Application of the Digital Twin for Condition Monitoring and Energy Management of Electrical Loads in Greenhouses

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ABSTRACT

In recent years, the development and widespread implementation of energy-saving measures, combined with digital transformation, have increased significantly worldwide. Among digital technologies, Digital Twin (DT) technology is regarded as a potential solution in the agricultural sector. Real-time control of energy consumption and monitoring the operational status of electrical equipment in agricultural production on a digital platform help farmers optimize farming processes, paving the way for more efficient and sustainable farming methodologies. Additionally, DT technology, which creates virtual replicas of physical systems, holds significant potential for advancing agricultural practices. The objective of this article is to propose a DT model for managing real-time energy consumption of electrical loads within the agriculture domain and components of DT in smart agriculture. It assesses the impact of DT on crop monitoring, resource management, and precision agriculture, evaluates the economic and

environmental benefits of DT adoption in agriculture, and addresses challenges associated with implementing DT technology in farming. The simulation results show that the DT model can help managers choose appropriate methods for managing energy consumption within electrical loads and effectively monitor the agricultural environment.

Keywords-renewable energy; agricultural energy; Digital Twins (DT); energy management; Supervisory Control and Data Acquisition (SCADA); smart grid; digital agriculture

I. INTRODUCTION

During the past few years, the integration of digital technologies, such as the Internet of Things (IoT), big data, cloud computing, Artificial Intelligence (AI), and DT technology in the agricultural production environment has been increasing and bringing new opportunities. The Internet of Agricultural Things (IoAT) builds upon the foundation of the IoT, enabling data-driven insights and automation in agricultural practices [1, 2]. A recent research approach for optimizing farming operations has been the introduction of DTs in agricultural applications. A DT is a digital replica of a physical entity, featuring bidirectional dynamic mapping between the physical object and its digital model [3]. DT technology can dynamically reflect the operation of physical entities in real-time on a digital platform to achieve synchronization with the actual physical entity and support the operator in making decisions. DT helps solve problems related to remote access, system design and failure analysis, intelligent decision-making, and real-time monitoring. In agricultural farming systems, DT technology has shown immense potential for optimizing resource management, improving productivity, and promoting sustainability. By continuously monitoring soil moisture and plant water stress in various sections of a field or orchard, DT systems help optimize irrigation scheduling and improve water use efficiency, ensuring that the plants receive the appropriate amount of water at different growth stages [4]. Authors in [5] concentrate their review on soil and irrigation management, along with DT applications for farming machinery and post-harvest processes. When agricultural duties are considered, power generation represents the largest carbon footprint, contributing to 78.7% [6]. The major issues facing the agriculture industry include rising energy costs, an accelerated pace of fossil fuel depletion, dwindling water supplies, opposition to agricultural chemicals, and preservation of environmental challenges. These issues also render the industry unsustainable. For many years, integrating renewable energy systems, including Solar Photovoltaic (PV) technologies, into agricultural production has been a significant trend to reduce emissions and environmental pollution caused by traditional energy sources while providing sustainable electricity for agricultural activities [7]. Embracing renewable energy in agricultural systems, particularly through Renewable Energy Sources (RES) technologies, signifies a substantial step toward reducing CO_2 emissions and minimizing reliance on fossil fuels, which contribute to global warming and other detrimental effects, ultimately fostering sustainable food production and energy efficiency [8]. The use of fossil fuels is mainly characterized by high emissions of CO_2 and other pollutants, expensive production, the necessity for transportation, uneven distribution of resources, and so on. Conversely, renewable energy sources are environmentally friendly, widely available, and can somewhat compensate for the need for fossil fuels [9]. On the other hand, RES are widely accessible, have reduced maintenance costs, and offer longer operational lifetimes. They are eco-friendly and can significantly decrease the reliance on fossil fuels for generating electricity and heating. PV systems shine as a promising source of solar energy, which is becoming increasingly important for promoting global sustainable development due to its renewable nature and low environmental impact [10]. Utilizing solar energy in the agriculture sector and implementing efficient energy management practices will help alleviate the strain on the electrical grid, reduce input costs, and ensure food security. The total temperature (solar radiation) is directly related to the water required for crop irrigation. This means that as the temperature increases, the need for water by plants also rises, and therefore, the amount of energy produced by solar panels is greater. On the other hand, lower temperatures require less water for plants and result in less energy produced by solar panels [11]. One of the primary advantages of using PV as a supplemental energy source in the design of pumping systems is that it can reduce greenhouse gas emissions and the amount of fossil fuel-derived grid power utilized [12]. Employing DTs in the energy sector, or simply Energy Digital Twin (EDT), can revolutionize how energy systems are managed, leading to improved energy efficiency, reduced downtime, and lower maintenance costs [13]. DT environments are considered essential due to their useful characteristics, including the timeliness and synchronization of object states, reliability and security for decision-making, analysis of the physical behavior of objects, and complexities in presenting a reflection of the physical independent objects [14]. However, most agricultural applications have yet to emerge past lab-scale implementations, where the focus has primarily been on the integration of computational intelligence and remote sensing devices for specific system optimization and informed management tasks. There are also some challenges associated with applying DTs in agriculture, including issues with data integration, sensor accuracy, and reliability, as well as high demands for computational resources. There are also challenges associated with applying DTs in agriculture, including issues with data integration, sensor accuracy and reliability, and high demands for computational resources [15]. Therefore, addressing these challenges is essential for maximizing the value derived from DT application in sustainable agriculture. Addressing these issues, this paper proposes a model of DT technology and its application in the agricultural energy sector, with the goal to evaluate and improve the smart agricultural farm design for the lowest energy consumption. This is achieved through simulation on virtual models, which allows for the determination of optimal layouts combining both capacity and size. The use of virtual models in monitoring and energy management for electrical loads enables operators to track energy consumption while enhancing system reliability and safety. This model facilitates real-time monitoring, predictive analysis, and optimization of energy usage in farming operations.

II. ARCHITECTURE OF THE DIGITAL TWIN MODEL

Overall, the application of DT in energy management can provide insights into energy consumption patterns and optimize power usage in agriculture. By modeling these objects, the DT can effectively simulate and monitor their operations, facilitating efficient energy management and control. Figure 1 illustrates the DT model architecture for the power monitoring and management system's electrical loads. The proposed DT-based architecture consists of five layers: Physical layer, virtual counterparts, communication layer, data management, and service layer. Each of these components presents unique challenges and requirements that the standards must address.

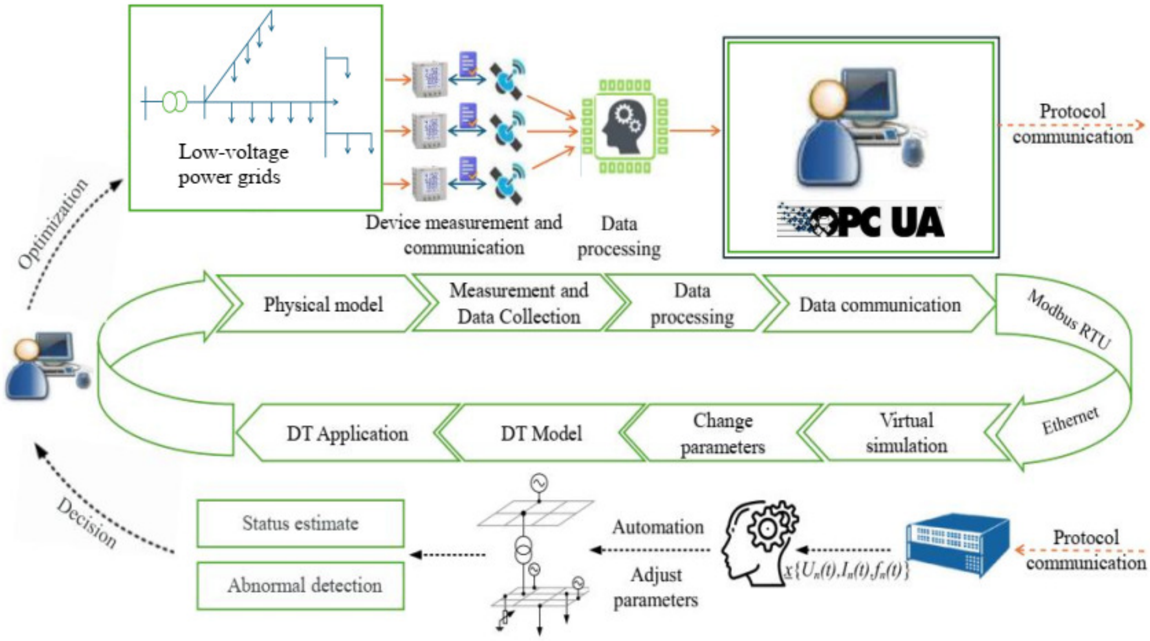

Fig. 1. Model structure of the electrical load monitoring and management system.

A. Physical Layer

The physical object or system is the real-world entity that the DT represents, including system behavior, rules, and data regarding physical space. A DT model is initially established based on the actual configuration of the physical grid system and electrical loads. The system hardware configuration includes PV systems, battery Energy Storage Systems (ESS), and electricity-consuming devices, such as engines, lighting, cooling/heating systems, and industrial actuators. Additionally, a Supervisory Control and Data Acquisition (SCADA) system can be used in an agricultural grid to gather data and automate its processes. This includes Remote Terminal Units (RTUs) and Programmable Logic Controllers (PLCs) that acquire data from diverse sensors and regulate the system through actuators. Data processing modules gather information through smart meters installed at each component location, measuring variables, such as voltage, current, temperature, and environmental factors. These data are then communicated to field devices in real-time and provided to the SCADA systems.

B. Virtual Counterpart

DTs are virtual object layers that act as a reflection or model of the physical layer and can be used to monitor their physical counterparts on the DT. The operation of the electrical loads is simulated by various simulation software tools using mathematical models and equations. Based on virtual models, technicians monitor the operations of the power grid and agricultural electrical load in real-time. The grid configuration, the physical parameters of the power system, and the physical power load operate in parallel and transmit data to the virtual model. Based on the datasets received, operators can monitor and manage load energy consumption. The DT model is simulated using MATLAB/Simulink, which allows simulation and prediction of energy consumption for electrical loads based on data read from sensors and Intelligent Electronic Devices (IEDs).

C. Communication Protocols

The connection layer establishes a communication link that can travel in both directions between the virtual model and the physical entity of the grid and electrical load. Energy data are collected from IEDs and field sensors via communication protocols, such as Ethernet, TCP/IP, PROFINET, OPC UA, and Modbus RTU. To enable efficient control and monitoring, a Raspberry Pi (RP) communication network employing MODBUS on TCP/IP and RS-485 protocols has been implemented. The RP controllers are responsible for overseeing the entire microgrid system. They collect and process data from energy meters, execute control algorithms, and communicate with other components to ensure optimal energy management. By using IoT technology, data from sensors and IEDs are collected and transmitted via series protocols, like RS422 and RS485 ports, to a central system to perform the function of preprocessing and real-time transmission of data from the physical layer to its digital counterpart. Authors in [16] successfully executed a supply chain attack that utilized an OPC UA server in conjunction with a Siemens S7–1500 PLC as a client. This was detected through the proposed method employing a one-class classifier, which attained a detection rate of up to 89.5%. Figure 2 illustrates the bidirectional data transfer relationship between the physical system and the digital model. MATLAB/SIMULINK supports OPC-UA communication and is able to establish it [17]. This allows MATLAB/SIMULINK to connect as a client to an OPC-UA compatible server, facilitating real-time data read/write and communication with the PLC. These protocols help the components of the measurement system integrate and operate smoothly with one another. The two-way communication between the data processing layer and the virtual layer allows interaction between the virtual space and the physical layer.

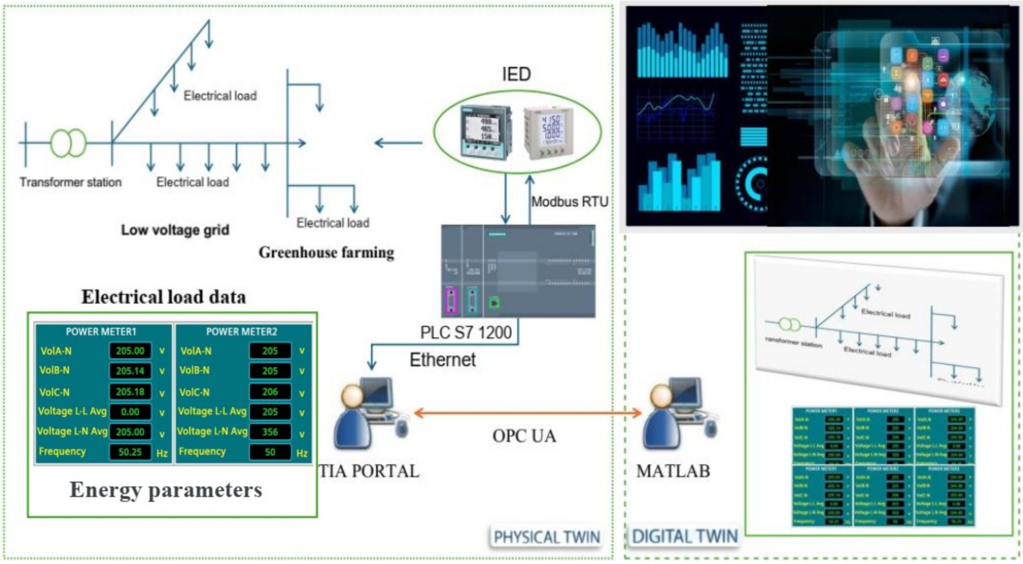

Fig. 2. Data transmission model.

D. Data Management

The data management layer is responsible for managing data information of renewable energy sources, such as solar panel facilities within the DT framework, electrical loads, and the environment, such as current, voltage, and temperature parameters collected through Smart Meters and sensors. These data are collected under various operating conditions and include both historical and real-time data. Real-time data from IoT sensors, seamlessly integrated into the DT infrastructure, further enrich the modeling process. MATLAB/SIMULINK is used to analyze and process both historical data and real-time data using advanced algorithms. The collected dataset is the basis for forecasting energy demand using algorithms and forecasting models. Relational databases (e.g., MySQL, PostgreSQL) or time-series databases (e.g., InfluxDB) are utilized for storing the collected data.

E. Support Services

The service layer is developed based on optimized modules in the WinCC environment using algorithms and decision support processes. These services assist operators in optimizing electrical load parameters. The cloud platform provides services such as real-time energy consumption monitoring, automatic load information updates, and operational information feedback. With DT technology, the continuous collection of real-time data flow, processing, and analysis in a high-fidelity environment is possible.

III. DATA ANALYSIS MODEL

The farm size is a key determinant of agricultural productivity. Typically, farm size is defined by the total area of managed cropland. In this study, farm size is considered to be the area of cropland operated by the farm. The assumptions underlying this analysis are as follows: The greenhouse measures 80 m in length and 18 m in width, resulting in a total floor area of 1440 m^2. Special fruits and vegetables, including grapes, strawberries, and tomatoes, are popularly grown here, primarily under the scale operation mode typical of greenhouse type. The collected data include temperature, air humidity, carbon dioxide concentration, light intensity, and soil temperature. Sensor data and operating data from the controller are connected through a data transmission device and a PLC controller to an Internet of Things Gateway. Protocols, like OPC UA and Modbus RTU, are employed at the application and device layers for real-time data transmission. The main types of power loads of energy consumption involved include irrigation water pumping systems, heating systems, ventilation fan systems, and supplemental lighting, which are examined in this section. The power of greenhouse agricultural electrical loads is displayed in Table I. The greenhouse agricultural electricity load model is depicted in Figure 3.

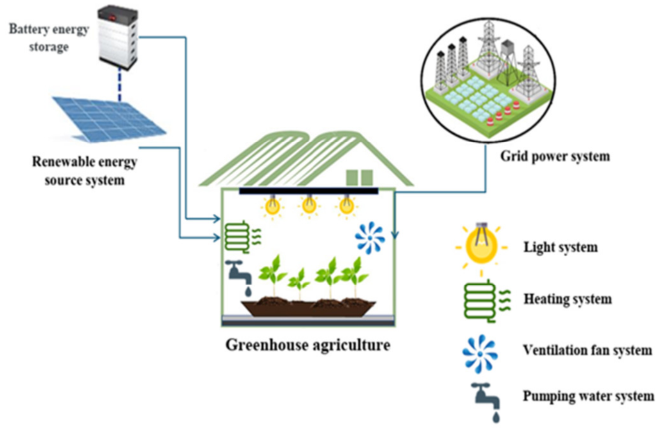

Fig. 3. Greenhouse agricultural farm model.

A. Model of PV Panels

PV power plants consist of modules/panels connected in series or parallel [18]. The PV supply, which includes tracking-integrated systems and an MPPT regulator, can be expressed in terms of the power output of PV modules based on solar radiation and ambient temperature. The power output of the PV module, which varies with solar irradiance and ambient temperature, can also be expressed. The power from the PV solar can be calculated using [19]:

$$P_{PV} = Y_{pv} \times f_{pv} \times \left(\frac{G_T}{G_{T,STC}}\right)\left[1+\alpha_P\left(T_C - T_{STC}\right)\right] \quad (1)$$

where P_{PV} is the power output (kW), Y_{pv} is the power output during standard test conditions in (kW), f_{pv} is the derating factor of solar PV (%), G_T is the incident solar irradiance in (kW/m^2), $G_{T,STC}$ is the incident radiation under standard test conditions (1kW/m^2), α_P is the temperature coefficient of power (%/◦C), T_c is the cell temperature of solar PV in ◦C, and T_{STC} is the cell temperature under standard test conditions, which is 25 (◦C).

B. Model Inverter

The inverter converts the Direct Current (DC) supplied by the photovoltaic plant into Alternating Current (AC) for use by the AC loads. The rated power of the converter is adjusted to meet peak loads [20]. The power supplied by the inverter is calculated by:

$$P_{inv}(t) = P_{pv}(t) \times \eta_{inv} \quad (2)$$

where $P_{inv}(t)$ denotes the power from the photovoltaic panels at a given time, $P_{pv}(t)$ represents the output power from the inverter at a given time, and $\eta_{inv}(t)$ denotes inverter efficiency.

C. Battery Model

The ESS size can be selected based on the required load and the need to maintain a consistent voltage in renewable energy generation during periods of generation capacity shortage. The power storage's maximum Battery Discharge (BD) is calculated by [21]:

$$B_D = \frac{crN_M + cN_I^{-c\Delta t} + crN_T\left(1-e^{-c\Delta t}\right)}{1-e^{-c\Delta t} + r\left(c\Delta t - 1 + e^{-c\Delta t}\right)} \quad (3)$$

The maximum battery storage is calculated by [21]:

$$B_C = \frac{cN_I e^{-c\Delta t} + crN_T\left(1-e^{-c\Delta t}\right)}{1-e^{-c\Delta t} + r\left(c\Delta t - 1 + e^{-c\Delta t}\right)} \quad (4)$$

where *c* represents the hourly constant rate of battery storage, *r* represents a scaling factor to quantify net energy dynamics, *Δt* is the time step duration in hours, N_M denotes the storage bank's total capacity in kWh, N_I is the energy initially accessible for storage (initial) stage in kWh, and N_T denotes the entire amount of energy stored in the system kWh.

D. Lighting Load Power Consumption Model

Common supplemental lights include LED lights, incandescent lights, fluorescent lights, and others. Incandescent lamps primarily emit infrared light, which is not conducive to plant photosynthesis. The emission spectrum of fluorescent lights is concentrated in blue-violet light, which does not meet the wavelength requirements for dragon fruit. Currently, LED lights are widely used in greenhouse artificial lighting compensation systems. The former have many advantages, such as a long lifespan, low power consumption, adjustable light wavelength, and light intensity. The power output of the LEDs and the light illumination per unit power is calculated by:

$$P_{light} = nP_l(t)\frac{S}{S_l}\frac{1}{1000} \quad (5)$$

where P_{light} represents the supplemental lighting power loads, measured in kW; *n* represents the number of supplemental lights; P_l represents the power of one light, measured in w; S_l represents the area lighting, measured in m^2; and *S* represents the area of the farmland, measured in m^2.

E. Irrigation Power Consumption of Water Pumping Systems

An irrigation system is commonly used in a greenhouse to supply water and maintain soil moisture for the plants. Depending on the demand, drip irrigation can be performed. Less alteration of soil moisture occurs with the drip irrigation method. Based on the crop water demand model, the formula for irrigation power consumption can be derived [22]:

$$P_{irrigation} = E_h \frac{100}{\eta} \quad (6)$$

$$E_h = V \times H \times \frac{\rho \times g}{n} \quad (7)$$

$$P_{irrigation} = \sum ET_c \times S \quad (8)$$

where $P_{irrigation}$ represents the irrigation power load, measured in W; η represents the efficiency of the pump, measured in %; *Eh* represents hydraulic energy in kWh; *V* represents irrigation water volume, measured in m^3; *H* represents the pumping head of water, measured in m; ρ represents the water density, whose value is 1000 kg/m^3; *g* represents the gravitational acceleration, whose value is 9.8 m/s^2. n represents irrigation duration, measured in s; ΣETc represents the total crop water requirements in the irrigation cycle; and S represents the area of the dragon fruit farmland, measured in m^2.

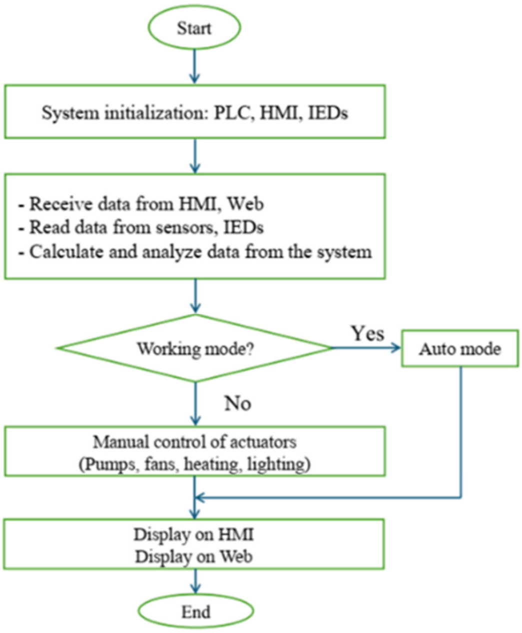

Fig. 4. Flowchart of system control optimization algorithm.

IV. SIMULATION RESULTS

Power management is essential for reducing environmental impact, and sustainable practices promote energy efficiency. This leads to adopting energy-efficient technologies that reduce energy usage and wastage. Virtual agricultural production environments and DT application for energy management are necessary to leverage recent developments in the digital landscape that enhance each step of the energy efficiency policy cycle. The DT can also be connected to control systems to monitor the energy system. This can be used to optimize the performance of the system and reduce the cost of operations, as illustrated in Figure 5, where the energy management system for greenhouse agricultural electricity loads in the MATLAB environment is described.

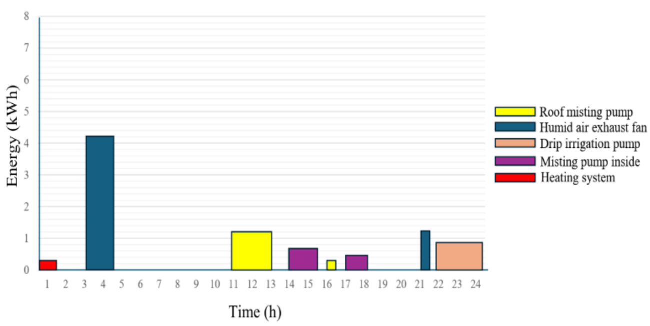

Fig. 5. Real-time electrical load energy consumption chart.

The PLC is an IoT Data Space Analytics Platform for the collection and visualization of data sent from different sensors. The proposed system relies on IoT sensors that collect data on various environmental parameters, such as temperature, moisture content, and soil humidity. One of the data acquisition procedures is the ability to pull the latest temperature and humidity readings from the PLC, as shown in Figure 6.

TABLE I. DATA FOR CALCULATING GREENHOUSE AGRICULTURAL LOADS

TT	Electrical equipment	Power (kW)	n	Simultaneus coefficient Kđt	Power consumption (kWh)
1	A fan exhausts moist air	0.63	6	0.55	4.158
2	Roof mist pump	0.65	1	0.31	0.4433
3	Drip pump	0.55	1	0.35	0.462
4	Misting pump inside	0.75	1	0.31	0.58125
5	Pump stirring bio-fertilizer tank	0.55	2	0.32	1.408
6	Heating system	0.1	5	0.44	0.22
7	Lighting system	0.11	30	1	33

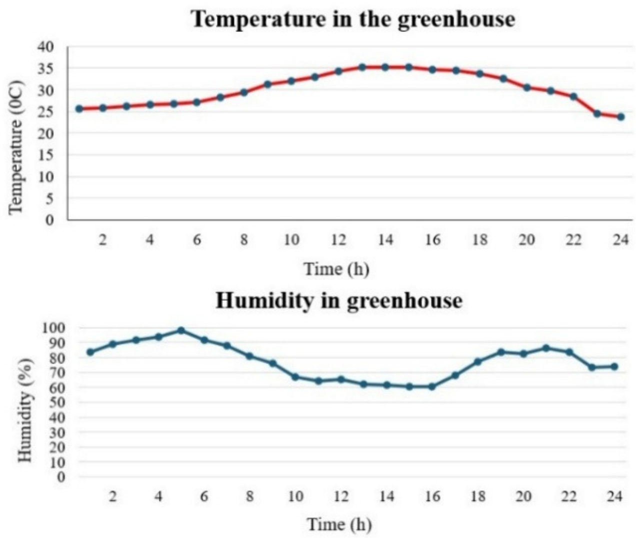

Fig. 6. Real-time temperature and humidity measurements.

Data from the TIA PORTAL control programming software are transmitted to the MATLAB environment via the OPC UA protocol. Through the OPC UA protocol, the dataset from TIA PORTAL is sent to the MATLAB/ environment and updated on the DT model in real-time. Figure 7 illustrates the energy management system for electricity loads in greenhouse agriculture within a Simulink-based DT environment.

Figure 7 portrays the energy management system for electricity loads in greenhouse agriculture within a Simulink-based DT environment.

Fig. 7. System for monitoring energy consumption and environmental parameters.

V. CONCLUSION AND FUTURE WORK

The study aimed to provide a comprehensive review of the application of Digital Twin (DT) technology in the fields of monitoring and energy management in agriculture. DT technology, capable of creating virtual replicas of physical systems, holds significant potential for advancing agricultural practices. The DT model represents a revolutionary approach to agricultural energy systems, enabling smart decision-making, optimizing energy use, and promoting sustainable farming. DTs show considerable promise for developing applications in the future and are regarded as one of the key technological solutions in the agricultural energy sector for Improved Energy Efficiency: By analyzing real-time data, DT helps reduce energy waste and optimize consumption. Sustainability: DT promotes the use of renewable energy sources, reducing carbon footprints in agriculture. Enhanced Decision-Making: Artificial Intelligence (AI)-driven analytics provide actionable insights for farm managers to improve productivity. Real-Time Monitoring and Control: Remote access to farm operations enhances management and decreases manual intervention. Despite its benefits, DT adoption in agricultural energy systems faces challenges: High Initial Investment; Setting up Internet of Things (IoT) infrastructure and AI models requires significant costs; Data Security and Privacy Concerns: Protecting farm data from cyber threats is crucial; Technical Complexity: Farmers need sufficient training to effectively utilize and interpret DT models. In conclusion, DTs show considerable promise for the development of applications in the future and are considered one of the key technological solutions in the agricultural energy field. Additionally, by using DT technology, farmers can monitor crop growth status and optimize irrigation systems in real-time to ensure an optimal growing environment for their crops. As adoption increases and technical barriers diminish, DT technology will play an integral role in shaping the future. The results from this initial research project indicate a promising direction for future work, although challenges persist concerning the management and automation of complex agricultural systems.

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