A Temperature and Humidity Control System based on Digital Twin

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ABSTRACT: In recent years, with the rapid development of the Internet of Things, smart homes have seamlessly integrated into our daily lives. People are increasingly seeking features such as human-computer interaction, remote control, and self-regulation as essential components of their smart home experience. As a technology capable of expediting the integration and advancement of emerging technologies, such as Artificial Intelligence (AI), digital twins have emerged as a pivotal driver for digital transformation globally. A digital twin, characterized by its multi-disciplinary, multi-physical, multi-scale, and multi-probability simulation process, harnesses a wealth of data sources, including physical models, sensor updates, and operational history. Notably, it has transcended its original application in thermostatic greenhouses and has become an integral part of intelligent temperature and humidity control systems in people's homes, providing a more convenient and intelligent self-control experience by seamlessly integrating advanced technology and data analysis.

Keywords: Digital twin, smart home, physical model, Internet of things

1 INTRODUCTION

The Internet of Things (IoT) represents a significant step towards revolutionizing the modern world and stands as a notable achievement in the realm of artificial intelligence [1]. While IoT technology is rooted in the inception of the Internet, there exist distinct differences between the two. In contrast to traditional Internet terminal servers, the foundation for the rapid advancement of the IoT lies in the utilization of sensors and intelligent hardware. An IoT ecosystem encompasses web-enabled smart devices that incorporate systems comprising processors, sensors, and communication hardware, enabling them to collect, transmit, and respond to the data they gather [2]. The latest generation of smart home products leverages IoT technology to immerse themselves in the IoT landscape, continually enhancing their technical capabilities through deep learning. This evolution significantly augments the interconnectivity between smart home devices and systems.

IoT greatly influences our daily lives [3]. With the rapid development of digital technologies, especially in computer science, communication, networking, and control, smart city initiatives have transformed urban lifestyles [4-6]. Smart home products, characterized as innovative intelligent devices, have become essential in optimizing user experiences and enhancing quality of life. These products enable users to interact via voice control, mobile apps, and more for remote device management and energy efficiency. Design considerations should encompass

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user needs, habits, and human-computer interactions to align with market demand. Key technologies include intelligent sensors, wireless communication, big data analytics, and M2M tech. The future of smart homes will involve collaboration among research groups and evolving expertise, necessitating sustainable human-machine interaction mechanisms. A 2020 report by Strategy Analytics projected global spending on smart home hardware, services, and installation to reach $89 billion in 2020, rising to $120 billion by 2021, and maintaining a 14% CAGR to reach $175 billion by 2025. It anticipates that 19% of households, equivalent to nearly 390 million homes worldwide, will feature at least one type of smart home system by 2025 [7].

The growing complexity of production in a competitive market is driving the integration of the physical and digital realms. Simultaneously, increasing practical demands for industrial products challenge the digital model's ability to interact with physical objects. This led to the emergence of the digital twin, sparking a transformative industry revolution [8,9]. Digital twin technology involves digitizing an object, simulating its real-world behavior, and virtually modeling products, manufacturing processes, and entire factories. In the era of the Internet of Everything, this design model plays a pivotal role. Achieving interaction between physical and digital entities requires multiple processes, fundamental supporting technologies, and evolutionary stages to replicate physical entities in the digital realm. When combined with sensory data acquisition, big data analytics, AI, and machine learning, digital twins enable monitoring, diagnostics, prognostics, and optimization [10,11]. It's important to note that digital twin builds upon existing technologies [12].

This paper commences with an exploration of the Internet of Things, its development trajectory, and future prospects. It proceeds to delve into the current applications of smart homes, defining the concept of smart homes and digital twins. Additionally, it elucidates the interplay and integration between smart homes and digital twins, elucidates various smart home use cases, and highlights the pivotal role played by digital twins in the context of smart homes. The paper then transitions to a detailed examination of a temperature and humidity control system, offering insights into its specific architecture, the distinctive functions of its four modules, applicable modeling and calculation techniques, and how to interpret and utilize the results of data analysis. Furthermore, it presents a greenhouse case study, culminating in reflections on the system, optimization strategies, potential refinements, and a conclusive summary.

2 SMART HOME SYSTEM AND DIGITAL TWIN

A smart home entails the utilization of Internet of Things (IoT) technology to establish internet connectivity for various smart and household devices, enabling intelligent and automated home management and control. Through sensors, wireless communication, and intelligent control systems, smart homes empower users to achieve intelligent control and automated operation of household equipment, encompassing lighting, security, temperature, audio, TV, home appliances, and more.

A digital twin is a virtual entity serving as a digital counterpart to a physical entity, be it a device, product, process, or any other tangible object. Drawing from real-time sensor data and other relevant sources, it replicates and represents the performance and conduct of these physical entities, offering opportunities for testing, simulation, optimization, and monitoring. Digital twins play a pivotal role in supporting physical entities across their entire lifecycle, facilitating more efficient, sustainable, and intelligent operations and maintenance. The connection between smart homes and digital twins can be chiefly attributed to four key aspects.

Data Integration and Analysis: Smart homes leverage the Internet of Things to interconnect various devices, generating a wealth of sensor data. This data serves as a foundation for constructing and continuously updating digital twins, facilitating simulations and optimizations of home devices, systems, and environments.

Prediction and Optimization: The digital twin model enables the prediction and optimization of smart home operations. Through simulations and analyses of diverse situations and scenarios, crucial factors like energy consumption, safety, and comfort within smart homes can be comprehensively understood and enhanced.

Remote Monitoring and Control: Digital twins facilitate remote monitoring and control of smart homes by providing real-time data feedback. Users can employ the digital twin to gain insights into the status, performance, and energy usage of home devices, enabling them to make corresponding adjustments and controls.

Feedback Loop and Improvement: Actual usage data and information from smart homes can be fed back into the digital twin for continuous model updates and enhancements. This iterative process serves to optimize smart home performance, energy efficiency, and user experience consistently.

In conclusion, a strong connection exists between smart homes and digital twins. Leveraging digital twin technology, smart homes can undergo ongoing optimization and enhancements, ultimately reaching a heightened level of intelligence, automation, and sustainable development. The aftermath of the COVID-19 pandemic has intensified the demand for more convenient situational experience designs, with increased interest in product self-perception and regulation. Figure 1 illustrates a typical scenario in a smart home environment. This paper's focus lies in the design of a temperature and humidity control system. Through the sensing of air humidity, the humidifier autonomously determines the need for humidification and adjusts temperature and humidity levels accordingly.

Figure. 1 A typical scenario in smart home

3 DT-BASED SMART HOME SYSTEM FRAMEWORK

Digital twin technology enables the interactive mapping of physical and digital spaces. It encompasses a comprehensive application of information technologies, including perception, calculation, modeling, and more. This technology is employed to describe, diagnose, predict, and make decisions regarding physical spaces through software-defined processes, facilitating the interactive mapping between physical and digital realms. The temperature and humidity control system can be broadly categorized into three main components, as depicted in Figure 2.

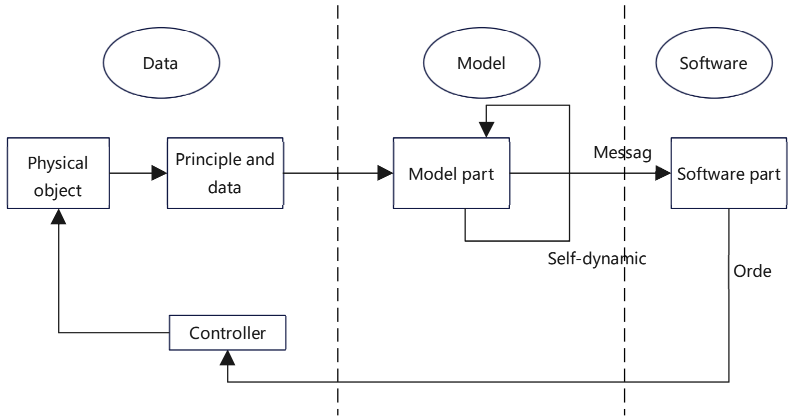

Figure. 2 The structure of temperature and humidity control system

Data forms the foundational layer, while the model serves as the central component, and software acts as the facilitating platform. The physical entity dynamically adjusts itself by transmitting principles and data to the model. Simultaneously, the model undergoes dynamic adjustments through the modeling process. Concurrently, information is relayed to the software, which executes the model algorithm, algorithmic code, and software coding. Once the software processing is complete, instructions are transmitted back to the physical entity, achieving self-regulation.

The temperature and humidity control system outlined in this paper can be segmented into five distinct layers: the application layer, model layer, data layer, physical layer, and user interface layer, as illustrated in Figure 3.

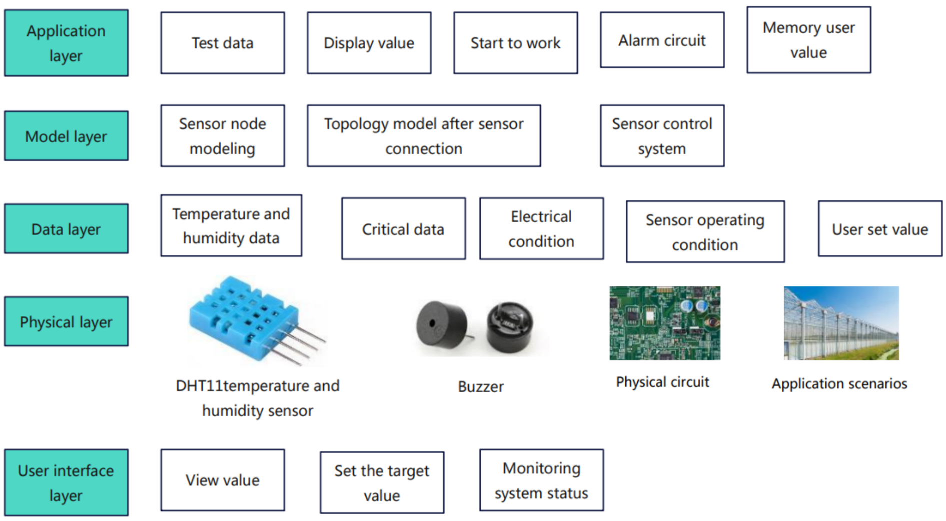

Figure. 3 Five parts of the control system

Physical Layer: The sensor layer serves as the system's foundation, continuously monitoring real-time greenhouse temperature and humidity. It encompasses multiple temperature and humidity sensors strategically placed throughout the greenhouse. These sensors gather environmental data and transmit it to the upper-level system for further processing.

Model Layer: The digital twin model layer stands as the system's core component, constructing a virtual greenhouse model based on sensor data and historical records. This model utilizes principles of physics and machine learning algorithms to meticulously simulate a greenhouse's structure, materials, heat conduction, and humidity distribution within a digital environment. The digital twin model possesses the capability to learn from and predict changes in the greenhouse environment, offering real-time forecasts and optimization strategies for temperature and humidity control.

Data Layer: Responsible for data collection, processing, and organization, this layer compiles information from sensors. The data acquisition and processing layer employ cutting-edge technologies and algorithms to dissect sensor data, performing operations such as preprocessing, filtering, and calibration to ensure data precision and reliability.

Application Layer: The control layer formulates temperature and humidity control strategies based on the digital twin model's predictions and predefined targets. It employs control algorithms and logic to adjust greenhouse actuators—such as heaters, coolers, humidifiers, or dehumidifiers—according to forecasted data, ultimately achieving the desired temperature and humidity conditions. This layer also remains receptive to real-time data, enabling continuous adjustments and feedback control to maintain the environment within the target range.

User Interface Layer: Offering a user-friendly interface, this layer facilitates interaction with the system. Users can monitor and control the temperature and humidity control system via a graphical user interface (GUI) or a mobile application. This interface empowers users to view temperature and humidity data, set target values, monitor system status, and execute manual adjustments and operations.

By seamlessly integrating these layers, the digital twin-based temperature and humidity control system excels in precise prediction and optimal control of temperature and humidity. It provides an ideal environment for plant growth and yield enhancement. Furthermore, the system exhibits flexibility and scalability, capable of customization and expansion according to specific requirements.

Compared with the traditional temperature and humidity control system, the temperature and humidity control system based on digital twin has its own advantages and characteristics in controlling temperature and humidity, reducing energy consumption and strengthening user experience. The digital twin system collects the temperature and humidity data in the greenhouse in real time, and analyzes and predicts it with the virtual model. This allows the system to control temperature and humidity parameters more precisely to meet the growth needs of crops. In addition, the digital twin system can optimize the energy consumption of greenhouses based on temperature and humidity data, crop growth models and energy efficiency algorithms. For example, in temperature control, the system can be intelligently adjusted based on predictive models and real-time data, reducing unnecessary heating or cooling operations and thus reducing energy consumption. Moreover, the digital twin system can infer the patterns and trends of temperature and humidity changes and the response of crops to temperature and humidity through algorithms and models. Based on this information, the system can automatically adjust the temperature and humidity control parameters, such as ventilation speed, heating intensity, humidity control, etc., to maintain the best growing environment. This can not only reduce the need for manual intervention, but also maintain stable temperature and humidity conditions, reducing the risk of human error. Finally, the digital twin is also more user-friendly, and users can remotely access the system through mobile devices or computers to monitor the temperature and humidity data in the greenhouse and adjust it as needed. This provides a convenient operation and management mode, and improves the user's experience and decision-making efficiency.

In general, the temperature and humidity control system based on the digital twin has the advantages of higher accuracy, real-time, intelligent control, visual management and energy efficiency, which can provide a more reliable, efficient and intelligent temperature and humidity control solution, which helps to improve the yield and quality of crops, reduce energy consumption and improve user experience.

3.1 Modeling

Digital twins employ diverse modeling methods for creating and representing digital counterparts of physical entities. Several common modeling techniques include:

Geometric Modeling: Geometric modeling, one of the fundamental and prevalent methods in digital twins, employs geometric shapes and structures to portray the appearance and form of physical entities. It may utilize computer-aided design (CAD) techniques or parametric modeling tools to craft detailed three-dimensional models, ensuring highly precise geometric representations.

Physical Modeling: Physical models encompass the physical properties and behaviors of a physical entity, adhering to physical laws, material properties, and equations of motion. These models leverage mathematical equations, physical simulations, and simulation tools to express and simulate the actions and responses of physical entities.

Statistical Models: Statistical models utilize statistical analysis methods and machine learning techniques to deduce the characteristics and behavior of physical entities. By analyzing extensive data and historical records, these models identify and model relationships and regularities among entities. Statistical models are instrumental in simulating and predicting the performance, failure risk, and optimization potential of physical entities.

Rule-Based Models: Rule-based models employ rules and logical expressions to describe and govern the behavior of physical entities. Rooted in expert knowledge and experience, these models utilize rules and conditional statements to guide entity operations and decisions, facilitating the development of automatic control policies and fault-handling rules.

Neural Network Models: Neural network models, inspired by the structure and functioning of the human brain, constitute an artificial intelligence technique. These models can be trained and learn to automatically identify features and patterns from data, subsequently applying them to model and predict complex nonlinear systems.

These modeling methods can be employed individually or in tandem, depending on specific application requirements and entity characteristics. Digital twin systems typically integrate a variety of modeling methods to achieve comprehensive digital modeling and simulation of physical entities.

3.2 Intelligent Computation

In the realm of digital twins, numerous intelligent computing and data analysis methods are available for processing and analyzing data to facilitate model construction, optimization, and prediction. Here are some common methods in this domain:

Machine learning is a method capable of learning from data and automatically extracting patterns and regularities. In digital twins, machine learning algorithms can be used to train models for recognizing and predicting the behavior of physical systems. For example, supervised learning can be employed to build predictive models, while unsupervised learning is suitable for data clustering and anomaly detection. Deep learning, a branch of machine learning, focuses on using deep neural networks for pattern recognition and analysis. In digital twins, deep learning can be applied to process complex data on a large scale, such as images and sounds. It is utilized for tasks like feature extraction, image recognition, speech recognition, and others.

Data mining is the process of automatically discovering valuable information and patterns in large data sets. In digital twins, data mining methods can be used to analyze and uncover hidden relationships and trends in data, supporting system optimization and decision-making processes. It can be applied to tasks including clustering, classification, and association rule mining. Time series analysis is an analytical method designed to process data arranged in chronological order. Within digital twins, time series analysis is employed to model and predict historical data for physical systems. It can be applied to tasks like seasonal analysis, trend analysis, cyclical pattern recognition, and more. Multimodal data analysis involves the fusion and analysis of different types of data, such as structured data, images, and text. In digital twins, multimodal data analysis can synthesize data from multiple sources to obtain comprehensive and accurate insights into the characteristics and behavior of physical entities. Optimization methods are employed to identify the best or optimal solutions. In digital twins, these methods are used to optimize the design and operating parameters of the physical system to achieve optimal performance, efficiency, and safety.

In digital twins, data preprocessing is a very important step in processing data, which can clean, filter, and repair errors and outliers in the data. Common data preprocessing methods include smoothing, interpolation, denoising and normalization. These methods can improve the quality and accuracy of data and provide a reliable basis for subsequent data analysis and control. The other is statistical analysis, one of the commonly used methods in digital twins, which can infer the distribution and correlation of data through statistical description of data, probability model fitting and hypothesis testing. Statistical analysis can be used to analyze the distribution characteristics, correlation and possible anomalies of temperature and humidity data to provide a basis for subsequent control decisions.

These intelligent computing and data analysis methods can be selectively combined based on specific problem requirements and data characteristics. By applying these methods, digital twins can detect patterns within large data sets, predict future trends, and provide insights and recommendations that support decision-making and optimization processes.

Combining artificial intelligence and machine learning techniques to optimize temperature and humidity regulation is mainly achieved through the following steps. First, data related to temperature and humidity regulation is collected, including sensor data, environmental parameters, and operational data of the regulation system. The second step is feature engineering, which selects the appropriate features to describe the state of the temperature and humidity regulation system based on domain knowledge and experience. Features may include current temperature and humidity values, time information, statistical characteristics of historical data, and other relevant sensor data. Then, according to the nature of the problem and the characteristics of the data, the appropriate machine learning algorithm or model is selected. Then there is the training and evaluation of the model. The selected machine learning model is trained using historical data and the performance of the model is evaluated using evaluation metrics. Common evaluation indicators include mean square error (MSE), mean absolute error (MAE) and correlation coefficient (R-squared). By iterating and tuning the model, the prediction accuracy and generalization ability of the model are improved. Finally, a trained machine learning model is combined with real-time sensor data to predict future trends in temperature and humidity. And continuous monitoring and feedback adjustment system.

3.3 System Optimization

To enhance the efficiency and performance of a digital twin-based temperature and humidity control system, consider the following recommendations:

Data Accuracy and Quality: Ensuring the accuracy and consistency of sensor data is crucial. Employ high-quality sensors, regularly perform calibration and maintenance, and implement data quality control algorithms to eliminate abnormal data. Additionally, explore redundant monitoring using multiple sensors to enhance data reliability.

Model Improvement and Calibration: Continuous improvement and calibration of the digital twin model are essential. Utilize actual monitoring data and historical records to regularly update and enhance the model, ensuring it accurately represents the greenhouse's performance and changes. Leverage machine learning and optimization algorithms to boost model accuracy and predictive capabilities.

Optimization of Prediction and Control Algorithms: Tailor prediction and control algorithms to the specific temperature and humidity control requirements. Consider incorporating machine learning algorithms, fuzzy control, PID control, or other methods that offer flexibility to adapt to varying conditions and targets.

Energy Efficiency Optimization: Aim for environmental protection and energy conservation by optimizing energy consumption within the system. Analyze historical data and model predictions to determine the most effective energy supply strategy and operational parameters. This may involve adjusting heating and cooling systems' timing and intensity in response to external meteorological conditions.

Real-Time Monitoring and Remote Control: Enhance system flexibility and responsiveness by implementing real-time monitoring and remote control capabilities. Employ Internet of Things (IoT) technology and remote communication interfaces to monitor and control temperature and humidity systems, even when not physically present in the greenhouse. This enables real-time adjustments and management.

Fault Detection and Maintenance: Early detection and handling of faults within the temperature and humidity control system are critical. Regularly monitor system performance indicators and key parameters to identify potential issues promptly. Implement appropriate maintenance and repair measures to ensure system reliability and stability.

These recommendations collectively contribute to optimizing the digital twin-based temperature and humidity control system's efficiency and performance. Depending on your specific circumstances and requirements, additional tailored optimization measures may also be necessary to address unique challenges and objectives.

4 AN EXAMPLE ABOUT GREENHOUSE VEGETABLE

Suppose a vast greenhouse dedicated to cultivating vegetables and plants, as depicted in Figure 4. To optimize the ideal growth conditions within this greenhouse, we've implemented a cutting-edge temperature and humidity control system powered by digital twin technology.

Our temperature and humidity control system is equipped with an array of sensors strategically positioned throughout the greenhouse, enabling real-time monitoring of environmental variables such as temperature and humidity. Leveraging the capabilities of digital twin technology, the system generates a virtual replica of the greenhouse. This digital model intricately simulates the greenhouse's architectural layout, material composition, heat conduction mechanisms, and humidity dispersion patterns. It accomplishes this by meticulously aligning and calibrating current sensor data with historical data gleaned from these sensors.

At the heart of this system lies the controller, intricately linked to the digital twin. This pivotal component processes the sensor-derived data and, upon meticulous comparison with the digital twin, leverages the model's predictive prowess to make informed decisions. The controller interfaces with an array of actuators, each serving as a mechanism directly controlled by the controller to manage temperature and humidity within the greenhouse. These actuators may include devices such as heaters, coolers, humidifiers, or dehumidifiers, each contributing to the system's comprehensive control capabilities.

The workflow of the entire system encompasses five crucial steps, each seamlessly following the other. The first step entails data acquisition, followed by digital twin model training, proceeding to control decision-making, then actuator operation, and culminating with monitoring and adjustment.

In the initial phase, temperature sensors and humidity sensors diligently capture real-time environmental data within the greenhouse. This data is then diligently transmitted to the controller. Utilizing both the current sensor data and historical data, we forge a digital twin model, meticulously training and calibrating it to perfection. This model is primed to acquire an intricate understanding of the greenhouse's distinct characteristics, the intricacies of heat conduction pathways, humidity distribution patterns, and more. Subsequently, this knowledge empowers the model to proficiently predict forthcoming temperature and humidity fluctuations.

Once equipped with these predictive insights, the controller receives real-time data and seamlessly cross-references it with the digital twin model. Leveraging the model's forecasts and the predefined temperature and humidity thresholds, the controller adeptly formulates precise decisions aimed at regulating the greenhouse's temperature and humidity levels. The controller then seamlessly communicates these instructions to the actuator, which promptly activates or deactivates the relevant devices. For instance, in the event of soaring temperatures, the controller can deploy a cooling mechanism or an automated ventilation system to rectify the situation. Likewise, if humidity levels dip below the desired range, the controller can swiftly initiate a humidifier to restore optimal humidity levels.

Additionally, the temperature and humidity control system diligently conduct periodic checks on the greenhouse's temperature and humidity. Subsequently, the digital twin model is flexibly adjusted based on current data. This perpetual cycle of model updates and calibration serves to continually enhance prediction precision and fine-tune control strategies to seamlessly adapt to ever-evolving environmental conditions.

In greenhouses, temperature and humidity are key environmental parameters for the healthy growth of cultivated crops. The traditional control method may have some problems such as low precision and slow reaction speed, but the temperature and humidity control system based on digital twin can provide more accurate and real-time monitoring and control. Digital twins can provide intelligent temperature and humidity control strategies by establishing virtual models of greenhouses, combining real-time data and algorithms. For example, parameters such as ventilation, heating, cooling and humidity control can be automatically adjusted according to the needs of the crop and changes in the growing environment to maintain optimal growing conditions.

In conclusion, the digital twin-based temperature and humidity control system harnesses the power of cutting-edge modeling and predictive technologies to deliver precise regulation of temperature and humidity within the greenhouse. Through real-time monitoring and adaptive adjustments, the system masterfully optimizes the growth environment for crops, subsequently boosting yield and quality while simultaneously curbing energy consumption.

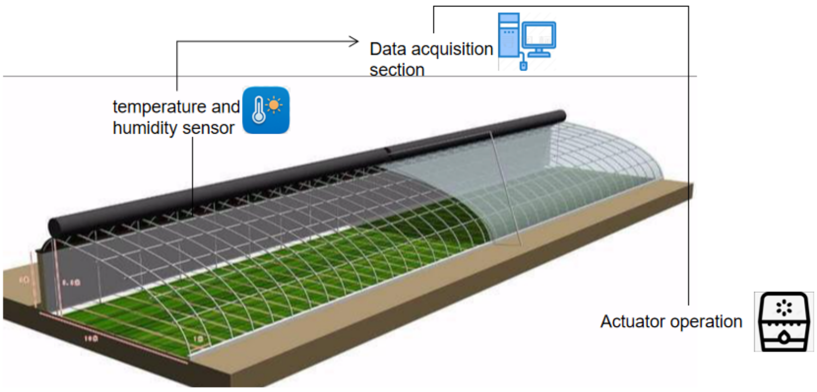

Figure. 4 A greenhouse example for growing vegetables and plants

5 CONCLUSIONS AND FUTURE WORK

The intelligent humidifier system, powered by digital twin technology, employs virtual modeling, sensor data, and machine learning algorithms to automate and enhance the humidification process. This system boasts several key advantages over conventional humidification systems. Firstly, it significantly improves humidification efficiency by leveraging digital twin technology to precisely model both the indoor environment and the humidifier's operational state. Real-time data monitoring and analysis enable intelligent adjustments to the humidifier's parameters, ensuring optimal humidity levels indoors. Secondly, digital twins forecast indoor humidity and temperature fluctuations, enabling personalized and environmentally responsive control of humidifier systems. This feature results in a more comfortable indoor environment, alleviating dryness and discomfort. Thirdly, the system promotes energy conservation and environmental sustainability by monitoring real-time energy consumption and performance metrics. It optimizes energy use, reducing carbon emissions and contributing positively to sustainable development. Finally, the abundant real-time data made available by digital twin technology facilitates data-driven decision-making through machine learning algorithms. By continuously improving and adapting its algorithms, the system autonomously adjusts the humidifier's operation mode to meet specific requirements, ultimately enhancing system performance and adaptability.

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