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Optimization of Irrigation in Open-Field Fruit Orchards Using an Intelligent Precision Control System: A Case Study of Durian

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Abstract. Precision irrigation systems (PIS) are essential for optimizing water use, crop yield, and fruit quality. Estimating crop water requirements has become increasingly complex due to growing variability in weather patterns, which increases the risk of irrigation mismanagement. Conventional PIS often rely on fixed schedules or pre-determined water quantities. While some offer decision-support capabilities, they typically require human intervention and lack the ability to control irrigation. To address these issues, an intelligent precision irrigation system (IPIS) was developed. The IPIS utilizes real-time meteorological data collected from local sensors and implements advanced control algorithms based on the Penman-Monteith evapotranspiration method to optimize water delivery. A four-month field experiment with 166 irrigation events conducted in a durian orchard in Rayong, Thailand, demonstrated the system's ability to dynamically adjust irrigation schedules and water volumes in response to fluctuating weather conditions while maintaining optimal soil moisture levels. This resulted in significantly improved irrigation accuracy and crop water use efficiency. The findings suggest that incorporating machine learning and artificial intelligence in future iterations could further enhance the system's adaptability, autonomous operation, and predictive capacity, advancing its application in precision agriculture.

Keywords: Precision irrigation system, intelligent irrigation, fruit orchard irrigation, crop evapotranspiration, autonomous control system.

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1. Introduction

Fruit production plays a vital role in economic growth across many developing countries, with tropical and subtropical crops like papaya, guava, avocado, and durian significantly contributing to export revenue. In 2023, Mexico exported 1.5 million tons of avocado, generating USD 3.28 billion, while Thailand's durian exported 1.2 million tons reaching a higher export value of USD 4.10 billion [1], [2].

Durian, a distinctive Southeast Asian fruit with over 200 known species, is primarily cultivated for its high economic value and increasing global demand, particularly from China. Each durian fruit weighs approximately 2-4 kilograms and is produced annually. Typically, the root zone is concentrated 72-87% from the soil surface at a depth of about 45 cm [3]. Durian thrives in temperatures ranging from 27-30°C and a relative humidity of 75-80% [4].

Maximizing crop yield and fruit quality requires effective management of nutrients, pests, diseases, and especially water in the root zone. In open-field orchards, irrigation is highly influenced by fluctuating weather patterns, making water requirements difficult to estimate. Moreover, climate change has exacerbated local variations in temperature, humidity, and solar radiation [4], further complicating irrigation planning.

Growers often rely on experience-based irrigation methods, which are prone to inaccuracies [5]. Delivering water precisely—applying the right amount at the right time—is crucial, particularly during key growth stages such as flowering and early fruit set. Durian trees are highly sensitive to water stress during these phases, and inadequate irrigation can drastically impact yield and quality [3]. During the flower induction period of durian buds, if rainfall or irrigation—whether excessive or insufficient—disrupts the plant's transition from vegetative to reproductive growth, it may result in the absence of flowering and potentially lead to yield losses ranging from 10% to 70% [6].

Precision irrigation (PI) offers an advanced solution, allowing growers to apply water and nutrients with high accuracy, tailored to the specific needs of each tree. This approach optimizes resource utilization, reduces water waste and operational costs, minimizes disease risks, and enhances crop productivity [7].

Over the past decade, various precision irrigation systems (PIS) have emerged, often in the form of mobile or web-based applications that provide weather forecasts, evapotranspiration data, and vapor pressure deficit insights to assist farmers in irrigation planning [8]. However, many of these systems lack water control capabilities, relying on fixed schedules that do not adjust to real-time weather fluctuations. As a result, uniform irrigation is often applied irrespective of actual crop needs, increasing the likelihood of over- or under-watering. Since most systems lack automated control mechanisms, manual adjustments are required, leading to discrepancies between recommended and actual water application.

This study aims to develop an **intelligent precision irrigation system** (IPIS) for open-field fruit orchards. Unlike conventional PIS, the proposed IPIS integrates real-time weather data with automated controls, dynamically adjusting water supply based on actual crop requirements without human intervention. This innovation ensures efficient, adaptive irrigation, enhancing accuracy and conserving vital resources.

2. Precision Irrigation System (PIS) for Open-Field Orchards

PIS, which leverage advanced sensors, data analytics, and intelligent control algorithms, have emerged as an effective solution for addressing the challenges of open-field fruit production [9], [10]. These systems support optimized water use by delivering irrigation and nutrients based on site-specific conditions, thereby enhancing resource efficiency and crop yield. PIS technologies have been widely adopted by fruit growers for irrigation monitoring, scheduling, and water conservation [11], [12]. A range of tools, platforms and technologies have been developed, including soil moisture sensors, Internet of Things (IoT), remote sensing, and machine learning (ML), with increasing attention to their integration.

Sensor-based PIS are widely adopted due to their simplicity and cost-effectiveness in small to medium-size orchards. Soil moisture sensors, in particular, help monitor soil water status and inform irrigation decisions. For instance, Martínez-Gimeno et al. [13] proposed a soil moisture threshold-based method to regulate irrigation in mandarin orchards located in Mediterranean climates, achieving water savings of up to 33%. Similar results were found in vineyards in Northern Italy, using variable-rate drip irrigation based on soil moisture data, with an 18% reduction in water use and no loss in yield or quality [14]. While these studies were conducted in temperate and Mediterranean zones with orchard sizes typically ranging from 1 to 5 hectares, the principles of sensor-based irrigation are believed to be adaptable to tropical durian orchards, which in Southeast Asia often range from 5 to 20 hectares. Gao et al. [15] emphasized the importance of combining meteorological and soil data in a litchi orchard while Vera et al. [16] determined irrigation factors using data from a nearby automatic meteorological station to adjust the soil water content for nectarine orchards. Increasing the number of soil moisture sensors installed in cultivated areas has been shown to improve the accuracy of water balance predictions, particularly in small fields. However, in large-scale applications, more soil moisture sensors demand greater power supply and a robust data communication network that supports high data volumes and long-distance transmission. In this regard, the Internet of Things (IoT) could mitigate these issues.

The emergence of IoT technology has benefited precision irrigation developers by integrating cloud computing, wireless networks, and various types of sensors for irrigation management [17]. IoT communication technologies such as LoRaWAN, ZigBee and MTTQ have contributed to the growing trend of IoT in agriculture [18] [19]. IoT systems developed by Goap et al. [20] and Kuma et al. [21] combined real-time weather data with predictive models and remote control features to improve irrigation accuracy. Typical architectures include sensors, cloud platforms, and user interfaces via mobile or web applications [22], [23], offering low-cost solutions suitable for small-scale orchards [24], [25]. However, in large fruit orchards, installing numerous soil sensors can be costly. Growers may opt for alternative techniques, such as remote sensing technologies including satellite and unmanned aerial vehicles (UAV) to provide spatially extensive data for irrigation planning.

Remote sensing-based models were found to have strong correlation to in-situ measurements. They were used for estimating evapotranspiration in walnut orchards during extreme weather condition in California [17]. Remote sensing with soil mapping was also used for regulated deficit irrigation in olive orchards [26]. Remote sensing technologies have been developed utilizing satellites and UAVs to collect crops data [27]. These technologies enable estimations to determine crop water stress index (CWSI), land surface temperature, vegetation health, and soil moisture [28]-[30]. Park et al. [31] used UAV-mounted sensors to assess CWSI and identify deficit areas in fruit orchards. Despite their advantages, remote sensing techniques often suffer from low spatial resolution, complex processing, and high image analysis costs, making them less practical for daily irrigation management.

The integration of machine learning (ML) into PIS has enabled predictive irrigation scheduling and autonomous control. ML approaches rely on large datasets to estimate crop water demand, using input variables such as soil moisture, weather, and crop growth indicators. Abioye et al. [9] and Sun et al. [32] applied deep reinforcement learning and neural networks to optimize irrigation timing and improve water use efficiency. Partial least squares regression and adaptive fuzzy inference systems were applied by Navarro-Hellin et al. [11] for predicting irrigation run times in citrus orchards. Torres-Sanchez et al. [33] demonstrated the effectiveness of ML across diverse farms and crops, while Tace et al. [34] developed IoT–ML integrated systems for predictive irrigation scheduling. Although promising, ML-based systems face challenges related to data collection, processing, and generalization. Inconsistent or missing data, overfitting, and limited satellite coverage can compromise model accuracy and performance [35].

To overcome the limitations of individual technologies, recent studies have explored multi-technology integration for enhanced irrigation control. Combined use of weather data, soil moisture sensors, and remote sensing has led to more precise and site-specific irrigation scheduling [36], [37], . Lozoya et al. [38] implemented prediction models based on integrated datasets to improve irrigation timing. Such systems dynamically adapt to environmental changes, crop phenological stages, and localized field variability. Nonetheless, practical implementation requires careful consideration of cost, reliability, ease of use, and environmental conditions. For instance, IoT devices may lack durability in high-moisture tropical environments, and ML models demand high-quality data to achieve reliable results. Despite growing interest, field-tested applications of integrated PIS using ML and remote sensing in open-field orchards remain limited, highlighting the need for further validation and system development tailored to tropical fruit production.

Given limitations on individual PIS technologies, this study opted for a combination of automated weather stations (AWS) and soil moisture sensors, which offer higher data resolution, reliable, lower operational complexity, and cost-effectiveness—making them more suitable for daily irrigation management in tropical durian orchards with medium-scale layouts and frequent rainfall variability.

3. Crop Water Requirement (CWR)

CWR is a critical parameter in PIS, representing the amount of water needed by crops. Accurate measurement of CWR is essential for optimizing irrigation schedules and improving water use efficiency in open-field fruit orchards. There are several methods used for measuring CWR, each method has its strengths and limitations, with some being more suitable for large-scale assessments. CWR can be measured directly using e.g. lysimeter, water fluxmeter and indirectly using e.g. water balance method, tensiometer and soil moisture content data [39].

Table 1 summarizes the advantages and disadvantages of each method, helping developers determine the most suitable option for their needs.

Table 1. Comparison of Methods for Measuring Crop Water Requirements.

No.	Methods	Advantages	Disadvantages
1.	**Evapotranspiration-based methods:** Evapotranspiration-based methods or the FAO Penman-Monteith equation is widely used to calculate reference evapotranspiration (ETo), which is then adjusted using crop coefficients (Kc) to determine crop-specific evapotranspiration (ETc). This method requires meteorological	• Widely accepted standard • Applicable to diverse climates • Provides reference evapotranspiration	• Requires multiple meteorological inputs • May need local calibration • Complexity of equation

No.	Methods	Advantages	Disadvantages
	data such as temperature, humidity, wind speed, and solar radiation.[40]		
2.	**Soil moisture monitoring:** Soil moisture sensors, including time-domain reflectometry (TDR) probes and capacitance sensors, provide real-time data on soil water content. These measurements help determine when irrigation is necessary and can be used to estimate crop water uptake.	• Direct measurement of water in soil • Real-time data • Helps with precise irrigation scheduling	• Requires proper sensor placement [41] • May need multiple sensors for large fields • Initial cost of equipment
3.	**Plant-based measurements:** Techniques such as stem water potential, leaf water potential, and sap flow measurements directly assess plant water status. These methods provide insights into the crop's actual water needs and can be used to fine-tune irrigation schedules.[42], [43]	• Directly assesses plant water status • Can detect early signs of water stress • Specific to crop type	• Can be labor-intensive • May require specialized equipment • Measurements can vary with time of day
4.	**Remote sensing:** Satellite imagery and unmanned aerial vehicles (UAVs) equipped with multispectral cameras can be used to estimate crop water stress and evapotranspiration rates over large areas. Vegetation indices like the Normalized Difference Vegetation Index (NDVI) are often used in these assessment. [44], [45], [46]	• Covers large areas quickly • Non-invasive • Provides spatial variability data	• Requires specialized interpretation • Cloud cover can interfere with data collection • May have lower resolution for small-scale assessments
5.	**Lysimeter:** Weighing lysimeters provide highly accurate measurements of crop water use by directly measuring changes in soil water content and plant biomass. While precise, this method is often limited to research settings due to its complexity and cost [42], [47].	• Highly accurate measurements • Useful for research and calibration • Provides detailed water balance data	• Expensive to install and maintain • Limited to small areas • May not well represent field conditions
6.	**Water balance:** This method involves tracking all water inputs (precipitation, irrigation) and outputs (runoff, deep percolation, evapotranspiration) to determine crop water use [26].	• Comprehensive view of water inputs/outputs • Can be applied at various scales • Useful for long-term planning	• Requires accurate measurement of multiple variables • May not capture short-term variations well • Prone to cumulative errors
7.	**Eddy covariance:** This micrometeorological method measures water vapor fluxes above the crop canopy, providing direct measurements of actual evapotranspiration. It is highly accurate but requires specialized equipment and expertise [48].	• Direct measurement of water vapor fluxes • Provides continuous data • Applicable over larger areas	• Requires complex and expensive equipment • Needs expert interpretation • May have limitations in certain terrains

Fruit trees grown in open fields are directly exposed to weather and environmental conditions. Given the current fluctuations in weather, it is essential to consider both weather factors and soil water content when measuring crop water demand. Therefore, combining evapotranspiration-based [40] (Penman-Monteith equation) methods and soil moisture sensors presents an appropriate method for this study. These methods are

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believed to provide sufficiently accurate crop water requirements and irrigation needs. The components of the Penman–Monteith equation shown in Table 1 are explained in the following sections.

3.1. Reference Crop Evapotranspiration Estimation (ETo)

While various methods can be employed to calculate ET_C, depending on the instruments used and the desired accuracy [49], the Penman-Monteith equation is widely adopted as a standardized method.

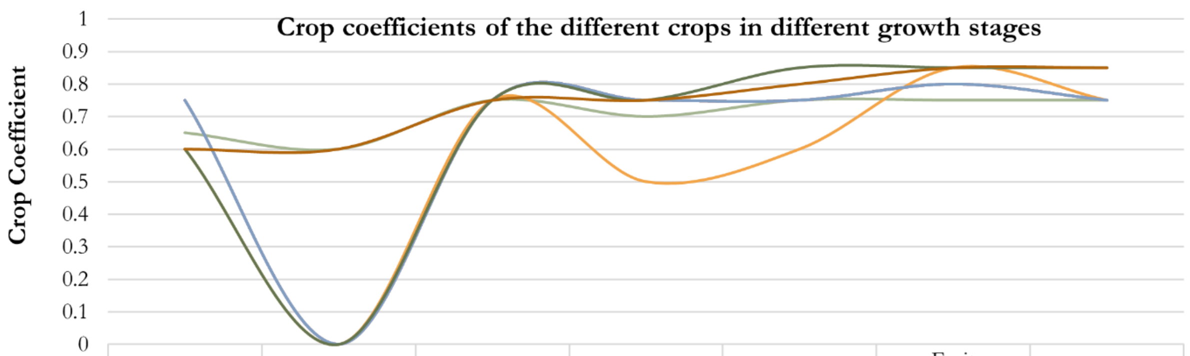
In 1998, the FAO published Irrigation and Drainage Paper No. 56, titled "Crop Evapotranspiration" [40]. This publication provides guidance on calculating crop evapotranspiration by using reference evapotranspiration (ETo) data from weather stations, which is then adjusted using a crop coefficient (Kc) specific to the crop type and its growth stage. The reference crop evapotranspiration can be computed using Eq. (1) below.

$$ET_O = \frac{0.408\Delta(R_n - G) + \gamma\frac{C_n}{T+273}U_2(e_s - e_a)}{\Delta + \gamma(1 + C_d\,U_2)} \quad (1)$$

Where ETo is the reference crop evapotranspiration or evapotranspiration reference (mm day^{-1}) R_n is net radiation (MJ m^{-2} day^{-1}), G is soil heat flux density (MJ m^{-2} day^{-1}), T is mean daily ambient temperature at 2 meter above ground level (°C), Δ is slope of the saturation vapor pressure against temperature curve (kPa °C^{-1}), γ is psychrometric constant (0.66 kPa °C^{-1}), e_s is the prevailing actual vapor pressure (kPa), U_2 is mean of wind speed at 2 m high (m s^{-1}) and C_n is numerator and C_d is denominator constants that varied on the type of reference surface and the calculation time step. It assumes that surface resistance under the fruit tree is equivalent to the cut grass thus C_n is equal to 37 in hourly during daytime and nighttime while C_d is equal to 0.24 in hourly during daytime and 0.96 in hourly during nighttime.

3.2. Crop Coefficient (Kc)

The Crop Coefficient (Kc) is the ratio of crop evapotranspiration (ET_C) to reference evapotranspiration (ETo), adjusting water needs for specific crops. It varies by variety, growth stage, climate, and farming practices.



Fruit Variety	Post flowering	Bud burst	Flowing	Fruit set	Young fruit	Fruit development	Fruit rippening
Citus	0.65	0.6	0.75	0.7	0.75	0.75	0.75
Durian	0.6	0	0.75	0.5	0.6	0.85	0.75
Longan	0.75	0	0.75	0.75	0.75	0.8	0.75
Longkong	0.75	0	0.75	0.75	0.75	0.8	0.75
Lychee	0.75	0	0.75	0.75	0.75	0.8	0.75
Mango	0.75	0	0.75	0.75	0.75	0.8	0.75
Mangosteen	0.6	0	0.75	0.75	0.85	0.85	0.85
Rambutan	0.6	0.6	0.75	0.75	0.8	0.85	0.85

Fig. 1. Crop Coefficient of Difference Fruits in Thailand.

Figure 1 illustrates the crop coefficient (Kc) of various fruit varieties at different stages of production, based on information published by the Department of Agriculture, Thailand [50]. It is to note that during the bud burst stage, certain fruit trees such as durian, mangosteen, and longan do not require, or very low quantities of water. This period is approximately 3-10 days for stimulating flowering.

3.3. Crop Water Requirement (ETc)

The crop water requirement (ETc) can be estimated using a standard procedure to multiply ETo by Kc as indicated in equation (2).

$$ET_C = ET_O * K_C \quad (2)$$

To improve the accuracy of Kc estimation, this study adopted the dual crop coefficient approach, which

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distinguishes between soil evaporation and crop transpiration, as outlined in FAO Paper No. 56.[40]. This method defines Kc as the sum of the basal crop coefficient (Kcb) and soil water evaporation efficiency (Ke), with values ranging between 0 and 1.4 as indicated in Eq. (3).

$$ET_C = ET_O * (K_{Cb} + K_e) \tag{3}$$

3.4. Total Water Requirement (TWR)

Total water requirement (TWR) for a tree can be calculated by multiplying the daily ET_C value by the tree's canopy area as shown in Eq. (4).

$$TWR = \sum_{i=0}^{24} ETc\ * Area \tag{4}$$

where TWR is the Total Water Requirement litters per day- for a tree. Area is estimated based on the radius (r) of the crop canopy using πr^2.

This study proposes determining crop water requirements using the Penman-Monteith evapotranspiration method, as it has been validated by the FAO and scientists for its accuracy and reliability. Soil moisture sensors are primarily used to monitor and cross-check the water content in the soil. These input sensors will transmit data to a controller, thereby creating a precision irrigation system.

4. Materials and Methods

An actual IPIS was developed, installed and tested in a durian orchard to evaluate its capabilities in self-adjusting the amount of daily water irrigation in response to weather conditions. The system also includes soil moisture monitoring and an alarm feature to notify when soil water content falls outside the established threshold.

The development of an IPIS encompasses several stages, including conceptual design, system prototyping, procurement, detailed design, field installation, and testing. The system integrates multiple technologies, including weather instruments, automation control, and crop water requirement algorithm. Design also considers critical factors, including operational costs, lifespan, ease of use, functionality, and profitability for fruit growers.

4.1. System Design

The system's core function is to dynamically determine and regulate water allocation per individual tree through advanced algorithmic control, leveraging real-time sensor data to modulate motor-pump actuation, motor-drive valves state, and comprehensive water distribution monitoring. The integrated control logic enables precise water resource management by translating analytical insights into automated irrigation interventions, thereby optimizing water utilization efficiency in fruit orchard environments.

While there are numerous advanced technologies available, it is crucial for developers to balance between cost, complexity, reliability, and maintainability. The most effective technology is considered the one that aligns best with the specific objectives of the application.

Although achieving precise irrigation in response to weather conditions is a primary goal, user acceptance and system utility must also be prioritized. With these considerations in mind, the automatic weather station, soil moisture sensors, and Programmable Logic Controller (PLC) were integrated to develop a novel system. The weather data is used to calculate the required water for crops while validating against soil moisture content. Multiple algorithms operate in the backend, with a touchscreen facilitating user interaction.

The IPIS comprises three main parts including (1) weather sensors and other instruments for data collection (2) signal quality validation and preprocessing, and (3) computational algorithms for water volume quantification and adaptive irrigation management.

Figure 2 illustrates the interconnection between each component. A compact programmable logic controller (PLC) functions as the central processing unit, collecting data from an automatic weather station, soil moisture sensors, a flow meter, and a water pressure sensor. The output from the PLC is linked to a variable speed drive (VSD), which subsequently connects to the pumps motor. There are three digital output signals connected to three motor-driven valves. A local panel comprises various switches and selectors used to turn the pump and valves on and off.

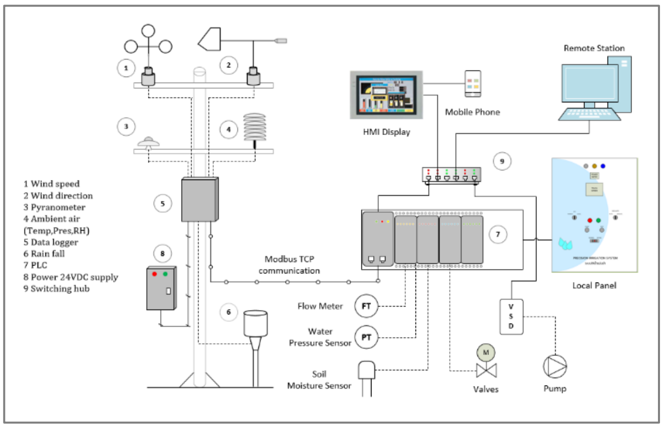

Fig. 2. IPIS Systematic Control and Instrument Diagram.

4.2. Equipment and Sensors Specifications

To estimate the evapotranspiration based on Penman-Monteith Eq. (1) [40], the instruments as listed on item 1-6 shown in Table 2 are required. The sensors came in a set of "Automatic Weather Station" which is also include a datalogger and a small LCD for data monitoring. The rainfall sensor, soil moisture sensor, flow meter, and water pressure sensor are individual components used for monitoring the irrigation system and for triggering interlocks when system malfunctions are detected. These sensors were calibrated before installation at the site.

Table 2. Sensors Basic Specification.

	Sensor	Unit	Resolution	Accuracy (%)	Measure range
1.	Air temperature	°C	1	± 0.5	0-60
2.	Air pressure	hPa	0.1	± 0.3	500-1100
3.	Relative humidity	%	0.1	± 3	0-100
4.	Wind speed	m s^{-1}	0.1	± 0.3	0-45
5.	Wind direction	Degree	1	± 3	0-360
6.	Solar radiation	W m^{-2}	1	± 2	0-2000
7.	Rainfall	mm	0.2	± 4	0-8
8.	Soil moisture	%	1	± 3	0-100
9.	Flow meter	m^3 hr^{-1}	0.1	± 0.5	0-600
10.	Water pressure	bar	0.1	± 0.1	0-10

The selection of sensors and equipment in this study prioritizes reliability, accuracy, quality, and operational capability under tropical conditions. This necessitates that all equipment functions effectively in environments characterized by high humidity, elevated temperatures, and dusty conditions.

4.2.1. Automatic Weather Station (AWS)

An automatic weather station (AWS) is a sophisticated meteorological monitoring system engineered to autonomously collect and record atmospheric data. It comprises a suite of sensors and instruments that measure various parameters, including temperature, humidity, wind speed and direction, atmospheric pressure, precipitation, and solar radiation. AWS is extensively used for data acquisition to compute evapotranspiration in accordance with the Penman–Monteith (FAO) recommendation [10].

The use of AWS for data collection provides a significant advantage in terms of data resolution, with a scanning rate measured in seconds. However, it is crucial to regularly inspect and monitor these instruments to prevent disruptions, particularly after the initial weeks of field installation. The quality of data is critical; the presence of outliers can lead to incorrect water estimations. To address this, we developed a sub-algorithm to manage outliers and trigger an audible alarm in the event of anomalies.

4.2.2. Rain sensor

Rain sensors were employed to detect precipitation and quantify rainfall. Data from the rain sensors were transmitted to the analog input of the PLC and utilized to automatically adjust the irrigation schedule and water quantity. If precipitation is detected during irrigation, the system will cease and cancel irrigation.

4.2.3. Soil Moisture Sensor (SMS)

Soil moisture sensors were employed to assess the soil water content. Two frequency-domain reflectometry soil moisture sensors were installed at depths 25 and 50 centimeters from the ground surface to capture moisture conditions in the upper and lower parts of the root zone, which is primarily located within the top 45 cm of the soil. The data from these sensors, which provide the percentage of water content in the soil, were transmitted to the PLC in real-time. This data was utilized to verify whether the water content in the root zone was within the range of 50-75%. If the water content fell outside this range, the PLC generated an audible alarm.

4.2.4. Flow meter

An electromagnetic flowmeter was installed to measure the water flow at the pump outlet. The device operates based on Faraday's law of electromagnetic induction, which states that voltage is induced when a conductor moves through a magnetic field. The flow meter indicates the water flow rate in cubic meters per hour and calculates the volume in cubic meters, enabling validation of the water supply quantity against the evapotranspiration calculation result.

4.2.5. Water pressure meter

A pressure sensor was installed at the main pipe to monitor the water pressure. The output signal from the sensor was sent to the PLC for monitoring and was used as a feedback control signal to control the water pressure.

4.2.6. Variable Speed Drive (VSD)

To ensure that water is sprayed equally through the sprinkler emitter, the water pressure must always remain stable. VSD has a duty to automatically control the water pressure by adjusting the speed of the pump-motor. Additionally, VSD can save electricity costs by reducing inrush current during motor startup by approximately 10-15%.

4.2.7. Programmable Logic Controller (PLC)

The selection of a PLC is driven by a combination of a high-performance processor, ensuring that it can handle large amounts of data and last long when operated in high-moisture and warm environments. Additionally, PLCs offer the advantages of logic programming, software development, software simulators for pre-test, and flexibility in scalability. The programming language used for the PLC differs from traditional hard-coded programming. Most modern PLCs support standardized languages such as ladder logic, function block diagrams, and structured text. For this project, the author selected function block programming due to its modularity and ease of visualization during development. Although the initial cost is slightly higher than a microcontroller board, the long-term operating cost is lower than cloud computing when the user does not require a subscription payment. The PLC (Siemens S7-1200) used in this study was an industrial-grade compact model. It features 14 digital outputs and 10 digital inputs, operating at 24V DC power. Additionally, it included two analog outputs and two analog inputs. The PLC can operate in environments with temperatures of up to 60°C and humidity levels of up to 95%. The CPU processing time of Boolean is 0.08 microseconds per instruction and includes 8 MB of memory. PLC reads data from the AWS and soil moisture sensors via the Modbus protocol while communicating to the VSD and HMI screens via Ethernet TCP/IP.

4.2.8. HMI (Human Machine Interface)

IPIS is equipped with a 7-inch HMI feature of a touchscreen installed on the front panel of the control cubicle for users to monitor, control, and perform irrigation processes. HMI is utilized to communicate between humans and systems using process control graphics that include an operation control panel, real-time data display, and equipment status. These interactive interfaces enable operators to monitor and control orchard irrigation using intuitive visual representations and real-time data updates. By providing user-friendly graphics for system interaction, HMI enhances operational efficiency, reduces human error, and enables quick decision making in various irrigation methods.

4.3. Data Collection and Communication

The overall accuracy of the system varies depending on the individual processes involved. This includes data collection, processing through the evapotranspiration (ET_O) computation and analysis module, and finally, transmission of the output signal to the equipment. The accuracy of the ET_O calculation largely depends on the quality of data collection. Each sensor's data is read by the datalogger and PLC every second. Data exchange between the PLC and other equipment and components such as datalogger, VSD and HMI are based on the Modbus TCP protocol while the communication between PLC and soil moisture sensor is Modbus RTU. Pressure and flow signals are connected to the PLC's analog input via a 4-20 mA current.

The quality of the data may be lower due to disturbances caused by external noise such as cellular phone signals, lightning, and electric surges. To reduce the issue of outlier data that can significantly skew the average and have the potential for inaccurate results, the raw data is averaged into one-hour datasets. The one-hour dataset is used for calculating crop evapotranspiration (ET_O). The daily ET_O value is then obtained by summarizing the one-hour data.

4.4. Processing Control Algorithms

The Intelligent Precision Irrigation System (IPIS) was developed to optimize irrigation management for open-field fruit orchards. It not only estimates the water requirements of crops but also autonomously controls water delivery. Advanced features, such as irrigation triggers based on light intensity, and preset irrigation times or quantity, provide fruit farmers with greater flexibility to align with their irrigation practices. The design algorithms consist of primary algorithms, which include data collection real-time crop water requirement calculation, and precision control of water supply quantity. Sub-algorithms are implemented for safety operations, error prevention, data repository management, and system alarms. The IPIS can be operated in either autonomous or manual mode, selectable via the HMI display. Each operation mode is designed for different purposes.

Figure 3 illustrates the overall equipment connection and process diagram. The PLC is the central processor interface to every component. Upon system initiation, the PLC resets memory and commences data scanning from all sensors. The raw data is utilized to validate quality and subsequently processed to analyze crop water demand. The system then awaits a command from the user, which may be received in either autonomous or manual operation mode. Upon receiving a command, the system proceeds by sending signals to the Variable Speed Drive (VSD) and valves to activate the pumps motor and open the valves, respectively. Once the commanded processes are successfully executed, the system sends a signal to stop the pump and enter standby mode.

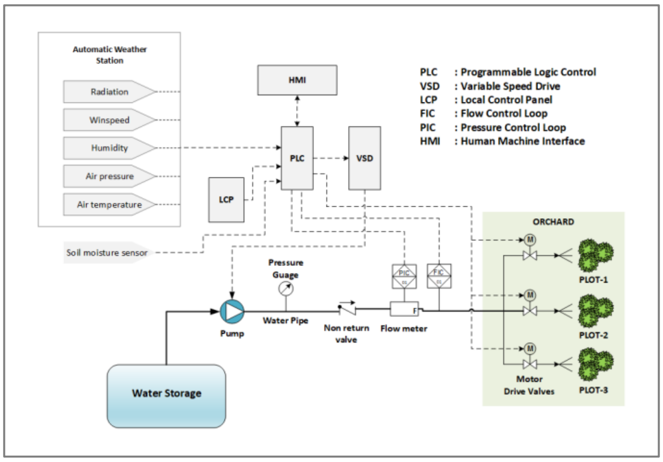

Fig. 3. Process Flow Diagram.

4.4.1. Autonomous operation mode

In autonomous operation mode, IPIS automatically irrigates crops daily, with water delivery triggered by either light intensity or a pre-set timer without human intervention. Utilizing light intensity, IPIS can be set to initiate irrigation at a specific light intensity on HMI, such as 50 μmol s^{-1} m^{-2}, equivalent to approximately 24.75 W m^{-2} (1 W m^{-2} ≈ 2.02 μmol m^{-2} s^{-1}), to start watering in the early morning.

As plants absorb nutrients and photosynthesize, even at low light levels, light intensity significantly affects the efficiency and rate of nutrient uptake [51]. The minimum light intensity required to activate photosynthesis is known as the light compensation point (LCP), at which photosynthesis balances respiration. This point varies by plant species, typically falling between 50 and 150 μmol.s^{-1}.m^{-2} of photosynthetic photon flux density (PPFD) [52].

4.4.2. Manual operation mode

In the manual operation mode, users can choose irrigation by specifying the amount of water in liters per tree or by setting the duration of irrigation to hours and minutes.

The design of IPIS aims to assist growers in various scenarios by providing flexible irrigation control. Growers can command the system to irrigate with specific quantities and frequency such as 300 liters per tree, when operated in manual mode. The system can be set to irrigate every 30 minutes, followed by a 15-minute pause, in a continuous cycle until the total amount of water reaches 300 liters, at which point the irrigation will stop. This method allows water to be absorbed slowly into the soil and helps reduce the ambient temperature at midday. Additionally, in the manual mode, users have the freedom to start or stop the pump at any time, and they can preset the start or stop time in advance.

4.4.3. Interlocking and error prevention

The system is enhanced with safety protection and interlocking mechanisms designed to prevent harm to people and equipment. The pump will not start unless at least one valve is open. Furthermore, if the water flow rate is less than 5 m^3.hr^{-1}, and the pressure drops below 1 bar within 15 seconds after the pump starts, the protection logic will stop the pump to prevent damage. Additionally, the IPIS will not initiate operation during rainfall or continue operation if rain is detected while watering. In the event of any equipment malfunction, the system will pause the process and produce an audible alarm until the user pushes the acknowledge button, the system will then continue the remaining process.

To ensure uniform water distribution across all trees, it is essential to maintain consistent water pressure throughout the sprinkler system. This is achieved by the PLC which adjusts the actual pressure, as measured by a pressure transmitter, to match the user-defined setpoint. The PLC communicates with the variable speed drive (VSD) to regulate pressure by controlling the motor's speed. When the pressure falls below the desired setpoint, the VSD increases the motor speed to compensate. Conversely, when the pressure exceeds the setpoint, the VSD decreases the motor speed to restore the pressure to the desired level.

The total quantity of water is measured by a magnetic flow meter, which is installed at the water outlet of the pump (see

Fig.). The flow meter measures flow rate in m3/hr and the totalizer in m3, when pump is on, the water flow will be measured. When the actual quantity is equal to the daily ETC, the pump will automatically stop.

4.5. Graphic User Interface for Controlling and Monitoring

To enhance irrigation efficiency and precision, an intelligent precision irrigation system (IPIS) must offer operational flexibility and adaptability in various scenarios. An effective system requires the presentation of essential foundational data to facilitate informed decision-making. It should feature an intuitive and straightforward control panel to minimize the learning curve and incorporate a reporting mechanism for the real-time monitoring of the irrigation progress and the long-term data analysis. Consequently, IPIS is equipped with a graphical user interface (GUI) capable of displaying real-time data on weather conditions, plant water requirements, soil moisture levels, and the actual amount of water received by the plants. Additionally, it includes a user-friendly control panel for the convenient scheduling and customization of irrigation regimes, as illustrated in Fig. 4

Fig. 4. User Graphic Interface.

The primary interface presents the current weather information in the upper frame, with the control panel located on the left and operational status indicators for the water pump, valves, water pressure, and flow rate displayed centrally. This graphical interface enables users to select between the automated and manual irrigation modes. The system supports various irrigation methods, allowing users to define light-intensity thresholds for irrigation initiation, set irrigation durations, or specify irrigation frequency. Furthermore, the system pressure can be adjusted by clicking on the pump icon and inputting the desired pressure value via a menu. As depicted in Fig. 4, this orchard comprises three distinct zones, and the farmer can selectively irrigate any individual

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zone. Control via a graphical interface offers significant advantages in terms of convenience, speed, and error reduction, leading to genuine optimization compared to traditional control panels. Nevertheless, the system also provides alternative on/off control options via physical switches and buttons to accommodate users who are less familiar with touchscreen interfaces.

Effective irrigation optimization relies on plant water use data for analytical adjustments to water application in accordance with plant needs. While IPIS calculates estimated plant water requirements based on standard crops references, growers need to refine parameters to align with their specific crop conditions such as canopy radius, crop water coefficient, and local environmental factors. Therefore, IPIS is designed to display weather conditions, plant water demand, and Vapor Pressure Deficit (VPD) as crucial information for farmer decision support, as shown in Fig. 5.

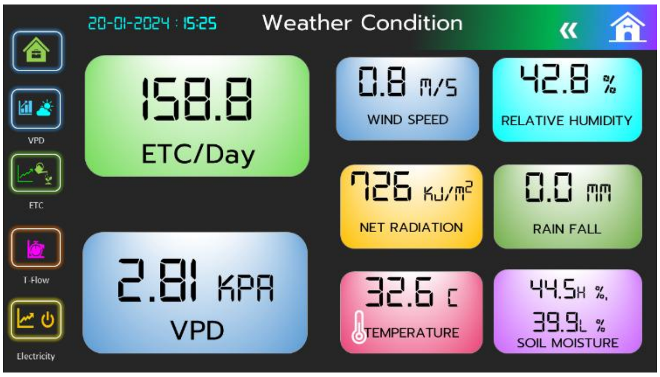

Fig. 5. Weather Data Monitoring.

To facilitate accurate tracking and analysis of water demand trends over time, a broader temporal perspective of data is essential for identifying clear patterns and changes. Figure 6 illustrates the dynamic relationship between the VPD, air temperature, and relative humidity. This demonstrates that as air temperature increases, VPD also increases, leading to increased plant transpiration and consequently, higher water demand. IPIS incorporates various graphical data representations to enhance the ease of irrigation analysis.

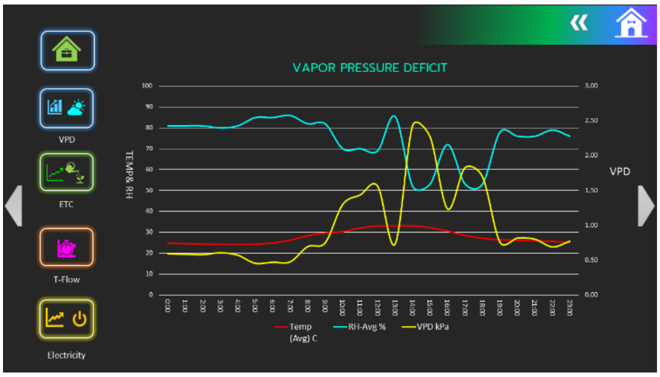

Fig. 6. Air Temperature, RH, VPD Chart.

In summary, the system features an intuitive graphic user interface on HMI screen that facilitates monitoring, configuration, and command execution, while also allowing for parameter adjustments tailored to specific crop and field conditions. A comprehensive display of weather conditions, plant water demand, and VPD provides farmers with critical information for informed irrigation decisions. By offering a broader temporal perspective on data, the system enables farmers to identify long-term trends and patterns in water demand, thereby allowing for more effective planning and resource management. This user-friendly interface not only streamlines the irrigation analysis process, but also helps reduce errors during the irrigation process, ultimately contributing to more efficient and sustainable agricultural practices.

5. Field Experiment and Testing Result

To validate IPIS efficacy, a field experiment was conducted to confirm that the system developed through the integration of sensors, a PLC, programming, and various equipment, functions as anticipated in a real-world fruit orchard environment. The following section offers a comprehensive account of the experimental procedures and results.

A field experiment was conducted at a durian orchard in Rayong Province, Thailand (12°46'46.5"N, 101°48'27.3"E) during January to April 2024.

Fig. 7. Weather Sensors.

Fig. 8. Soil Moisture Sensor.

This orchard contains three plots with 250 durian trees in total with an average height of 7.5 meters and a canopy radius of 4 meters in a total cultivator area of 6.8 acres on loam soil. The water is distributed by a 7.5 kW 3-phases motor driven pump with nominal pressure of 1.5 bar and maximum flow rate of 69 $m^{-3}.hr^{-1}$. The water flows through the polyvinyl chloride pipe and is delivered to each tree by two mini-sprinkler emitters, each with a flow rate of 150 Liters per hour. The weather sensors were only calibrated at vendor's laboratory. These sensors were mounted on a metal pole at high of 2 meters (see

Fig. 7). Soil moisture sensors were calibrated against soil in the field then the sensors were put below the ground surface at 25 cm and 50 cm (see

Fig. 8).

Fig. 9. Pumping Station and Control Panel.

The PLC, VSD, and other control devices were mounted in a control cubicle at shop before transport and installation at field. The motor-drive valves, magnetic flow meter, and pressure transmitter were installed to the existing pipes (see Fig. 9). The installation of equipment took 12 weeks from mid-October to December 2023. A final inspection was conducted to ensure that sensors, wiring, system communication, datalogger, and controller all functioned properly with no errors.

The testing was conducted over a four-month period from January to April 2024. However, as the system required adjustments during the initial months, only the data from April, which is the most complete and of highest quality, are presented in this study. The test includes three parts which are data collecting and monitoring, automatic control function, and precision of irrigation system. All data were recorded in internal memory of the HMI and downloaded to a computer once a week for analysis.

5.1. Data Collecting and Quality Analysis

The first part of the testing involved analysing the quality of data using visualization techniques to identify patterns, outliers, and missing data, as well as conducting statistical analysis to assess the distribution, mean, and standard deviation. The input data were analysed and the result presented as Table 3.

Table 3. Descriptive Statistic Data.

	Temperature (C)	Pressure (kPa)	Relative Humidity (%)	Radiation (MJ M^{-2})	Wind Speed (M S^{-1})	Soil Moisture (1) (%)	Soil Moisture (2) (%)
Mean	30.3	100.9	56.3	0.5	0.8	57.7	27.0
Standard Error	0.11	0.02	0.9	0.0	0.0	0.9	0.3
Median	30.1	100.7	54.5	0.0	0.6	61.3	28.6
Mode	N/A	101.7	99.9	0.0	0.0	50.5	34.2
Standard Dev.	2.9	0.5	22.8	0.7	0.8	15.2	7.2
Sample Variance	8.5	0.3	518.5	0.5	0.6	231.5	51.1
Kurtosis	-1.3	5.6	-0.9	-0.9	-1.6	-0.8	-1.5
Skewness	0.0	-0.2	0.3	0.9	0.3	-0.4	0.2
Range	11.1	4.9	82.9	2.0	2.3	56.4	23.8
Minimum	24.7	97.1	17.0	0.0	0.0	30.4	18.0
Maximum	35.7	102.0	100.1	2.0	2.3	86.8	41.8
Count	696	696	696	696	696	696	696

The dataset presented in this research comprises 1-hour interval averages derived from 1-second data collected throughout April which is the best quality of available data, totalling 30 days. A descriptive statistic technique is used to assess the quality of the data shown in Table 3. This results in a dataset with 696 data points. The dataset is complete, with no missing values. The distribution of the data is approximately normal, though there are some variations observed in relative humidity and radiation. Specifically, radiation values are zero during nighttime, and relative humidity frequently reaches 100% The relative humidity distribution exhibits slight platykurtosis (kurtosis = -0.9), indicating a flatter distribution with fewer extreme values compared to a normal distribution, which contributes to more stable VPD calculations in the Penman-Monteith equation. Despite these variations, the dataset maintains a high quality, with minor skewness and kurtosis deviations that do not significantly impact overall accuracy.

5.2. IPIS Control Function Testing

The second part of testing involved validating the algorithms used in autonomous and manual irrigation. To verify the system's ability, IPIS was set to "AUT" (autonomous), and daily irrigation was initiated by light intensity. set at 24.75 W/m²—the threshold at which crops initiate photosynthesis. The irrigation cycle was configured with an ON duration of 30 and HOLD 360 minutes, respectively. This means the trees receive water for 30 minutes, followed by a 360-minute hold period. If the amount of water applied was still less than the daily ET_C, the system would continue to irrigate in subsequent 30-minute batches, repeating the cycle until the actual amount of water matched the daily ET_C, at which point the irrigation would stop. The number of irrigation events conducted in autonomous mode was based on a daily irrigation schedule. Consequently, the IPIS system automatically performed one or two irrigation cycles daily upon testing program, in total there were 166 events, with a few instances operated manually by the orchard owner. These manual interventions occurred due to activities such as grass cutting, fertilizer application, and plant pruning. The test results from April 1st to April 7th are presented in the form of water flow, as shown in Fig. 10.

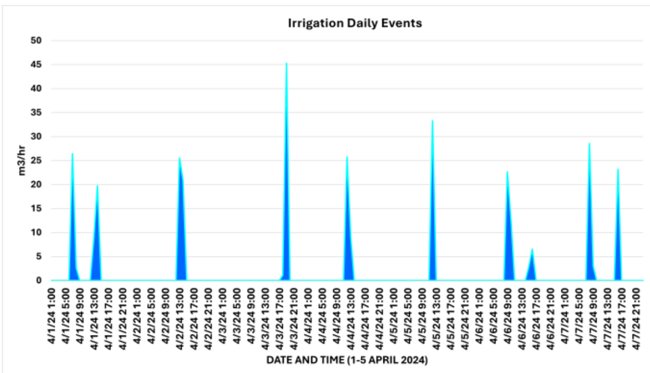

Fig. 10. Water Volume and Frequency Record.

On April 1st, 6th, and 7th, the system operated in autonomous mode. Irrigation occurred in two batches: the first around 7.45-8.15 AM and the second approximately at 1.45-2.15 PM. The water flow rate varied depending on the number of selected tree plots. On the 2nd, 3rd, 4th, and 5th of April, the control mode was switched to "MAN" (manual) in afternoon because the grower needed to adjust the irrigation timing to accommodate activities such as grass cutting or pruning. This operational flexibility enables growers to manage irrigation in accordance with farm management activities. When autonomous mode is selected and remains unchanged, the system self-operates and optimizes, ensuring the highest precision in irrigation.

5.3. IPIS Accuracy and Performance Test

In the final stage of testing, the accuracy and performance of the Intelligent Precision Irrigation System (IPIS) in supplying water to the orchard were evaluated. Specifically, the assessment focused on the precision with which the system estimated and delivered the required irrigation volume to meet the crop's water demand.

Due to the amount of water for irrigation is from the value of ET_C, the result of ET_C calculated was used to validate the performance of the system. The hourly consumption of ETC was plotted in a bar chart for a period of five days, as show in

Fig. 11, to demonstrate performance of crops water estimation and if they were adjusted along time and weather conditions.

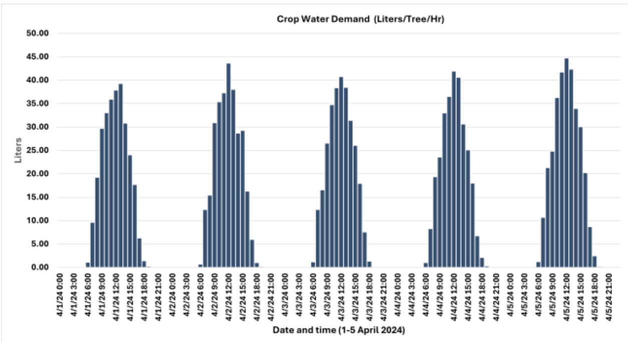

Fig. 11. Hourly Crop Evapotranspiration.

As a result, ET_C was varied along the times and changed by weather conditions. An example of this is the values of the bar chart in mid-day were higher than the values in the mornings and evenings due to the higher temperature of the ambient air, radiation, and other parameters. In addition, we monitored daily water irrigation against radiation and vapor deficits, which are the most influent factors of evaporation, for a month to ensure that the system was performing correctly for crops water estimation.

To further assess the system's reliability, daily irrigation volumes were monitored in relation to key climatic variables—solar radiation and vapor pressure deficit (VPD)—over the course of one month.

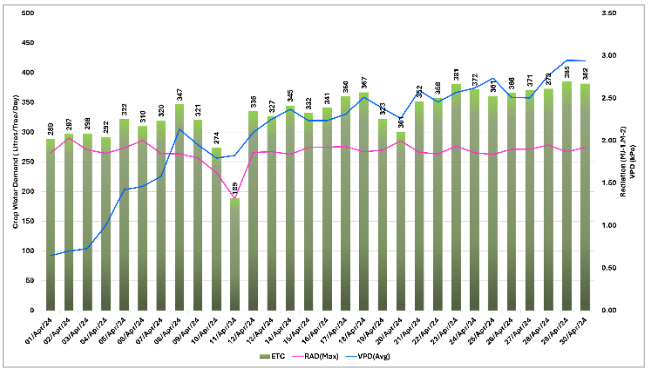

Fig. 12. Crops Water Demand, Radiation and VPD.

The results, depicted in

Fig. 12, show the daily irrigation volume (Liters per tree) recorded throughout April. The data reveal a progressive increase in water usage, from 289 Liters per tree on April 1 to higher values by April 29. This increase corresponds to rising temperatures and decreasing humidity during the month. Compared to the traditional fixed-schedule irrigation method used in this orchard, which consistently delivered 350 litres per tree per day totalling 10,500 litres, IPIS dynamically adjusted water delivery between 189 and 385 litres per tree per day, totalling 9,991 litres. This resulted in a monthly water saving of approximately 5.10%, representing a substantial improvement in water use efficiency. The observed trend underscores a strong correlation between crop water demand and both VPD and solar radiation levels.

Additionally, irrigation precision was verified by comparing real-time soil moisture measurements with the estimated ET_C values as shown in

Fig. 13. The soil moisture was monitored, and if it remained within the range of 40-75%, the crops were deemed to have received an adequate amount of water.

The water content in soil was correlated to volume of water, the soil moisture sensors were presented that the moisture content measured by SMS-A ranged between 50-70%, whereas SMS-B showed values between 19-24%. This indicates effective water distribution within the root zone. However, the substantial disparity between SMS-A and SMS-B readings suggests the presence of localized dry pockets or potential depth misalignment in sensor placement, which could indicate heterogeneous soil conditions or preferential water flow patterns within the orchard profile. Despite this variation, the higher moisture content detected by SMS-A likely ensures adequate water availability for the primary root zone, as durian trees typically develop extensive surface root systems within the upper soil layers where SMS-A was positioned. For future deployments, implementing a more comprehensive sensor network with additional measurement points at strategic depths and lateral positions would provide enhanced spatial resolution of soil moisture distribution, enabling more precise irrigation zone management and reducing the risk of localized water stress in heterogeneous soil conditions.

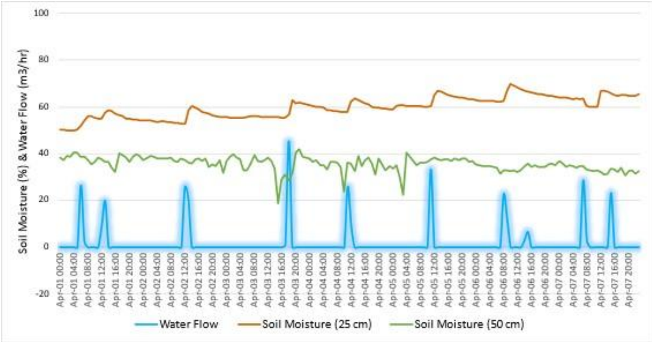

Fig. 13. Irrigation and Soil Moisture.

In summary of the experiment, the system underwent a comprehensive evaluation with a focus on performance, accuracy, data integrity, and both automated and manual functionalities. The results demonstrated that the volume of water supplied to the crops was accurately estimated and effectively controlled. Furthermore, the system exhibited flexibility in irrigation management and was designed to be user-friendly and easy to operate and learn.

6. Discussion and Conclusions

The optimization of irrigation using an Intelligent Precision Irrigation System (IPIS), which is based on the Penman-Monteith evapotranspiration model, has demonstrated superior water management compared to traditional irrigation methods. The experimental results confirm that IPIS delivers variable water volumes daily, dynamically responding to fluctuating weather conditions. Notably, the system adjusts irrigation schedules in real time based on solar radiation intensity, ensuring crops receive water precisely when required. This intelligent responsiveness ensures improved water-use efficiency.

The flexibility of the system allows users to choose between fully automatic and manual control modes. This enables growers to manage the timing, frequency, and volume of irrigation according to their preferences or field activities, such as mowing, fertilization, and pesticide application, which may require deviations from the automated schedule. Users residing in remote areas need not be concerned about manually operating the pump, as the system autonomously executes these tasks daily, thereby saving both time and travel costs.

A significant advancement of the proposed Intelligent Precision Irrigation System (IPIS) is the implementation of sophisticated estimation algorithms that calculate crop water requirements at hourly intervals. This temporal resolution represents the maximum precision achievable within the theoretical framework of the evapotranspiration equation (Eq. (1)), thereby substantially enhancing the accuracy and efficacy of irrigation management protocols. Consequently, the IPIS demonstrates considerable potential for mitigating water wastage attributed to excessive irrigation practices, as water is automatically distributed and regulated to correspond with actual physiological crop demands. Moreover, the precision in water application facilitates optimized fertilizer utilization through the significant reduction of nutrient leaching and surface runoff phenomena, thus addressing both water conservation and agrochemical efficiency objectives simultaneously.

During the experimental phase, the system was configured for data acquisition at one-second intervals to maximize measurement precision. However, this high-frequency sampling potentially introduces anomalous values due to transient environmental perturbations. For operational deployment, the sampling rate can be calibrated to achieve an optimal balance between measurement fidelity and signal-to-noise ratio. In scenarios where extreme precision is not critical, reducing the sampling frequency to one-minute intervals could effectively mitigate outlier occurrences while simultaneously decreasing computational load and, consequently, system implementation costs.

It is imperative to acknowledge that IPIS precision is fundamentally contingent upon sensor reliability, as any measurement anomalies directly impact irrigation volume calculations. High-precision sensors with superior durability characteristics inevitably entail elevated acquisition and maintenance expenditures. System developers must therefore establish an appropriate equilibrium between measurement accuracy, implementation costs, and user acceptance parameters. Excessively complex or cost-prohibitive systems may encounter adoption resistance despite technical superiority, as documented in previous studies [53], [54].

Soil moisture data integrity is critical for effective irrigation control protocol implementation. Sensor placement should prioritize representativeness of the broader edaphic conditions throughout the orchard ecosystem. While increased sensor density correlates with enhanced measurement resolution, it simultaneously escalates initial capital investment and recurring maintenance requirements, necessitating careful cost-benefit analysis.

Throughout the evaluation period, the control infrastructure comprising the Programmable Logic Controller (PLC) and peripheral hardware components demonstrated remarkable operational stability under challenging environmental conditions characterized by elevated temperatures, high humidity levels, and significant particulate contamination, despite the absence of dedicated environmental control mechanisms. This demonstrated resilience suggests suitability for extended field deployment scenarios. Nevertheless, systematic preventive maintenance protocols remain essential for preserving measurement accuracy. For instance, vegetation encroachment around soil moisture sensors can generate artificially elevated moisture readings, while ambient light pollution initially compromised nocturnal net radiation measurements until remediated through strategic relocation of artificial light sources.

Operational efficiency gains were also evident. The labour requirements for daily irrigation tasks were reduced by 50%, decreasing from two workers to one. Furthermore, the orchard owner expressed confidence that irrigation volumes delivered by IPIS were consistently optimal—neither excessive nor inadequate.

User feedback confirmed that the system's human-machine interface (HMI) is intuitive and user-friendly. The graphical interface resembles modern mobile applications, reducing the learning curve and simplifying system interaction. Workers no longer need to manually monitor irrigation schedules or water volumes, improving overall workflow efficiency.

Despite its advantages, the performance of IPIS depends heavily on the underlying irrigation infrastructure. A well-designed pumping and piping network is essential to ensure uniform water distribution across all trees. Inadequate hydraulic design could result in uneven irrigation, compromising crop health. Additionally, the crop coefficient (Kc) used in evapotranspiration calculations must be regularly calibrated to reflect the specific spatial and phenological conditions of the orchard.

It is also important to note that the effectiveness of precision irrigation is contingent upon healthy crop conditions and good agronomic management. In cases of biotic or abiotic stress—such as Phytophthora infections impairing water uptake in durian roots, or arthropod infestations—automated irrigation may require manual intervention. Under such circumstances, growers may need to adjust crop coefficient values to compensate for altered water demand. Future research could address this limitation by integrating machine learning (ML) or artificial intelligence (AI) techniques. These could analyse multivariate agricultural datasets to detect anomalies and autonomously adjust irrigation parameters in real time, enhancing system adaptability and resilience.

In conclusion, the initial investment in IPIS is justified, as sensor and controller costs continue to decline. With an initial investment of 10,761 USD, the system demonstrates a potential revenue increase 5% within one year, indicating approximately one year return on investment. The technology offers significant potential for widespread adoption in open-field orchard agriculture, supporting sustainable water management practices and long-term agricultural productivity. Nevertheless, growers with a basic understanding of electrical and control systems would benefit from improved system configuration, maintenance, and troubleshooting.

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