricult. Water Manage.*, vol. 98, no. 1, pp. 148–156, Dec. 2010, doi: 10.1016/j.agwat.2010.08.013.
[28] H. Kirnak, H. A. Irik, and A. Unlukara, ''Potential use of crop water stress index (CWSI) in irrigation scheduling of drip-irrigated seed pumpkin plants with different irrigation levels,'' *Scientia Horticulturae*, vol. 256, Oct. 2019, Art. no. 108608, doi: 10.1016/j.scienta.2019.108608.
[29] M. Poirier-Pocovi and B. N. Bailey, ''Sensitivity analysis of four crop water stress indices to ambient environmental conditions and stomatal conductance,'' *Scientia Horticulturae*, vol. 259, Jan. 2020, Art. no. 108825, doi: 10.1016/j.scienta.2019.108825.
[30] K. Xu, Q. Sheng, X. Zhang, P. Li, and S. Chen, ''Design and calibration of the unilateral sensitive soil moisture sensor,'' *IEEE Sensors J.*, vol. 15, no. 8, pp. 4587–4594, Aug. 2015, doi: 10.1109/jsen.2015.2423697.
[31] G. Kargas and K. X. Soulis, ''Performance analysis and calibration of a new low-cost capacitance soil moisture sensor,'' *J. Irrigation Drainage Eng.*, vol. 138, no. 7, pp. 632–641, Jul. 2012, doi: 10.1061/(asce)ir.1943-4774.0000449.
[32] C. Jamroen, E. Usaratniwart, and S. Sirisukprasert, ''PV power smoothing strategy based on HELES using energy storage system application: A simulation analysis in microgrids,'' *IET Renew. Power Gener.*, vol. 13, no. 13, pp. 2298–2308, Oct. 2019, doi: 10.1049/iet-rpg.2018.6165.
[33] M. Kocakulak and I. Butun, ''An overview of wireless sensor networks towards Internet of Things,'' in *Proc. IEEE 7th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2017, pp. 1–6, doi: 10.1109/ccwc.2017.7868374.
[34] M. E. E. Alahi, N. Pereira-Ishak, S. C. Mukhopadhyay, and L. Burkitt, ''An Internet-of-Things enabled smart sensing system for nitrate monitoring,'' *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4409–4417, Dec. 2018, doi: 10.1109/jiot.2018.2809669.
[35] Radi, Murtiningrum, Ngadisih, F. S. Muzdrikah, M. S. Nuha, and F. A. Rizqi, ''Calibration of capacitive soil moisture sensor (SKU:SEN0193),'' in *Proc. 4th Int. Conf. Sci. Technol. (ICST)*, Aug. 2018, pp. 1–6, doi: 10.1109/icstc.2018.8528624.
[36] T. Liu. *Digital-Output Relative Humidity & Temperature Sensor/Module DHT22*. Aosong Electronics. Accessed: Sep. 17, 2020. [Online]. Available: https://www.sparkfun.com/datasheets/Sensors/Temperature/DHT22.pdf
[37] J. Martínez, G. Egea, J. Agüera, and M. Pérez-Ruiz, ''A cost-effective canopy temperature measurement system for precision agriculture: A case study on sugar beet,'' *Precis. Agricult.*, vol. 18, no. 1, pp. 95–110, Aug. 2016, doi: 10.1007/s11119-016-9470-9.
[38] K. X. Soulis and S. Elmaloglou, ''Optimum soil water content sensors placement for surface drip irrigation scheduling in layered soils,'' *Comput. Electron. Agricult.*, vol. 152, pp. 1–8, Sep. 2018, doi: 10.1016/j.compag.2018.06.052.
[39] I. Reda, T. Stoffel, and D. Myers, ''A method to calibrate a solar pyranometer for measuring reference diffuse irradiance,'' *Sol. Energy*, vol. 74, no. 2, pp. 103–112, Feb. 2003, doi: 10.1016/s0038-092x(03)00124-5.
[40] J. H. Lilly, ''Takagi-Sugeno fuzzy systems,'' in *Fuzzy Control and Identification*. Hoboken, NJ, USA: Wiley, Nov. 2010.
[41] A. Benzaouia and A. El Hajjaji, ''Advanced Takagi-Sugeno fuzzy systems,'' in *Stud. Syst., Decis. Control*. Cham, Switzerland: Springer, 2014.
[42] S. Khriji, O. Kanoun, D. El Houssaini, C. Viehweger, M. W. Jmal, and M. Abid, ''Precision irrigation based on wireless sensor network,'' *IET Sci., Meas. Technol.*, vol. 8, no. 3, pp. 98–106, May 2014, doi: 10.1049/iet-smt.2013.0137.
[43] Y. Zhou, X. Yang, L. Wang, and Y. Ying, ''A wireless design of low-cost irrigation system using ZigBee technology,'' in *Proc. Int. Conf. Netw. Secur., Wireless Commun. Trusted Comput.*, Apr. 2009, pp. 572–575, doi: 10.1109/nswctc.2009.231.
[44] J. Gutierrez, J. F. Villa-Medina, A. Nieto-Garibay, and M. A. Porta-Gandara, ''Automated irrigation system using a wireless sensor network and GPRS module,'' *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 166–176, Jan. 2014, doi: 10.1109/tim.2013.2276487.

CHAOWANAN JAMROEN (Member, IEEE) received the B.Eng. and M.Eng. degrees in electrical engineering from Kasetsart University, Bangkok, Thailand, in 2013 and 2016, respectively. He is currently a Lecturer with the Division of Instrumentation and Automation Engineering Technology, King Mongkut's University of Technology North Bangkok, Rayong Campus, Thailand. His research interests include power system analysis and stability, smart grid technology, synchrophasor measurement technique, power system optimization, distributed generation, and sustainable technology.

PREECHA KOMKUM received the B.Eng. degree in electrical engineering from Dhurakij Pundit University, Bangkok, Thailand, in 2000, and the M.S. degree in electrical engineering education from the King Mongkut's University of Technology North Bangkok, Thailand, in 2004. He is currently an Assistant Professor with the Division of Instrumentation and Automation Engineering Technology, King Mongkut's University of Technology North Bangkok, Rayong Campus. His research interests include image processing, fuzzy logic systems, and control system engineering.

CHANON FONGKERD is currently pursuing the B.Eng. degree in instrumentation and automation engineering technology with the Division of Instrumentation and Automation Engineering Technology, King Mongkut's University of Technology North Bangkok, Rayong Campus, Thailand.

WIPA KRONGPHA is currently pursuing the B.Eng. degree in instrumentation and automation engineering technology with the Division of Instrumentation and Automation Engineering Technology, King Mongkut's University of Technology North Bangkok, Rayong Campus, Thailand.