Agricultural Irrigation Control using Sensor-enabled Architecture

Khaled Abdalgader[1,*] and Jabar H. Yousif[2]
[1]Department of Computer Science and Engineering, American University of Ras Al Khaimah (AURAK)
Ras Al Khaimah, 72603, UAE
[e-mail: khaled.balawafi@aurak.ac.ae]
[2]Faculty of Computing and Information Technology, Sohar University
44, Suhar 311, Oman
[e-mail: jyousif@su.edu.om]
[*]Corresponding author: Khaled Abdalgader

Received November 30, 2021; revised February 28, 2022; accepted June 9, 2022; published October 31, 2022

Abstract

Cloud-based architectures for precision agriculture are domain-specific controlled and require remote access to process and analyze the collected data over third-party cloud computing platforms. Due to the dynamic changes in agricultural parameters and restrictions in terms of accessing cloud platforms, developing a locally controlled and real-time configured architecture is crucial for efficient water irrigation and farmers management in agricultural fields. Thus, we present a new implementation of an independent sensor-enabled architecture using variety of wireless-based sensors to capture soil moisture level, amount of supplied water, and compute the reference evapotranspiration (ETo). Both parameters of soil moisture content and ETo values was then used to manage the amount of irrigated water in a small-scale agriculture field for 356 days. We collected around 34,200 experimental data samples to evaluate the performance of the architecture under different agriculture parameters and conditions, which have significant influence on realizing real-time monitoring of agricultural fields. In a proof of concept, we provide empirical results that show that our architecture performs favorably against the cloud-based architecture, as evaluated on collected experimental data through different statistical performance models. Experimental results demonstrate that the architecture has potential practical application in a many of farming activities, including water irrigation management and agricultural condition control.

Keywords: Agricultural Parameters, Wireless Sensors, Reference Evapotranspiration, Real-Time Monitoring, Irrigation Performance.

This work has been funded and supported by MoHERI, Oman under the URG Grant [FURAP/SU/18/002].

http://doi.org/10.3837/tiis.2022.10.004 **ISSN : 1976-7277**

1. Introduction

Sensing, processing, and analyzing agricultural and environmental parameters play an important role in various farming activities, e.g., water irrigation control and crop management. Several studies have discussed developing efficient irrigation strategies that allow farmers to schedule irrigation timing and reduce water consumption [1] [2] [3] [4]. Farmers seek to improve the quality of yields to obtain commercial products at minimum product cost [5] [6]. Farmers also seek to improve fertilizer processes, which are necessary for the productivity and efficiency of crop growth [7] [8]. Thus, a self-controlled agricultural related architecture that incorporates sensing, communication, and analysis technologies is required to help the farmers effectively monitor and manage their fields in an efficient manner.

The demand for high quality food production at a minimum cost and environmental impact (e.g., pollution) has led to increasing attention to precision agriculture in recent years. Wireless-based sensor network infrastructures have been exploited to realize these goals. This technology aims to supply an optimal tool to collect (sense), process, manage, and analyze relevant agricultural information (i.e., parameters) and farming activities [9] [10]. The main advantages of such technologies are their capability to establish a wireless-network of sensed devices such as sensors that sense relevant environmental data and transmit these data parameters to a predefined application for processing and analysis [4] [11]. This type of wireless sensor network comprises components known as nodes, which typically perform parameter sensing and data transmission over different communication channels. However, in agriculture fields, various agricultural characteristics (plantations' attributes), e.g., types of soil, fertilizer method, required water level, and surroundings weather environment, involve different requirements and considerations [12] [8] [13]. For example, water requirements (i.e., irrigation process) different for each plant type, even in the similar agricultural location and weather environment. Therefore, wireless sensors can capture these diverse requirements to support monitoring and decision-making processes. It also would be valuable to use wireless-based sensor capability towards improving the management of water irrigation and to discover plant state in terms of growing and water needs. Several environmental sensors are used in agricultural fields, including pressure, soil temperature and moisture, solar radiation, humidity, air temperature, leaf wetness, pluviometer, and anemometer sensors.

The main contribution of this paper is the modified development of an autonomous sensor-enabled architecture that uses different wireless sensors to improve the performance of precision agriculture. The proposed architecture supports the measurement of soil moisture content and water irrigation volume, as it computes reference evapotranspiration (ETo). In this study, the using both of soil moisture content and ETo values was companied to schedule a water irrigation process in a small-scale agriculture field for 356 days. This leads to better exploiting the behavior of continuously changes of the environmental parameters of the agriculture fields, which can be next utilized for data predications for more efficient control and monitoring in achieving superb irrigation process (i.e., water-saving) in these fields. The proposed architecture ensures that interoperability among different sensors is unified, centralized, and fair in terms of allocating time slots to contending sensor nodes to support the measurement and analysis of self-controlled agricultural parameters. Several experimental data samples were collected to evaluate the performance of the proposed architecture under different agriculture parameters and conditions, which have a significant influence on realizing real-time monitoring of agricultural fields. Unlike most existing cloud-based architectures and domain-specific control systems that require a connection to a cloud platform to analyze the obtaining analyzed data, our proposed architecture provides farmers to locally manage their fields in real-time and receive analyzed environmental information about their farming activities without accessing third-party platforms. In this paper, we present the implementation details of the proposed architecture, and we present an evaluation of the proposed architecture using real-world scenarios contained different aspects of agriculture processes. In a proof of concept, we provide empirical results that show that our architecture performs favorably against the cloud-based architecture, as evaluated on collected experimental data through different statistical performance models. The experimental results show that our proposed architecture has potential practical applications in various agricultural activities, including irrigation water control and agricultural condition monitoring.

The rest of the paper is organized as follows. Section 2 presents a related work to the study, and Section 3 describes our sensor-enabled developed architecture. Section 4 shows empirical results, and Section 5 concludes the paper.

2. Related Work

Various agricultural-related architectures that use wireless sensor networks have been proposed previously. Generally, such architectures can be classified into two main approaches, i.e., cloud-based architectures [2] [14] [15] [16] [17] [18] [4] [19] and standalone-based architectures (i.e., autonomous) [20] [21] [22] [11]. Cloud-based architectures are based on Internet of Things (IoT) concepts, where distributed sensors and other smart devices collect data and then transmit the data over an Internet connection to a cloud platform for processing and analysis [23]. With such systems, users can access and monitor their fields remotely based on the type of architecture. The standalone-based architecture commonly processes and analyzes the sensed data locally by transmitting the data to other applications. An Internet connection is not required for this type of architecture; thus, users may need to develop or integrate a local application to further process and analyze the sensed data [22]. Due to the cloud-based architectures processing and analysis, the collected agricultural data can be accessed remotely. Thus, such systems typically receive more attention than standalone-based architectures that process and analyze the data locally with limited remote access [20].

Most agricultural-related wireless sensor architectures provide real-time monitoring and utilize electronic devices that can accumulate sensor data and convert the data to appropriate formats for further observation and analysis. The early work that influenced this assumption used a network of different interconnected devices to collect information was conducted by Ashton in 1999 [24], who described a technology that allows the interconnection between different devices over the Internet (i.e., the IoT) to realize sensing, and analyzing of environmental factors and parameters. These devices typically use a well-known networking protocols to communicate with each other [10]. Ashton's method attempted to present distributed devices that generate reports independently in a real-time manner to improve effectiveness and acquire related information compared to traditional manual methods [25]. Contemporary applications of IoT-based approaches can be observed in various domains, e.g., home automation, wearable devices, smart cities, smart retail, smart healthcare, smart farming, and precision agriculture [26]. However, the proposed autonomous agriculture-related architecture benefits from IoT-based approaches; thus, we focus on approaches that are related to the agriculture domain.

The first approach that used network technology to realize precision agriculture was based on computer applications that use conventional communication technologies, e.g., the Internet, to access, control, and manage agriculture fields [1] [10]. For example, Marhaenanto et al. (2013) [27] proposed a crop management system that can be accessed remotely using computer-hosted applications. This client/server approach was followed by an agriculture controlling system that used web connections to remotely access wireless sensors and control actuation nodes distributed in the agricultural field [28]. This system used a set of Arduino nodes connected via sensors and actuators (i.e., managed by web application) using an Internet connection. However, many of these early systems were small-scale agriculture-related architectures. In practice, the performance and results often suffered from a lack of distance controlling (i.e., area coverage) between the devices surrounding the target crops. Therefore, a large-scale architecture that provides long-distance coverage control on the connected devices and sensors is required. Regarding large-scale architectures employed in the agriculture domain using IoT technologies, Duan (2011) [29] proposed a management information system for smart farming. However, that study only presented a description of the intelligent agriculture system, and it did not provide details about using wireless sensor networks or how they integrate with Internet-based applications. Cloud computing platforms are required to develop interoperable IoT-based smart farming systems based on wireless sensing devices. Thus, Taylor et al. (2013) [30] used semantic web techniques to develop warring conditions about agricultural data in which can be viewed in a stream management system.

Kamilaris et al. (2016) [15] presented a semantic approach for smart farming applications based on IoT that facilitates real-time reasoning on different types of sensor data streams using web interface. In addition, a comprehensive survey on the applicability of wireless sensing devices in agriculture and related associated challenges was presented in the literature [10]. The approach proposed by Srbinovska el al. (2015) [14] involved real-time monitoring of agricultural areas to improve crop growth and production quality using a wireless-based sensors approaches. They motivated on the faulty tolerance and energy efficiency of sensors using to capture relevant agriculture data. Water is an essential resource in the agriculture domain; thus, several studies have investigated efficient utilization of water resources [31]. For example, Ofrim et al. (2010) [32] used a wireless sensor network to develop an automated irrigation system that determines an irrigating timing schedule based on sensed soil moisture parameters. As a result, watering requirements can be determined by measuring the soil moisture, which leads to efficient water utilization and high-quality crops. This system also addressed power consumption using a low-power communication protocol based on ZigBee technology. In addition, the applicability of IoT-based architectures in different aspects of farming has been explored previously [33] [34] [35] [36] [37]. For example, Zhao et al. (2010) [38] presented a framework to remotely monitor agriculture fields using Internet-dependent sensors to highlight the benefits of cultivating and monitoring plants in a greenhouse rather than open fields. Smart farming is a well-known research area, and many commercial platforms based on IoT have been proposed to automate and improve the effectiveness of farming activities [26] [25] [13].

The irrigation method is important in the crop management domain, where several irrigation approaches are used to manage and control the issue of water losing by using a regular irrigation processes. For instance, Damas et al. (2001) [39] presented a cloud-based approach for water irrigation in different agricultural areas. They applied tools offered by computer network infrastructures to associate all agricultural fields with a unified controller unit to self-manage the water irrigation supplied process. Experimental results confirmed that this approach saved-up around 30% to 60% of the amount of the supplied water. The system presented by Evans and Bergman (2003) [40] also managed the irrigation process by applying wireless-based sensors to capture environmental agricultural data in order to understand the required irrigation scheduling.

Wireless sensors can help control irrigation water, which leads to better utilization of water resources and improved crop production, and various sensor-based systems have been proposed [31]. For example, Basu et al. (2006) [41] proposed a self-controlled irrigation framework that used sensors to collect environmental parameters relevant to agriculture fields. They also shown that saving the captured environmental data for further analysis and prediction is valuable to realizing the amount of the need water (i.e., irrigation requirements) in different agricultural fields. Kim et al. (2008) [42] presented a sensor-based irrigation approach that remotely manages different agricultural features such as soil moisture level, using wireless network technologies to improve yield production and decrease the consuming of water amount. Additionally, Kim and Evans (2009) [43] proposed a location-specific sprinkler irrigation method employing wireless sensors, and they applied these sensors to incorporate a location-specific controller to provide real-time judgment creating related to water irrigation processes. Commonly, employing wireless-based sensed devices in the agriculture fields is currently in progressive stages of development [23] [25] [13].

The system proposed by Fourati et al. (2014) [2] uses wireless sensors to measure humidity, temperature, solar radiation, and other environmental attributes for a browser-based API decision support framework that presents irrigation scheduling. In addition, Chen et al. (2014) [44] monitored multi-layer temperature and soil moisture content in agriculture fields using wireless sensor networks to realize a smart precision irrigation system, and Kaewmard and Saiyod (2014) [45] presented an agriculture self-controlled method based on continuing sustainability in which the connected wireless-based sensors can be installed in fields to captured dynamic changes in agricultural environmental data. Hashim et al. (2015) [3] proposed ab approach that based on Arduino infrastructure to sense and monitor soil moisture content and temperature parameters via a mobile phone platform. They matched the benefits of small to large-scale systems, and they demonstrated that small-scale architectures cost less compared to a large-scale system that required expensive components. With few exceptions, typical architectures to monitor agriculture parameters use cloud platforms to process, analyze, and access the collected sensor data. However, such architectures require an Internet connection to transmit and access the collected data, which may not be available in rural agriculture areas. In addition, most of these cloud-based agriculture-related architectures are restricted to services that focus on specific agricultural parameters, e.g., soil moisture and leaf wetness. Therefore, in the agriculture domain, various related parameters, e.g., weather conditions, solar radiation, and ETo, have significant influence on realizing precision agriculture. We analyze and summarize the existing literature for both categories of agricultural-related architectures that use wireless sensor networks in **Table 1**.

Table 1. The existing agriculture-related architectures

Category	Architecture Type	Hardware Platform	Reference
Cloud-based Approaches	IoT-based Architecture	Microcontroller and Wireless Sensor Network	[2]
	IoT-based Architecture	Raspberry Pi 3 Microcontroller and Environmental Sensors	[6]
	IoT-based Architecture	Wireless Sensors, Wireless Information and Radio Transceivers Units	[9]
	IoT-based Architecture	Raspberry Pi 3 Microcontroller and Environmental Sensors	[13]
	Cloud of Things (CoT) Architecture	Thermal image and Environmental Sensors	[16]
	IoT-based Architecture	Arduino, Raspberry Pi, Libelium Sensors nodes and Environmental Sensors	[17]
	IoT-based (user-centric) Architecture	IoT Gateway and wireless Environmental Sensors	[19]
	IoT-based Architecture	Sensors, Microcontroller, Switches, Computer, Webcam and Actuators	[27]
	Internet-based Architecture	Arduino Microcontroller and Environmental Sensors	[28]
	IoT-based Architecture	Microcontroller and Wireless Environmental Sensors	[33]
	IoT-based Architecture	Microcontroller and Wireless Environmental Sensors	[34]
	IoT-based Architecture	Microcontroller and Wireless Environmental Sensors	[42]
	Internet-based Architecture	Microcontroller and Wireless Environmental Sensors	[44]
	IoT-based Architecture	Wireless Environmental Sensors	[46]
Standalone-based Approaches	IoT-enabled Architecture	Microcontroller and Wireless Sensor Network	[4]
	IoT-based Architecture	Wireless sensors	[8]
	IoT-based Architecture	Wireless sensors	[14]
	IoT-based Architecture	Wireless sensors	[15]
	Web-based Architecture	Microcontroller and Wireless Sensor Network	[18]
	Wireless Sensor and Actuation Network (WSAN-based Architecture)	Wireless Sensors	[21]
	IoT-based Architecture	API Gateway	[22]
	Web-based Architecture	Microcontroller and Wireless Sensor Network	[45]
	IoT-based Architecture	Microcontroller and Wireless Environmental Sensors	[47]

3. Proposed Sensor-enabled Architecture

In this section, we describe the main components of our proposed autonomous architecture, which supports the measurement of soil moisture content and water irrigation volume and computes the ETo over various heterogeneous sensing data streams using different wireless sensors. As shown in **Fig. 1**, the proposed architecture includes five layers named as *data source*, *data collection*, *transmission scheduling*, *data processing*, and *data viewing*. These five layers with the associated components that comprise the proposed architecture are bellow described in more details.

3.1 Data Source Layer

This layer is in charge of capturing surrounding agricultural parameters (i.e., environmental data) from the crops (i.e., agricultural fields) using installed wireless sensors [46]. Soil moisture sensors are mainly founded to be waterproof and normally capture parameters relevant to the content of soil moisture, degree of soil temperature, and other soil features. The neighboring environmental sensors sense several environmental parameters, e.g., atmospheric pressure, degree of air-temperature, level of air relative humidity, rain level, wind speed and direction, leaf-wetness and solar radiation. In the data source layer, each installed sensor transmits the captured parameters to the data processing layer via a network structure comprising sensor nodes that operate under standard communication protocols. Sensors that are commonly used to measure agricultural parameters are: *Temperature*, *humidity*, *and pressure sensors*, *Soil moisture and temperature sensors*, *Solar radiation sensor*, *Leaf wetness sensor*, *Wind speed and direction sensor*, *Rain-level sensor*.

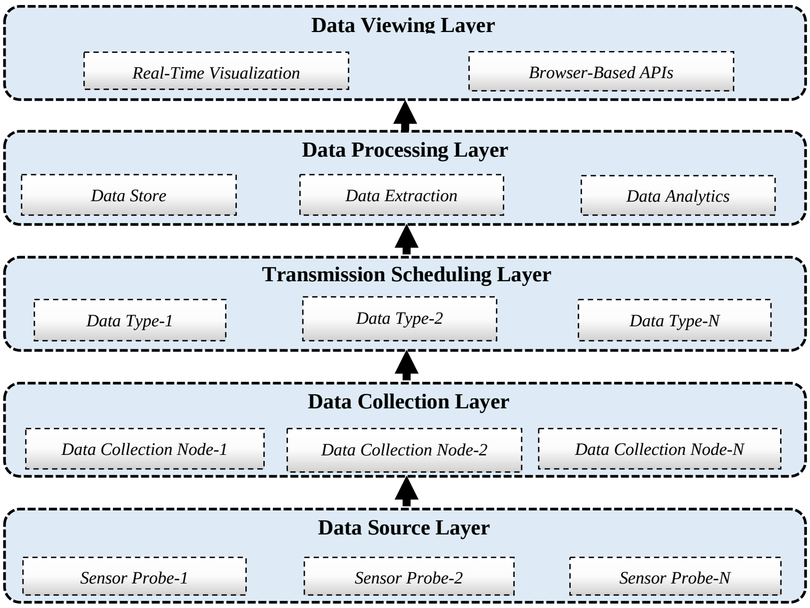


Fig. 1. Proposed autonomous sensor-enabled architecture

3.2 Data Collection Layer

This layer wirelessly transmits the data acquired by the installed environmental sensors to the data processing layer (i.e., a gateway) through the data transmission scheduling layer using different radio interfaces. This layer comprises multiple sensor nodes that receive all sensed data and send the data in a single frame (i.e., for each node) to the data processing layer. Here, each data frame comprises a single value from each sensor. In the experimental implementation of the proposed architecture, each installed sensor node was configured to transmit a data-frame of captured environmental data to the system gateway (i.e., data processing layer) every 15 minutes because this transmission frequency helps to reduce the power consumption, which reduces the need to charge the battery using an external solar panel. In addition, each sensor node in this layer comprises four main units, i.e., *the communication and interfacing* unit, *the programming and computation* unit, *the memory* unit, and *the battery* unit. The communication and interfacing unit controls and manages the communication ports used for sensors, inquiries (i.e., programming), and data transmission tasks. The programming and computational unit coordinates and manages all activities associated with other units in the sensor node. The memory unit stores all acquired data temporarily in frames until they are transferred. Finally, the battery unit supplies the sensors and all units within the node with energy to ensure sufficient network processing lifetime.

3.3 Transmission Scheduling Layer

The transmission scheduling layer sends the acquired data from the data collection layer to the data processing layer. It provides fair allocation of transmission opportunities to the participating wireless sensor nodes. Here, a time slot is allocated to all sensor modes relative to their distance from the main gateway. This layer is also dealt with the underlying communication technologies used to send the acquired data into consideration during scheduling. The proposed architecture can use three types of these technologies, i.e., *LoRa*, *WiFi*, and *ZigBee* [47] in this layer.

3.4 Data Processing Layer

The data processing layer receives, stores, extracts, and processes, and analyzes the data acquired by the sensors (i.e., which was sent by the data collection layer). First, every 15 minutes, the layer obtains a data frame containing the sensed data, which are stored with a timestamp in a local MySQL database. Then, the stored data can be extracted for the processing and analysis layer, which sends the results to the data viewing layer to control, manage, and displays services to the end users.

3.5 Data Viewing Layer

The data viewing layer provides visualization facilities that allow farmers to check, control, and monitor the data analyzed by the data processing layer in sufficient ways, e.g., trend graphs. In addition, farmers can view current, daily, weekly, monthly, and annual analyses of historical data. Interaction with this layer is realized using any web browser. The main parts of this layer are presented below.

- **Browser-based APIs:** Browser-based APIs allow users to deploy, control, and manage data analysis tools using a web-enabled interface. This includes several elements, e.g., tools, protocols, and methods that allow users (i.e., the farmers) to develop agricultural irrigation applications that satisfy their needs.
- **Real-time visualization:** Real-time visualizations allow farmers to view (i.e., monitor) the sensed data in a values diagram or trend graph and check the same environmental parameters on many times and dates to identify trends between different time periods. This can be performed in real-time, or on a daily, weekly, or monthly basis.

4. Implementation of Proposed Architecture

The proposed autonomous sensor-enabled architecture was implemented using the *Libelium Smart Agriculture Vertical Kit* (www.libelium.com), which includes various agricultural related sensors. For comparative purposes, we also provide a cloud-based architecture implementation that uses Arduino microcontroller and Think-Speck cloud (https://thingspeak.com/pages/smart_farming) to evaluate the effectiveness of our architecture on the sensed experimental data. Here, we first describe the design implementation of the proposed architecture, the experimental design and setup, the study area, and the deployment scenario, and then we discuss the obtained results, which show the efficiency of our architecture compared with cloud-based architecture.

4.1 Architecture Implementation Design

The implementation design of the proposed architecture can be classified to three main components: sensor design (Data Source Layer), sensor node design (Data Collection & Transmission Layers), and data processing (Data Processing Layer) and viewing gateway design (Data Viewing Layer). In the proposed architecture, sensor nodes act as a coordinator of the connected agricultural sensors to manage and monitor transmitting the acquired data to the data processing and viewing gateway. The gateway receives and stores the data transmitted by the sensor nodes in the local database for processing and analysis to identify trends. The connection between actual experiment and proposed architecture is illustrated in **Fig. 2**, which reflects all the experiment results that are based on our proposed architecture.

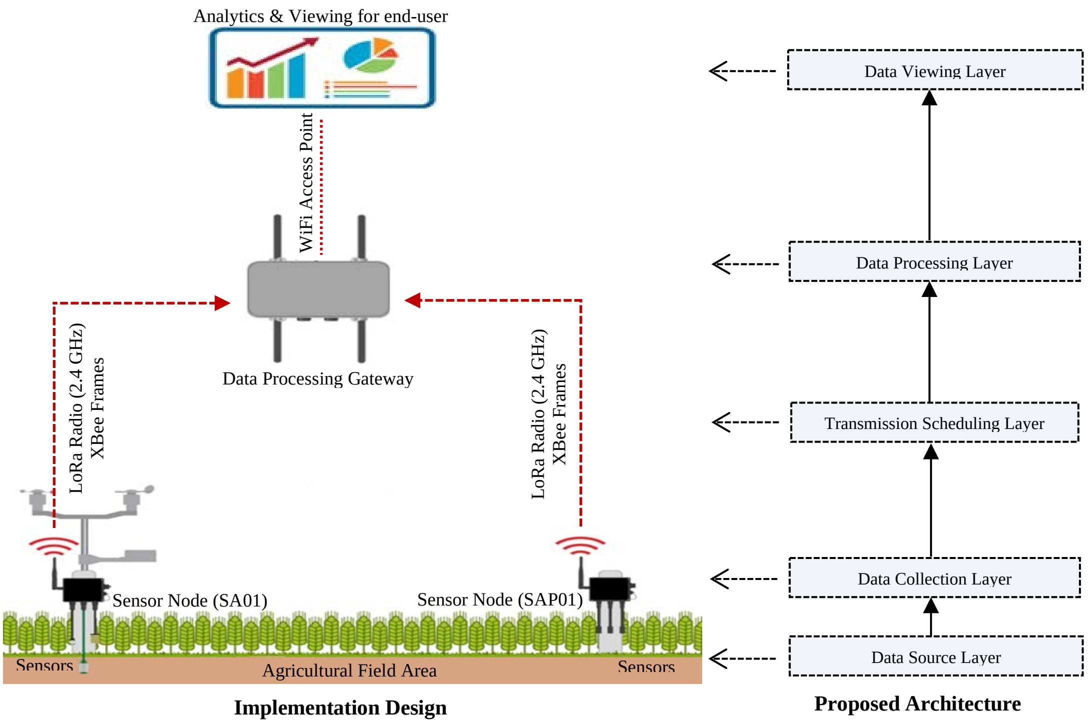


Fig. 2. Implementation design of autonomous sensor enabled architecture

4.1 Experimental Design and Setup

Efficient sensor-enabled architecture which is important for the agricultural irrigation control is required to sense the weather dynamic changes in the agricultural parameters such as soil, weather and plant characteristics. In order to achieve this, a smart agricultural platform that based on IoT technologies called "*Libelium Smart Agriculture Vertical Kit*" comprising of browser-based API, weather station and data processing gateway as controller was interfaced with two sensor nodes (i.e., SA01 and SAP01) that connected with various environmental sensors (i.e., solar radiation, soil moisture, air-temperature, relative-humidity, pressure, leaf-wetness, wind-speed and wind-direction, and rain-level) to setup and implement a proposed architecture for automatic irrigation control and scheduling system as shown in **Fig. 3**. The weather station was installed with one of the sensor node (SA01) where the Evapotranspiration values (ETo) was calculated to measure the water wastage in the experimented agricultural areas. ETo value is a computational process that relays to the loss amount of water from the agricultural field as well as surface of the soil, which is directly concerned by environmental parameters.

(a) Data Processing & Viewing Gateway **(b)** Sensor Node (SA01) **(c)** Sensor Node (SAP01)

Fig. 3. Architecture implementation in the study area

Reducing power consumption is a significant issue in the design and development of a wireless-based sensor network; then, we configured the sensor nodes to send data every 15 minutes only for saving its charged energy by the solar panel. As a result, sensor nodes remain in sleep mode most of the time, which saves energy. When the configured sleep time is finished, the sensor node obtains the current time and wake up to be ready to send data (i.e., an XBee data frame) to the data processing and viewing gateway. Each sensor node keeps repeating this action for all running times.

The bandwidth (i.e., the data rate) in transmission scheduling layer is categorized based on employed communication technology. For example, 0.3–50 Kbps traffic uses LoRa communication, and its proportional load is 10. In addition, 2–54 Mbps traffic uses WiFi communication, and its proportional load is 20. Finally, 20–250 Kbps traffic uses ZigBee, and its proportional load is 30. Thus, the total proportional load is defined as the sum of a node's own proportional load and all of its children's proportional loads. Here, a priority queue is constructed from the total proportional load, which starts from the outermost level and moves toward the innermost level, i.e., is the closest to the main gateway. In each level, we give higher priority to nodes with the greatest total proportional load.

4.2 Study Area and Deployment Scenario

The proposed architecture was tested and evaluated in the water irrigation control domain. To test and evaluate the performance of our independent sensor-enabled architecture, we have conducted all the experiments in this geographical area; latitude: 24.3501° N; longitude: 56.7133° E (i.e., Sohar City, Sultanate of Oman) as shown in **Fig. 3**. Due to some logistic restrictions, the empirical scenario of the experiments was designed as two plant mezzanines with 10 kilograms of soil in each mezzanine. Sensor node SA01 was installed in one plant mezzanine, which was irrigated relay on the data sensed by the associated sensors, i.e., soil temperature and moisture level. Sensor Node SAP01 was installed in the other plant mezzanine, which was irrigated at regular scheduled times (daily). The main purpose of this empirical scenario was to demonstrate how the proposed architecture helps to reduce water wastage by generating an efficient water irrigation strategy.

The amount of water supplied (i.e., irrigated water) in each time was 0.5 liters for both designed plant mezzanines. These two mezzanines were located in the same geographical location under the same environmental conditions through the experimental time, which involved 356 days of data recording starting on March 1st, 2021. The total amount of sensed data was around 34,200 XBee frames. An excerpt of this sensed data and daily water amount consumed by each plant during the experimental period are shown in **Fig. 4** and **Fig. 5** respectively.

Date	SA01-HS ETo	SA01-PM ETo	PAR	SA01-STC	SA01-TC	ANE	SA01-HUM	SA01-SOIL	SAP01-HS ETo	SAP01-PM ETo	SAP01-STC	SAP01-TC	SAP01-HUM	SAP01-SOIL	Water SA01	Water SAP01
1-Mar	2.2	-0.8	0.100742	32.14519	30.41923	12.38154	12.1723559	6.16E+03	1.9	-3.3	31.040948	29.766615	33.45482278	5.87E+03	0.5	0.5
7-Mar	1.2	-0.9	0.111233	32.13411	31.55458	4.675	33.3606262	5909.2286	2.5	-1.7	33.322046	30.813125	34.96174109	7083.62545	0	0.5
14-Mar	1.8	-4.5	0.115117	33.65027	32.59277	4.26383	40.2827045	7114.8962	2.9	-5.2	34.380088	31.80883	41.15817585	8890.66927	0.5	0.5
22-Mar	2.6	1.4	0.119088	35.85091	33.85063	4.258333	32.2798767	5210.5312	3.1	0.7	35.872217	32.977872	33.36624213	5538.8439	0	0
29-Mar	0	-5.9	0.067803	32.00065	33.54479	5.258333	40.577474	7924.942	2.2	-6.1	34.570322	32.779896	41.64332069	9432.41034	0	0
1-Apr	2.1	-16.7	0.085483	34.16406	32.67385	3.741667	54.2482095	5015.6826	3.2	-17.6	35.170927	31.683333	54.98581361	6389.42632	0	0.5
8-Apr	0	1.9	0.070924	35.20964	35.76479	3.7	31.2224121	6247.3596	3	1.8	37.48007	34.954787	32.20975326	7139.19242	0.5	0.5
15-Apr	1.7	-1.3	0.079272	36.85439	35.0666	3.651064	38.9657683	5609.5386	3.3	-1.9	38.154392	35.222105	40.31130949	2663.66026	0	0
23-Apr	0	4.7	0.060045	35.42358	37.03453	4.168421	24.5554041	7089.8087	2.5	4.6	38.080775	36.277789	26.42618217	9642.01096	0.5	0.5
30-Apr	2.6	-46.1	0.112117	32.77083	30.32594	3.525	70.4354554	8834.1427	3.2	-47.8	33.092294	29.153958	70.80431114	9520.24708	0	0
1-May	2.3	-36.2	0.091757	32.78776	30.89625	3.916667	64.5724485	7063.8294	3	-38.3	33.12902	29.888211	65.33175368	7381.54586	0	0
8-May	2.1	-16.7	0.085483	34.16406	32.67385	3.741667	54.2482095	5015.6826	3.2	-17.6	35.170927	31.683333	54.98581361	6389.42632	0	0.5
15-May	1.3	-37.1	0.069959	30.80404	30.21677	6.383334	57.7155559	5481.095	2.5	-38.5	31.510931	29.325158	58.22096006	7140.25788	0	0.5
23-May	0	4.5	0.084608	35.8125	36.94042	4.042105	25.2008738	6156.5478	2.6	4.5	37.894018	35.07234	26.15529178	10149.628	0	0.5
30-May	2.3	-45.9	0.080697	34.24349	32.35208	4.183333	69.23937	6176.1344	3.2	-44.6	35.229906	31.430729	68.72176084	7791.49689	0	0.5
1-Jun	0.2	-28.6	0.079158	34.21289	34.20188	3.383333	64.5653584	9801.3992	3.1	-27.6	36.675117	33.312447	64.68806077	10499.8576	0	0
8-Jun	1.7	1.8	0.123112	38.38963	37.62372	3.617021	34.0738965	5260.4653	3.2	1.4	39.341684	36.687872	35.06408549	8156.38149	0	0.5
15-Jun	1.7	-13.9	0.117371	27.40234	26.20917	4.341667	44.7338461	9425.2264	2.8	-14.8	28.553784	25.348298	45.63293721	9415.35333	0	0
23-Jun	2	-13.4	0.121098	31.86382	30.35095	3.2	50.9337682	4434.5703	3.3	-12.9	33.466629	29.611935	50.7946277	4962.32778	0	0
30-Jun	2	-6.2	0.117184	35.44401	33.96729	4.558333	43.4154458	8511.8472	2.4	-7.5	35.322786	33.119688	44.51058578	9100.47982	0.5	0.5
1-Jul	1.8	2.4	0.111127	35.72656	34.62927	3.7	29.5152556	6269.9443	2.4	1.7	35.861963	33.767789	31.05135308	7727.36264	0	0
8-Jul	1.3	-37.1	0.069959	30.80404	30.21677	6.383334	57.7155559	5481.095	2.5	-38.5	31.510931	29.325158	58.22096006	7140.25788	0	0.5

Fig. 4. An excerpt of sensed experimental dataset

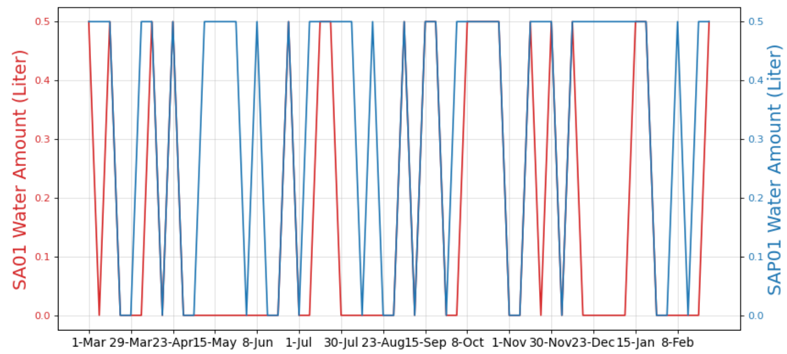


Fig. 5. Average water irrigation volumes of sensor nodes SA01 and SAP01 over time

The sensed environmental data were stored in a local MySQL database (i.e., in data processing gateway) and displayed on the browser-based API for end-users (farmers) to view all the analysed data, trends and overall system performance (i.e., analyzed offline). The irrigation scheduling algorithm applied on the system gateway is based on the integration of the real-time evapotranspiration value and volumetric water content which are used to provide the irrigation action or schedule of the architecture using Python computational software.

4.3 Experimental Results

The proposed architecture was implemented in an agriculture area to sense the related agricultural parameters for a water irrigation schedule, which was expected to reduce water consumption. The data obtained from the sensors comprised 34,200 XBee frames with 10 different parameters (i.e., temperature, humidity, air pressure, soil moisture, soil temperature, solar radiation, leaf wetness, wind speed, wind direction, and rain level) in each frame. Due to space limitations and the scope of the study area, we only considered, processed, and analyzed six parameters (i.e., air and soil temperature, air relative humidity, soil moisture, solar radiation, and wind speed and direction) in these experiments. Over the duration of the experiment, the total amount of water irrigated by the plant under sensor node SA01 was 90 liters, and the plant under sensor node SAP01 consumed 190 liters of water. The irrigation processes for both plants occurred between March, 2021 to February, 2022. As can be seen from **Fig. 5**, there is a half of the irrigated water to plant under SAP01 (i.e., the plant irrigated on the daily basis without considering the sensed agriculture information) was wasted. Therefore, the proposed system reduced water wastage by increasing the effectiveness of capturing the most vital data automatically.

A well-performed monitoring architecture, which is fundamental for precision crop management, is required to capture changing soil dynamics, weather, and other agriculture parameters. To realize this, a weather station was integrated with sensor node SA01. Here, the amount level of water wastage from the water suppled (irrigated) plant mezzanines was measured by calculating the ETo values. These values are relevant to the low level of wasted water from an agricultural area (plant) and the surface of the soil, which is impacted by sensed weather environmental data [48]. The daily computations and estimations of the ETo values were computed using standardized Penman-Monteith [49] and Hargreaves-Samani [50] equations (Eq. (1) and Eq. (2), respectively) based on the measured weather data. The input data for these equations included the daily mean air-temperature, relative-humidity wind-speed (m s^{-1}), and solar radiation (MJ m^{-2} d^{-1}).

$$PM - ETo = \frac{0.408\Delta(R_n - G) + \gamma(^{900}/_{(T+273)})u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

Here, R_n is the solar radiation value on the soil surface, u_2 is the wind-speed computed at 2 m height, T is the average of daily captured temperature, G is heat of the soil density, $e_s - e_a$ is the saturation of pressure deficit, Δ is the pressure curve gradient, and γ is the constant of psychometric parameter.

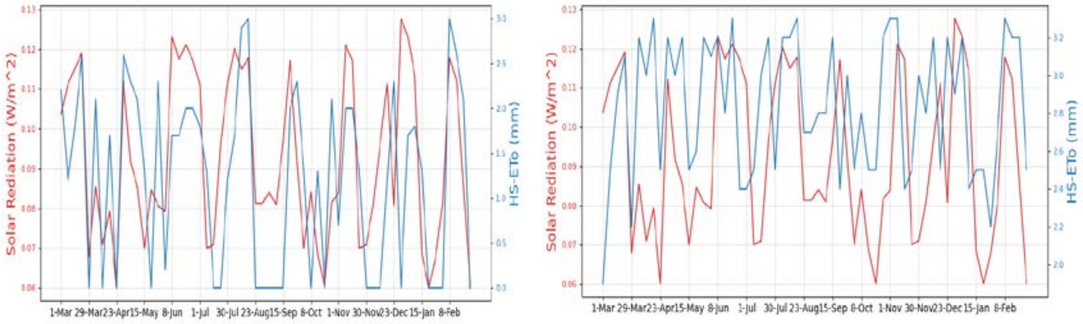
$$\text{HS-ETo} = 0.0135K_{R_s}\frac{R_a}{\lambda}\sqrt{(T_{max} - T_{min})(T + 17.8)} \quad (2)$$

Here, R_a is the radiation of extraterrestrial, λ is the vaporization latent-heat for the average of air-temperature T (normally equal to 2.45 $MJkg^{-1}$), and k_{R_s} is the modification of coefficient radiation (normally equal to 0.17). For more information about parameters in equation (1) and (2), see [49][50].

The sensed environmental data were saved in a local MySQL database and displayed on the local dashboard (System Gateway and browser-based API, **Fig. 3** (a)) [51] to access and visualize trends (analyzed offline). The irrigation schedule method developed on the gateway was based on the computing of the ETo value and the water content of real-time soil volumetric, which were applied to determine the irrigation decision of the architecture (i.e., the plant under sensor node SA01). When the ETo increased, more water was given to feed the loss the water, and the water content of the soil volumetric was checked to fit with the capacity of the used plant mezzanines.

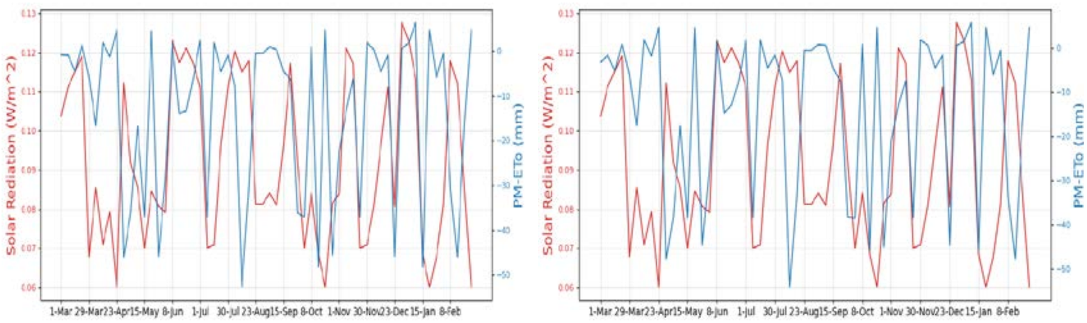
4.5 Analysis of Results

Here, we describe the results of the changing trends of the soil, plant, and weather during the experimental period. **Fig. 6** and **Fig. 7** show graphs of the average daily estimations of the reference ETo value obtained using the Penman-Monteith (PM-ETo) and Hargreaves-Samani (HS-ETo) equations and the solar radiation value obtained by both sensor nodes SA01 and SAP01, respectively. As can be seen, the trends of ETo values and solar radiation are very close of each other, with ETo values straightforward to the solar radiation parameters. The ETo value is peaks by midday, which is dependent on daily weather changes.



(a) (b)

Fig. 6. (a) SA01 average daily estimation of HS-ETo (mm) and solar radiation (W/m^2), and (b) SAP01 average daily estimation of HS-ETo (mm) and solar radiation (W/m^2)



(a) (b)

Fig. 7. (a) SA01 average daily estimation of PM-ETo (mm) and solar radiation (W/m^2), and (b) SAP01 average daily estimation of PM-ETo (mm) and solar radiation (W/m^2)

A similar trend between the daily average values of temperature and humidity that calculated between March, 2021 to February, 2022, is shown in **Fig. 8**. Here, the average highest temperature and lowest temperature measured was 39 ℃ at midday and approximately 24 ℃ in the early evening, respectively, and the humidity decreased by midday as the temperature increased, with highest and lowest values of 80% and 23%, respectively.

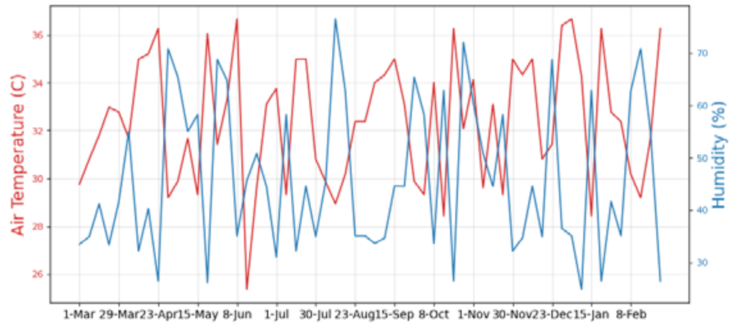
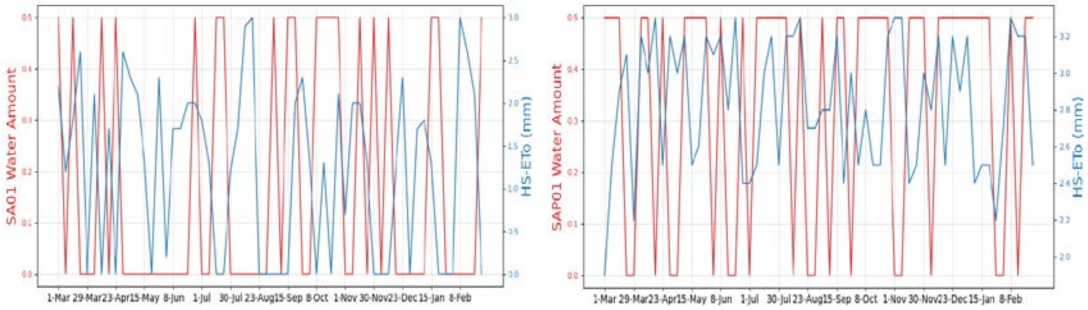


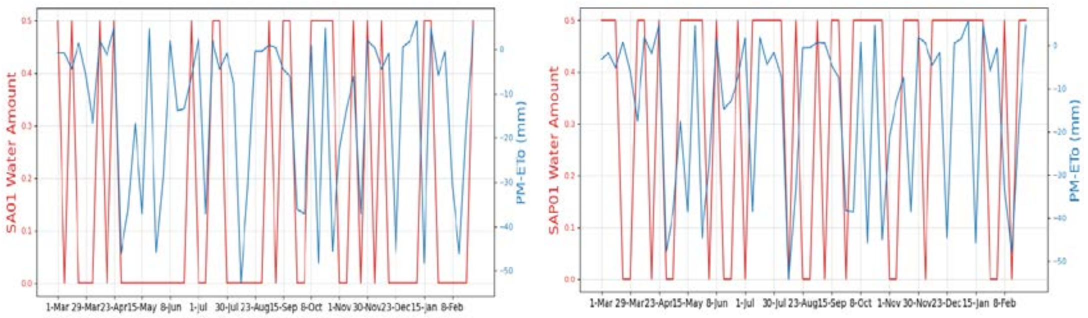
Fig. 8. Average air temperature (˚C) and humidity (%)

The amount of irrigation water in liters sensed by the flow-meter was matched to the daily estimation of the reference ETo value using the PM-ETo and HS-ETo equations for sensor nodes SA01 and SAP01 (**Fig. 9** and **Fig. 10**, respectively). The irrigation amount applied compensated for the water loss for each measured value while managing the water content of the volumetric soil. However, as shown in **Fig. 11** and **Fig. 12**, the environmental parameters trend is exchanging due to the effects of the plants' water curiosity and the weather conditions. As the amount of water consumed because of ETo values increased or decreased, a relevant effect on the water content of soil volumetric was observed, demonstrating that high or low water amount was needed for irrigate the target plant. Thus, both parameters have a straight effect on the amount of water to be provided to the plants.



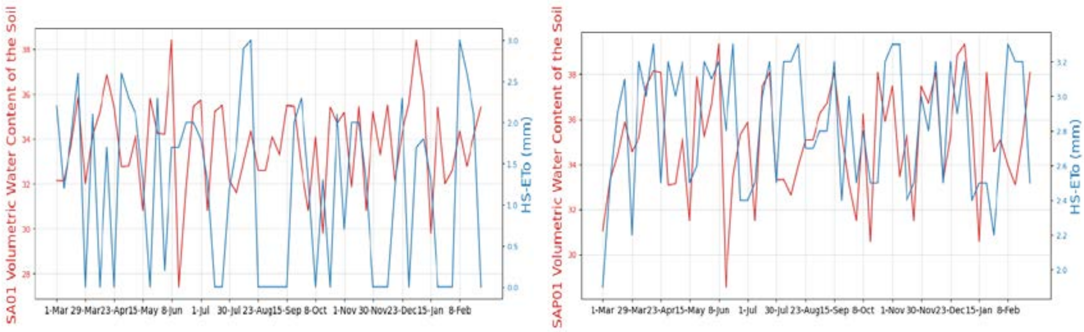
(a) (b)

Fig. 9. (a) SA01 average daily estimation of HS-ETo (mm) and amount of irrigated water (liter), and (b) SAP01 average daily estimation of HS-ETo (mm) and amount of irrigated water (liter)



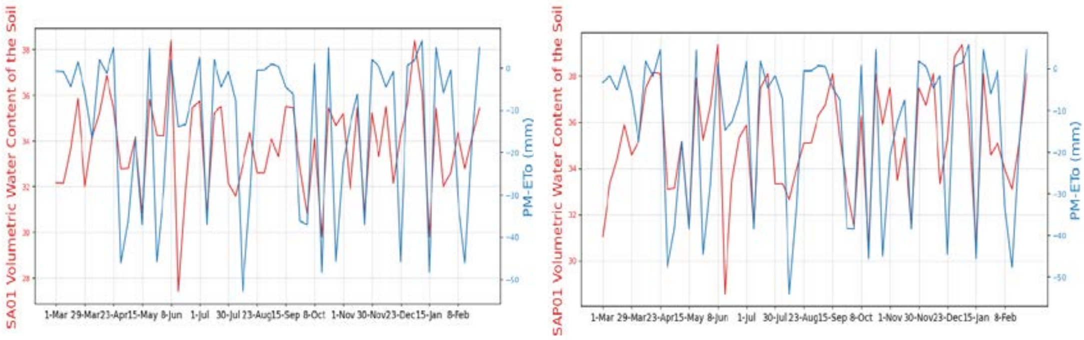
(a) (b)

Fig. 10. (a) SA01 average daily estimation of PM-ETo (mm) and average amount of irrigated water (liter), and (b) SAP01 average daily estimation of PM-ETo (mm) and average amount of irrigated water (liter)



(a) (b)

Fig. 11. (a) SA01 average daily estimation of HS-ETo (mm) and volumetric water content of the soil, and (b) SAP01 average daily estimation of HS-ETo (mm) and volumetric water content of the soil



(a) (b)

Fig. 12. (a) SA01 average daily estimation of PM-ETo (mm) and volumetric water content of the soil, and (b) SAP01 average daily estimation of PM-ETo (mm) and volumetric water content of the soil

Fig. 13 shows the soil moisture (i.e., soil humidity level) trends for the plant mezzanines for sensor nodes SA01 and SAP01. As can be seen, that plant under sensor node SAP01 consumed more water compared to the plant under sensor node SA01, which indicates that the irrigation process based on measuring of soil humidity was more efficient than the process based on manual measurement or daily biases. It also appears that the total amount of spent water by the plant that irrigated using sensor node SA01 was approximately half that of the water consumed by the plant under sensor node SAP01.

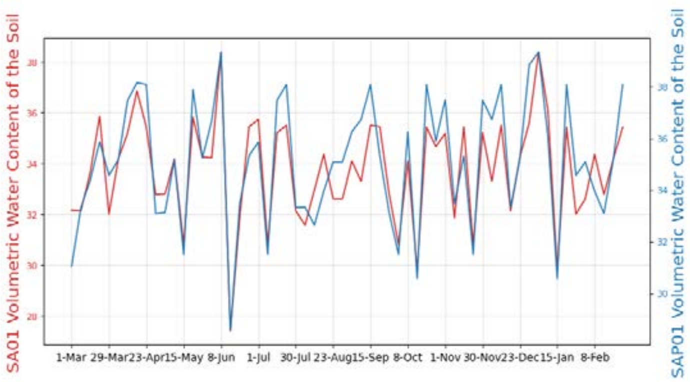


Fig. 13. SA01 average soil volumetric water content against SAP01 soil volumetric water content

Fig. 14 shows box plot patterns of the quantitative data for the irrigation processes under sensor nodes SA01 and SAP01 as determined by the median values of each data sensed by the sensor nodes. As can be seen, the median values of the data collected by sensor nodes SA01 and SAP01 are 78.59, and 33.69, respectively. As a result, using this information, farmers can determine whether their crops in a given time require water, which leads to significant reduction of water wastage [52].

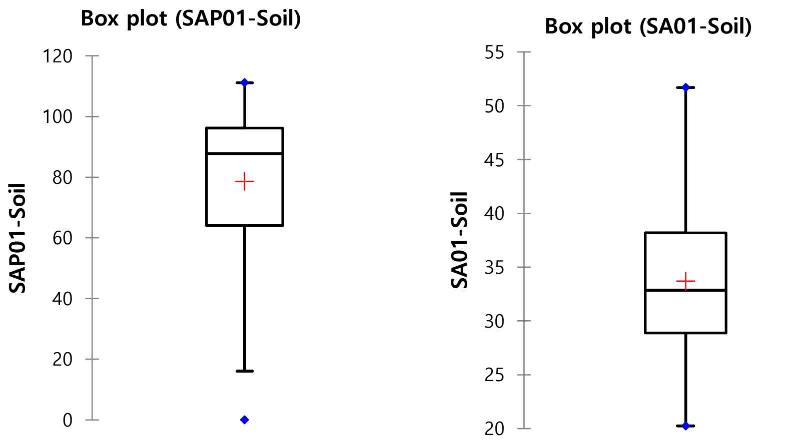


Fig. 14. Quantitative patterns for soil volumetric water content for SA01-Soil and SAP01-Soil

4.6 Comparison with Cloud-based Architecture

Comparing the performance of the proposed architecture with other well-known cloud-based architecture that have achieved promising results is informative [53]. Herein, we compared our architecture with the cloud-based architecture that includes three main or layers, i.e., the *data source layer*, *data collection and transmission layer*, and *data visualization and analytics layer* as shown in **Fig. 15**. The data source layer is in charge of sensing the environmental parameters from agricultural study area using the relevant sensors. The data collection and transmission layer captures, then transmits sensed environmental agriculture data to the next layer i.e., visualization and analytics. This part of the architecture is also a part of the underlying wireless network technologies needed to send the collected environmental data. The visualization and analytics layer then process the received data and provide the analytical view to the end-user.

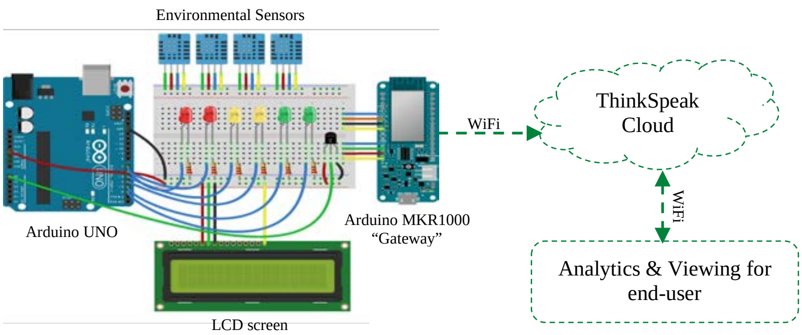


Fig. 15. Compared cloud-based sensor-enabled architecture

In the compared architecture, the two Arduino boards are installed, which are prepared to deal with the captures environmental data to the cloud platform called ThingSpeak for analytical and visualization process. Here, cloud platform saves all received data sent Arduino board, which facilitate analyzing of data trends. The compared architecture continuously tracked the environmental parameters in around 15 minute intervals. The captured environmental data received by the cloud via WiFi were processed to detect trends in the collected data from the studied agricultural fields.

Table 2 compares the statistical information of the sensed data by our architecture and compared cloud-based architecture during the same location and experimental period (356 days). Here, for all received data by the architecture gateways, the daily and total sensed data of 96 and 34,200 XBee frames received using the proposed architecture are higher than the compared cloud-based architecture of 72 and 25,600 XBee frames respectively. This indicates that there is a transmission latency of the sensed data to the processing gateway; thus, we consider that the proposed architecture performs very favorably and effective compared with cloud-based architecture.

Table 2. Comparative statistical information of sensed data

Architecture	Experimental Period	Data Processing Gateway	Daily Received Data by the Gateway (Sensed Data)	Total Received Data by the Gateway (Sensed Data)
Our Architecture	356 Days	Local Data Processing Gateway	96 XBee frames	34,200 XBee frames
Cloud-based Architecture	356 Days	ThinkSpeak Cloud	72 frames	25,600 frames

Fig. 16 and **Fig. 17** show the graphical trends of the average daily air temperature and relative humidity measured by our architecture and compared cloud-based architecture during the same period of the experiment respectively. From the figures, there exists slightly differences between compared trends, which due to the transmission time of the sensed data and total amount of the received data in both compared gateways. An illustration of the trend curve between water content of soil volumetric captured by our architecture and water content of soil volumetric captured by cloud-based architecture can be found in **Fig. 18**. It can be seen again that the analytical trend is changing, because of the effect of the supplied water amount, environmental parameters, quality of used soil moisture sensors and data transmission time. At this point, however, as the water loss due to the change of ETo value in both experiments, there is also a relevant impact on the water content of soil volumetric. This is illustrating the actual need of water required to be supplied for irrigation process.

To demonstrate how the proposed architecture reaches a reasonable statistical performance and less computation complexity, we applied the Multiple-Input Single-Output (MISO) [54] model in Python environment to show the interaction behavior between sensed data corresponding to the amount of supplied water, ETo values and volumetric water content of the soil using different model structures [55]. These models include: the autoregressive with external input model (ARX), the Box Jenkins (BJ) model, Output Error (OE) model and the state space (SS) model [56]. The statistical performance of the proposed architecture can be then evaluated using standard evaluation metrics. In this experiment, we have used model evaluation metrics known as estimated best fit, final prediction error (FPE) and mean square error (MSE) [56]. For more details about the mathematical formula of these models structures and evaluation metrics, see [56][57].

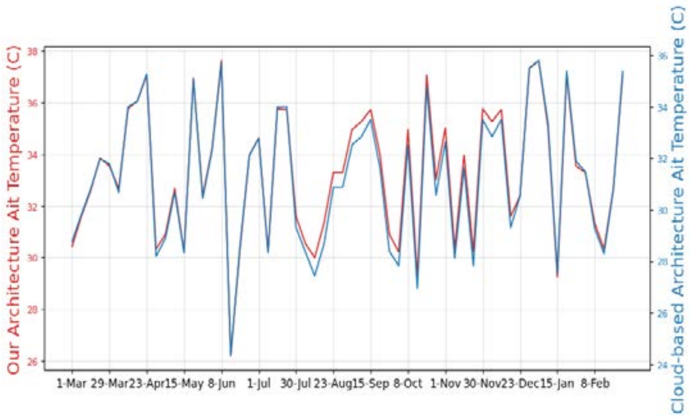


Fig. 16. Our architecture vs compared cloud-based architecture average air temperature (C)

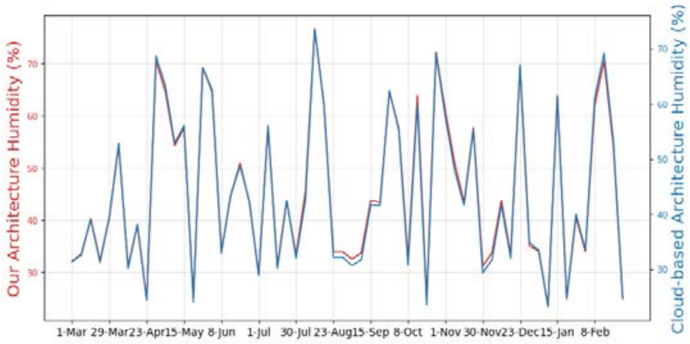


Fig. 17. Our architecture vs compared cloud-based architecture average humidity (%)

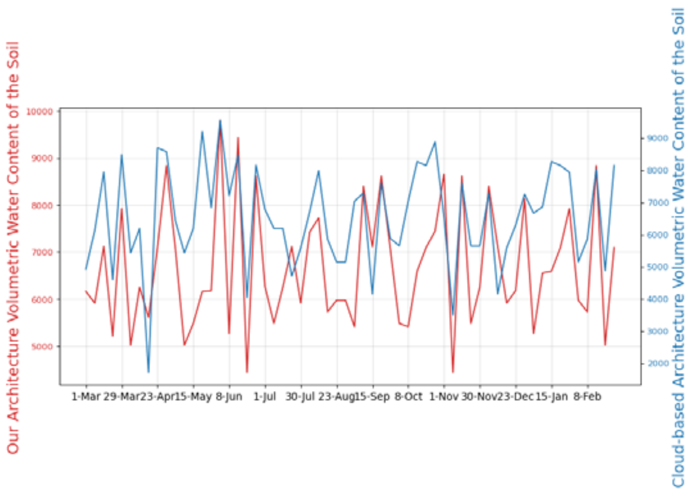


Fig. 18. Our architecture vs compared cloud-based architecture average volumetric water content of the soil

The FPE is basically describe the effectiveness of the architecture using different datasets, and the MSE is a statistical matric that evaluate the performance (i.e., quality) of these datasets. In this experiment, we use both datasets that have been captured be our architecture and compared cloud-based architecture. The effectiveness of our proposed depends on how small (i.e., close to the zero) is the value of FPE and MSE. The Estimated fit (%) is a measure of the correlation between amount of supplied water and volumetric water content of the soil parameters. **Table 3**, however, shows the statistical performance results of different models that were used to evaluate the effectiveness of both compared architecture. The used ARX model with the estimated fit of 93.39% with the least MSE and FPE values of 0.714 and 0.971 respectively, was selected from over all other used models that has achieved good performance. As can be seen from this table, our proposed architecture performs favorably against the compared cloud-based architecture, as evaluated on same agricultural area (i.e., same cultivation experiment) through different models of evaluation.

Table 3. Statistical Performance of different evaluation models

Model	**FPE**		**MSE**		**Estimated Fit**	
	Our Architecture	Compared Cloud-based Architecture	Our Architecture	Compared Cloud-based Architecture	Our Architecture	Compared Cloud-based Architecture
ARX	0.714	0.971	0.720	0.828	93.39	90.11
BJ	1.121	1.901	1.481	1.756	94.55	91.21
ARMX	1.151	1.891	1.705	1.991	94.70	91.51
State Space	1.494	1.711	1.651	1.821	94.35	90.95

5. Conclusion

The exponential growth in the human population has created an increased demand for water resources. This demand can be handled using wireless networking technologies to reduce water consumption. Thus, in this paper, an autonomous sensors-enabled architecture is proposed, which employs various self-powered wireless sensors to monitor various agricultural parameters over a heterogeneous array of data streams. Farmers can then be remotely measured and monitored their agricultural area in real-time using the proposed architecture without the need for third-party platforms.

In order to test and evaluate the proposed architecture, real-world scenarios covering various aspects of precision agriculture were used. The experimental results show that the proposed architecture is suitable and efficient for managing irrigation water and monitoring agriculture conditions. It is crucial to monitor soil moisture in agriculture since it aids farmers in controlling and managing irrigation methods more powerfully. Measuring soil moisture and other related agricultural parameters allows farmers to increase yields and crop quality through continuous monitoring of agricultural parameters during the different growth stages of plants. Therefore, the proposed automatic sensor-enabled architecture is expected to help farmers manage irrigation effectively, reduce water wastage, and enhancing productivity.

However, certain limitations of the proposed architecture must be addressed to improve its effectiveness. For example, the proposed architecture is based on large volumes of sensor-collected agriculture data, which is a key concern. In addition, smart methods to search relevant information in the proposed architecture must be developed to minimize the delivery time of analytical services.

In addition, a large-scale experiment is required to combined, explore, and process more information about the impacts of weather parameters on agricultural and the irrigation processes in Oman. Additional sensors can also be added to discover and explore several other agricultural and environmental parameters. Furthermore, in the main gateway, the database tables that receive and store the acquired data can be modified to recognize other data formats from new sensors. Finally, different types of sensing can be added, e.g., video, to extend the real-time monitoring of crops.

Appendix

The dataset generated during the current study is available in the Mendeley repository, [http://dx.doi.org/10.17632/3w3pf3vnd4.1].

Acknowledgement

The research leading to these results has received funding from Ministry of Higher Education, Research and Innovation (MoHERI) of the Sultanate of Oman under the Block Funding Program. MoHERI Block Funding Agreement No: FURAP/SU/18/002.

References

[1] M. Dursun and S. Ozden, "A wireless application of drip irrigation automation supported by soil moisture sensors," *Sci. Res. Essays*, vol. 6, no. 7, pp. 1573-1582, 2011. Article (CrossRef Link)

[2] M. Fourati, W. Chebbi and A. Kamoun, "Development of a web-based weather station for irrigation scheduling," in *Proc. of 3rd IEEE International Colloquium in Information Science and Technology (CIST)*, 2014. Article (CrossRef Link)

[3] N. Hashim, S. Mazlan, M. Aziz, A. Salleh, A. Jaafar and N. Mohamad, "Agriculture monitoring system: a study," *J. Teknologi*, vol. 77, pp. 53-59, 2015. Article (CrossRef Link)

[4] B. Keswani, A. Mohapatra, A. Mohanty, A. Khanna, J. Rodrigues, D. Gupta and V. Albuquerque, "Adapting weather conditions based IoT enabled smart irrigation technique in precision agriculture mechanisms," *Neural Computing and Applications*, vol. 31, pp. 277-292, 2019. Article (CrossRef Link)

[5] D. Sreekantha and A. Kavya, "Agricultural crop monitoring using IoT - A study," in *Proc. of 2017 11th International Conference on Intelligent Systems and Control (ISCO)*, Coimbatore, India, 2017. Article (CrossRef Link)

[6] C. Gonzalez-Amarillo, J. Corrales-Munoz, M. Mendoza-Moreno, A. Hussein, N. Arunkumar and G. Ramirez-Gonzalez, "An IoT-Based Traceability System for Greenhouse Seedling Crops," *IEEE Access*, vol. 6, pp. 67528-67535, 2018. Article (CrossRef Link)

[7] D. Ehlert, J. Schmerler and U. Voelker, "Variable rate nitrogen fertilisation of winter wheat based on a crop density sensor," *Precision Agriculture*, vol. 5, no. 3, pp. 263-273, 2004. Article (CrossRef Link)

[8] R. Prabha, E. Sinitambirivoutin, F. Passelaigue and M. Ramesh, "Design and development of an IoT based smart irrigation and fertilization system for chilli farming," in *Proc. of WiSPNET*, 2018. Article (CrossRef Link)

[9] J. Gutierrez, J. Villa-Medina, A. Nieto-Garibay and M. Porta-Gandara, "Automated irrigation system using a wireless sensor network and GPRS module," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 1, pp. 166-176, 2014. Article (CrossRef Link)

[10] T. Ojha, S. Misra and N. S. Raghuwanshi, "Wireless sensor networks for agriculture: the state-of-the-art in practice and future challenges," *Computer Electron Agriculture*, vol. 118, pp. 66-84, 2015. Article (CrossRef Link)

[11] A. Khaled, A. A. Rahma and S. Dinesh, "IoT-based system to measure thermal insulation efficiency," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1-14, 2020. Article (CrossRef Link)

[12] A. Rehman, A. Abbasi, N. Islam and Z. Shaikh, "A review of wireless sensors and network applications in agriculture," *Computer Standards & Interfaces*, vol. 36, pp. 263-270, 2014. Article (CrossRef Link)

[13] A. Emmanuel, A. Mohammad, M. Mohd, B. Salinda, A. Muhammad, O. Abdulrahaman, R. Muhammad and D. Ona, "IoT-based monitoring and data-driven modelling of drip irrigation system for mustard leaf cultivation experiment," *Information Processing in Agriculture*, vol. 8, no. 2, pp. 270-283, 2021. Article (CrossRef Link)

[14] M. Srbinovska, C. Gavrovski, V. Dimcev, A. Krkoleva and V. Borozan, "Environmental parameters monitoring in precision agriculture using wireless sensor networks," *J. Clean. Prod*, vol. 88, pp. 297-307, 2015. Article (CrossRef Link)

[15] A. Kamilaris, F. Gao, F. X. Prenafeta-Boldu and M. I. Ali, "Agri-IoT: A Semantic Framework for Internet of Things-Enabled Smart Farming Applications," in *Proc. of 2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, Reston, VA, USA, 2016. Article (CrossRef Link)

[16] M. Roopaei, P. Rad and K. Choo, "Cloud of things in smart agriculture: Intelligent irrigation monitoring by thermal imaging," *IEEE Cloud Computing*, vol. 4, no. 1, pp. 10-15, 2017. Article (CrossRef Link)

[17] T. Popovic, N. Latinovic, A. Pesic, Z. Zecevic, B. Krstajic and S. Djukanovic, "Architecting an IoT-enabled platform for precission agriculture and ecological monitoring: A case study," *Computers and Electronics in Agriculture*, vol. 140, pp. 255-265, 2017. Article (CrossRef Link)

[18] J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekhangpong, A. Wanichsombat and P. Nillaor, "IoT and agriculture data analysis for smart farm," *Computers and Electronics in Agriculture*, vol. 156, pp. 467-474, 2019. Article (CrossRef Link)

[19] A. Sinha, G. Shrivastava and P. Kumar, "Architecture user-centric internet of things for smart agriculture," *Sustainable Computing: Informatics and Systems*, vol. 23, pp. 88-102, 2019. Article (CrossRef Link)

[20] M. Okada, A. Ueki, N. Jonasson, Y. Masato, C. Norlin, H. Sunahara, J. Formo, M. Anneroth and M. Inakage, "Autonomous Cooperation of Social Things: Designing a System for Things with Unique Personalities in IoT," in *Proc. of the 6th International Conference on the Internet of Things (IoT'16)*, pp. 35-42, 2016. Article (CrossRef Link)

[21] F. Viani, M. Bertolli, M. Salucci and A. Polo, "Low-cost wireless monitoring and decision support for water saving in agriculture," *IEEE Sens. J.*, vol. 17, pp. 4299-4309, 2017. Article (CrossRef Link)

[22] O. Uviase and G. Kotonya, "IoT Architectural Framework: Connection and Intergration Framework for IoT Systems," *Electron. Proc. Theor. Comput. Sci.*, vol. 264, pp. 1-17, 2018. Article (CrossRef Link)

[23] T. Devadas and R. Subramanian, "Paradigms for Intelligent IoT Architecture," *Principles of Internet of Things (IoT) Ecosystem: Insight Paradigm*, vol. 174, pp. 67-100, 2020. Article (CrossRef Link)

[24] K. Ashton, "That 'Internet of Things' Thing," *RFID Journal*, vol. 22, pp. 97-114, 2009. Article (CrossRef Link)

[25] A. Pravin, P. Jacob and G. Nagarajan, “A comprehensive survey on edge computing for the IoT,” in *Edge Computing and Computational Intelligence Paradigms for the IoT*, Hershey, IGI Global, 2019, pp. 37-45. Article (CrossRef Link)

[26] G. Mei, N. Xu, J. Qin, B. Wan and P. Qi, "A Survey of Internet of Things (IoT) for Geo-hazards Prevention: Applications, Technologies, and Challenges," *IEEE Internet of Things Journal*, pp. 4371-4386, 2019. Article (CrossRef Link)

[27] B. Marhaenanto, P. Soni and V. M. Salokhe, "Development of an internet-based greenhous control system," *International Agricultural Engineering Journal*, vol. 22, pp. 72-83, 2013. Article (CrossRef Link)

[28] L. Bajer and O. Krejcar, "Design and realization of low cost control for greenhouse environment with remote control," *IFAC-PapersOnLine*, vol. 48, pp. 368-373, 2015. Article (CrossRef Link)

[29] Y. Duan, "Design of intelligent agriculture management information system based on IoT," in *Proc. of 2011 Fourth International Conference on Intelligent Computation Technology and Automation*, vol. 1, pp. 1045-1049, 2011. Article (CrossRef Link)

[30] K. Taylor, C. Griffith, L. Lefort, R. Gaire, M. Compton, T. Wark, D. Lamb, G. Falzon and M. Trotter, "Farming the web of things," *Intelligent Systems IEEE*, vol. 28, no. 6, pp. 12-19, 2013. Article (CrossRef Link)

[31] J. Haule and K. Michael, "Dployment of wireless sensor networks (WSN) in automated irrigation management and scheduling systems: a review," in *Proc. of the 2nd Pan African international conference on science, computing and telecommunications (PACT 2014)*, 2014. Article (CrossRef Link)

[32] D. Ofrim, B. Ofrim and D. Sacaleanu, "Improved environmental monitor and control using a wireless intelligent sensor network," in *Proc. of 2010 3rd International Symposium on Electrical and Electronics Engineering (ISEEE)*, pp. 211-215, 2010. Article (CrossRef Link)

[33] M. Kassim, I. Mat and A. Harun, "Wireless sensor network in precision agriculture application," in *Proc. of 2014 International Conference on Computer, Information and Telecommunication Systems (CITS)*, pp. 1-5, 2014. Article (CrossRef Link)

[34] S. Nikolidakis, D. Kandris, D. Vergados and C. Douligeris, "Energy efficient automated control of irrigation in agriculture by using wireless sensor networks," *Computer Electronic Agriculture*, vol. 113, pp. 154-163, 2015. Article (CrossRef Link)

[35] L. Rajaoarisoa, N. M'Sirdi and J. Balmat, "Micro-Climate Optimal Control for an Experimental Greenhouse Automation," in *Proc. of CCCA12*, 2012. Article (CrossRef Link)

[36] J. Yin, Y. Yang, H. Cao and Z. Zhang, "Greenhous environmental monitoring and closed-loop control with crop growth model based on wireless sensors network," *Trans. Inst. Meas. Control.*, vol. 37, no. 1, pp. 50-62, 2015. Article (CrossRef Link)

[37] Z. Yongheng and Z. Feng, "Research on the smart wireless sensor perception system and its application based on internet of things," *Computer Modelling New Technology*, vol. 18, no. 1, pp. 44-51, 2014. Article (CrossRef Link)

[38] J. Zhao, J. Zhang, Y. Feng and J. Guo, "The study and application of the IoT technology in agriculture," in *Proc. of 2010 3rd International Conference on Computer Science and Information Technology*, 2010. Article (CrossRef Link)

[39] M. Damas, A. Prados, F. Gomez and G. Olivares, "HidroBus system: fieldbus for intergrate management of extensive areas of irrigated land," *Microprocessors and Microsystems*, vol. 25, no. 3, pp. 177-184, 2001. Article (CrossRef Link)

[40] R. Evans and J. Bergman, "Relationships between cropping sequences and irrigation frequency under self-propelled irrigation systems in the Northern Great Plains (NGP)," *USDA Annual Report Project*, pp. 003-002, 2003. Article (CrossRef Link)

[41] T. Basu, M. Thool, Thool R.C. and A. Birajdar, "Computer based drip irrigation control system with remote data qcquisition system," in *Proc. of Computers in Agriculture and Natural Resources, 4th World Congress Conference*, 2006. Article (CrossRef Link)

[42] Y. Kim, R. Evans and W. Iversen, "Remote sensing and control of an irrigation system using a distributed wireless sensor network," *IEEE Transactions on Instrumentation and Measurement*, vol. 57, no. 7, pp. 1379-1387, 2008. Article (CrossRef Link)

[43] Y. Kim and R. Evans, "Software design for wireless sensor-based site-specific irrigation," *Computers and Electronics in Agriculture*, vol. 66, no. 2, pp. 159-165, 2009. Article (CrossRef Link)

[44] K. Chen, H. Zhang, T. Wu, J. Hu, C. Zhai and D. Wang, "Design of Monitoring System for Multilayer Soil Temperature and Moisture Based on WSN," in *Proc. of 2014 International Conference on Wireless Communication and Sensor Network*, 2014. Article (CrossRef Link)

[45] N. Kaewmard and S. Saiyod, "Sensor data collection and irrigation control on vegetable crop using smart phone and wireless sensor networks for smart farm," in *Proc. of 2014 IEEE Conference on Wireless Sensors (ICWiSE)*, 2014. Article (CrossRef Link)

[46] D. Vasisht, Z. Kapetanovic, J. Won, X. Jin, R. Chandra, S. Sinha, A. Kapoor, M. Sudarshan and S. Stratman, "FarmBeats: An IoT Platform for Data-Driven Agriculture," in *Proc. of the 14th USENIX Symposium on Networked Systems Design and Implementation (NSDI 17)*, Boston, pp. 515-529, 2017. Article (CrossRef Link)

[47] S. Sebastian and S. Petros, "Wireless technologies for smart agricultural monitoring using internet of things devices with energy harvesting capabilities," *Computers and Electronics in Agriculture*, vol. 172, p. 105338, 2020. Article (CrossRef Link)

[48] R. Tayeb and P. Luis, "Estimation of ETo with Hargreaves–Samani and FAO-PM temperature methods for a wide range of climates in Iran," *Agricultural Water Management*, vol. 121, pp. 1-18, 2013. Article (CrossRef Link)

[49] R. G. L. S. P. Allen, D. Raes and a. M. Smith, "Crop Evapotranspiration-Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56," *FAO*, p. 300:6541, 1998. Article (CrossRef Link)

[50] G. H. Hargreaves and Z. A. Samani, "Reference Crop Evapotranspiration from Temperature," *Applied Engineering in Agriculture*, vol. 1, no. 2, pp. 96-99, 1985. Article (CrossRef Link)

[51] J. H. Yousif, H. A. Kazem, N. N. Alattar and I. I. Elhassan, "A comparison study based on artificial neural network for assessing PV/T solar energy production," *Case Studies in Thermal Engineering*, vol. 13, p. 100407, 2019. Article (CrossRef Link)

[53] J. H. Yousif and A. Khaled. “Experimental and Mathematical Models for Real-Time Monitoring and Auto Watering Using IoT Architecture,” *Computers*, vol 11, no, 7, 2022. Article (CrossRef Link)

[54] M. N. M. Hussain, A. M. Omar and A. A. A. Samat, "Identification of Multiple Input-Single Output (MISO) model for MPPT of Photovoltaic System," in *Proc. of 2011 IEEE International Conference on Control System, Computing and Engineering*, pp. 49-53, 2011. Article (CrossRef Link)

[55] Rahman MKIA, Abidin MSZ, Mohd SAM Salnda B, Mahmad HII, and Emmanuel AA., “Advancement of a smart fibrous capillary irrigation management system with an internet of things integration,” *Bulletin of Electrical Engineering and Informatics*, vol. 8, no 4, pp. 1402-1410, 2019. Article (CrossRef Link)

[56] Araghinejad S., *Data-Driven Modeling: Using MATLAB in water resources and environmental engineering*, Springer Dordrecht Heidelberg New York London Library, 2014. Article (CrossRef Link)

[57] G. E. Searle, J. W. Gardner, M. J. Chappell, K. R. Godfrey and M. J. Chapman, "System identification of electronic nose data from cyanobacteria experiments," *IEEE Sensors Journal*, vol. 2, no. 3, pp. 218-229, 2002. Article (CrossRef Link)

Khaled Abdalgader received his BSc degree in computer science from the Sebha University, Libya, in 2001, MSc degree from the University Utara Malaysia in 2004 and PhD degree in the area of natural language processing from La Trobe University, Australia, in 2012. He has been an Assistant Professor in Artificial Intelligent with the Department of Computer Science and Engineering, American University of Ras Al Khaimah (AURAK), UAE. Prior to joining AURAK, he was at the Sebha University, Libya, from July 2004 to August 2007 as a Lecturer and then at Sohar University, Oman, from September 2013 to August 2022 as an Assistance Professor in Computer Science. His research focuses on natural language processing and understanding, particularly word sense disambiguation, semantic text similarity, text mining, sentiment analysis, and knowledge discovery from textual collections.

Jabar H. Yousif is Associate Prof. at Faculty of Computing and Information Technology, Sohar University, Oman. Ph.D. in Information Science & Technology, M.Sc. & B.Sc. in Computer Science. Postdoctoral fellowship in Virtual Reality- UKM Malaysia. More than 25 years of teaching experience. I have published more than 90 papers& books in Artificial Intelligent, Cloud Computing, Soft Computing, Artificial Neural Networks, Natural Language Processing, Arabic text Processing& Virtual Reality. Editorial board & reviewer for many scientific journals and conferences.