UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Faculty of Business Administration and Management

Design and Business Validation of an AI-Powered Resource Management System for Smart Greenhouses: A Sustainable Approach to Agricultural Innovation

Master's Thesis

Master's Degree in Business, Product and Service Management

AUTHOR: Arianfar, Ramin

Tutor: González Ladrón de Guevara, Fernando Raimundo

ACADEMIC YEAR: 2024/2025

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Abstract

This thesis deals with the design and implementation of an AI-based smart resource management system for smart greenhouses, which enables precise control of environmental parameters by combining system dynamics and machine learning techniques. Among the innovations of this research is the use of a machine learning method to optimize system performance and the provision of a model for managing financial risks, including unforeseen costs and uncertainty in investment returns. Also, a preventive plan is presented to reduce maintenance costs and modeling resource losses during the transition period. The results of implementing this approach in a smart greenhouse in Taiwan showed that environmental parameters such as temperature and humidity are controlled with high precision and provide favorable environmental stability for plant growth even in conditions of sudden climate changes. This system saves significant resources by reducing water and energy consumption and reduces operating costs. In addition, economic analyses have shown that although the initial investment for the deployment of this system is high, in the long run, the reduction in resource consumption costs and increased productivity prove its economic justification. The evaluation of the system in four areas of efficiency, production, sustainability and cost showed that this method is superior to traditional methods in all dimensions. Also, the stable performance of the system in variable weather conditions confirms its reliability for use in regions with different climates. This research is an effective step towards the development of smart and sustainable agriculture and shows that artificial intelligence-based technologies can simultaneously achieve economic and environmental goals.

Keywords: Resource management, artificial intelligence, smart greenhouses, machine learning, increasing productivity, reducing costs.

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Chapter One

INTRODUCTION

1. 1. INTRODUCTION

Agriculture, as one of the oldest and most vital human activities, has always faced numerous challenges such as climate change, depletion of natural resources, and increasing global demand for food. With population growth and limitations on agricultural land, the need for new and sustainable methods to increase productivity and reduce waste is increasingly felt. In this regard, smart greenhouses, as an advanced solution, provide the possibility of precise control of environmental conditions and optimization of resources. Using modern technologies, these systems not only increase crop yields, but also minimize the consumption of water, energy, and other inputs [1].

Using sensors, the IoT, and automated control systems, smart greenhouses collect and analyze data on temperature, humidity, light, and other environmental parameters in real time. This data helps farmers make more informed decisions and provide optimal conditions for plant growth. However, effective management of this data and resources requires more advanced systems that can use artificial intelligence to identify complex patterns and provide accurate predictions. With the ability to analyze massive amounts of data, artificial intelligence can help improve resource management, reduce costs, and increase sustainability in greenhouses [2].

1. 2. STATEMENT OF THE PROBLEM

Rapid population growth and urbanization have led to a corresponding increase in demand for food. The decline in arable land is an inevitable consequence of population growth, urbanization, and the resulting industrial culture and life. Climate change and its resulting damages, soil degradation, and environmental pollution are among the factors that have negatively affected the production of agricultural products and have affected food security [3].

Meeting the food needs of society in traditional agricultural patterns requires more land, water, energy, and human resources, which are impossible to obtain given the current conditions on Earth. The increased use of technology has been one of the solutions that societies have used to reduce these problems and their negative consequences. Among the various technologies, special emphasis should be placed on information and communication technologies in recent decades. These technologies have further increased the mechanization and automation of various work and professional processes, to the extent that work tools and processes have also become information-centric [4]. Smartification is perhaps the culmination of the application of information and communication technologies in all types of human actions and human-made tools in all scientific, technical, industrial, agricultural, etc. fields. Smart agriculture is one of these fields. Smart greenhouses are a subset of smart agriculture, which in recent decades, like other fields, has used modern information and communication technologies to improve the production of various greenhouse products. That is, by using smart tools, the consumption of various production resources, such as water, energy, human power, etc., is reduced. In smartification, by optimizing the planting, storage, and harvesting processes, the quantity and quality of the product is increased [5].

Growing agricultural products in smart greenhouse environments outside of crop fields is an important and innovative topic in the field of agriculture. Monitoring weather conditions and facilitating access to products at the point of consumption are among the prominent advantages of this method. The monitoring system usually includes sensors, actuators, LCD displays, and microprocessors. In addition, other equipment such as fans, heaters, and other devices are also used. But the key point is that these devices automatically and intelligently monitor environmental conditions. For example, controlling temperature (high or low), humidity, carbon dioxide concentration, aeration, irrigation, and water evaporation are among the main challenges for producers in traditional greenhouses. Monitoring various environmental indicators is essential to achieve maximum greenhouse efficiency and create an optimal environment with efficient use of energy and other vital resources [6].

In recent decades, environmental crises and the need to optimize resources in the agricultural sector, especially in smart greenhouses, have become one of the fundamental challenges. The increase in global population, climate change, and the limitation of natural resources such as water and energy have placed increasing pressure on agricultural systems. Greenhouses, as one of the modern solutions in agriculture, have the potential to increase production and improve product quality by providing a controlled environment. However, improper management of resources such as water, energy, and nutrients can lead to increased operating costs, reduced productivity, and environmental damage [7].

Current management systems in greenhouses mainly face limitations that affect the efficiency of these resources. These limitations include inefficiency in resource allocation, lack of flexibility in response to environmental changes, and inability to accurately predict plant needs. For example, traditional irrigation systems may waste water, or temperature and humidity control systems may consume more energy than is actually needed. These problems not only increase operating costs, but also threaten environmental sustainability [8].

Given these challenges, the need to develop more advanced resource management systems that can intelligently and automatically optimize resources is increasingly felt. Artificial intelligence, as an emerging technology, has great potential to solve these problems. Using machine learning algorithms and real time data analysis, artificial intelligence can help improve resource allocation decisions, reduce waste, and increase productivity in greenhouses [9].

This thesis aims to design and validate an advanced resource management system using artificial intelligence that can address the challenges of smart greenhouses by optimizing resource allocation. To achieve this goal, a detailed analysis of the shortcomings and problems of existing systems must first be conducted. This analysis includes evaluating current resource allocation methods and identifying their weaknesses in the areas of water, energy, and plant nutrition. In addition, assessing financial and operational risks, including higher than expected costs, uncertainty in return on investment, maintenance costs, and resource loss during transportation, are other important aspects of this research. By identifying these risks and developing preventive plans and control measures, a comprehensive and sustainable picture can be achieved for implementing an AI system.

On the other hand, this research also focuses on the commercial and market aspects of the proposed system and analyzes its market opportunities and commercial potential. Given the increasing demand for quality and sustainable agricultural products, intelligent resource management systems can be considered as an innovative solution in the market. Therefore, the results of this research can help implement an acceptable business model that benefits farmers, consumers, and the environment, in addition to reducing operating costs. Overall, the research aims to contribute to the advancement of sustainable agricultural practices and innovation in agricultural resource management. Also, by providing practical solutions based on rigorous scientific processes and efficient validation, this research seeks to improve resource management in smart greenhouses and develop sustainable agriculture.

1. 3. SIGNIFICANCE OF RESEARCH

Given the increasing challenges facing the agricultural sector in optimizing resources in controlled environments such as smart greenhouses, the development of an AI-based resource management system is of great importance. Current management systems have limitations in the efficiency of water, energy, and nutrient use, which not only affects operational costs but also environmental sustainability. Aiming to address these challenges, this research designs and validates an intelligent resource management system that can help improve efficiency and reduce costs.

On the other hand, innovation in agriculture, especially in controlled environments such as greenhouses, requires sustainable and technology-driven approaches. The system proposed in this research enables forecasting and resource optimization using machine learning algorithms. This not only helps reduce resource waste, but can also be used as a sustainable business model for large-scale implementation. Therefore, this research is important not only from a technical perspective, but also from an economic and commercial perspective.

Considering potential financial risks such as higher than expected costs, uncertainty in investment returns, maintenance costs, and resource waste during the transition, this research presents a prevention plan, control measures, and monitoring indicators to manage these risks. This comprehensive approach not only helps reduce financial risks but also increases the possibility of successful implementation of the system in real-world environments. Ultimately, the results of this research can help advance sustainable agricultural practices and provide a viable business model for commercial implementation of the system.

1. 4. RESEARCH QUESTIONS

The most important questions of this research are as follows:

1) How can we optimize the allocation of resources (water, energy, and nutrients) in greenhouses using artificial intelligence to reduce waste and increase productivity?

2) What are the barriers and risks in implementing AI-based resource management systems? How can these barriers and risks be identified and managed?

3) What is the commercial potential of the proposed system? What impact will it have on agricultural business models and how can it be brought to market?

4) How can the proposed system help reduce the environmental impact of agriculture and increase sustainability?

1. 5. RESEARCH OBJECTIVES

The most important objectives of this research are as follows:

1) Investigating and presenting artificial intelligence-based solutions to optimize resource allocation (water, energy, and nutrients) in greenhouses, with the aim of reducing waste and increasing productivity in agricultural processes.

Here, machine learning will be used as one of the artificial intelligence methods. Also, the resource allocation optimization criteria include reducing water and energy consumption in percentage terms and increasing greenhouse crop production in kilograms per square meter.

2) Identifying potential obstacles and risks in implementing AI-based resource management systems and providing practical solutions to manage and mitigate these risks.

Here, barriers can specifically include technical difficulties, initial costs, and the need for staff training. At least three practical ways to manage and mitigate each of these risks will be presented.

3) Analyzing the commercial potential of the proposed system and examining its impact on agricultural business models, along with providing appropriate strategies for the introduction and commercialization of this technology in the market.

This goal will include a comparative economic evaluation of the system and market forecast, along with presenting at least two business models based on this technology and estimating revenue and operating costs for each.

4) Evaluating the role of the proposed system in reducing the environmental impacts of agriculture and increasing environmental sustainability through optimizing resource consumption and reducing waste.

This goal specifically focuses on the percentage reduction in water and energy consumption, as well as the reduction in environmental pollution from waste generated (in kilograms of waste reduced).

1. 6. THE CONCEPTUAL MODEL

Based on the objectives stated in the previous section, finally, the conceptual model of the present research is as shown in Fig. (1.1).

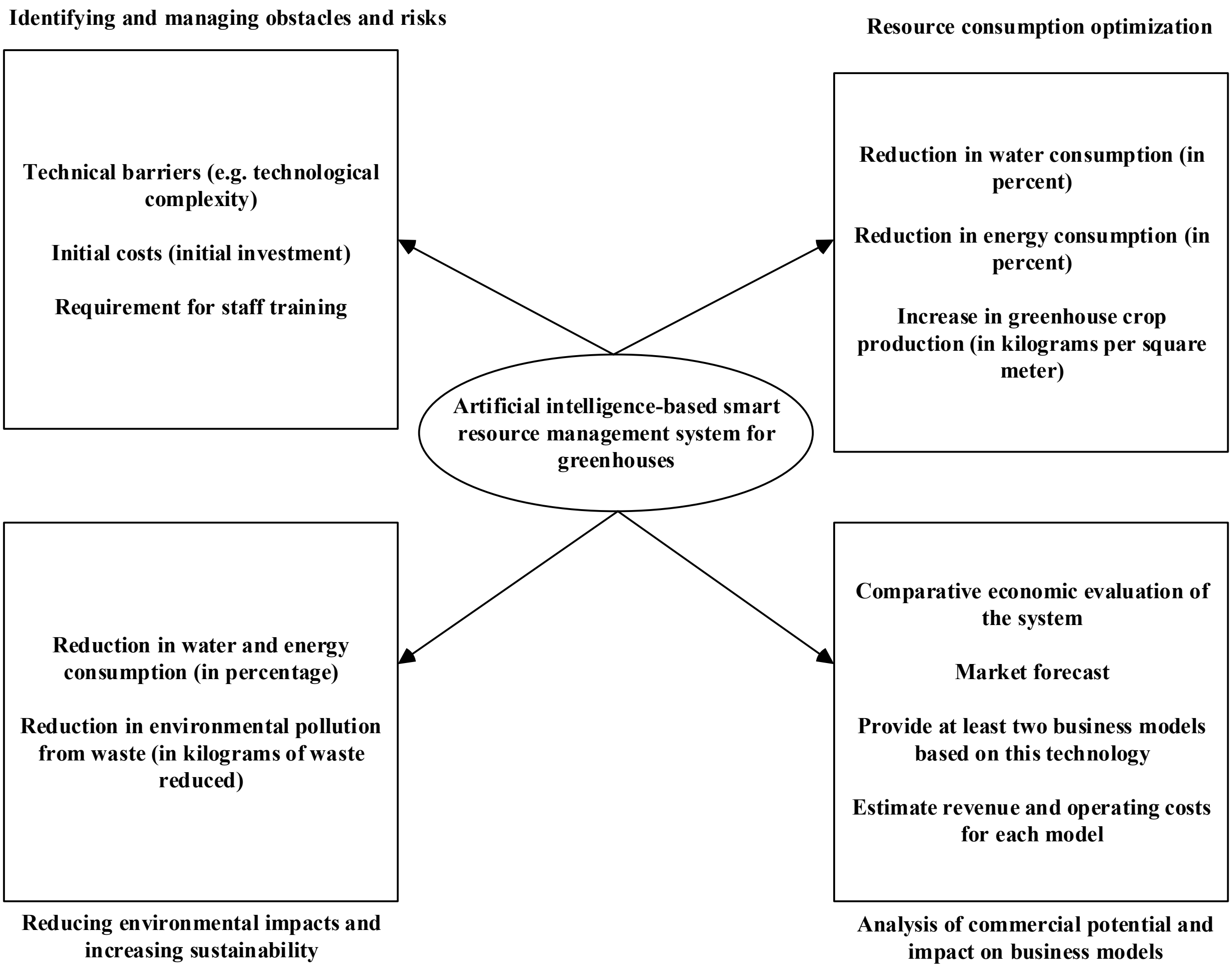

Fig. (1. 1): Conceptual model of the research

1. 7. RESEARCH ORGANIZATION

In the first chapter, the problem statement, importance and necessity of the research, as well as the research objectives and questions, were presented. In the second chapter, the theoretical foundations and background of research conducted in this field are discussed. In the third chapter, the proposed business model based on artificial intelligence for optimal resource management in smart greenhouses is discussed, which is an innovative approach towards sustainable management in the field of agriculture. In the fourth chapter, the results obtained from the implementation of the proposed plan are presented and discussed. Finally, in the fifth chapter, while presenting conclusions, suggestions for future research are presented.

Chapter Two

LITERATURE REVIEW

2. 1. INTRODUCTION

This chapter explores innovations in agriculture, particularly smart greenhouses, and the role of advanced technologies such as artificial intelligence (AI) in managing and controlling these systems. Given global challenges such as climate change, depletion of natural resources, and increasing food demand, the use of modern technologies in agriculture has become a necessity. This chapter begins by examining concepts related to innovation in agriculture, the differences between mechanization, automation, and smart greenhouses, and the main components of smart greenhouses. Next, the various types of sensors used in smart greenhouses and the benefits of these systems are analyzed. Subsequently, the applications of AI in soil management, crop health, weather forecasting, smart irrigation, and harvesting are discussed, along with the steps for designing and implementing AI algorithms for smart greenhouses. Finally, a review of the existing literature in this field is provided to establish the theoretical framework necessary for developing an AI-powered resource management system.

2. 2. INNOVATION IN AGRICULTURE

Smart agriculture is a fundamental transformation in the agricultural sector, using new technologies such as the IoT, artificial intelligence, robotics and data analytics to increase productivity, reduce costs and improve environmental sustainability. In this approach, networked sensors collect data on soil, water, air and plant health conditions in real time and send it to central systems. This data is analyzed using artificial intelligence and machine learning algorithms to help farmers make more accurate and faster decisions. For example, smart irrigation systems use soil moisture data and weather forecasts to optimize water use and prevent resource waste [10].

Another emerging innovation in agriculture is the use of robots and drones to perform tasks such as planting, spraying, monitoring fields, and harvesting crops. These technologies not only increase the accuracy and speed of agricultural operations, but also reduce the need for human labor. Equipped with advanced cameras and sensors, drones can monitor plant health through multispectral and thermal imaging and identify areas damaged or infested by pests. Harvesting robots use computer vision and artificial intelligence algorithms to detect ripe crops and harvest them with high precision. These technologies are particularly useful in areas with labor shortages or harsh environmental conditions [10].

In addition, emerging technologies such as vertical farming and smart greenhouses are also changing the face of agriculture. Vertical farming, using multi-layer systems and artificial lighting, allows for the production of crops in limited space and close to consumption centers. This method not only reduces water and land consumption, but also makes it possible to produce crops all year round. Smart greenhouses also use sensors and automated control systems to precisely regulate environmental conditions such as temperature, humidity, and light, increasing crop yields. Together, these innovations are driving the future of agriculture toward more sustainable, efficient, and climate-resilient systems.

Architecture based on IoT protocols and development of AI applications is shown in Fig. (2. 1) [10].

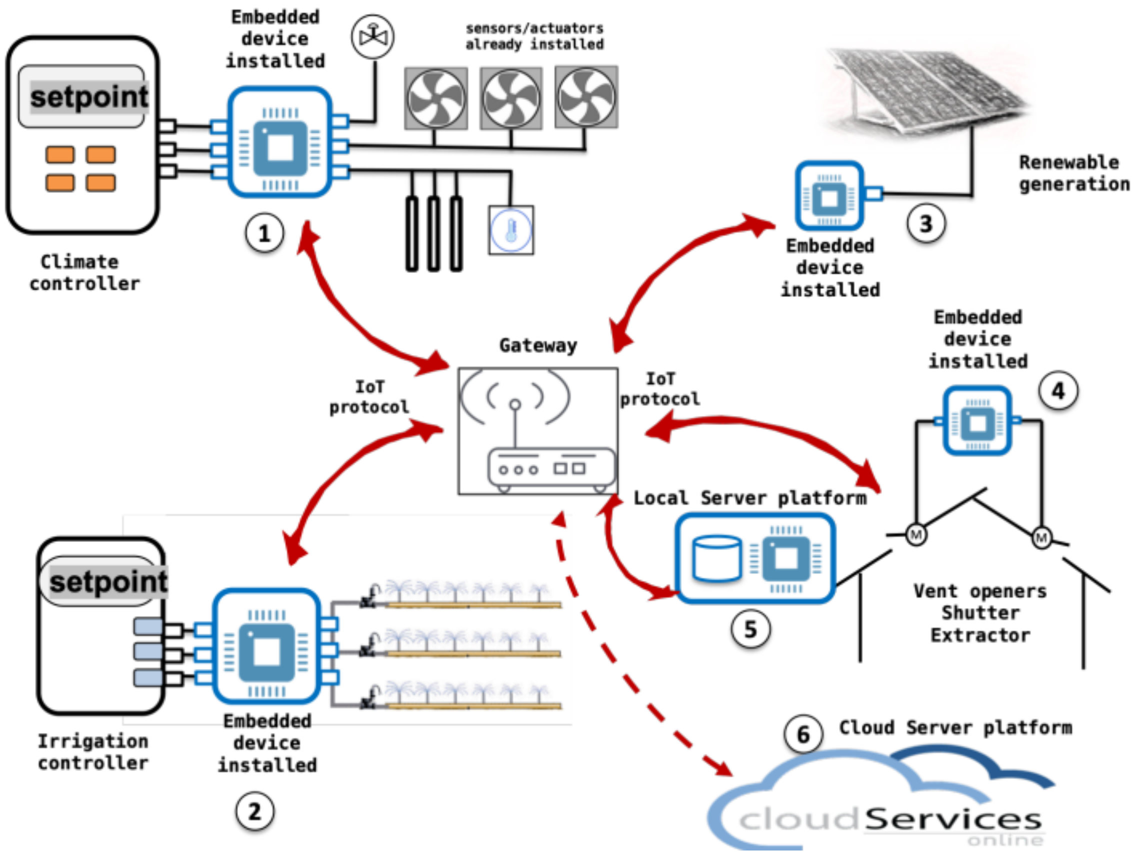

Fig. (2. 1): Architecture based on IoT protocols and development of AI applications [10]

Therefore, smart greenhouses are considered one of the important innovations in the field of agriculture, and the focus of this study is on optimal resource management in these greenhouses.

2. 3. SMART GREENHOUSES AND THEIR FEATURES

A smart greenhouse is a greenhouse that is managed remotely and as automatically as possible using a variety of interconnected hardware and software. In fact, the informationization of tools and processes is the greatest feature of smart greenhouses. Using a variety of collection methods, various data are collected and sent to the software platform with communication tools. The main task of this platform is data analysis and decision-making. This platform, like all information systems, has hardware, software, and communication tools. Other tools used in smart greenhouses, such as various types of water valves and gates, cooling and heating systems, sprinkler irrigation, and other equipment, are also mainly equipped with automated information and communication technologies [11].

Smart greenhouses can maintain ideal climate conditions. IoT sensors allow farmers and professionals to collect data from multiple locations in unprecedented detail. They provide precise information about climate factors such as temperature, humidity, light intensity and carbon dioxide throughout the greenhouse. By analyzing this data, the temperature, ventilation inside the greenhouse, and lighting can be adjusted to maintain the best plant growth conditions and increase energy efficiency [12]. A variety of motion/acceleration sensors also monitor and manage the opening and closing of doors. Irrigation and fertilization are optimized based on the actual needs of the plant and to ensure maximum performance. For example, soil volumetric water information indicates whether the soil is in water stress or not. Information related to soil salinity also provides insight into the quantity and quality of plant fertilization. Based on this data, irrigation and sprinkler systems can be automatically turned on to meet crop needs at the right time, while also reducing manual intervention [13].

In these greenhouses, crop infections can be monitored to prevent the spread of disease. Crop contamination is a constant challenge in agriculture. Any disease will cause plant loss as well as huge financial losses. There are also devastating environmental impacts, producer and consumer safety, and the spread of some more widespread diseases. In smart greenhouses, a variety of methods are available to combat agricultural pests and diseases. However, greenhouse owners may not have enough information about the best time to treat plants and the methods. Intelligent systems connected to various learning systems and databases can not only provide farmers with much of this information, challenges, and mechanisms to solve them when needed, but they can also implement a large part of the solutions with the help of various software and hardware, automatically, intelligently, and with minimal cost and human intervention [14].

Increased safety and theft prevention are also important, especially in greenhouses with special and valuable products. Traditional surveillance networks, even with CCTV cameras, are expensive and lack many of the benefits and functions of intelligent systems. A variety of IoT sensors in smart greenhouses, connected to alarm systems and automated operations, are a cost-effective and efficient infrastructure for monitoring the environment and identifying suspicious activities [15].

Fig. (2. 2): Process flowchart for the prototype of the smart system embedded in smart greenhouses [16]

The flowchart of the process for the prototype of the intelligent system embedded in smart greenhouses is shown in Fig. (2. 2) [16].

2. 4. THE DIFFERENCE BETWEEN MECHANIZATION, AUTOMATION, AND SMART GREENHOUSES

Human-made tools that facilitate human activities are called machines. A close look at the development and operation of machines reveals that these tools are becoming more and more automated. Intelligent machines should be considered simple or automated machines that also simulate some of the human brain's abilities. For example, they can calculate and announce the number, weight, color, size, and some other characteristics at the same time as they are being picked up. The simplest smart devices are moisture and soil sensors. More advanced smart machines can remotely detect and report crop area, harvest rate, and even pests and diseases. In addition to performing the activities mentioned, various types of drones can also be helpful in spraying, transportation, and many other agricultural activities [17]. In all of these cases, they can also record, transmit, process, and even make decisions about the detailed and aggregated data related to those activities. It is this feature of automatic data generation and processing that makes them intelligent. In other words, in all these cases, the levels of automation as well as the integration of actions and functions in different agricultural processes are different. It should be noted that smart machines are advancing automation to levels of intelligence or human brain function. Thus, they reduce the amount of physical and even mental human intervention in the operation of machines and various production processes, etc [18].

The aforementioned developments show that it is somewhat difficult to determine the boundary between automation and intelligence in advanced machines. Most intelligent machines are also automated. It should even be said that most advanced automated machines are also intelligent. The difference lies more in the levels of automation, intelligence, and their quantity and quality [19].

Automated and smart greenhouses also have different levels. From making some specific and limited tools smart to making an entire greenhouse and its dimensions and size smart. Therefore, when using the term smart for all types of greenhouses, this important point should be noted and this term should not be easily used for every greenhouse. In fact, a smart greenhouse is a greenhouse in which all processes related to monitoring and managing its basic indicators are managed automatically and by receiving data collected using a variety of sensors. In a system equipped with a variety of hardware and software, this data is analyzed and the feedback or result is transmitted to other automated equipment and tools in different parts of the greenhouse. In other words, this data is used to identify current problems in the greenhouse. Thus, air conditioning, lighting, irrigation, spraying, etc. are carried out as needed. This is of great importance in countries with limited water resources due to severe water resource constraints. In such countries, natural cultivation may not be possible or traditional agriculture may cause irreparable environmental damage. For this reason, the expansion of smart and automated greenhouses could be vital for the agricultural industry and self-sufficiency in agricultural production.

2. 5. COMPONENTS OF SMART GREENHOUSES

Sensors are one of the most widely used information and communication hardware or technologies in smart greenhouses. The main task of sensors is to automatically collect data from the environment. Tools such as cameras and video cameras are also used to monitor the environment. To collect information in large or remote and dangerous environments, sensors and cameras may be installed on other tools such as satellites and drones. These same sensors and cameras are installed on a variety of vehicles and machines widely used in the agricultural field to collect data and information necessary for analysis, decision-making, and implementation. Automation is used in the operation of a variety of traditional machines for planting, tending, harvesting, and other processes. Using various sensors and cameras, these tools can collect data and send it to various software and vice versa through various communication tools. Communication tools may be wired or wireless. Telephone, satellite, and internet are also part of communication tools. The main task of these tools is to transfer data received from tools, sensors, cameras, people, etc. to the platform or analysis software and vice versa [20].

Various types of displays also display data and information. Most of these displays allow the user to interact with the software and execute related commands using a keyboard or touch. A software platform is a set of interconnected software and hardware whose main function is to receive and store data, process and analyze data, display information, and send it to other tools and software [21].

The important point in all types of information and communication technologies and systems is that they are becoming increasingly integrated. That is, sensors, cameras, communication tools, analysis software, etc. are integrated on a single chip or small devices. For this reason, it is often difficult to separate them into separate hardware, software, and communication tools. For example, mobile phones, laptops, and even some small chips have integrated thousands of separate functions. Today, the IoT and artificial intelligence have provided a broad opportunity for all fields to connect various tools and software and monitor and manage them remotely. These tools and systems are also widely used in agriculture, horticulture, animal husbandry, and other fields. Connecting tools, farms, greenhouses, etc. to various databases and application software has made it possible for farmers, industrialists, marketers, consumers, etc. to connect to each other and to knowledge that is scattered in different parts of the world. Using these scattered but interconnected components and using various information and communication technologies, it is possible to manage a flower or any other product from production to consumption. It is as if all these scattered components are connected to each other and to the goods being grown and consumed locally and globally. The information about the plant from production to consumption is stored on a small chip and everyone knows about it, even when it is being transported in a car or plane to a buyer or consumer on the other side of the world. In the following, some components of smart greenhouses, especially sensors and monitoring platforms, are briefly introduced [22].

2. 6. SMART GREENHOUSE SENSORS

Applying IoT and AI-based methods in smart greenhouses requires the use of a variety of advanced sensors to collect accurate and real time data on environmental conditions and plants. These sensors act as the eyes and ears of the smart system, measuring information such as temperature, humidity, light, carbon dioxide levels, soil moisture, and other vital parameters. Generally, sensors used in smart greenhouses include temperature sensors, humidity sensors, light sensors, soil sensors, gas sensors, and motion sensors. Each of these sensors plays a key role in optimizing plant growth conditions, reducing resource consumption, and increasing productivity. In fact, the effectiveness of AI in managing smart greenhouse resources is mainly achieved through intelligent management and control of sensors. By analyzing data collected by various sensors, such as temperature, humidity, light, and soil sensors, AI identifies complex patterns and makes optimal decisions to adjust environmental conditions [23]. These systems are able to automatically perform actions such as adjusting irrigation systems, controlling temperature and humidity, and adjusting light intensity, which leads to reduced consumption of resources such as water, energy, and fertilizer. In this way, AI not only increases the efficiency of greenhouses, but also contributes to environmental sustainability by more precise resource management. The following is an introduction and examination of the performance of each of these sensors to better understand their importance in creating a controlled and automated growing environment [24].

2. 6. 1. Temperature and humidity sensor

High or low temperature and dryness and humidity are some of the obstacles to plant growth and development. For example, high humidity makes mold and other types of pests common in greenhouses. Accordingly, by precisely adjusting temperature and humidity, the best environment for plant growth can be provided. For this purpose, a sensor is needed that provides accurate information about temperature and humidity. There are many options available to choose from depending on your needs. Often, a sensor that can monitor temperature and humidity simultaneously is appropriate [25].

The temperature and humidity sensor can be connected to an external monitor. It is natural that direct sunlight will increase the temperature or humidity of the greenhouse too much. In this situation, the temperature and humidity sensor uploads its value to the public platform. After observing and processing this data, the public platform sends a message to the greenhouse fan monitor or other equipment related to cooling, heating and anything else to make the necessary adjustments [26].

2. 6. 2. Light sensor

Proper lighting can maximize plant growth and development while minimizing energy consumption. By properly adjusting lighting, plant growth can be increased and this data can be used to automate supplemental lighting and direct light to different parts of the greenhouse. A light sensor is a suitable tool for assessing the light reception status of plants. Two types of sensors are commonly used to measure light in greenhouses: 1) Total radiation, which is usually called an energy unit, and 2) Photosynthetically active radiation [27].

The first type of sensor measures all the light from the sun using a light-receiving surface. This sensor usually uses the sun, which is in the wavelength range of 0.3 to 3 microns. If the sensor is mounted horizontally and pointing downwards, it measures the reflected radiation. Therefore, to measure the scattered radiation, the scattered light shield can be added to the reflected radiation value.

Photosynthetically active radiation is the main source of energy for biomass formation. The effective photosynthesis rate of plants affects their growth, development and performance. The photosynthetically active radiation sensor actually uses a photoelectric sensor and can be used to measure photosynthesis in the spectral range of 400 to 700 nm. When light is present, a signal proportional to the intensity of the radiation is produced [28].

2. 6. 3. Carbon dioxide sensor

Carbon dioxide is a raw material for photosynthesis in green plants. 95% of the dry weight of crops is obtained from photosynthesis. Therefore, carbon dioxide is an important factor in crop performance. If the greenhouse is closed for a long time, the air circulation inside it is stopped. With sunrise, due to the acceleration of plant photosynthesis, the concentration of carbon dioxide inside the greenhouse decreases sharply and sometimes reaches below the carbon dioxide compensation point (0.01-0.008%). Under such conditions, greenhouse plants can hardly have normal photosynthesis. This affects the growth and development of plants and challenges their performance. Therefore, the use of carbon dioxide sensors to monitor carbon dioxide concentrations in greenhouses is very crucial. Currently, non-dispersive infrared technology is the most common carbon dioxide sensor [29].

The carbon dioxide sensor should be selected and installed according to the area of the greenhouse. In relatively small areas, the equipment should be installed in the center of the greenhouse so that the entire greenhouse can be monitored with one device. Installing the sensor on the wall is more appropriate. Of course, most greenhouses do not have good installation conditions. In this case, it is better to install the sensor on a steel pipe and install it in the greenhouse [30].

2. 6. 4. Planting bed moisture sensor

The amount of water in the soil is the driving force for plant growth. When the water content in the soil is relatively high, water enters the plant along with the nutrients in the substrate. However, with insufficient water content in the soil, its concentration in the plant root is lower than in the surrounding growth medium. This causes the main root activity to be directed more towards the soil environment and the elements present in the substrate to enter the plant. The low amount of water available to the plant affects its growth. Monitoring the soil moisture in the greenhouse can help increase the yield [31].

It is recommended to choose a soil moisture sensor with a stainless steel rod because it can be placed or buried in the growing bed for long-term monitoring without worrying about damage to the sensor. The growing bed moisture sensor is connected to a monitor. After detecting a decrease or increase in soil moisture, the monitoring platform sends a signal to the controller to turn the drip irrigation system on or off [31].

2. 6. 5. pH sensor of cultivation bed

The effect of soil pH on crop growth is mainly manifested in the appearance and shape, metabolism, growth and development, quality and yield of plants. Excessively acidic or alkaline soil affects the growth of plant roots to some extent and consequently the natural growth and development of plants. An imbalance in the acid-base balance of the soil can reduce the availability of nutrients in the growing medium and affect the fertility of the medium. Therefore, it is necessary to monitor the pH of the growing medium with a sensor for the growth of greenhouse crops. If this indicator is inappropriate, the medium can be amended with proper fertilization to improve its fertility.

Multi-purpose sensors can be used to better monitor various indicators of the growing medium. Thus, with one sensor, the growing medium temperature, humidity, conductivity, pH, and the amount of nitrogen, phosphorus, and potassium can be monitored simultaneously [32].

2. 6. 6. Wind speed and direction sensor

Wind speed and direction sensors are usually installed outside the greenhouse and in the open air. When the wind speed exceeds a predetermined threshold, the monitoring mast sends a signal to the supervisor to close the shutters. As a result, damage caused by strong winds is prevented. An anemometer is the most common method of measuring wind speed. The wind rotates the anemometer around a vertical axis, and the number of rotations in a given time interval is used to determine the wind speed [33].

2. 6. 7. Rainfall sensor

A rain gauge is the most common sensor for measuring rainfall. This sensor is installed outside the greenhouse. The monitoring platform prevents problems caused by rainfall by measuring the amount of rainfall, closing or restricting roof vents or retracting the roof [34].

2. 7. BENEFITS OF SMART GREENHOUSES

In this section, the most important benefits of smart greenhouses are introduced.

Precise control of environmental conditions: Using intelligent systems, smart greenhouses can precisely control light, temperature, humidity, and other environmental parameters. This allows plants to grow in the best possible way.

Reducing water consumption: Smart systems can estimate the amount of water needed by plants based on environmental conditions and actual needs, thereby helping to reduce water consumption and save money.

Increased crop yield: Optimized environmental conditions help farmers increase production and quality of crops.

Reducing the use of chemical fertilizers and pesticides: By carefully controlling the environment and plant growth conditions, the use of chemical fertilizers and pesticides is reduced, ultimately leading to more sustainable agriculture [35].

Disease prediction and prevention: Smart systems use data analysis to predict plant diseases and pests and provide preventive measures.

Reducing crop waste: By improving the control and management of environmental conditions, crop waste is reduced because conditions for optimal growth and development of plants are provided.

Precision farming: Using integrated data from various sensors and devices, farmers will make better decisions about their planting, irrigation, and greenhouse management practices.

Remote control: Through smart systems, farmers are able to control and manage their greenhouses remotely.

Cost Reduction: One of the most important benefits of smart greenhouses is that they can be very effective and useful in reducing costs for farmers. Given the reduction in energy and water consumption by making greenhouses smart, it can be expected that greenhouse maintenance costs will also decrease in the same proportion [35].

2. 8. SMART GREENHOUSE CONTROL AND MONITORING SYSTEM USING ARTIFICIAL INTELLIGENCE

The AI-based control scheme for resource management in smart greenhouses is shown in Fig. (2. 3) [36]. As can be seen, this scheme includes a climate control system. This system adjusts the air conditioning equipment installed in the smart greenhouses by receiving feedback from changes in weather parameters through various sensors. The operation of this system is based on predicting parameters such as humidity, temperature, light intensity, etc., which, with the help of artificial intelligence technology and an expanded model based on artificial intelligence, can optimize resource management in a way that achieves the highest level of energy savings.

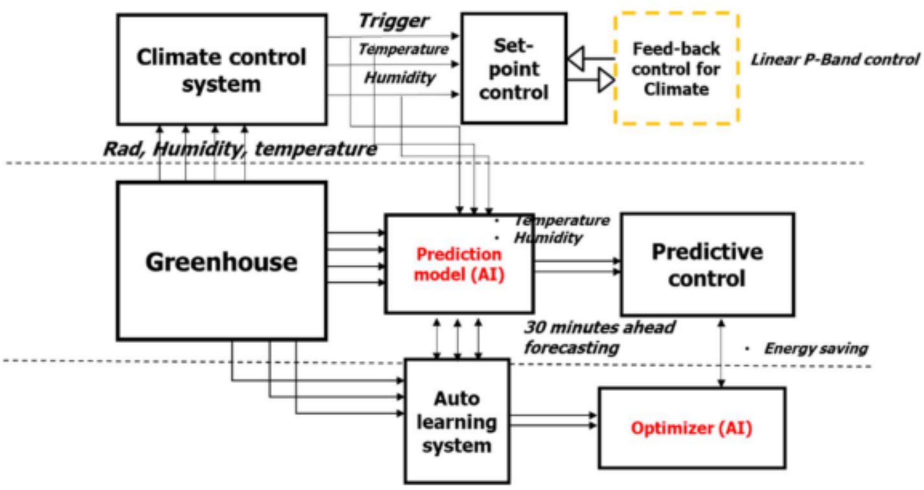

Fig. (2. 3): Artificial intelligence-based control scheme for resource management in smart greenhouses [36]

The smart greenhouse system consists of a data collection unit, a data communication unit, a data processing unit, and a system control section. Fig. (2. 4) shows this system with a detailed flowchart along with its main sections [37]. In the following, the different sections of this smart greenhouse control and monitoring scheme are described, the aim of which is to optimally manage resources in these greenhouses.

1) Data acquisition unit: Continuous environmental variables such as ambient temperature, humidity, soil moisture and light intensity inside the greenhouse are measured by sensors. DHT11 sensor can be used to measure temperature, YL-69 sensor to measure soil moisture and photoresistor sensor to measure sunlight intensity. All these sensors periodically collect environmental conditions in real time and send the data to the ANFIS system.

2) Data communication unit: Protocols such as MQTT (Message Queuing Telemetry Transport) are used to send and receive data wirelessly between sensors and the microcontroller board. Communication between Arduino and other mobile devices is established via GSM or TCP/IP.

3) Data processing: The fuzzy logic controller receives input data from sensors and calculates the sensor data to generate output to adjust greenhouse parameters and make intelligent decisions for the environment.

4) Control section: The control section includes actuators such as fans, heaters, humidifiers, motors, and exhaust fans that operate based on sensor data. The fuzzy logic controller manages the operation of heating, fans, humidifiers, etc. By adding new sets and rules in ANFIS, the temperature, humidity, soil moisture, and light intensity of the greenhouse can be adjusted based on the status of the data processing section [37].

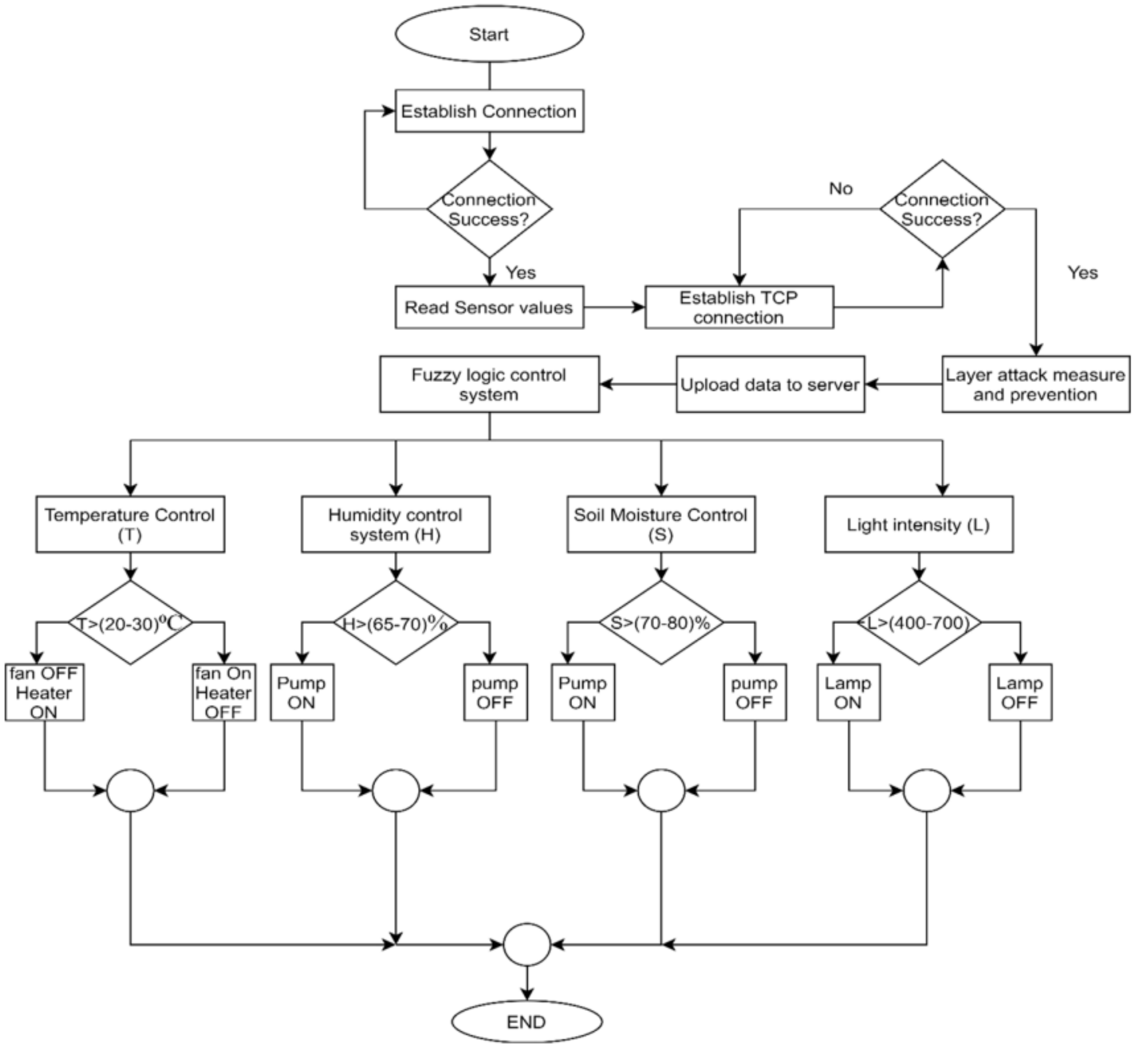

Fig. (2. 4): Smart greenhouse control and monitoring system [37]

2. 9. APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN SMART GREENHOUSES

This section examines the applications of artificial intelligence in smart greenhouses. By analyzing data collected from various sensors, artificial intelligence enables automatic management and optimization of environmental conditions such as temperature, humidity, light, and irrigation. This technology helps increase productivity and improve product quality by predicting plant needs and reducing resource consumption. The following are practical examples and benefits of using artificial intelligence in greenhouses.

2. 9. 1. Soil management

Monitoring soil characteristics such as soil salinity, pH, soil moisture, concentration of plant nutrients in the soil, as well as the extent of degradation and any damage and injury to the soil are among the functions of artificial intelligence in soil science, and proper monitoring and control of these factors leads to soil health and optimal management, and ultimately sustainable soil management.

Artificial intelligence also determines in what type of soil and with what characteristics the plant can be planted so that it grows better and ultimately produces a more suitable product, by examining the physical and chemical properties of the soil, analyzing and monitoring the soil, soil texture type, soil classification, estimating the percentage of soil moisture and temperature, predicting the swelling behavior of clay soils, etc [38].

In tillage operations, which are a difficult and time-consuming process that involves breaking up the compacted surface of the earth to a certain depth and loosening the soil mass to destroy weeds and increase water absorption capacity, tillage depth plays an important role in crop growth. Tillage depth has traditionally been determined by manual measurement with steel rulers, which is time-consuming and labor-intensive. Recent advances in tillage depth monitoring have focused on technologies used to achieve automated, real time measurements, and are divided into two categories: contact and non-contact [39].

The unevenness of the soil surface has a great impact on plant germination, and leveling the land using traditional methods is not accurate, which causes uneven distribution of irrigation water in the land. One of the advanced methods for leveling the land is the laser system. This system consists of a laser transmitter unit that rotates 360 degrees to create an infrared beam, and the receiver senses the infrared beam and converts it into an electrical signal to control the hydraulic valves and leveling blade. This operation is performed automatically from start to finish without operator intervention [39].

2. 9. 2. Product health management

New artificial intelligence methods are able to monitor insects, pests and diseases and thus identify them. Image sensing and analysis ensure that the plant leaves are divided into diseased and healthy areas. Remote sensing techniques with hyperspectral imaging and 3D laser scanning are also of great importance [40].

For example, a small vineyard in Albemarle, Virginia, has a crop health analysis system that consists of three main components:

1) Sensor array with multispectral camera,

2) UAV with flight automation,

3) Web-based decision-making information system whose task is to analyze multispectral images.

In this system, a drone is used because of its flexibility and ease of modification. Objects reflect ambient light differently depending on their chemical composition and emit infrared radiation depending on their temperature. Due to this feature, it is possible to identify objects, their chemical composition and temperature from a distance [41].

The multispectral camera used in this system consists of five separate cameras, with a sixth camera for measuring thermal infrared radiation. Each of these cameras measures the reflectance of light in distinct wavelength bands. The data obtained from these cameras can be used to calculate the NDVI, NDRE and VARI indices. These indices are used to monitor plant health [42].

2. 9. 3. Weather forecasting

Weather plays an important role in farmers' decision-making and planning. Meteorological data is of great importance for the timing of planting, harvesting, spraying and other agricultural activities. Also, the prediction of this data can play a significant role in pest management. Technological advances have made it possible to provide meteorological forecasts using mathematical models. Increasing the number and complexity of models increases the accuracy of predictions.

This complexity is the result of adding parameters that affect weather, such as temperature, humidity, wind, rain, etc. Weather forecasting requires intelligent calculations to read nonlinear data and generate rules and patterns that can use the observed data to predict future weather. One of the techniques used in weather forecasting is the neural network technique with backpropagation algorithm. This technique uses 28 input parameters to make the forecast with the least possible error [43].

2. 9. 4. Smart irrigation

Artificial intelligence plays a key role in water resource management in smart greenhouses. Using advanced algorithms, AI is able to predict water demand based on environmental conditions, plant type and growth stage. By analyzing sensor data, these systems quickly detect leaks and water waste and prevent the wastage of this vital resource. In addition, AI monitors water quality to ensure that the water used is chemically and microbially suitable for plants. It also optimizes irrigation systems to reduce water consumption and provide it to plants in a precise and targeted manner. This approach not only saves water, but also helps increase the productivity and environmental sustainability of greenhouses [44].

Smart irrigation systems are divided into two categories: weather-based smart irrigation systems and soil moisture-based smart irrigation systems. In weather-based smart irrigation systems, local meteorological data is used to adjust the irrigation schedule, and monitors adjust the timing of watering plants by collecting this data. The smart irrigation system based on soil moisture uses sensors that accurately measure soil moisture when buried in the root zone and then transmit this information to monitors. This system itself is classified into two methods. The first method is the suspended cycle irrigation system, in which the start and end times of irrigation are specified, and if there is sufficient moisture in the soil, the next scheduled irrigation is stopped. The second method is the irrigation system according to need, in which a lower and upper threshold is defined for the monitors, and if there is not enough moisture in the soil and it falls below the minimum required level, irrigation begins [45].

Traditional automatic irrigation systems are not suitable due to their lack of coordination with variable rainfall patterns and lack of response to geographical changes. Currently, systems have been designed that can study rainfall patterns in an area and predict weather conditions, and by estimating the amount of water needed for irrigation, reduce water waste and increase crop yield.

2. 9. 5. Smart harvesting

Artificial intelligence and machine learning technologies are revolutionizing harvesting and post-harvest processes by improving efficiency and reducing losses. Robotic systems equipped with AI vision algorithms can automatically harvest ripe produce. Artificial intelligence algorithms can also optimize post-harvest control logistics, including sorting, grading, and packaging. Computer vision systems can also quickly analyze the quality of harvested products and sort them based on specified criteria. Then, provide packaging and storage methods. This will improve the supply chain, reduce post-harvest waste, and increase the shelf life of the products [46].

2. 10. STEPS TO CREATE AN ARTIFICIAL INTELLIGENCE ALGORITHM FOR A SMART GREENHOUSE

To create an artificial intelligence algorithm in greenhouse automation, you can consider the following steps:

1. Data collection

Data collection is the foundation of any AI project. For greenhouses, this data includes environmental parameters such as temperature, humidity, light intensity, CO2 concentration, and even soil properties. To collect this information, various sensors are used that continuously and in real time measure the environmental conditions of the greenhouse. These sensors can be connected wirelessly or wired to a central system that records and stores the information obtained, creating a comprehensive database of greenhouse environmental conditions.

This data can be collected both through physical sensors and through other technologies such as digital cameras and drones. For example, digital cameras can automatically detect changes in color and condition of plants using machine vision algorithms to assess their health. Accurate and comprehensive data collection helps researchers and greenhouse growers better understand growth patterns and plant needs and make decisions based on them [47].

2. 10. 1. Data preprocessing

After collection, the data preprocessing stage begins, which is of particular importance. The collected data may have errors, noise, or various imperfections that can lead to incorrect or irrelevant results. For example, some sensors may provide incorrect information or the data may be incomplete due to environmental disturbances. Preprocessing involves cleaning the data, filling in missing values, and removing invalid data. This process helps to refine the data to improve its quality for training the AI model.

In addition to data cleaning, the preprocessing stage involves extracting features from the data that directly affect the quality of the results of machine learning models. These features may include normalizing the data, bringing it to a common scale, and selecting important features based on statistical analysis. For example, for a prediction model that aims to control humidity, other parameters such as temperature and light intensity may also be considered as effective features. This preprocessing step ultimately helps optimize the performance of the algorithm [48].

2. 10. 2. Algorithm design

Algorithm design is a key step in AI projects, as the algorithm must be able to make logical and useful decisions based on the collected environmental data. There are various algorithms for data analysis, including machine learning algorithms, deep neural networks, evolutionary algorithms, and other AI methods. The exact choice of algorithm depends on the type of project and specific needs. For example, if the goal is automatic temperature control, predictive algorithms such as linear regression or neural networks may be used.

At this stage, factors such as algorithm complexity, computational power, and data availability should be considered. In addition, the algorithm should be designed in a way that is flexible enough to provide fast and accurate responses to environmental changes. Algorithm design also includes the selection of evaluation metrics that will be used to measure its performance during training and evaluation. These metrics allow the greenhouse operator to measure the quality and efficiency of the algorithm and improve it if needed [48].

2. 10. 3. Algorithm training

Training an algorithm means introducing training data to it so that the algorithm can learn the patterns and relationships in the data. This step involves using different learning techniques, such as supervised learning and unsupervised learning. In supervised learning, the training data contains the desired features and outcomes that the algorithm needs to identify. Following this, the algorithm tries to identify patterns and make predictions based on them.

The training process usually involves dividing the data into training and test sets. This division allows the algorithm to work on one set during training and then evaluate its performance on the test set. In addition, optimization techniques such as error reduction and hyperparameter tuning may be used to maximize the performance of the algorithm and allow it to be optimized. Hence, this step can help to enhance the accuracy and efficiency of the algorithm [49].

2. 10. 4. Algorithm implementation

Once the algorithm has been trained and has reached a reasonable level of accuracy, it can be run on new data. This stage involves deploying the algorithm in an operational environment, where it can process information and make decisions in real time. For example, the algorithm can automatically monitor the temperature, humidity, and lighting of a greenhouse and make the necessary changes based on new data. In this case, speed and accuracy in decision-making are very important.

The algorithm should be able to run automatically without human intervention. For this reason, there may be a need to consider security and safety aspects during the execution of the algorithm. The algorithm also needs to be designed to be able to continuously learn from new data. By doing so, the algorithm can gain more accuracy in its decisions over time, especially in unusual or exceptional situations that may arise in greenhouse conditions [49].

2. 10. 5. Improvement and optimization

The improvement and optimization phase is a good opportunity to review the algorithm and make necessary changes. After the algorithm is implemented, evaluating its performance can lead to identifying strengths and weaknesses. If the algorithm fails to consistently provide accurate predictions, the factors that are causing the lack of accuracy should be identified and necessary changes should be made accordingly. These changes may include selecting new features, changing the algorithm, or even using multiple algorithms simultaneously (algorithm fusion) to improve the results.

Optimization techniques such as genetic algorithms or reinforcement learning methods can be used to improve the performance of the algorithm. For example, in genetic algorithms, different units can be used to select the best features and parameters to achieve the most optimal form. This step also includes documenting the changes and results of the optimizations, to allow for further review and analysis. Likewise, the improvement and optimization process should be considered a continuous and incremental cycle, through which the algorithm will undergo continuous improvement and learning to achieve maximum efficiency in changing greenhouse conditions [50].

2. 11. LITERATURE REVIEW

So far, many studies have been conducted in this field, and in this section, some of the most important ones are organized and presented in several sections.

1. Optimization for Crop Yield and Resource Efficiency

Reference [1] reviews the current status and advancements of AI technologies in smart greenhouses. The study analyzes methods for optimizing crop yield, water and fertilizer efficiency, and pest and disease reduction through robotic systems, nature-inspired algorithms, and image recognition techniques. It also examines the economic benefits of AI technologies and the challenges such as cost, commercialization, and technological differences in different countries. The results indicate the effectiveness of AI-based methods in improving the mydriatic process in smart greenhouses.

In reference [51], an AI-based resource control system for smart greenhouses is developed. This research emphasizes the importance of maintaining temperature, humidity, and carbon dioxide concentration, as adverse changes in these factors can lead to plant damage and economic losses. In this study, linear algorithms and deep learning models such as RNN-LSTM and CNN have been used to predict environmental conditions. The results show that these methods have high accuracy and can help reduce energy consumption and optimize costs. This system is proposed as an effective tool to improve environmental control in the horticultural industry and other industries.

2. Integrated Monitoring Systems

In reference [37], an intelligent system for monitoring and optimal resource management in smart greenhouses is investigated, which uses the IoT, adaptive neural fuzzy inference system, and artificial intelligence techniques. This system helps farmers to optimally manage conditions and resources by collecting real time data related to temperature, humidity, sunlight, and soil moisture. Also, this method ensures data security by detecting IoT attacks, with the system being able to detect 93.62% of attacks. These results indicate that the combination of AI and IoT technologies can improve the efficiency and accuracy of prediction in smart greenhouses and serve as an effective and economical solution for realizing sustainable agriculture.

In reference [52], an AI-based platform for remote monitoring of greenhouse conditions and resource management is designed. The platform includes sensor nodes to collect data related to temperature, humidity, carbon dioxide, and light. Also, four 1D convolutional neural network models are developed to predict sensor data and increase tolerance to sensor errors. The results show that these models have high prediction accuracy and can effectively detect sensor errors. This study emphasizes the importance of using artificial intelligence technologies and cloud resources in improving environmental monitoring and control, as well as related management in greenhouses.

In reference [53], an automated system for monitoring and controlling the environment of smart greenhouses using mobile robots and artificial intelligence technologies is presented. The system monitors environmental parameters such as temperature, soil moisture, air humidity, and pH in real time and identifies unhealthy plants using image processing and machine learning. The data is stored and analyzed on a server and displayed through an application. The goal is to reduce costs and increase productivity in greenhouse agriculture. The results demonstrate the effectiveness of the method based on the integration of robotics and artificial intelligence in improving resource management in smart greenhouses.

3. Environmental Control Innovations

In reference [36], a new technology and architecture for predicting frost in greenhouses using a hybrid method based on the IoT and artificial intelligence is investigated. This smart system uses a station equipped with artificial neural networks for optimal irrigation control in frost conditions. Neural networks help predict greenhouse internal temperatures and provide fuzzy control of agricultural temperatures to activate different levels of water pumps. The results of this research show that ANN models are more effective in predicting temperatures than existing traditional models with an accuracy of over 90%. This paper emphasizes the importance of using smart technologies to address climate risks in agriculture and improve management decisions in greenhouses.

Reference [54] examines the challenges of agriculture caused by climate change and temperature increase in greenhouse cultivation in Taiwan. This research introduces an artificial intelligence-based environmental control system called AI-GECS, which includes weather forecasts and plant physiological indicators. This system uses the Multi-Model Super Ensemble (MMSE) framework to produce accurate hourly forecasts and predicts microclimate using the CLSTM-CNN-BP deep learning model. AI-GECS helps optimize cooling settings and automate greenhouse operations, providing an efficient and cost-effective solution for optimal management of agricultural conditions in the face of climate change. The results of experiments in the smart greenhouse indicate the positive adaptation of this system to the needs of greenhouse resource management, ultimately leading to cost and energy savings.

4. Cloud-based and Automated Solutions:

In reference [55], new solutions for automatic control of greenhouses have been investigated. In this regard, using technological advances such as artificial intelligence, Internet of Things, and cloud computing, a solution called iGrow has been presented for automatic control of greenhouses. This paper innovatively formulates the resource management problem in smart greenhouses as an optimization problem. Also, a neural network-based simulator has been designed to simulate the cultivation process in automated greenhouses. Also, a two-level optimization algorithm has been proposed to optimize the dynamics of the control strategy. Experimental results show a 10.15% increase in crop yield and a 92.7% increase in net profit compared to traditional greenhouse management methods.

In reference [56], an online monitoring and control system for resource management in smart greenhouses is presented, which uses a combination of artificial intelligence and LoRa communication technology. The system uses environmental sensors to collect data such as temperature, humidity, light, and soil pH and transmits it wirelessly to a remote port. A cloud-based portfolio has been created to optimize plant growth. Also, by using automation and dividing the greenhouse into smaller areas, labor costs have been reduced and monitoring and control have been facilitated. The results indicate that the combination of AI and LoRa can help improve greenhouse management and increase agricultural productivity.

5. Challenges in Implementation

In reference [57], the impact of integrating AI into resource management in smart greenhouses is investigated, with an emphasis on improving sustainability and crop production efficiency. This research uses advanced public data analytics to identify new trends and compare AI and traditional farming methods. The findings show that AI significantly reduces heating energy consumption, but the improvements in CO2 reduction and electricity and water consumption are insignificant. Also, the quality and profitability of products influenced by AI are similar to traditional methods. The study emphasizes that despite significant potential, the effectiveness of AI in some aspects of sustainability is limited and highlights the need for further research and education in this area.

Reference [58] examines the role of new technologies such as smart greenhouses and artificial intelligence in advancing sustainable agriculture. Automation (robots, drones, and autonomous vehicles) improves efficiency and resource management. Smart greenhouses with IoT sensors and temperature control systems reduce water and energy consumption and increase production. Artificial intelligence also enables crop health monitoring and performance prediction through data analysis. This study examines the combination of these technologies and challenges such as high costs and technical complexity, and suggests future directions for improving the sustainability of global agriculture.

6. Business Models

Reference [59] examines the effects and potential of artificial intelligence in greenhouse agriculture. This study analyzes the significant changes that artificial intelligence can bring to greenhouse performance. The results of this research show that the use of artificial intelligence-based control solutions can significantly reduce energy consumption, especially heating loads, without affecting crop quality and production. In some cases, the performance of artificial intelligence systems has even been better than traditional methods. However, the article points out issues such as carbon dioxide emissions and water use that need attention and improvement. In addition, this research examines the ability of artificial intelligence to predict production outcomes in greenhouses and shows that the Radial Basis Function model is able to provide accurate predictions with a root mean square error of 0.8 and an R-squared value of 0.98. Overall, this study not only addresses the production of various materials in greenhouses, but also points out the importance of optimizing inputs and making forward-looking inferences regarding the quality and quantity of greenhouse production, paving the way for future research in this area.

Reference [60] examines the applications of artificial intelligence in smart agriculture, especially in smart greenhouses. Given the challenges posed by climate change and population growth, this study emphasizes the use of technologies such as machine learning and the IoT to improve productivity and sustainability in agricultural production. Among the benefits of smart agriculture are real time monitoring of crop growth, early warnings for identifying diseases and pests, and automated irrigation. This article explains the technologies and algorithms associated with modern agriculture and how traditional methods are evolving into more efficient ones, and shows that the use of artificial intelligence plays an important role in the optimal management of resources in smart greenhouses.

7. Other related works

Reference [61] examines the use of artificial intelligence to automate and monitor resource management in smart greenhouses. This research focuses on developing a control system for greenhouse temperature, soil moisture, and air humidity. Experimental results show that temperature and humidity vary throughout the day and improvements are needed to achieve ideal standards. This study emphasizes the reduction in technology costs and the emergence of control systems in agriculture, and suggests that GSM and SMS capabilities be added to the system so that users can be notified of unusual changes in greenhouse conditions. Overall, the results indicate the important role of AI in optimizing greenhouse performance and increasing agricultural productivity through optimal resource management.

In reference [62], the applications of artificial neural networks in smart greenhouses and their role in agricultural development are reviewed. This research analyzes the feedforward network structures and the limitations of recurrent and mixed networks, and examines training and optimization techniques in this field. The advantages and disadvantages of ANNs in various greenhouse applications are also analyzed. The findings of this study can be used as a guide for developers of smart agricultural technologies.

Reference [63] investigated the use of artificial intelligence to control the environment of smart greenhouses according to regional characteristics. In this study, environmental data from four farms were collected and analyzed using an LSTM model to predict ventilation and heating temperature settings. The results showed that the LSTM model had the highest accuracy in short-term predictions, and no significant difference in model performance was observed when considering long-term data and regional characteristics. This study shows that artificial intelligence can help optimize growing conditions in greenhouses and achieve sustainable agriculture.

In reference [64], a simplified model for energy management in smart greenhouses equipped with photovoltaic systems is presented. This model uses machine learning algorithms and the IoT to eliminate the dependence on physical sensors such as temperature and humidity and predict environmental data with high accuracy. Also, a priority-based energy management scheme is introduced that reduces the need for PV and storage capacity by 63.27%. The results show that the combination of AI and IoT can reduce costs and improve energy efficiency in smart greenhouses.

According to the aforementioned studies, the approaches and technologies discussed in the literature have been compared with each other and their advantages and limitations are presented in Table (2. 1).

Table (2. 1): approaches and technologies discussed in the literature

Reference	Approach/Technology	Advantages	Limitations
[1]	AI technologies, nature-inspired algorithms	Optimization of crop performance, cost reduction, and increased efficiency	Commercialization challenges and high costs
[37]	IoT and AI-based intelligent systems	Optimal management of resources and conditions with high accuracy and real-time data collection	Need for data security and IoT challenges
[36]	AI methods for frost prediction	High accuracy in predicting environmental conditions	Need for complex infrastructure
[51]	AI-based resource control system	Cost optimization and reduced energy consumption	Requirement for quality data for accurate predictions
[52]	AI-based remote monitoring platform	High prediction accuracy and effective sensor error detection	Dependency on cloud technologies
[53]	Monitoring and control systems using robotics	Reduced costs and increased productivity	Need for hardware infrastructure
[54]	AI-GECS environmental control system	Accurate predictions and optimization of cooling management	Complexity in design and implementation
[55]	iGrow and resource optimization	10.15% increase in yield and 92.7% increase in net profit	Need for development and implementation of new technologies
[56]	Online monitoring and control system with AI and LoRa	Improved greenhouse management and reduced labor costs	Internet access limitations and network issues
[57]	AI integration in resource management	Reduced heating energy consumption	Limited impact on CO2 and water consumption
[58]	Smart technologies and AI for sustainable agriculture	Improved resource management and increased production	High technology costs and technical complexity

Reference	Approach/Technology	Advantages	Limitations
[59]	AI-based control solutions	Reduced energy consumption and maintained product quality	Issues related to CO_2 emissions and water usage
[60]	Machine learning and IoT applications	Real-time monitoring and disease identification	Integration challenges and need for specialized skills
[61]	AI-based environmental control system	Optimizing quality and agricultural productivity	Need for further improvements in temperature and humidity control
[62]	Applications of artificial neural networks	Analyzing features and optimizing training techniques	Limitations regarding the structure of neural networks
[63]	Uses LSTM	High short-term prediction accuracy	Limited long-term prediction performance
[64]	machine learning and IoT	Significant cost reduction	IoT integration poses security risks

As can be seen, studies conducted in the field of integrating AI in smart greenhouse management have provided significant advances and many applications for optimizing resource allocation and increasing agricultural productivity. However, a critical review of this literature reveals several research gaps that will be addressed and filled in this study. In the following, we will discuss and highlight the research gaps in previous studies. One of the gaps in previous studies is the limited scope of AI applications. In fact, most of the cited studies, such as [1], [37], and [51], focus on specific AI methods (e.g., IoT integration, neural networks) and do not address the interoperability of multiple AI technologies. While these studies provide effective approaches to resource management, they often do not address how combining different AI technologies can provide more robust solutions.

Another research gap is the lack of real-world implementation studies. Although various methods for intelligent monitoring and management of greenhouse environments have been proposed (e.g., [54] and [55]), there is a lack of research evaluating these systems in real-world or large-scale conditions. Most studies do not implement their proposed designs in real or simulated environments that may not reflect the complexities of real agricultural conditions. The approach proposed in this study will emphasize the implementation of an AI-based resource management system in real conditions and evaluate its effectiveness in practical scenarios, which has been widely neglected in the existing literature.

Another research gap in previous studies is the lack of consideration of risk management in AI implementations. References such as [37] and [54] mention security and system reliability concerns, but do not focus enough on identifying and mitigating risks arising from the transfer of AI technologies in agriculture. The present study will address this gap and systematically assess potential risks, including cyber threats and operational failures, and provide practical strategies to mitigate these risks.

Another challenge or research gap in previous studies is the lack of commercial feasibility and integration of business models. Although some studies such as [56] address the economic implications of AI in agriculture, few provide a detailed analysis of how these technologies can be commercially deployed within existing agricultural business models. The present study will not only present an AI-based solution for innovative resource management, but also assess its commercial potential and develop strategic paths for market introduction.

The lack of comprehensive consideration of environmental sustainability metrics is another research gap in previous studies in this area. Although the existing literature mentions many benefits of AI technologies for improving agricultural sustainability (e.g. [56] and [64]), comprehensive metrics to measure these benefits are lacking. Existing studies have often relied on anecdotal evidence or general claims, whereas the present study will focus on developing explicit metrics to assess the environmental impacts of AI-based resource management systems.

Another important research gap in the field is the lack of adaptation to climate change. Many papers, such as [55] and [61], mention climate adaptation in the context of smart greenhouses, but little research has addressed the long-term climate impacts and their interaction with AI technologies. However, in the present study, climate adaptation strategies are integrated into the framework of AI applications in greenhouses, and the resilience of agriculture to environmental changes will be increased.

2. 12. METHODOLOGICAL ASPECTS TO CONSIDER FOR LATER CHAPTERS

2. 12. 1. Business model validation

In this research, a case study method will be used to validate the AI-based resource management system model in smart greenhouses. By selecting several different greenhouses operating under similar agronomic conditions, the proposed system implementation and its performance in resource allocation (water, energy, and nutrients) will be closely examined. The collected data, including resource consumption, crop production, and quality, will be analyzed before and after the system implementation. These comparisons will help to identify the positive and negative effects of the system and provide a detailed analysis of its economic and environmental benefits. Also, the results obtained can be a good basis for making decisions about scaling this technology and identifying possible challenges in other greenhouses. Through this method, more practical and tangible information about the efficiency and impact of the system in the real world will be obtained.

2. 12. 2. System evaluation criteria

To evaluate the success of the proposed system, various criteria can be considered:

1) System performance

- Prediction accuracy: The ability of the system to predict resource needs (water, light, nutrients) and environmental conditions.

- Process optimization: The degree of optimization in resource consumption and increased production efficiency.

2) Measuring economic impacts

- Cost reduction: Comparing costs before and after implementing the system in order to reduce operating costs.

- Increasing financial efficiency: Analyzing the increase in production and product quality compared to the initial investment and ongoing costs.

3) Environmental Sustainability

- Carbon footprint reduction: Examining the reduction of energy and water consumption and the positive effects on the environment.

- Resource efficiency: Assessing optimization in the use of natural resources and its impact on the ecosystem.

4) Product Health and Quality

- Product Quality: Investigating the improvement in the quality of products managed under the system.

- Plant Health: Investigating the reduction in diseases and pests compared to traditional greenhouses.

5) Scalability and Flexibility

- Scalability: Assessing the system's ability to expand to larger or different greenhouses.

- Flexibility: The system's ability to adapt to changing conditions (such as climate change or changes in market needs).

2. 12. 3. Limitations

One of the most important potential limitations of this study is its dependence on quality input data. In this study, data collection from various sources such as sensors, simulation systems, and government databases can face challenges such as inaccuracy, inconsistency, and lack of relevant data. These problems may lead to improper performance of AI algorithms, thereby negatively affecting the final results. For this purpose, efforts will be made to ensure the accuracy and precision of the data used. Furthermore, the adoption of new technologies always requires a change in organizational behavior and culture. If farmers or greenhouse managers are reluctant to adopt AI technologies, investments made in design and validation may not yield the desired results. This challenge requires effective training and awareness strategies, which may be complex and time-consuming. Also, scalability limitation can be considered as another possible limitation of the approach proposed in this study. In fact, the success of this system may depend on a specific scale of operation. If the system is efficient at a small scale, but faces challenges at a larger scale, this could negatively impact its commercial viability. Therefore, ensuring the scalability of this system is a major challenge.

2. 13. SUMMARY

Chapter Two, through a comprehensive review of concepts and technologies related to smart greenhouses, highlights the critical role of these systems in transforming sustainable agriculture. Smart greenhouses, equipped with advanced sensors and automated control systems, enable precise management of environmental conditions and optimization of resource usage. These systems not only increase crop yields but also contribute to environmental conservation by reducing water, energy, and agricultural input consumption. Artificial intelligence, as a key technology, facilitates prediction, decision-making, and intelligent control of agricultural processes by analyzing collected data.

Ultimately, this chapter demonstrates that the integration of modern technologies such as the IoT, sensors, and artificial intelligence can lead to the development of sustainable and intelligent agricultural systems. However, challenges such as high initial costs, technical complexity, and the need for user training remain and must be addressed during the design and implementation phases. This comprehensive review provides a solid foundation for developing an AI-powered resource management system for smart greenhouses and paves the way for future research in this field.

Chapter Three

METHODOLOGY

3. 1. INTRODUCTION

The aim of this study is to design and validate an innovative management system that optimizes resource allocation in greenhouse environments in a way that optimizes temperature and humidity in smart greenhouses. This method implements an iterative development approach and incorporates machine learning algorithms as one of the artificial intelligence methods for resource prediction and optimization.

In this regard, a resource management system based on system dynamics and artificial intelligence methods has been proposed, which aims to increase the resource efficiency of the smart greenhouse. In the first step, data related to the smart greenhouse and also data obtained from the greenhouse performance monitoring system based on Internet of Things technology are collected. These data are considered as the initial data of the problem. In the second step, the system dynamics model for the smart greenhouse is simulated in two states before and after using water resources for irrigation and also spraying to regulate the ambient temperature.

In the next step, using data obtained from the use of Internet of Things technology, a neural network model is presented to predict greenhouse temperature and relative humidity, which can predict the aforementioned data in short-term time intervals, for example, hourly. Based on this prediction, a spray mechanism is designed to manage water resources while maintaining the temperature and relative humidity of the environment at normal values. In order to evaluate the performance of this water resources management system, a comparison is also made between the proposed water management system and the traditional systems used. In addition, the efficiency of this system in reducing agricultural losses is also examined.

In addition to the technical aspects, the financial risks of the proposed plan for resource management in smart greenhouses should also be considered. These financial risks can be referred to as the higher budget required compared to the expected costs. Also, the uncertainty of the rate of return on investment is one of the most important financial risks, and in this study, the point estimation method has been used to model this uncertainty. In addition, maintenance expenses are another factor that creates financial risk, and in this study, a prevention plan is used to reduce maintenance costs. Also, monitoring is performed to reduce resource waste during transition.

In this study, the system dynamics method is used to model the nonlinear and complex behavior of resource management in smart greenhouses. Compared to agent-based methods, this method is more suitable for analyzing dynamic and macroscopic systems such as water and energy resource management due to its focus on cause-effect relationships and feedback loops between variables. While agent-based modeling is more applicable to simulating individual behaviors and interactions between independent components (such as the behavior of plants or greenhouse workers), this study is based on a systematic analysis of the effects of variables such as temperature, humidity, and resource consumption on each other, which system dynamics is well able to perform. Also, system dynamics, by integrating the physical relationships governing the greenhouse (such as mass and energy conservation equations), allows for more accurate predictions than agent-based methods.

Also, in this study, a neural network model was used to predict the temperature and humidity inside the greenhouse. This choice is due to the ability of neural networks to process complex, nonlinear, and time-dependent data (such as data from IoT sensors). The advantage of this method compared to traditional methods such as linear regression is that it is able to identify hidden patterns in multidimensional data. Also, compared to other machine learning methods such as decision trees or SVM, neural networks perform better, especially in processing time-series data (such as hourly temperature changes). On the other hand, the use of hybrid methods was also possible, but due to the limited volume of greenhouse data studied and the need for fast calculations, a standard feedforward neural network with hidden layers was used as a more suitable option.

Combining two methods of system dynamics and machine learning for resource optimization is one of the innovations of this study. System dynamics models the long-term behavior of the system and the machine learning model makes short-term predictions. This approach is used to fill the gap in the research literature, namely the lack of integration of physical models with artificial intelligence for resource management. Alternative methods such as rule-based optimization or fuzzy control, although simpler, are less flexible in the face of nonlinear environmental changes.

In addition, in this study, a point estimation method has been used to manage uncertainty in investment returns. This method is more cost-effective than Monte Carlo simulation, which requires heavy calculations, and provides acceptable accuracy for medium-sized systems (such as smart greenhouses). Also, a proactive approach to reducing maintenance costs with nonlinear optimization is another innovation of this study, which is used to respond to the research gap in the field of financial risk management in smart greenhouses.

In summary, the selection of the above methods has been based on the need for accuracy (in predicting parameters), flexibility (in dealing with uncertainties), and computational efficiency for practical implementation in real environments.

3. 2. THE STUDY AREA AND THE SCALE OF THE PROBLEM

In this study, data recorded by IoT devices installed in a smart greenhouse in Taiwan was used.

This smart greenhouse is 52 meters long, 30 meters wide, and 6 meters high. Parameters such as temperature inside and outside the greenhouse, relative humidity inside and outside the greenhouse, sunlight intensity, wind speed and direction are measured by the measuring instruments.

In this study, environmental data is collected using advanced sensors and high-precision IoT systems. In this regard, the following parameters are continuously measured:

1) Temperature and humidity inside and outside the greenhouse: These parameters are measured and recorded every 5 minutes using digital thermistor sensors and capacitive hygrometer sensors.

2) Sunlight intensity: Measured with high accuracy every 5 minutes.

3) Wind speed and direction: Measured and recorded every 5 minutes using ultrasonic anemometers.

4) Carbon dioxide concentration: measured by NDIR sensors every 5 minutes.

Table (3. 1): Summary of key features of the smart greenhouse dataset

Feature	Measurement Unit	Sensor Type	Sampling Frequency	Range
Indoor Temperature	°C	Digital Thermistor	5-min intervals	10°C – 40°C

Feature	Measurement Unit	Sensor Type	Sampling Frequency	Range
Outdoor Temperature	°C	Digital Thermistor	5-min intervals	-5°C – 45°C
Indoor Humidity	%	Capacitive Sensor	5-min intervals	20% – 95%
Outdoor Humidity	%	Capacitive Sensor	5-min intervals	15% – 100%
Solar Radiation	W/m^2	Pyranometer	5-min intervals	0 – 1,200 W/m^2
Wind Speed	m/s	Ultrasonic Anemometer	5-min intervals	0 – 20 m/s
CO_2 Concentration	ppm	NDIR Sensor	5-min intervals	300 – 2,000 ppm
Soil Moisture	m^3/m^3	TDR Probe	15-min intervals	0.1 – 0.5 m^3/m^3

5) Soil moisture: This parameter is measured and recorded at three different depths (10, 20, and 30 cm) using TDR probes every 15 minutes.

The data used in this study is from a full crop year (January to December 2023), covering seasonal variations such as monsoon rains and summer heat. It is important to note that in order to maintain the accuracy of the measurements, the sensors must be calibrated every three months.

A summary of the key features of the dataset is shown in Table (3. 1).

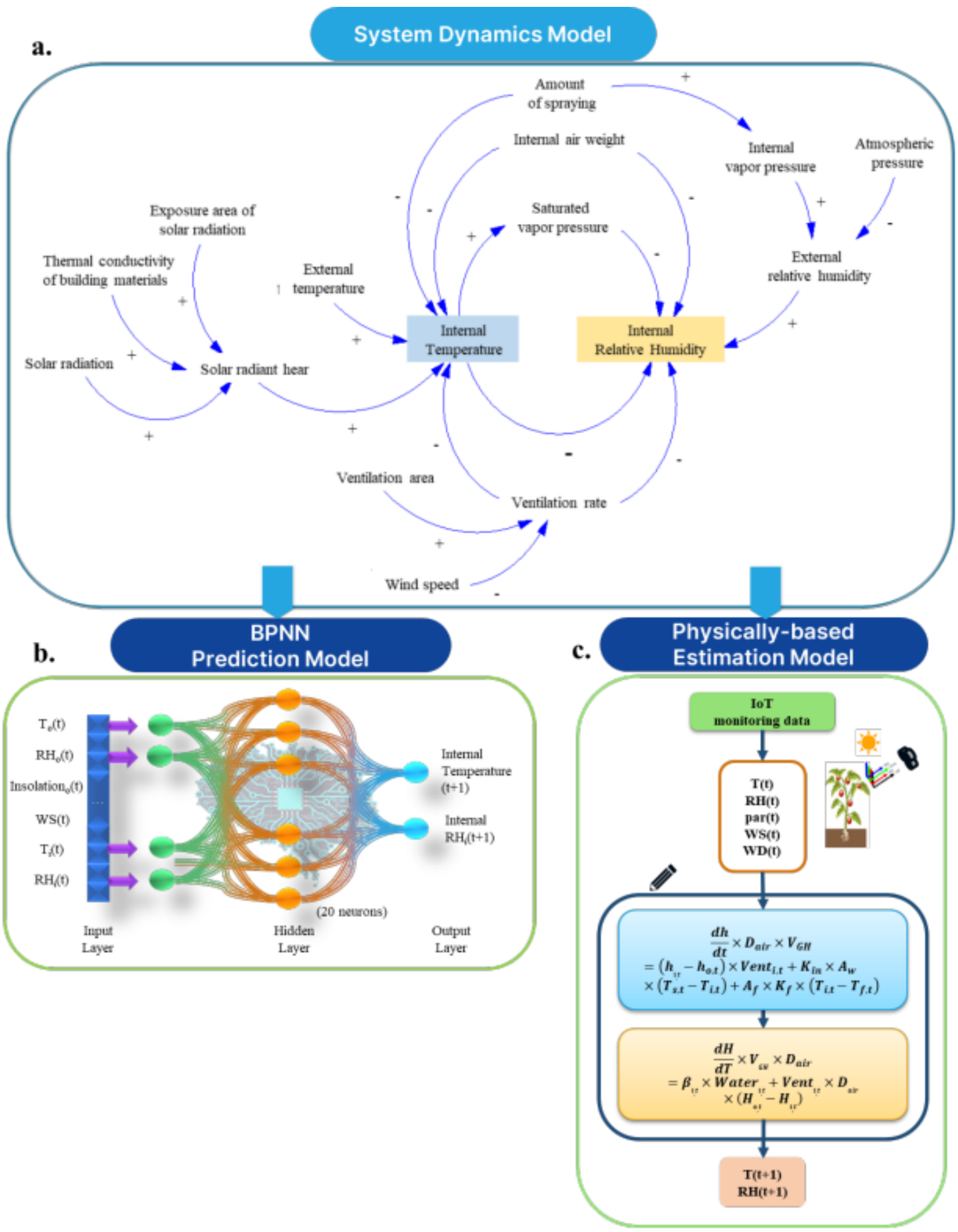

Fig. (3.1): Smart greenhouse control model with water resource management through spraying. a) System dynamics model b) Humidity and temperature prediction model using artificial intelligence method c) Estimation model based on physical principles and data obtained from Internet of Things devices

3. 3. SIMULATION OF THE SMART GREENHOUSE ENVIRONMENT BASED ON SYSTEM DYNAMICS

System dynamics modeling is a process-oriented method that is based on causal relationships and feedback between different variables and high-order nonlinear systems [65- 67]. This method can be used to simulate nonlinear behaviors in complex systems such as resource management in smart greenhouses. Temperature and humidity management is very important in smart greenhouses. By managing water resources and controlling the increase in water pressure, temperature and relative humidity can be achieved to achieve the desired level of coolness and humidity. The general framework of the system dynamics model, which is combined with the estimation model based on physical principles, is shown in Fig. (3.1).

3. 4. CONTROLLING RELATIVE HUMIDITY IN A SMART GREENHOUSE

The relative humidity and internal temperature of a smart greenhouse can be considered a function of the law of conservation of mass and the law of conservation of energy, which consists of two general parts. The first part estimates the internal relative humidity by calculating enthalpy and thermal conductivity. The second part also estimates the internal temperature by calculating changes in air humidity. The formulation of relative humidity and internal temperature of the smart greenhouse is presented and explained below.

The physics-based estimation of relative humidity inside the smart greenhouse is modeled based on mass and energy conservation equations [68].

$$\frac{dH}{dt} \times V_{GH} \times D_{air} = \beta_{i,t} \times Water_{i,t} + Vent_{i,t} \times D_{air} \times \left(H_{o,t} - H_{i,t}\right) \tag{3. 1}$$

where, dH/dt is the rate of change of absolute humidity inside the smart greenhouse over a given time period. Also, $\beta_{i,t}$ represents the spraying efficiency of water resources in percent. In addition, $Water_{i,t}$ represents the amount of water sprayed in kilograms. $Vent_{i,t}$ represents the internal ventilation and $H_{i,t}$ ($H_{o,t}$) represents the internal (external) absolute humidity. Also, VGH represents the total greenhouse capacity and D_{air} is the air density.

$$H_{i,t} = 0.62198 \times \frac{RH_{i,t} \times esi_{i,t}}{\left(P_{atm} - RH_{i,t} \times esi_{i,t}\right)} \tag{3. 2}$$

$$H_{o,t} = 0.62198 \times \frac{RH_{o,t} \times esi_{o,t}}{\left(P_{atm} - RH_{o,t} \times esi_{o,t}\right)} \tag{3. 3}$$

In the above equations, $RH_{i,t}(RH_{o,t})$ represents the indoor (outdoor) relative humidity in percent. Also, $esi_{i,t}(esi_{o,t})$ represents the indoor (outdoor) saturated vapor pressure at time t. In addition, P_{atm} also represents the atmospheric pressure.

$$esi_{i,t} = 0.6178 \times e^{\frac{17.2694 \times T_{i,t}}{\left(T_{i,t} + 237.3\right)}} \tag{3. 4}$$

$$esi_{o,t} = 0.6178 \times e^{\frac{17.2694 \times T_{o,t}}{\left(T_{o,t} + 237.3\right)}} \tag{3. 5}$$

In the above equation, $T_{i,t}(T_{o,t})$ also represents the temperature inside (outside) the smart greenhouse in time interval t.

$$\beta_{i,t} = 1.1906 - 0.09077 \times RH_{i,t} \tag{3. 6}$$

$$Vent_{i,t} = C_{i,t} \times WS_t \times A_{GH} \tag{3. 7}$$

Where, $C_{i,t}$ is the ventilation utilization factor at time t. Also, A_{GH} is the area under ventilation and WS_t is the wind speed.

$$H_{i,t+1} = H_{i,t} + \frac{dH}{dt} \tag{3. 8}$$

In the above equation, $H_{i,t+1}$ and $H_{i,t}$, respectively, represent the absolute humidity inside the smart greenhouse at times t+1 and t.

$$ei_{i,t+1} = \frac{H_{i,t+1} \times P_{atm}}{H_{i,t+1} + 0.62198} \tag{3. 9}$$

In the above equation, $ei_{i,t+1}$ is the internal partial pressure of water vapor at time t+1.

The indoor relative humidity in time interval t+1 is also calculated according to the following equation.

$$RH_{i,t+1} = \frac{ei_{i,t+1}}{esi_{i,t+1}} \tag{3. 10}$$

3. 5. CONTROLLING THE INTERNAL TEMPERATURE OF THE GREENHOUSE

The internal temperature is also modeled through the mass and energy conservation equations.

$$\frac{dh}{dt} \times D_{air} \times V_{GH} = \left(h_{i,t} - h_{o,t}\right) \times Vent_{i,t} + K_{in} \times A_w \times \left(T_{s,t} - T_{i,t}\right) + A_f \times K_f \times \left(T_{i,t} - T_{f,t}\right) \tag{3. 11}$$

In the latter equation, dh/dt represents the rate of change of enthalpy over a period of time. $h_{i,t}$ and $h_{o,t}$ are the internal and external enthalpies of the air at time t, respectively. Also, the ventilation rate at time t is represented by $Vent_{i,t}$. V_{GH} represents the total capacity of the greenhouse. K_{in} is the thermal convection parameter of the inner covering material in the air. $T_{s,t}$, $T_{i,t}$ and $T_{f,t}$ also represent the inner covering material temperature, the temperature inside the greenhouse and the internal ground temperature at t, respectively. A_f is the area of the smart greenhouse and K_f is the thermal convection parameter of the ground to the internal air [68].

$$h_{i,t} = 1.006 \times T_{i,t} + H_{i,t} \times \left(2501 + 1.085 \times T_{i,t}\right) \tag{3. 12}$$

$$h_{o,t} = 1.006 \times T_{o,t} + H_{o,t} \times \left(2501 + 1.085 \times T_{o,t}\right) \tag{3. 13}$$

$$T_{s,t} = T_{o,t} + a \times \left(\frac{Rn_{o,t}}{K_{out}}\right) \tag{3. 14}$$

In the latter equation, a is the solar absorption rate. Also, $Rn_{o,t}$ represents the solar radiation intensity at t, and K_{out} is the thermal conductivity.

$$Rn_{o,t} = \left(1 - ref\right) \times par_{o,t} + Rn_{lon} \tag{3. 15}$$

In the above equation, ref is the Earth's reflectance coefficient, $par_{o,t}$ is the external radiation at time t, and Rn_{lon} is the atmospheric longwave radiation.

$$T_{f,t} = T_{o,t} + \frac{Rn_{o,t} - B \times \left(T_{o,t} + 273.15\right)^4}{\left(4 \times B \times \left(T_{o,t} + 273.15\right)^3\right)} \tag{3. 16}$$

In the above equation, B is the Boltzmann constant.

As mentioned earlier, in this study, water spray was used to humidify and cool the smart greenhouse. Therefore, the internal heat generated by spraying must be calculated.

$$Q_t = \beta_{i,t} \times Water_{i,t} \times H_{fg} \tag{3. 17}$$

In the above equation, Q_t represents the heat removal due to water spraying. Also, $\beta_{i,t}$ is the indoor spray efficiency at time t. In addition, H_{fg} is the latent heat of evaporation of water.

$$dT = \frac{\frac{dh}{dt} \times V_{GH} \times D_{air} - Q_t}{4.186 \times C_p \times V_{GH} \times D_{air}} \tag{3. 18}$$

In the above equation, dT is the rate of change in the internal temperature over a period of time and C_p is the specific heat of the air. The internal temperature at time t + 1 is calculated according to the following equation [68].

$$T_{i,t+1} = T_{i,t} + dT \tag{3. 19}$$

3. 6. MACHINE LEARNING METHOD FOR PREDICTING ENVIRONMENTAL PARAMETERS INSIDE A SMART GREENHOUSE

Machine learning methods are a set of computational methods that simulate the functioning and learning of the human nervous system. These methods are widely used to solve various environmental problems. In this study, a machine learning method was used to predict the greenhouse internal temperature and relative humidity using information such as the greenhouse external temperature, external relative humidity, external radiation, wind speed, current internal temperature, and current internal relative humidity (Fig. (3.1.a)). 64, 16 and 20% of the data are randomly allocated to the training, validation and testing stages, respectively. The structure of the proposed model is shown in Fig. (3.1.b).

The data required to model the greenhouse environmental parameters is collected through sensors installed in the greenhouse environment. These sensors include sensors for temperature, humidity, light, CO_2, and other relevant parameters that continuously record and store information. The collected data is usually stored in the form of time series, because the changes in environmental parameters over time are of great importance. In addition to the internal greenhouse data, external data such as weather conditions (wind speed, precipitation, external temperature and humidity) can also be effective in improving the accuracy of the model. This data is extracted from weather stations or open data sources. Collecting accurate and comprehensive data is a fundamental foundation for building a robust and reliable machine learning model.

After data collection, a preprocessing step is performed to prepare the data for use in machine learning models. This step includes noise removal, missing data filling, and data normalization. Noise in the data may be due to sensor errors or environmental interferences, which are removed using digital filters or statistical methods such as moving averages.

Missing data can also be caused by temporary sensor failures or data transmission problems. To fill in this data, methods such as linear interpolation or the use of algorithms such as K-Nearest Neighbors (KNN) are used. Finally, data normalization is performed to equalize the scale of the parameters so that the model can learn more effectively.

The choice of the appropriate model for predicting environmental parameters depends on the nature of the data and the modeling goal. For time series data, models such as recurrent neural networks are well suited, as they have the ability to learn temporal dependencies between data. For more structured data, a support vector machine model can be a good option.

The choice of model also depends on the required accuracy and computational complexity. For example, models based on neural networks usually have higher accuracy but require more computational resources. In contrast, simpler models such as linear regression or decision trees may run faster but have lower accuracy. Therefore, the choice of model should be made considering the balance between accuracy and efficiency.

After selecting the model, the data is divided into two parts: training and testing. The training part is used to train the model, and the testing part is used to evaluate its performance. In the training phase, the model tries to learn the patterns in the data and optimize its parameters. This process is usually done using optimization algorithms such as gradient descent.

Model evaluation after training is a critical step to ensure its accuracy and efficiency. Evaluation metrics such as mean square error, mean absolute error, and coefficient of determination are used to measure the model’s performance. MSE and MAE measure the model’s prediction error, while R^2 indicates how well the model explains the variation in the data.

After training and evaluation, the model is ready to be used to predict environmental parameters in real time. These predictions can be sent to the greenhouse control system to take necessary actions to adjust the environmental conditions. For example, if the model predicts that the temperature will increase in the coming hours, the system can automatically activate the cooling system. The model can also be continuously updated with new data to improve the accuracy of predictions. This process, known as online learning, allows the model to adapt to environmental changes and maintain its performance over time.

The predicted model can be integrated with the greenhouse control system to automatically adjust environmental conditions. The greenhouse control system can make decisions and take necessary actions to adjust temperature, humidity, light and other parameters based on the model's predictions. This integration not only helps improve plant growth conditions, but also increases the economic efficiency of the greenhouse by reducing energy and resource consumption. Ultimately, this system can be used as an intelligent tool in smart greenhouse management.

In this study, a feed-forward neural network with a three-hidden layer architecture is used. The input layer is designed to consist of 8 neurons corresponding to the input features (indoor/outdoor temperature, indoor/outdoor humidity, light intensity, wind speed, CO_2 concentration, and soil moisture). The hidden layers have 32, 16, and 8 neurons, respectively, which operate with the ReLU activation function. This choice was made considering the nonlinear nature of the relationships between environmental parameters and the ability of ReLU to prevent the vanishing gradient problem. The output layer with two neurons (predicting temperature and humidity) and a linear activation function provides the final results. The training parameters include a learning rate of 0.001 with exponential decay, a batch size of 32, and 200 full training cycles, which provide a good balance between training time and model accuracy.

The preprocessing steps began with Pearson correlation analysis between features, which resulted in the elimination of low-impact features (such as wind direction). Data normalization was performed using the Z-Score method, which was considered a more optimal choice due to the presence of sparse data in some features such as light intensity. To avoid overfitting, a Dropout technique with a rate of 0.2 was used in the hidden layers, as well as an L2 adjustment with a coefficient of 0.001. These choices were based on numerous preliminary experiments on a subset of the data, which resulted in the best combination of parameters in terms of prediction accuracy and computational time.

In this study, a feedforward neural network with three hidden layers is used to predict the temperature and humidity inside the greenhouse. However, optimization of meta-parameters such as the number of layers, the number of neurons, and the learning rate is also an essential part of this process. In the following, how to optimize these parameters and some related methods are discussed.

1. Metaparameter Optimization

- Number of Layers and Neurons:

The number of layers and neurons in each layer directly affects the network's ability to learn and generalize its performance. In this study, three hidden layers with 32, 16, and 8 neurons were used, depending on the complexity of the input data. This choice was made based on initial experiments with smaller data to gain better insight into the network's performance.

Optimization of the number of layers and neurons can be done using methods such as random search or network search. These methods can combine different parameters and identify the best settings based on the accuracy of the model.

- Learning rate:

The learning rate of 0.001 with exponential decay is chosen to strike a balance between the

convergence speed and the accuracy of the model. This parameter can be optimized by methods such as finding the ideal learning rate through successive experiments or using optimization algorithms such as Adam. In this case, it is necessary to investigate different learning rate settings to achieve the best model performance.

2. Analysis and implementation of random research or other methods

To optimize and strengthen the model, a trial and error structure is used. This structure allows us to examine various parameters using random algorithms and select the best one based on the accuracy of the model. After testing and checking the performance of the model using training data, the data is randomly divided into two parts: training and testing, with 64% allocated for training and 20% for evaluation. Random division allows us to achieve valid and reliable results because it prevents bias in the data.

3. Optimization process

Based on the initial results and a detailed examination of the performance of each layer and neuron, techniques such as Cross-Validation can be used to ensure the accuracy of the model performance and reduce the risk of overfitting. These methods help determine which settings achieve the best accuracy. Also, considering input features, such as correlation analysis, helps to eliminate features with little effect and can therefore help the model be optimal.

3. 7. SPRAY MECHANISM

Fig. (3.2) shows the flowchart of the water spray mechanism for temperature and humidity management and control. Based on the predictions made for the temperature and relative humidity inside the smart greenhouse, a spraying mechanism is designed to determine the appropriate time for spraying. In this section, this mechanism is described.

According to studies conducted in references [69. 70], a relative humidity of 70% and a maximum temperature of 28°C can represent the optimal environmental conditions in smart greenhouses. Therefore, when the relative humidity falls below 70%, and also when the indoor relative humidity and indoor temperature exceed 90% and 28°C, respectively, the spray system should be activated to re-adjust the temperature and humidity to the permissible values.

To prevent excessive resource consumption, sprayers will not activate if the relative humidity is above 90% or the indoor temperature is below 25°C. The process of turning the spray system on and off is based on predicted values of relative humidity and temperature. The spraying process stops when either the temperature and humidity provide suitable conditions for plant growth or the total spray rate exceeds the maximum allowed amount in one hour.

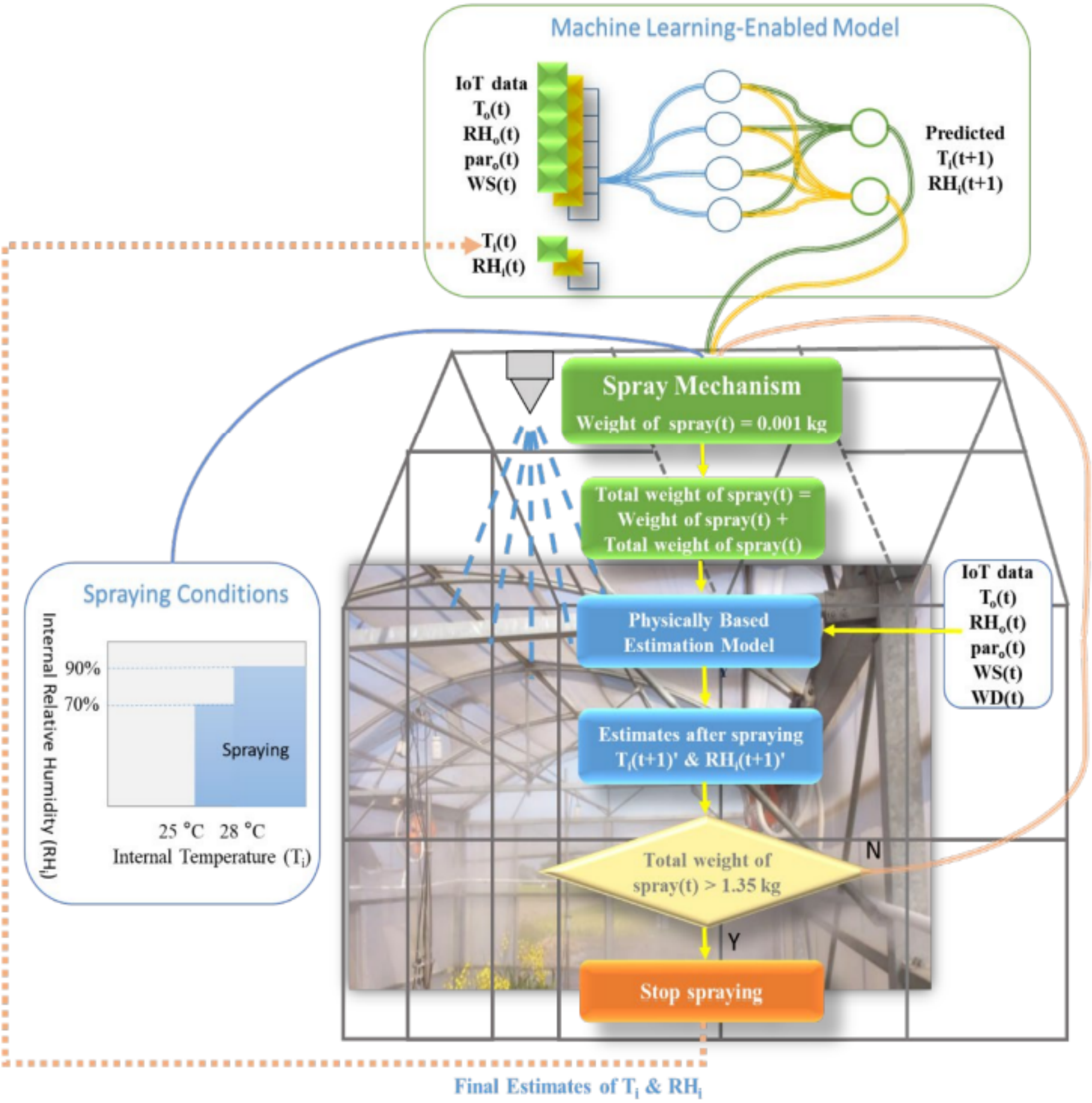

Fig. (3.2): Flowchart of water spray mechanism for temperature and humidity management and control

If there is no need for the smart greenhouse environment cooling process through the spray mechanism, the predictions made for temperature and relative humidity will be fed back to the system and used as initial input values in subsequent steps (orange dashed line in Fig. (3.2)). If any of the above activation conditions for the cooling process are met, spraying is performed, which results in a recalculation of the internal temperature and relative humidity after spraying. The spraying process is repeated until the stopping criteria are reached. If the required spray rate is less than the minimum available spray volume, the spraying process will not be activated. For the greenhouse under investigation and the spray system selected for this study, three spray systems are required to cover the entire greenhouse.

3. 8. MODELING AND MANAGING FINANCIAL RISKS IN SMART GREENHOUSE RESOURCE MANAGEMENT PROBABILISTICALLY

One of the important financial risks in the issue of smart greenhouse resource management that has not been considered so far is the risk arising from the investment required to build and operate a smart greenhouse being higher than the expected costs or the available budget. The amount of investment for building and operating a greenhouse is limited to a maximum amount each year, which is expressed as follows.

$$\mathrm{Inv}_y \le \mathrm{Bud}_y^{\max} \tag{3. 20}$$

In the above equation, Inv_y is the amount of investment made in year y and Bud_y^{max} is the maximum possible investment in year y.

The amount of investment is an uncertain parameter. Therefore, instead of the above equation, the following equation can be considered.

$$\int_0^{Bud_y} PDF_{Inv}^{y} d\, inv \ge P_a^{Inv} \;, \forall y = 1, 2, \ldots, N_y \tag{3. 21}$$

Here, Bud_y is the upper limit of investment in year y, PDF_{Inv}^{y} is the probability density function of investment in year y, and P_a^{Inv} is the acceptable probability that the required capital falls within the permissible range. The permissible range is the range in which the required investment amount is less than or equal to the amount of available budget.

Due to the time-consuming nature of integral calculation and in order to reduce the calculation time, here, instead of the above equation, the following approximate equation has been used to satisfy the investment constraint. This equation, while reducing the calculation time, has a very high accuracy.

$$\mu\left(Inv^{y}\right) + \lambda_1 \times \sigma\left(Inv^{y}\right) \le B_y \;,\; y = 1, \ldots, N_y \tag{3. 22}$$

where, B_y, is the budget of the yth year.

Furthermore, since the maximum amount of investment possible in each year depends on the amount of income and expenses in previous years, and the amount of these income and expenses is a probabilistic parameter, therefore, the maximum amount of annual investment is also a probabilistic parameter. This constraint can be expressed as shown in the following equation.

$$\int_{Bud_y}^{\infty} PDF_{Bud}^{y} d\, bud \geq P_b \,, \forall y = 1, 2, ..., N_y \tag{3. 23}$$

Similarly to equation (3. 21), the above equation can be written as follows.

$$\mu\left(Bud_y\right) - \lambda_2 \times \sigma\left(Bud_y\right) \geq B_y \,, \; y = 1, ..., N_y \tag{3. 24}$$

Therefore, considering the probabilistic nature of both parameters, the constraint expressed in equation (3.19) can be rewritten as shown below.

$$\mu\left(Inv_y\right) + \lambda_1 \times \sigma\left(Inv_y\right) \leq \mu\left(Bud_y\right) - \lambda_2 \times \sigma\left(Bud_y\right), \; y = 1, ..., N_y \tag{3. 25}$$

By bringing the expressions on the right side of the equality to the left side, the following equation is obtained.

$$\mu\left(Inv_y\right) + \lambda_1 \times \sigma\left(Inv_y\right) - \mu\left(Bud_y\right) + \lambda_2 \times \sigma\left(Bud_y\right) \leq 0, \; y = 1, ..., N_y \tag{3. 26}$$

Here, $\mu(Inv_y)$ and $\sigma(Inv_y)$ are the expected value and standard deviation of the desired investment in year y, respectively, and $\mu(Bud_y)$ and $\sigma(Bud_y)$ are the expected value and standard deviation of the available budget in year y, respectively. Also, λ_1 and λ_2 are fixed coefficients, which are chosen here to be equal to 3 so that investment is possible with a probability of more than 99 percent. That is, the amount of capital required in a year is not more than the budget available in that year.

The maximum amount of capital required in year y must always be less than the minimum amount of budget available in year y. For this reason, in equation (3. 26), λ_1 is given with a positive sign and λ_2 with a negative sign. This point is shown in Fig. (3. 3).

As can be seen, the required capital and the budget each have their own probability density functions. According to the figure, the maximum required capital is equal to $\mu(Inv_y) + \lambda_1 \times \sigma(Inv_y)$ and the minimum budget is equal to $\mu(Bud_y) - \lambda_2 \times \sigma(Bud_y)$. To satisfy constraint (3. 19), $\mu(Inv_y) + \lambda_1 \times \sigma(Inv_y) \leq \mu(Bud_y) - \lambda_2 \times \sigma(Bud_y)$.

Establishing the above equation means managing financial risks resulting from required costs being higher than expected costs.

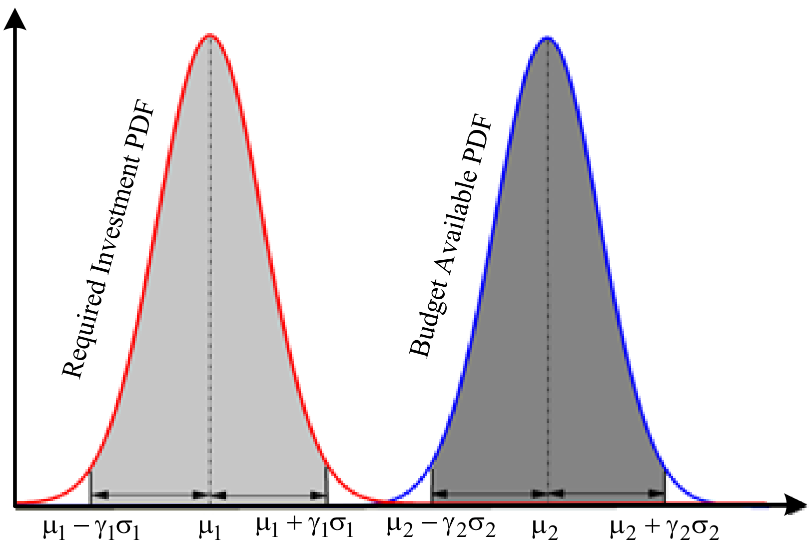

Fig. (3.3): Examining the necessary conditions for satisfying the budget constraint based on typical probability density functions

In addition to financial risks, technical risks can also pose significant challenges that will have a lasting impact on the implementation of advanced systems such as AI-based resource management systems in greenhouses. The following identifies these risks and provides strategies to mitigate them:

1. Risk associated with data quality

Incorrect or low-quality data can affect machine learning models and make inaccurate predictions. To mitigate these risks, approaches such as implementing accurate sensor measurement and calibration systems, performing careful data preprocessing (removing noise and filling in missing data), and employing data verification techniques to ensure the quality of the collected data can be used.

2. Risk associated with machine learning algorithms

The selected algorithms may not produce the desired results or the settings may be incomplete leading to overfitting or underfitting. To mitigate this risk, continuous testing and optimization should be performed using techniques such as cross-validation and random/network search to optimally tune the hyperparameters.

3. Risk of system integrity

It involves problems in communication and integration between the various system components (sensors, data processing, and control) that may occur. These types of risks can be mitigated by using standard protocols and modular design to ensure component interchangeability, along with performing system integrity tests.

4. Scalability Risk

Project scale growth can create challenges in data management and resource optimization. To mitigate these risks, transparent infrastructure design with scalable solutions such as cloud technologies and robust data management innovations can be used.

5. Performance and sustainability risk

This includes risks such as performance degradation or failure of memory and processing systems due to technical problems. These risks can be mitigated by setting up monitoring and reporting mechanisms to identify and resolve problems before they become a crisis, and implementing regular system maintenance and update processes.

Various technical risks and their mitigation strategies are shown in Table (3. 2).

Table (3. 2): Risks and mitigation approaches

Risk type	Challenge	Reduction strategy
Data quality	Incorrect or low-quality data	Implementing sensor calibration systems and precise data preprocessing
Machine learning algorithms	Inappropriate results or incomplete settings	Continuous testing and optimization using Cross-Validation and Random Search
Lack of system integrity	Problems with communication and integration of components	Use of standard protocols and modular design
Scalability	Challenges in data management	Designing scalable infrastructures and using cloud technologies
Performance and stability	Reduced performance or system failure	Setting up regular monitoring and maintenance mechanisms

In general, it is necessary to investigate and identify technical risks as an essential part of implementing AI systems in smart greenhouses. By adopting appropriate strategies, technical challenges can be successfully managed after identification and analysis to achieve better achievements in the field of sustainable agriculture and agricultural innovations.

3. 9. UNCERTAINTY OF THE RATE OF RETURN ON INVESTMENT

The rate of return on investment is one of the uncertain parameters in smart greenhouse management. In this study, the point estimation method was used to model this uncertainty, which is explained below.

The input of a given function is the set of given input variables, so the nonlinear function of the problem can be represented in the following general form.

$$S = F(z) \tag{3. 27}$$

The emergence of uncertainty in the input variables of the problem, z, causes uncertainty to appear in the set of output variables, S. The goal is to describe the behavior of the set S based on the statistical information z [71].

The 2m+1 point estimation method calculates the moments of each output variable Si, which is a function of m input random variables.

$$S_i = F(z_1, z_2, z_3, \ldots, z_m) \tag{3. 28}$$

The only statistical information required for each of the input variables z_l with the probability density function fz_l is the first three central moments. The various stages of this method are described in the following in the form of 11 steps.

Step 1: Determine the value of parameter *m*, the number of input random variables.

Step 2: Set the first and second moments of the *i*th output random variables to zero.

$$E\left(S_i^h\right) = 0 \text{ , } h = 1,2 \tag{3. 29}$$

Step 3: Select the probabilistic parameter z_l

Step 4: Calculate the parameter skewness coefficient z_l

$$\lambda_{l,3} = \frac{E\left\lfloor \left(z_l - \mu_{zl}\right)^3 \right\rfloor}{\left(\sigma_{zl}\right)^3} \tag{3. 30}$$

where $\lambda_{l,3}$ is the skewness coefficient, μ_{z_l} is mean, σ_{z_l} is standard deviation, and E is the operator representing mathematical expectation [72].

Step 5: Determine two standard locations

$$\xi_{l,1} = \frac{\lambda_{l,3}}{2} + \sqrt{m + \left(\frac{\lambda_{l,3}}{2}\right)^2} \tag{3. 31}$$

Step 6: Calculate the two estimated location parameters

$$z_{l,k} = \mu_{zl} + \xi_{l,k}.\sigma_{zl} \ , \ k = 1,2 \tag{3. 32}$$

Step 7: Perform non-probabilistic load distribution for the two estimated position parameters

$$S_{i(l,k)} = F\left(\mu_{z1}, \mu_{z2}, ..., \mu_{zk}, ..., \mu_{zm}\right) \ , \ k = 1,2 \tag{3. 33}$$

Step 8: Calculate the two weighting factors

$$\omega_{l,k} = \frac{1}{m}\left(-1\right)^k \cdot \frac{\xi_{l,(3-k)}}{\xi_{l,1} - \xi_{l,2}} , k = 1,2 \tag{3. 34}$$

Step 9: Update the first and second moments of the output random variables

$$E(S_i^h) = E(S_i^h) + \sum_{k=1}^{2} \omega_{l,k} \cdot \left(S_{i(l,k)}\right)^h , h = 1,2 \tag{3. 35}$$

Step 10: Repeat steps 4-9 for all input variables with uncertainty [71]

Step 11: Calculate the mean and standard deviation of the output variable S_i

$$\mu_{S_i} = E\left(S_i\right) \ , \ \sigma_{S_i} = \sqrt{E\left(S_i^2\right) - \left(E\left(S_i\right)\right)^2} \tag{3. 36}$$

3. 10. PREVENTIVE PLAN TO REDUCE MAINTENANCE COSTS IN SMART GREENHOUSES AND MANAGE FINANCIAL RISKS

In this section, a preventive plan is presented to reduce maintenance costs in smart greenhouses and manage financial risks. This model is considered as an optimization cost function, which aims to reduce overall costs.

The objective is to minimize the total costs of smart greenhouses, which include preventive costs and emergency repair costs. The cost function is defined as follows. These costs include preventive costs and repair and maintenance costs.

$$TC=\left(C_p.x_1+C_s.x_2+C_t.x_3+C_f.x_4\right)+C_r.\left(\lambda.\left(1-\alpha x_1\right).\left(1-\beta x_3\right).\left(1-\gamma x_4\right)\right) \tag{3. 37}$$

where, x_1 is the number of preventive inspections per year. Also, x_2 is the number of spare parts stored in the warehouse. In addition, x_3 is the number of training hours per year and x_4 is the percentage of equipment equipped with IoT technology. C_p is the cost of each preventive inspection, C_s is the cost of each spare part in stock, and C_t is the cost of each hour of personnel training. Also, C_f is the cost of investment in new technologies, and C_r is the cost of emergency repairs. In addition, λ is the equipment failure rate and α is the failure reduction coefficient due to preventive inspections. Also, β is the failure reduction coefficient due to personnel training and γ is the failure reduction coefficient due to new technologies.

Based on the above equation, it can be said that the cost of emergency repairs depends on the number of failures. The number of failures is reduced by taking preventive measures.

The most important limitations of the problem include the following:

1) Budget Constraint

This constraint was examined in detail in Section (3. 8).

2) Limited demand for spare parts

As shown in the following equation, the number of spare parts stored should be at least equal to the annual demand.

$$x_2 \geq D \tag{3. 38}$$

This model is a nonlinear optimization problem and can be solved using optimization algorithms such as the non-dominated sorting genetic algorithm. This formulation helps smart greenhouse managers reduce overall maintenance costs and manage financial risks by optimally allocating resources such as inspections, spare parts, personnel training, and new technologies.

3. 11. WASTE OF RESOURCES DURING TRANSMISSION

One of the significant financial risks in smart greenhouses is the waste of resources, including water, fertilizer, energy, and raw materials, during the transportation process. This loss can be caused by factors such as leaks in transmission systems (such as water pipes or irrigation systems), human errors in regulating the flow of resources, equipment failures such as pumps or sensors, and mismatches between supply and demand (such as over- or under-irrigation). To manage this risk, monitoring indicators can be used. These indicators are introduced below:

1) Resource wastage rate

$$RLR = \frac{S_l}{S_s} \times 100 \tag{3. 39}$$

Where S_l and S_s are the amount of resources wasted and the amount of resources sent, respectively. This index measures the percentage of resources lost during transmission.

2) Transmission efficiency

$$TE = \frac{S_i}{S_s} \times 100 \tag{3. 40}$$

where S_i and S_s are the amount of resources received and the amount of resources sent, respectively. This index measures the percentage of resources that are transferred correctly.

3. 12. PERFORMANCE EVALUATION CRITERIA OF THE PROPOSED MODEL

In this study, three main criteria are used to accurately evaluate the performance of the proposed model:

1) Root Mean Square Error (RMSE) This metric is used to measure the accuracy of the model's predictions in the main units of measurement (degrees Celsius for temperature and percentage for humidity). An RMSE value of less than 0.5 degrees for temperature and less than 3% for humidity is considered the threshold for success.

2) Mean Absolute Error (MAE): This index is calculated to measure the average absolute value of errors, and its acceptable threshold is set at 0.3 degrees for temperature and 2% for humidity.

3) Coefficient of Determination (R^2): The value of this indicator should be greater than 0.9 to indicate that the model was able to explain more than 90% of the data variation.

To compare the proposed model with traditional methods, two main approaches are examined. First, time-based control systems that operate according to predetermined schedules. Second, threshold control systems that are activated based on fixed values of temperature and humidity. Comparisons will be made based on three indicators of resource consumption reduction (water and energy), environmental control accuracy, and performance stability over time. In addition, to ensure the reliability of the results, the k-fold cross-validation method with k=5 is used. In this method, the data is divided into 5 equal subsets. In each step, 4 subsets are used for training and 1 subset for testing. This process is repeated 5 times and the results are averaged.

3. 13. INTEGRATION OF TECHNICAL APPROACH AND BUSINESS MODEL

The proposed method in this study is a fully integrated method. In fact, the proposed approach consists of three main layers that interact dynamically with each other.

1) Monitoring and data collection layer: In this layer, data from IoT sensors is collected in real time with a frequency of 5 minutes and after preprocessing (including noise removal, missing data filling and normalization) is sent to two paths. The first path is fed into the system dynamics model and the second path is fed into the machine learning model.

2) Processing and prediction layer: In this layer, the system dynamics model simulates the long-term behavior of the system using the physical equations governing the greenhouse environment. At the same time, the neural network model with a three-hidden layer architecture performs short-term hourly predictions. The output of these two models is sent to the intelligent decision-making module.

3) Execution and Feedback Layer: In this layer, the decision-making module issues optimal commands to the spray mechanism by combining the outputs of the two models and considering financial uncertainties using the point estimation method. The system performance is continuously evaluated through RMSE, MAE and R^2 indices and the results are fed back to the models.

The decision-making process in the proposed approach is based on four main steps. The first step involves analyzing the current situation. In this step, real-time data from sensors is received and compared with the predictions of the neural network model. A difference of more than 5% between the actual data and the prediction activates the model retraining mechanism. The second step is resource optimization, in which the system dynamics model evaluates different resource allocation scenarios, taking into account budget constraints and the rate of return. The third step involves intelligent decision-making. Accordingly, the spray mechanism is activated only when all three of the following conditions are met:

- Machine learning model predictions indicate deviations of temperature or humidity from the desired range.

- System dynamics simulation confirms the positive effect of the spray.

- Financial risk analysis (with a probability of 99%) shows the economic feasibility of the action.

In the fourth step, after each corrective action, new data is added to the training set and the models are updated. This cycle is repeated every 6 hours so that the system can adapt to

seasonal and environmental changes.

The financial risk management model is also integrated into the technical approach at three different levels. The first level is the operational decision-making level. At this level, each spray order must pass the cost-benefit analysis filter. The second level is the medium-term planning level, where system dynamics simulations are run with different budget scenarios. The third level is the strategic level, where the return on investment is calculated monthly and based on this, suggestions are made for adjusting strategies.

The proposed method in this study links the technical and business dimensions through a three-layer architecture and enhances the capabilities of the business model by adding detailed cost-benefit analysis mechanisms.

The financial risk management model uses multi-level cost-benefit analysis at operational, tactical, and strategic layers to ensure alignment with the sustainability goals of the business model.

In the operational decision-making layer, each irrigation action undergoes real-time cost-benefit analysis with the following components:

- Cost parameters, which include direct costs such as water, energy, nutrient consumption, and equipment depreciation, and indirect costs including labor and maintenance costs.

-Benefit parameters, which include maintaining product yield, saving resources, and reducing risks.

- Decision threshold:

Actions are only approved if their net present value is greater than a certain amount. The net present value is calculated from the following equation.

$$\mathrm{NPV} = \sum \left(\frac{\mathrm{Benefits}_t - \mathrm{Costs}_t}{(1+r)^t} \right) \tag{3. 41}$$

where, r represents the discount rate and t represents the time horizon.

- Uncertainty modeling is performed using the point estimation method, and price fluctuations and environmental changes are modeled in this way.

In the tactical planning layer, system dynamics simulations and budget allocation scenarios are evaluated over a 6-month horizon. In this section, the ROI index is used, which is calculated as follows.

$$\mathrm{ROI} = \frac{\text{Net Benefits}}{\text{Total Costs}} \times 100 \tag{3. 42}$$

At the strategic layer, monthly business performance reviews align technical outputs with financial goals. Key performance indicators include operational cost savings, increased product yield, and customer lifetime value.

By embedding detailed financial analytics at every layer, the system ensures that technical innovations are translated into measurable business results and reduces the risks of technology adoption and deployment.

This integrated architecture allows for simultaneous management of physical and financial parameters, thereby achieving the main objective of the study.

3. 14. PERFORMANCE EVALUATION OF THE PROPOSED RESOURCE MANAGEMENT SYSTEM

In order to evaluate the performance of the proposed AI-based resource management system, quantitative metrics are provided to compare this system with traditional methods. The aim is to strengthen the validation framework. The most important quantitative metrics considered in this study include the following:

1) Water consumption (liters per square meter per day).
2) Energy consumption (kilowatt hours per growing period).
3) Crop yield (kilograms per square meter).
4) Operating cost (dollars per month).

In order to make the comparisons based on the aforementioned criteria accurate, comparative experiments should be conducted on two separate groups called the control group and the experimental group. In the control group, traditional systems are used. While in the experimental group, the proposed system based on artificial intelligence will be used. Also, parameters such as environmental conditions (temperature, humidity, light), type of cultivated plants and growth period (in terms of weeks or months) are considered the same in both groups in order to obtain reliable results.

In this study, the term “traditional methods” refers to the conventional methods of greenhouse environmental management and control that have been used in the agricultural industry for many years. These methods are mainly based on fixed rules, human experience, and simple automation systems. For example, in many traditional greenhouses, environmental parameters such as temperature, humidity, and irrigation are adjusted manually and based on direct observations. Farmers rely on their personal knowledge and experience to assess environmental conditions and make decisions. Although this approach is effective in some cases, it faces limitations such as human error and lack of dynamics in responding to environmental changes due to its dependence on human judgment.

Another characteristic of traditional methods is the use of automation systems based on fixed settings. In these systems, devices such as thermostats, timers, and simple sensors are used to control the greenhouse environment. For example, a thermostat might be set to turn fans on or off at a certain temperature. However, these systems lack the ability to dynamically adapt to changing environmental conditions or specific plant needs. In other words, they operate only based on predetermined instructions and lack the ability to analyze real-time data or learn from environmental changes. Resource management in traditional methods is also usually done in a static and planned manner. This means that the consumption of water, light, and fertilizer is adjusted based on a fixed schedule without taking into account real-time data or intelligent predictions. For example, irrigation may be applied at specific times of the day without taking into account soil moisture levels or the actual needs of the plants at that moment. This approach not only results in inefficient use of resources, but may also have a negative impact on plant growth and overall greenhouse productivity.

The main limitation of traditional methods is their lack of flexibility and excessive dependence on individual knowledge and experience. Since these systems are unable to continuously analyze data or predict future conditions, their response to environmental changes is often delayed or inefficient. Furthermore, it is difficult to optimize the use of resources such as water and energy in these methods, which can increase operating costs and affect environmental sustainability. In contrast, the proposed system in this study, which is designed based on artificial intelligence, enables dynamic and intelligent management of the greenhouse environment. This system is not only able to adapt to changing conditions, but also can optimize resource consumption by more accurately predicting the needs of plants.

The following methods are also used to measure the aforementioned quantitative criteria:

Water consumption: Use water flow sensors to accurately record daily consumption.

Crop yield: Measure the weight of harvested crop per square meter of greenhouse.

Energy consumption: Record energy consumption data by heating/cooling/lighting systems.

Operating cost: Calculate labor costs, repairs, and resource consumption.

Finally, the results of the proposed method and the traditional method are presented in the form of a table and the percentage of improvement of each method compared to the other is calculated and presented. It is obvious that any method that can perform better in the four quantitative criteria mentioned can be a better choice for realizing a sustainable approach in agriculture.

3. 15. IMPLEMENTATION CHALLENGES AND TECHNICAL LIMITATIONS OF THE PROPOSED APPROACH

The implementation of the smart management approach proposed in this study may face several technical and implementation challenges that need to be addressed. The first challenge is the high computational requirements for real-time data processing. In addition, the scalability of the system for larger greenhouses requires more powerful hardware and more optimized algorithms. Processing sensor data at a frequency of 5 minutes and simultaneously running system dynamics and machine learning models requires significant processing resources, which may be cost-constrained in real environments.

The transition from a test environment to production also presents its own challenges. The variability of environmental conditions in different regions, the differences in the quality and accuracy of commercial sensors, and the need to recalibrate model parameters for each new environment are among the challenges ahead. Also, the current system relies on constant communication with sensors for decision-making, and any disruption in the network can disrupt its performance, which can be considered another challenge.

On the other hand, the accuracy of machine learning model predictions depends on the quality of training data and its performance may decrease in case of unexpected weather conditions. Also, the current system dynamics model does not consider some important parameters such as the effects of plant diseases on resource consumption, which can also be considered as one of the implementation challenges of this approach.

Finally, the flowchart of the proposed method is as shown in Fig. (3. 4). To explain how data flows in a flowchart, the different steps can be outlined in a precise and orderly manner to provide a clear representation of the movement of information between the various components of the system. Below are the different steps in a flowchart and how data is transferred between them:

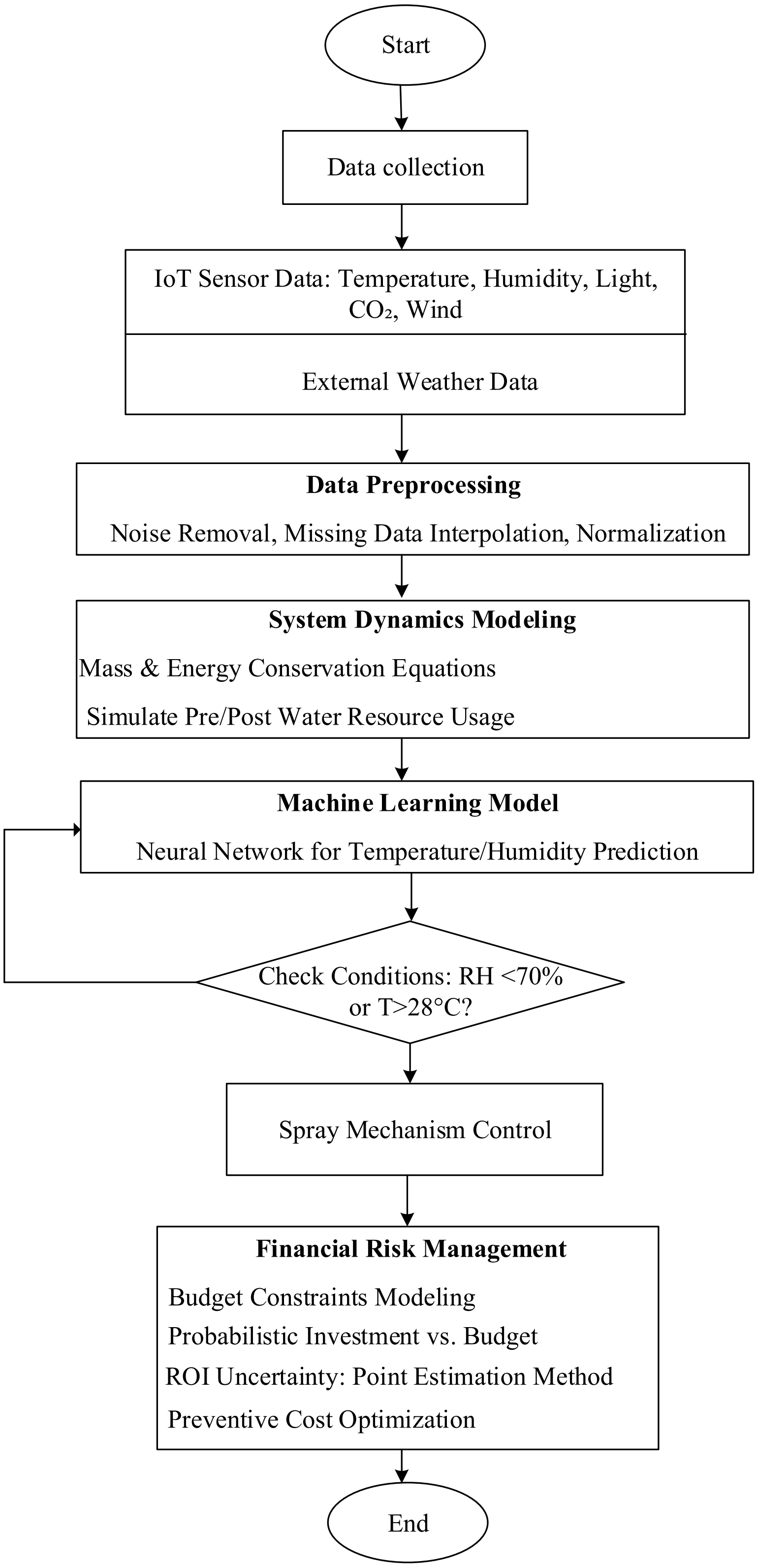

Fig. (3. 4): The flowchart of the proposed method

1. Step One: Collect Data

In this step, data is collected from IoT-based sensors. The collected data includes parameters such as temperature, humidity, light, wind speed, and carbon dioxide concentration. This data is sent to a central server using IoT networks. External meteorological data is also collected directly from reliable sources or weather APIs. This data will be used as additional inputs for modeling and forecasting.

2. Step 2: Data preprocessing

In this step, the collected data undergoes preliminary processing. This includes noise removal, outlier removal, and data normalization. The preprocessing process ensures that the data used in the subsequent steps is of high quality and reliable. The preprocessed information is then fed into two dynamic and machine learning models.

3. Third stage: Dynamic modeling of the system

In this step, the preprocessed data is used for dynamic modeling, which includes mass and energy conservation equations and water resource simulation. This modeling helps to provide a comprehensive picture of the system and understand the dependencies between key variables. In addition, the output of this step is a dynamic model of the system behavior, which will be used in the next steps for prediction and control.

4. Step 4: Running the machine learning model

In this step, the modeled data is fed into machine learning algorithms. The algorithm used in this step predicts environmental parameters such as temperature and humidity. These predictions are provided as input for decision making in the spray mechanism control step.

5. Step Five: Decide on the Spray Mechanism

The predictions made are compared with the current situation. If the predictions indicate the need to control humidity or temperature through the spray mechanism, a command is sent to the spray system. Otherwise, the system continues to operate. This control mechanism helps in the optimal use of water resources and provides better performance compared to traditional systems.

6. Step Six: Managing Financial Risks

In this phase, modeling data and forecast results are used in financial risk management and cost optimization. This includes modeling budget uncertainty and return on investment. Budget and financial forecast information is fed directly into this process to enable economic evaluation and investment risk analysis.

According to these explanations, it can be said that the data of the system is continuously transferred from one stage to another in a logical cycle. This cycle includes collection, preprocessing, modeling and decision-making, which is designed in such a way that each stage provides the necessary inputs for the next stage. The result of this effective interaction is an optimal approach to resource management in greenhouses that is not only technically but also economically successful.

3. 16. CONCLUSION

In this chapter, an intelligent control system is proposed for optimal resource management in smart greenhouses, which combines system dynamics with machine learning techniques and uses a spray system to cool the environment and adjust the relative humidity of the smart greenhouse. In this regard, a machine learning method has been used, which can be considered as one of the innovations of this study. Also, as a second innovation, in this study, a method for modeling and managing financial risks was presented. In this regard, the risks arising from the higher required costs than expected costs were modeled. In addition, the uncertainty of the rate of return on investment was also modeled using the point estimation method. Another innovation of this study is the provision of a preventive plan to reduce maintenance costs in smart greenhouses. The resource loss during the transition period has also been modeled, and parameter monitoring has been carried out for their optimal management.

Chapter Four

Results Analysis

4. 1. INTRODUCTION

In this chapter, the results of implementing an AI-based resource management system in a smart greenhouse in Taiwan are analyzed. The purpose of this analysis is to evaluate the efficiency, effectiveness, and sustainability of the designed system in improving agricultural processes, reducing resource consumption, and enhancing productivity in greenhouse environments. For this purpose, first, the initial data related to water consumption, energy, etc. are presented. Then, the results of implementing the proposed approach are presented, reviewed, and analyzed.

4. 2. INTRODUCING SMART GREENHOUSE DATA

The data of the smart greenhouse is presented in Table (4.1). These data are the basic inputs for designing and implementing the smart greenhouse management system. Based on this information, control parameters, efficiency improvement algorithms, and equipment requirements can be planned.

Table (4.1): Smart Greenhouse Data

Index	Value / Description	Unit / Details
Total area of the greenhouse	2000	Square meter
Type of greenhouse structure	Steel and polycarbonate cover	-
Ceiling height	4	meter
Number of air inlets/windows	10	Number
Type of plant cultivated	Cucumber, tomato, bell pepper	-
Cultivation period (per year)	3	Course
Soil surface or planting bed	1500	Square meter
Type of irrigation system	Drip, automatic	-

Index	Value / Description	Unit / Details
Environmental control system type	Temperature, humidity, light, ventilation and heating sensors	-
Primary energy sources	Mains electricity (Taiwan, 220V)	-
Artificial lighting system	LED	-

4. 3. ANALYSIS OF RESULTS AND DISCUSSION

The proposed AI-based resource management system is designed to continuously improve its performance through machine learning algorithms and real-time data integration. Initially, the system may require a calibration period to adapt to specific greenhouse conditions, crop types, and environmental variables. However, as more operational data is processed, its forecasting accuracy and decision-making efficiency increase, and the need for manual intervention is reduced.

A key component of the system's adaptability is dynamic learning. The AI model uses reinforcement learning and adaptive control mechanisms to improve resource allocation strategies based on historical data and real-time sensors. Another important component is the integration of user feedback. Farmers can provide feedback on the system's recommendations, which allows for adjustments to supervised learning to better match practical farming needs. In addition, scalability across different environments is another important component. The system's modular architecture allows for customization, allowing the system to remain efficient in greenhouses of different sizes, climates, and crop types.

Over time, the system's learning curve stabilizes, leading to higher automation reliability, reduced resource waste, and improved crop performance predictability. This adaptability ensures the long-term sustainability of the system, making it a suitable solution for the new challenges of smart agriculture.

In the following, the results of the dynamic simulation of the smart greenhouse system are examined. The temperature curve of the smart greenhouse over time is as shown in Figure (4.1).

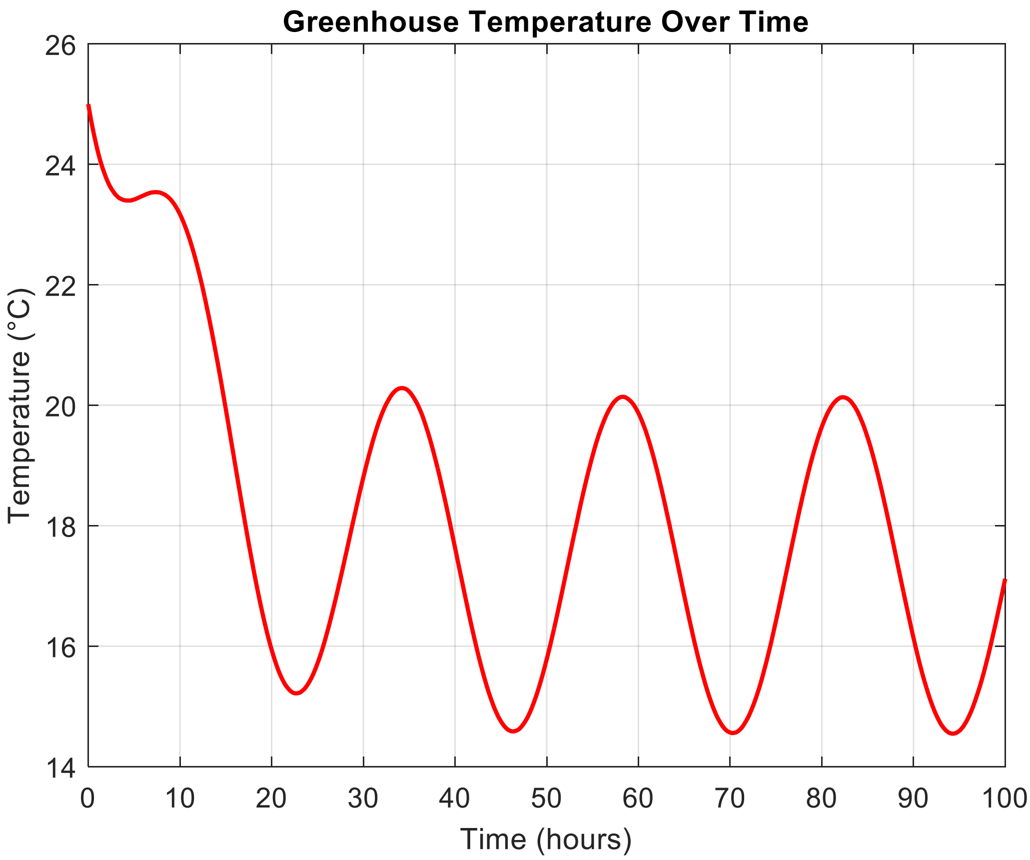

Figure (4.1): Smart greenhouse temperature over time

As can be seen, this graph shows the optimal performance of the feedback control system in maintaining the internal temperature of the smart greenhouse within the desired range.

Temperature fluctuations are caused by the system's response to changes in the external environment. Daily and sinusoidal fluctuations in the external temperature cause the temperature inside the greenhouse to rise and fall periodically, but the control system tries to reduce these changes and keep the temperature within the desired range. In this study, in order to make the simulation conditions of the system behavior more realistic, the presence of random noise that can be caused by environmental conditions or sensor errors has also been considered. However, it is observed that the proposed approach is able to perform well even in such conditions and maintain the ambient temperature inside the smart greenhouse at the desired level, which is important both from the perspective of maintaining optimal conditions for plant growth and from the perspective of optimal energy consumption.

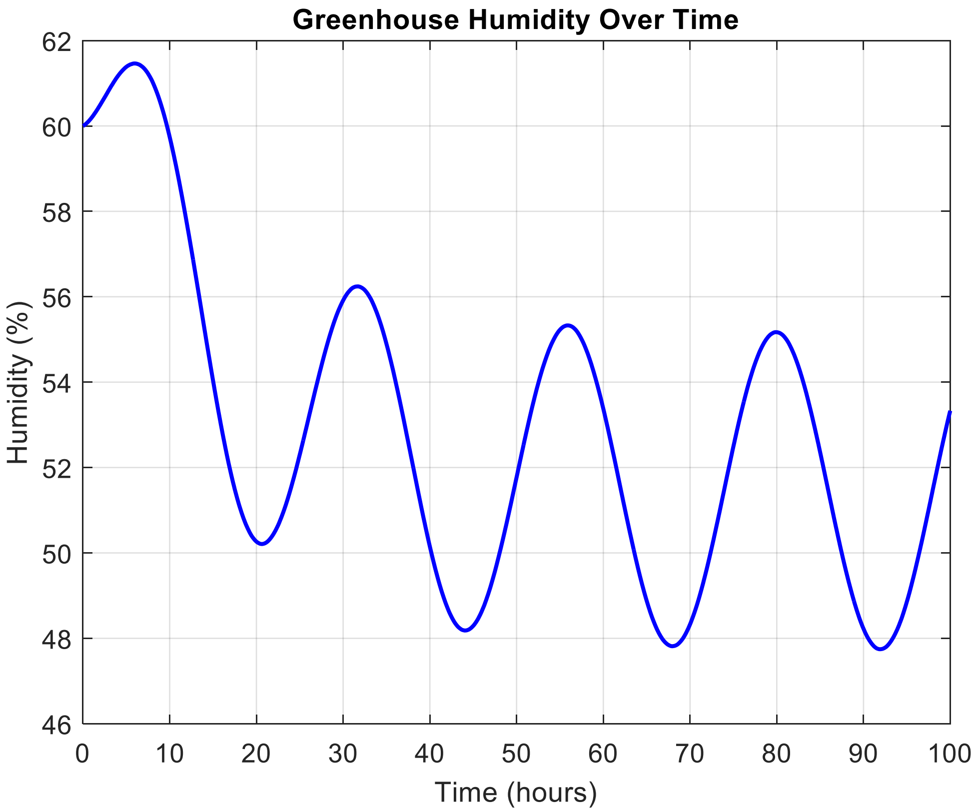

Figure (4.2): Smart greenhouse humidity over time

The humidity curve of the smart greenhouse over time is as shown in Figure (4.2). As can be seen, this graph represents the proposed optimal performance in controlling the humidity level inside the smart greenhouse. In this graph, the humidity level fluctuates around the humidity value of 52%. The humidity response is gradual and delayed relative to changes in the environment outside the greenhouse, which means that the control system reacts to daily changes. Random noise, which represents momentary instabilities and sensor errors, is also considered in the simulations. Humidity control in a greenhouse requires constant adjustment, and the system must continuously strive to maintain optimal conditions, especially in the face of natural and daily environmental changes. This highlights the importance of adaptive and intelligent control in maintaining the right humidity for plant growth.

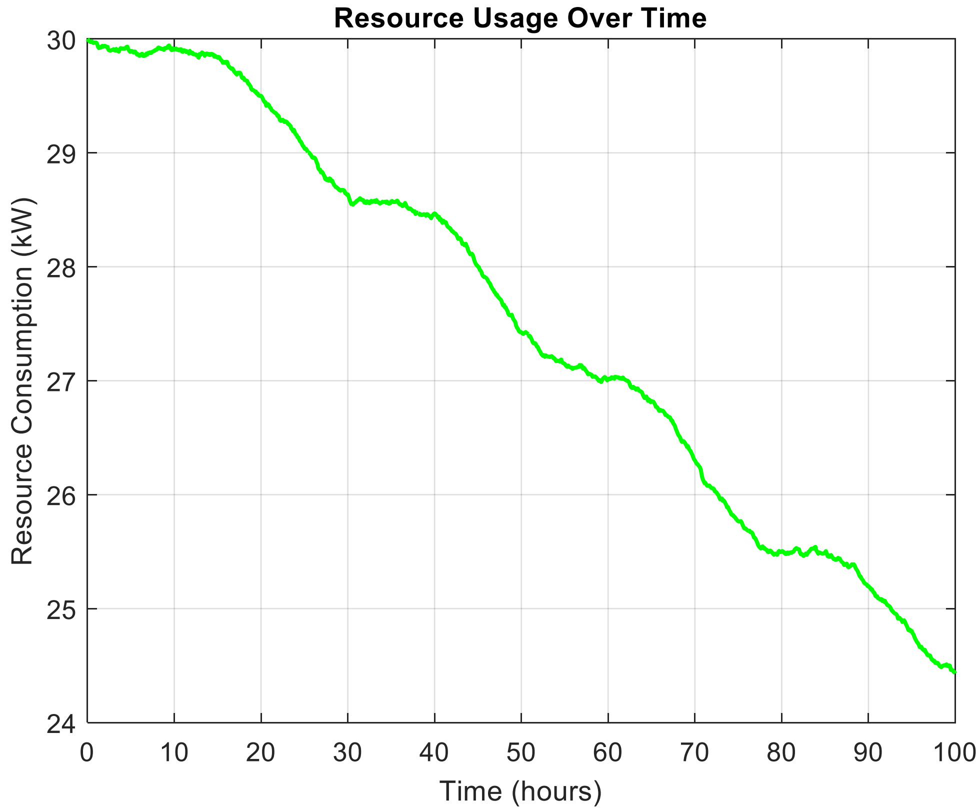

Figure (4. 3): Energy resource consumption diagram in a smart greenhouse

Figure (4.3) shows the energy consumption diagram in the greenhouse. As can be seen, initially, the amount of energy required to regulate the temperature and humidity in the greenhouse was high, but gradually it decreased. The reason for this is that the difference between the normal temperature and humidity (environment outside the greenhouse) and the standard values of the greenhouse was greater, so more energy was needed to bring the values of the mentioned parameters to the standard values. But over time, weather conditions have become such that this difference has become smaller, so less energy has been needed to maintain temperature and humidity in the permitted areas. Overall, this diagram shows that optimal resource management requires reducing fluctuations and maintaining stable conditions, because the less variation, the lower the energy consumption and the higher the system efficiency. This analysis highlights the importance of energy efficiency and improved control systems in the design and operation of modern greenhouses.

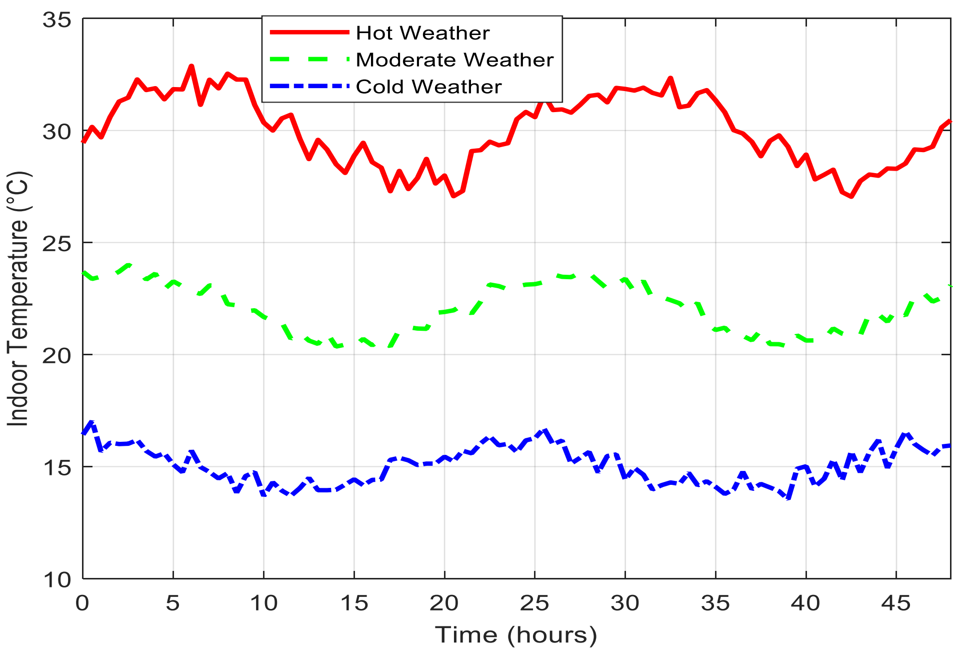

Figure (4. 4): Temperature changes inside the smart greenhouse over a 48-hour period under three different weather conditions

The temperature changes inside the smart greenhouse over a 48-hour period under three different atmospheric conditions are shown in Figure (4.4).

As can be seen, in hot weather, the internal temperature fluctuates around 30°C, showing the daily variations and the system's response to external heat. Although these fluctuations are visible, the system has managed to keep the temperature within an acceptable range and prevent excessive temperature increases. Also, in moderate weather, the internal temperature fluctuates around 22 degrees Celsius and has fewer fluctuations than in hot weather, which shows that the system works better in these conditions and keeps the internal environment stable. In cold weather, the temperature is around 15 degrees and has very few fluctuations, which shows that the system has been able to control the temperature well and maintain the appropriate environment even in cold conditions.

The resource management system reacts actively and dynamically to changes in ambient temperature. The degree of fluctuation in each case indicates the efficiency of the system; less fluctuation indicates better control and greater stability. The system can react to and predict daily temperature cycles. Therefore, the system is able to maintain the temperature within the desired range in all weather conditions, which is essential for proper plant growth and energy efficiency. Therefore, the results presented confirm that the proposed method is suitable for sustainable and optimal agriculture.

The distribution of temperature and humidity control errors in the smart greenhouse resource management system is shown in Figure (4.5). This image helps to identify error distribution patterns and critical points where the control system is less effective. Also, this diagram shows in which areas the control errors are concentrated and whether this distribution is uniform or has specific areas that need improvement.

Most of the temperature and humidity control errors are concentrated in certain ranges. The pattern of error accumulation in certain intervals is mainly related to two main factors. The first reason is the nonlinear behavior of the greenhouse environment. Rapid changes in environmental conditions, such as a sudden increase in temperature in the middle of the day or the formation of dew in the morning, prevent the control algorithms from responding optimally. The second reason is hardware challenges. The uniform distribution of sensors in the initial version of the system does not cover some blind spots (such as the vicinity of ventilation vents or awnings), which can cause delays in the activation of the humidifiers and, as a result, the error concentration in a specific area. In order to overcome this problem, fuzzy adaptive controllers can be used to better manage environmental instabilities. Also, installing additional sensors at critical points and updating control hardware such as using piezoelectric foggers with a response time of less than 30 seconds can be very efficient. This shows that in addition to using intelligent control methods such as artificial intelligence-based methods for resource management in smart greenhouses, the location of sensors should also be done optimally, because otherwise, the accuracy of the proposed approach may decrease.

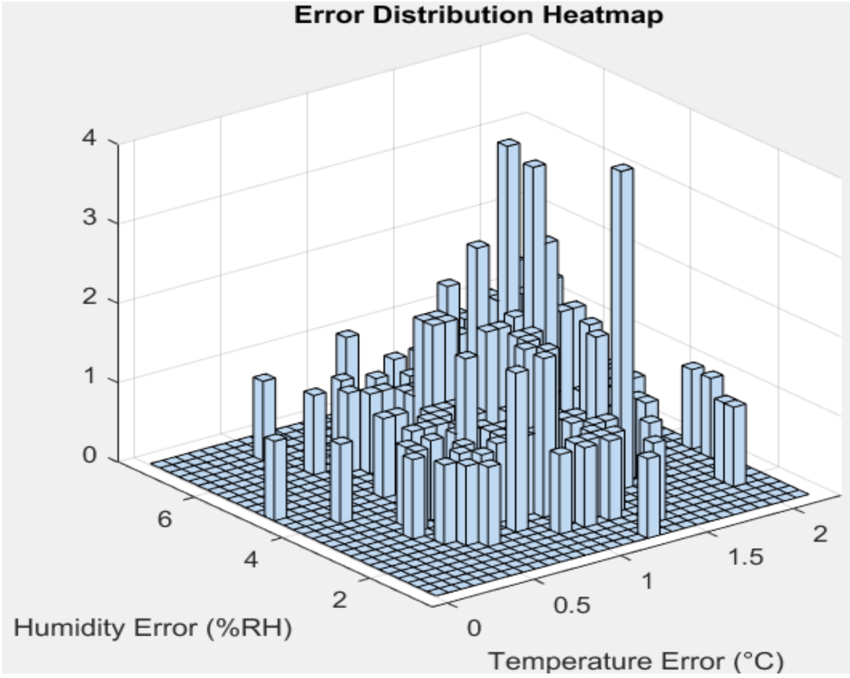

Figure (4.5): Distribution of temperature and humidity control errors in the smart greenhouse resource management system

The distribution of errors in this graph shows the importance of continuous monitoring and improvement of intelligent systems in reducing these errors and increasing productivity.

The error rate in humidity and temperature control by the proposed method, which is due to errors in predictions made for the values of the mentioned parameters, is within an acceptable range, which indicates the efficiency of the proposed method.

To better demonstrate the accuracy of the proposed method in controlling temperature and humidity, the histogram of error distribution for both parameters is shown in Figure (4.6). As can be seen, the error rate in both graphs is not high. In other words, the proposed approach has high accuracy in controlling temperature and humidity of smart greenhouses.

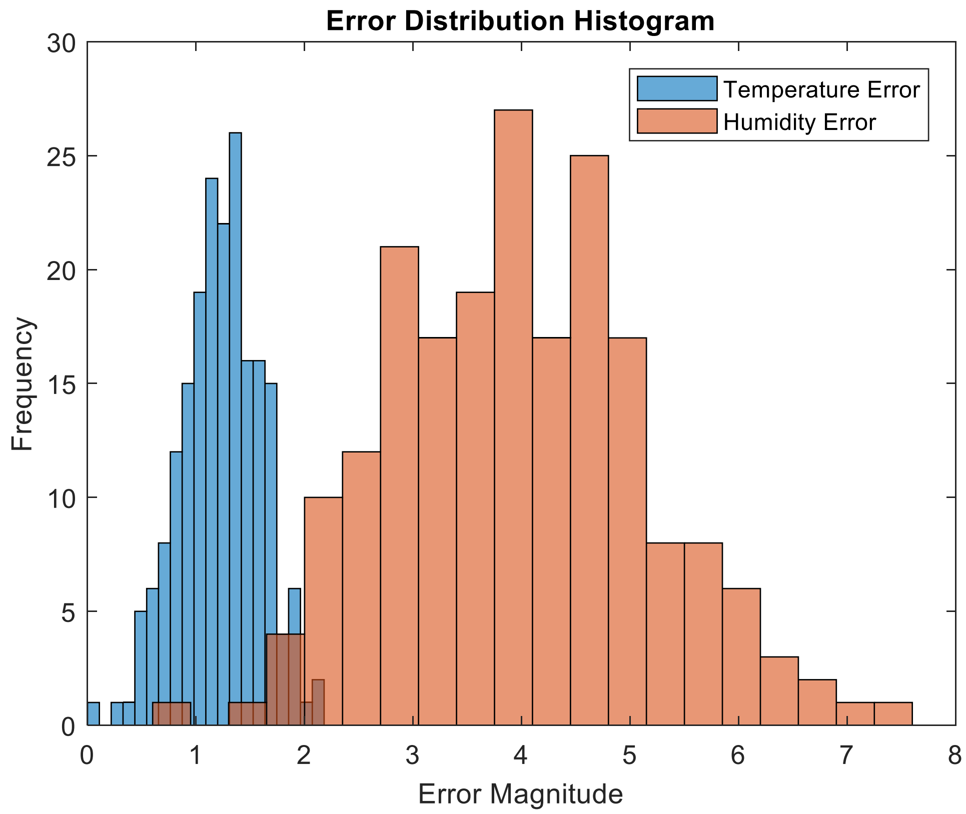

Figure (4.6): Error distribution histogram for temperature and humidity in smart greenhouses

Figure (4.7) shows the comparison of the results of water consumption using the AI-based method and the traditional method. As can be seen, the results of the AI-based method always show lower water consumption compared to the traditional methods. In fact, the proposed method has been able to control water consumption better and has performed better in reducing consumption than the traditional method. In addition, there is less fluctuation in the results of the proposed method compared to the traditional one, which indicates that this method works more stably and reliably. While the results of the traditional method have a lot of fluctuation on most days, this indicates a lack of efficiency and stability in water consumption management. Therefore, based on this analysis, it can be argued that the proposed method not only reduced water consumption, but this reduction was sustainable and in line with the set goals.

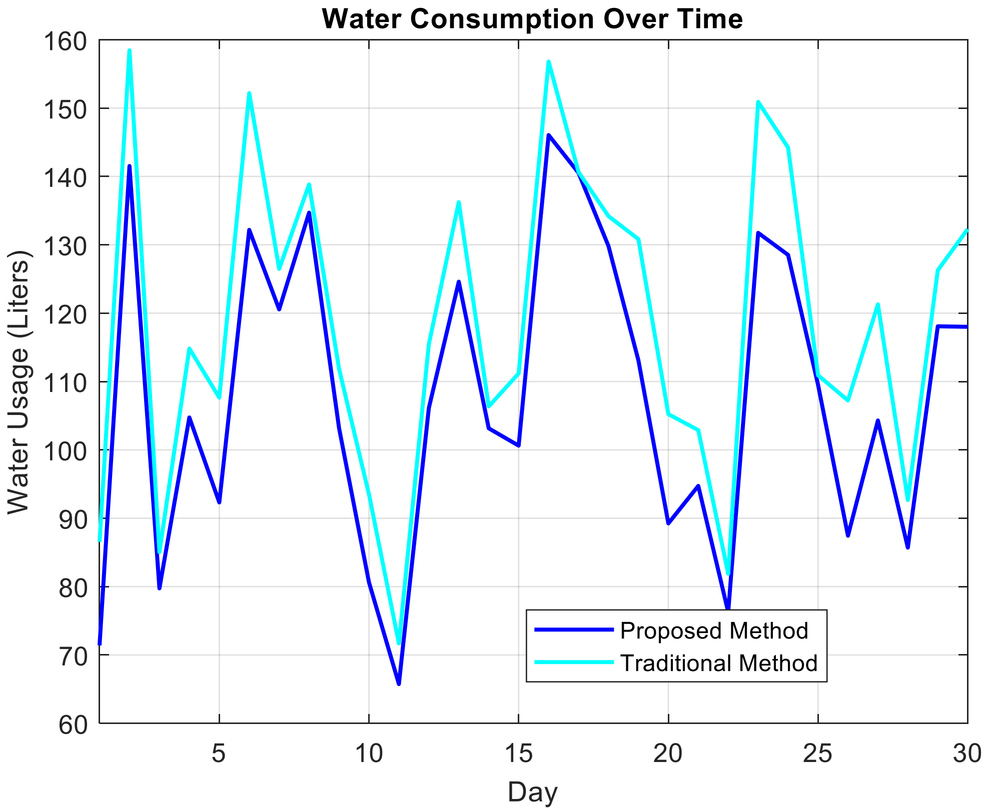

Figure (4.7): Comparison of results related to the amount of water consumed using the artificial intelligence-based method and the traditional method

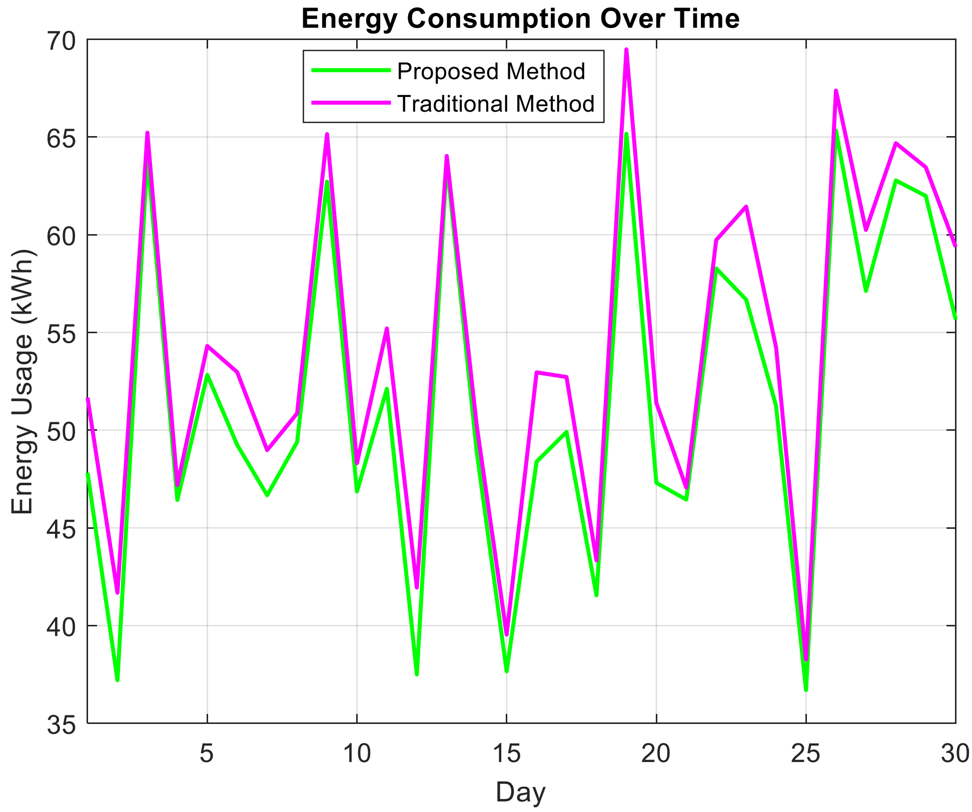

Figure (4.8): Comparison of the average energy consumption graph in two cases: the traditional method and the proposed method

The average energy consumption graph in the two cases of the traditional method and the proposed method is shown in Figure (4. 8). As can be seen, the artificial intelligence-based method has been able to significantly reduce energy consumption. This average reduction shows that this method has a better performance in optimizing energy consumption and can be effective in saving energy resources. The reduction in consumption in this case shows that the proposed method, by using intelligent algorithms or improved techniques, reduces energy consumption continuously and efficiently, which is a very important advantage in reducing costs and negative environmental impacts.

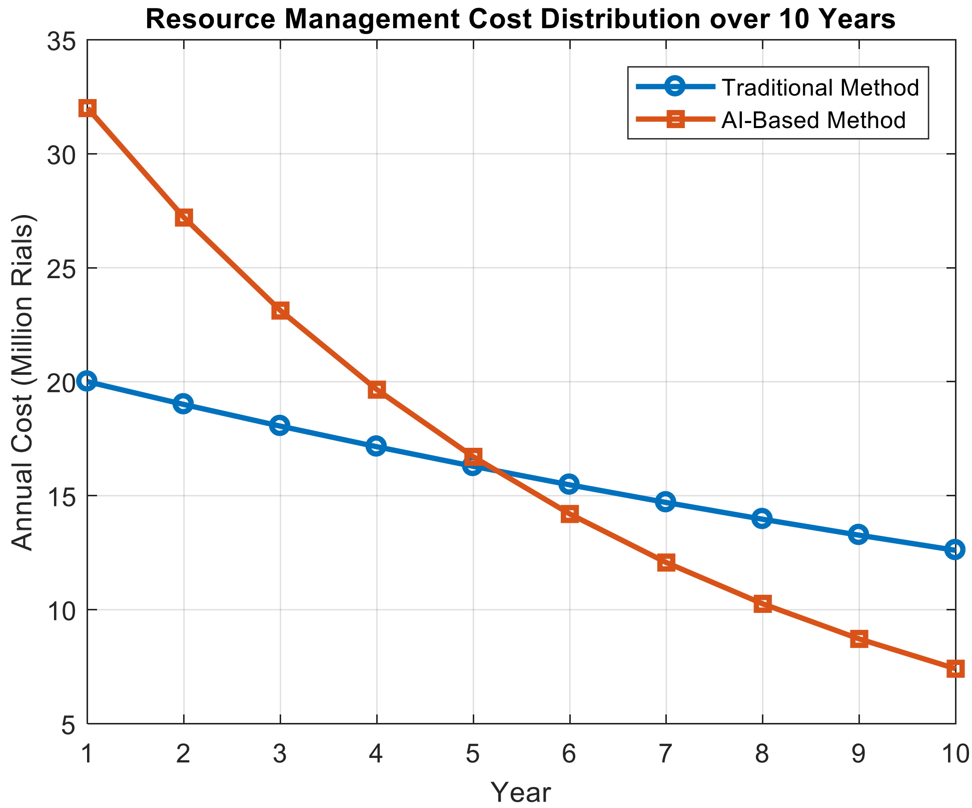

Figure (4.9): Comparison of costs in greenhouses using two methods based on artificial intelligence and the traditional method

The results of comparing greenhouse costs using two methods based on artificial intelligence and the traditional method are presented in Figure (4. 9).

These results show the change in annual costs over 10 years for two greenhouse resource management methods: the traditional method and the AI-based method. In this graph, the costs associated with the traditional method are shown to decrease slightly each year, indicating a decrease in operational and management costs over time due to improved processes and reduced human resources. In contrast, the costs of the intelligent method are higher at the beginning, which is due to the costs required to purchase equipment, but due to the high efficiency and greater automation of intelligent systems, the costs decrease rapidly. In fact, from the analysis of this graph, it can be deduced that at the beginning of the period, the costs of the smart system are higher than the traditional method, but over time, the resulting savings make the total costs of this system lower at the end of 10 years. This shows that the initial investment in smart technologies, in the long run, leads to significant economic savings. Also, the faster cost reduction in the smart method shows that modern technologies can increase productivity and efficiency and effectively reduce operating costs. As a result, based on this analysis, it can be argued that intelligent management systems based on artificial intelligence, despite the need for initial investment, reduce the overall costs of resource management in greenhouses in the long run and are a more economical option than traditional methods.

In addition to reducing costs, one of the goals of resource control in smart greenhouses is to increase the amount of agricultural products. The amount of production in smart greenhouses using two methods based on artificial intelligence and the traditional method is shown in Figure (4.10). As can be seen, using the proposed method increases the amount of agricultural products produced. This is due to the accuracy and timeliness of the control commands. For example,

using an artificial intelligence-based method, temperature and humidity are adjusted in such a way that these parameters do not go out of the allowed range at any time, while in traditional methods, these parameters may temporarily go out of the allowed range at some times, which can affect the quality and growth rate of the products.

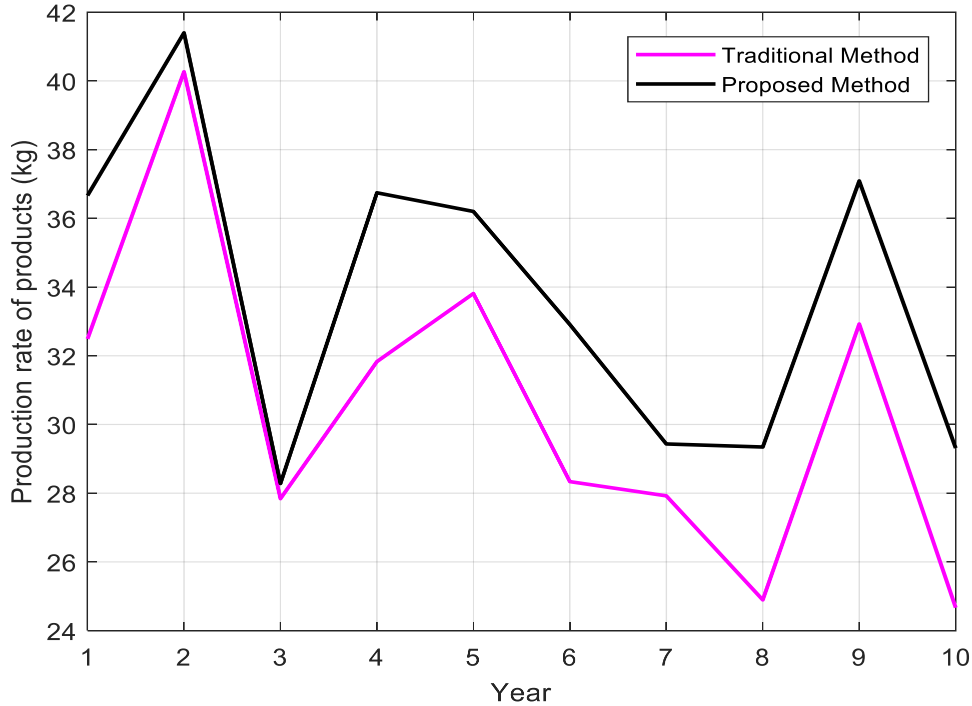

Figure (4.10): Comparison of production rates in greenhouses using two methods based on artificial intelligence and traditional methods

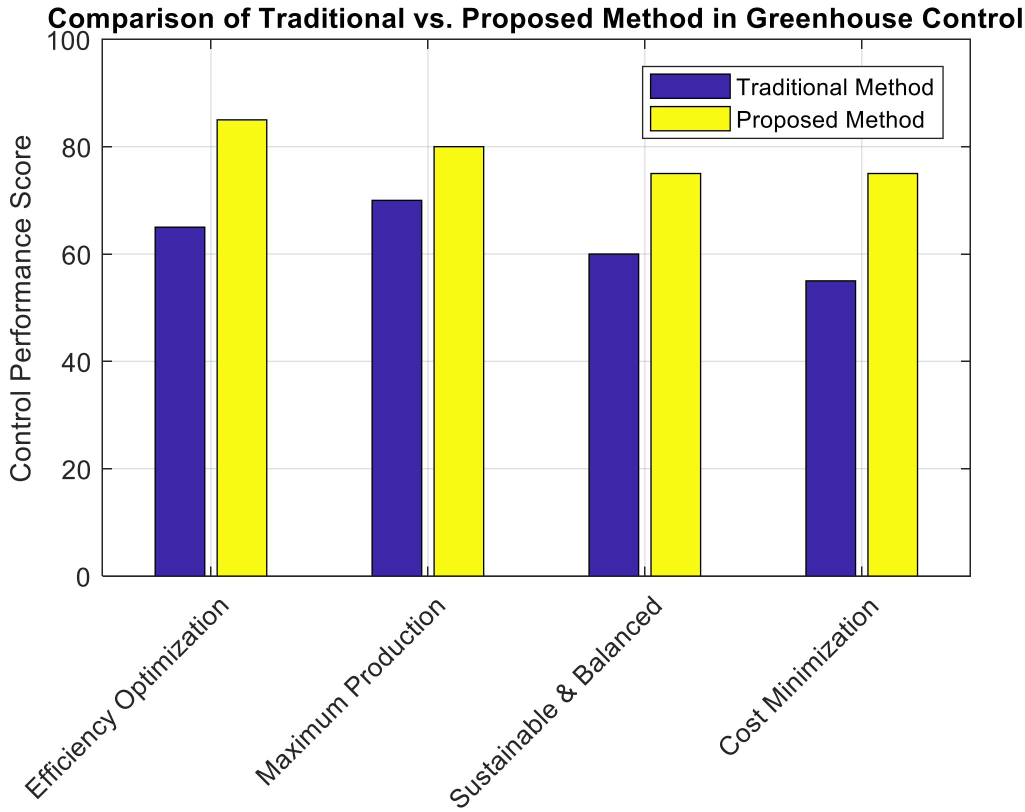

Figure (4. 11): Comparison of the impact of the artificial intelligence-based control method with the traditional method from the perspective of 4 different scenarios

The impact of the AI-based control method has been compared with the traditional method from the perspective of 4 different scenarios including efficiency, product production rate, sustainability, and cost, and the results are presented in Figure (4.11).

As can be seen, in all scenarios, the proposed method performs better than the traditional method. The largest difference is observed in the scenarios of "productivity optimization" and "cost level", which indicates that these methods have a significant impact on increasing the efficiency and productivity of the greenhouse system. In scenarios such as "production optimization", the performance gap between the two methods is smaller, but it still indicates the superiority of the proposed method, which may be due to the optimal level of control in this area.

The results of the operational risk analysis in the event of sensor failure and extreme weather conditions are shown in Figure (4. 12).

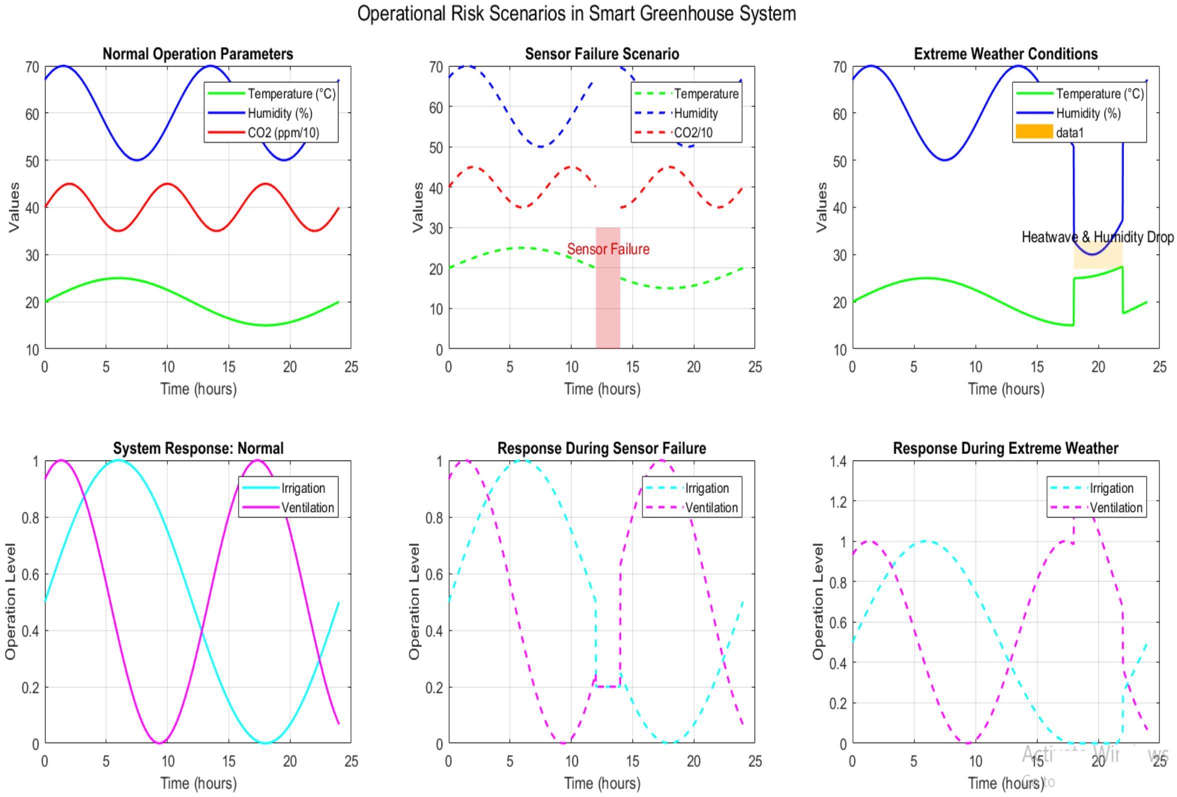

Figure (4. 12): Operational risk scenarios in smart greenhouses

As can be seen, under normal conditions, environmental parameters such as temperature, humidity, and CO_2 levels change in a periodic and controlled manner. These natural fluctuations indicate a balance in environmental control systems that, based on intelligent algorithms, maintain optimal settings for plant growth. This situation confirms the correctness of the system's performance in maintaining optimal conditions and, based on control and stability theory, shows that the system can well manage natural environmental changes without the need for human intervention.

In the sensor failure scenario, as seen in Figure (4. 12), the sensor data is erratic and unstable in the time interval 12 to 14, which is a symbol of sensor failure. In this case, the system is faced with a lack of correct information and is forced to fallback to default states, which in this example are the minimum operating levels for irrigation and ventilation. This analysis is based on the concepts of risk management and reliability of smart systems, where the design must ensure that in the event of a failure, the system operates correctly and safely and prevents damage or biological damage. This simulation shows that smart systems must have the ability to be stable and resilient to sensor errors.

In extreme weather conditions, which occurred between 18 and 22, as shown in Figure (4. 12), the temperature increased significantly and the humidity decreased sharply, indicating a heat wave. These environmental conditions pose serious challenges for the environmental control system, because plants need to maintain temperature and humidity within a certain range. The system tries to compensate for these conditions by increasing ventilation and reducing irrigation. This analysis is based on the concepts of climate change and the response of intelligent control systems to critical conditions, which indicates that the system must be able to adapt quickly and effectively to sudden environmental changes in order to maintain plant health and productivity.

The response of the system under normal conditions is shown in Figure (4. 12). This state indicates that the system makes the necessary adjustments based on environmental parameters to maintain a suitable environment for plant growth. According to adaptive control theories, this state indicates the correct functioning and stability of the system under normal conditions, which is important in ensuring the productivity and health of agricultural products over time. This state is the basis for evaluating how the system performs in the face of natural and daily changes.

The analysis of the system response in the event of sensor failure indicates that in this case, the system, assuming sensor failure, reaches a safe and minimal performance state, i.e., reducing irrigation and ventilation activities. This behavior indicates that the system is designed in such a way that, in the event of a lack of access to accurate information, it takes protective measures and reduces the risk of damage to plants or waste of resources. This analysis is based on the concepts of stability and security of intelligent control systems, the importance of which is in preventing damage caused by lack of information or system error. This approach indicates the system's ability to manage risk and ensure safe operations.

The response of the system to extreme weather conditions shows that in this case, the system tries to maintain environmental balance by increasing ventilation and reducing irrigation in response to heat waves and decreasing humidity. These strategies show that the system dynamically and actively responds to extreme environmental changes to avoid environmental stresses and maintain plant health. Based on the concepts of adaptation of control systems in climate crises, this state indicates the flexibility and rapid adaptability of the system. This is of strategic importance, because in the face of climate change, the system must be able to provide appropriate and effective behaviors to ensure productivity and sustainability.

Figure (4. 13) shows the performance of the proposed system for the types of agricultural products grown in this greenhouse.

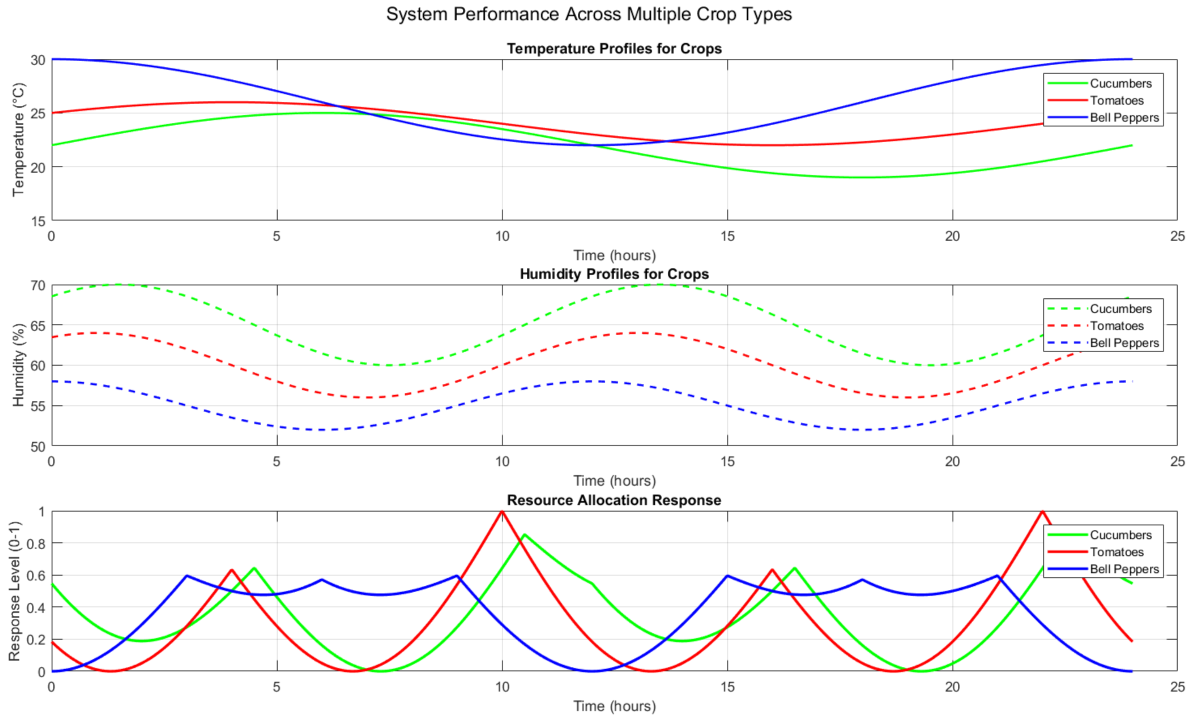

Figure (4. 13): The performance of the proposed system for the types of agricultural products grown in this greenhouse

The first part of this figure shows the graph of different temperatures for each crop. This figure shows that over time, the ambient temperatures for each crop (cucumber, tomato, bell pepper) fluctuate in a wave-like manner with different amplitudes. These natural fluctuations are considered based on climatic factors and intelligent system controls. Each crop has its own specific heat requirements, which are shown in this graph; for example, bell pepper requires higher temperatures and, as a result, its heat wave is more pronounced than other crops. This analysis is based on the principles of plant physiology, which shows that plants grow optimally and produce more in certain temperature ranges, and the system must dynamically manage these requirements to ensure crop health and productivity.

The second part shows the environmental humidity graph for each crop. This graph shows that during the day, the relative humidity level in the environment for each crop fluctuates, and based on the specific needs of each plant, the intelligent system controls this humidity with

different settings. Different plants require a certain humidity in the photosynthesis and growth processes; for example, plants such as tomatoes require moderate humidity, while bell peppers may grow better in a relatively drier environment. The scientific reasoning here is based on the principles of plant physiology, which shows that precise regulation of environmental humidity has a direct effect on the processes of respiration, photosynthesis and nutrient absorption, and the control of these parameters by the intelligent system ensures improved growth uniformity and reduced environmental stresses.

The third part of this figure shows the system response to environmental changes for each crop. In this diagram, the system response level in regulating resources and controlling the environment for each crop against environmental changes is shown. The system response fluctuates based on the degree of deviation from the optimal conditions of each crop, and as a result, the system helps to optimize resource consumption and maintain growth conditions by reducing the response level in critical times and increasing it in times of need. This argument is based on the concepts of adaptive and intelligent control, which shows that the system, in the face of sudden changes, actively and dynamically makes adjustments to maintain plant growth and health indicators. This approach shows that the system is able to intelligently cope with environmental changes and ensure crop stability, which is a fundamental principle in smart and sustainable agriculture.

Figure (4. 14) shows different ROI scenarios over time. In this figure, different scenarios of annual profit, including low profit, medium profit, and high profit, are compared. In all cases, the trend of increasing ROI is linear, with the rate of return on investment increasing as the number of years of investment increases. This result is consistent with conventional financial principles, since, assuming that the initial capital and time period are constant, the relationship between periodic profits and ROI is linear. The slope of each line indicates the level of profit; therefore, the higher the annual profit, the steeper the slope of the line and the faster the ROI grows. This shows that improving operational efficiency and increasing periodic profits can significantly reduce the payback period and increase the attractiveness of the project, since returns are achieved more quickly.

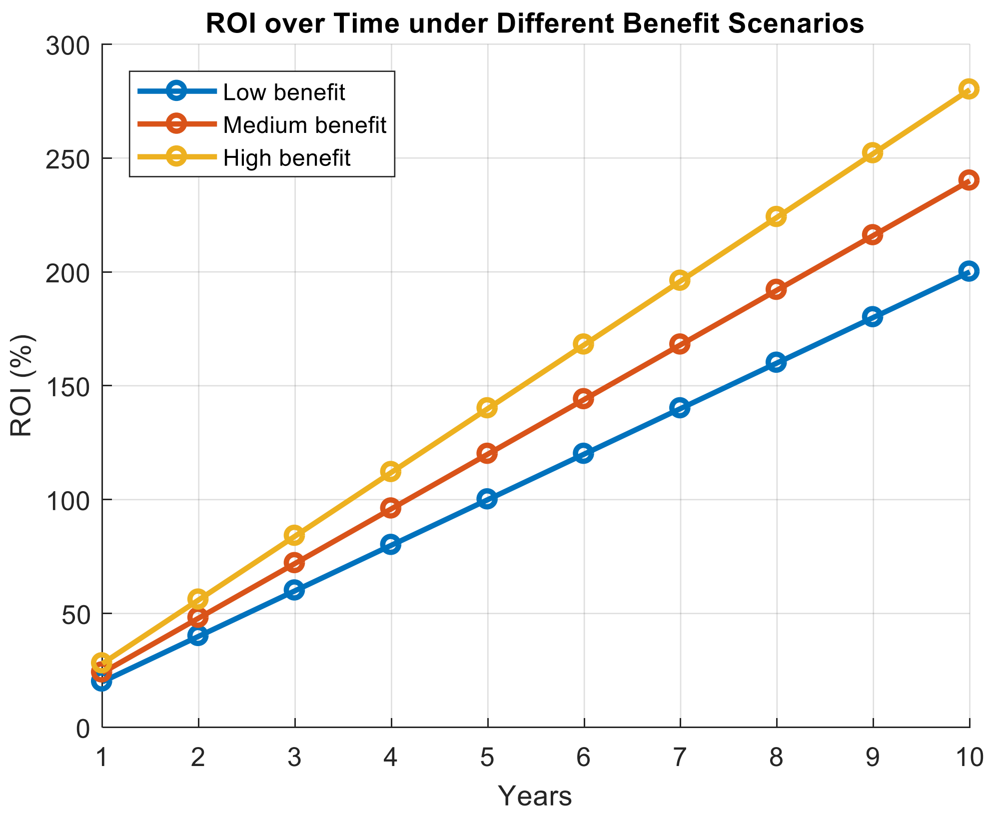

Figure (4. 14): different ROI scenarios over time

On the other hand, comparing these scenarios highlights the strategic importance of operations, as it shows how small changes in profitability can have significant effects on the rate of return on investment. From a scientific perspective, the linearity of this trend indicates that over this time period, the effects of operations and periodic profits do not decrease or increase exponentially, and therefore, financial forecasting and analysis are simple and reliable. This transparency is crucial for decision makers, as it allows for a quick and accurate assessment of the impact of different profitability scenarios on ROI and helps to better manage resources and risks. As a result, investments that generate higher annual profits are more financially profitable, emphasizing the importance of operational efficiency in long-term planning.

Figure (4.15) shows the cumulative trend of the system's financial savings over time. These graphs are shown in the normal case and in the case of a 10% increase in energy costs. As can be seen, as these costs increase, the amount of energy savings also increases. Increasing energy costs, although they may increase operating costs, have a relative impact on the payback period and can play an important role in investment decisions. In particular, this analysis shows that the systems designed must be resilient and flexible to changes in the energy market within an economic framework.

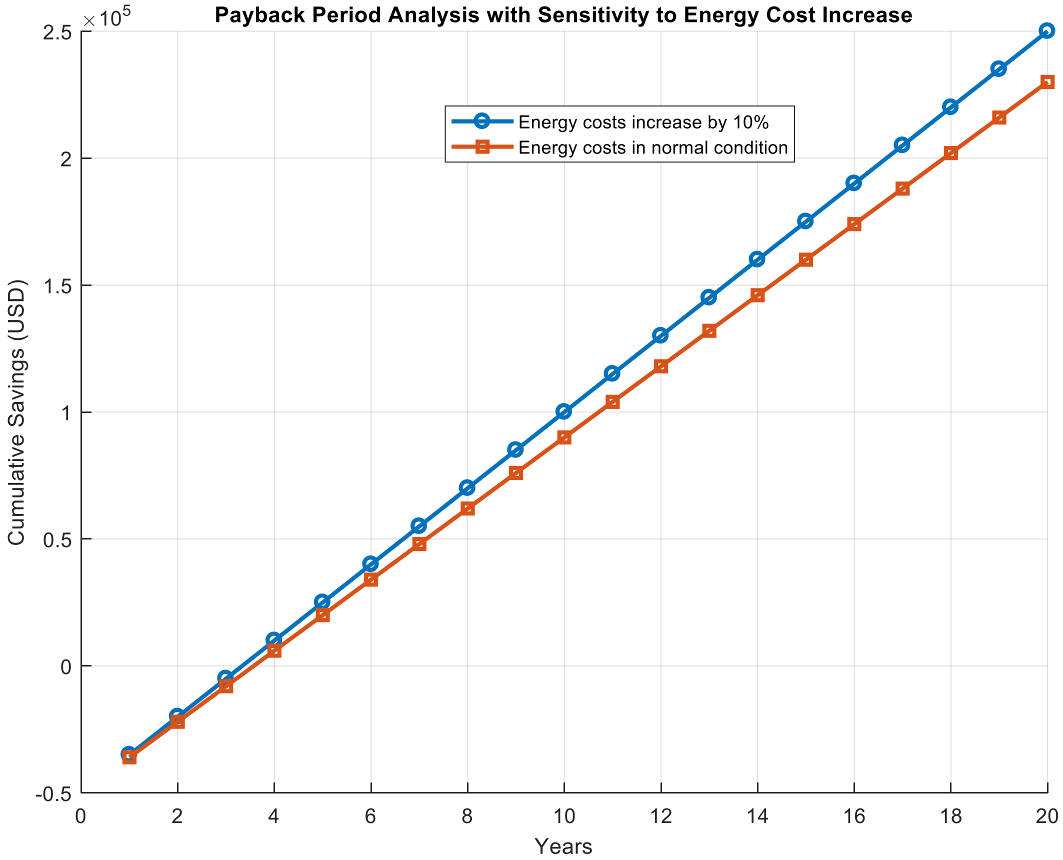

Figure (4. 15): The cumulative trend of the system's financial savings over time

Figure (4. 16) compares resource consumption in two cases before and after using the artificial intelligence-based method.

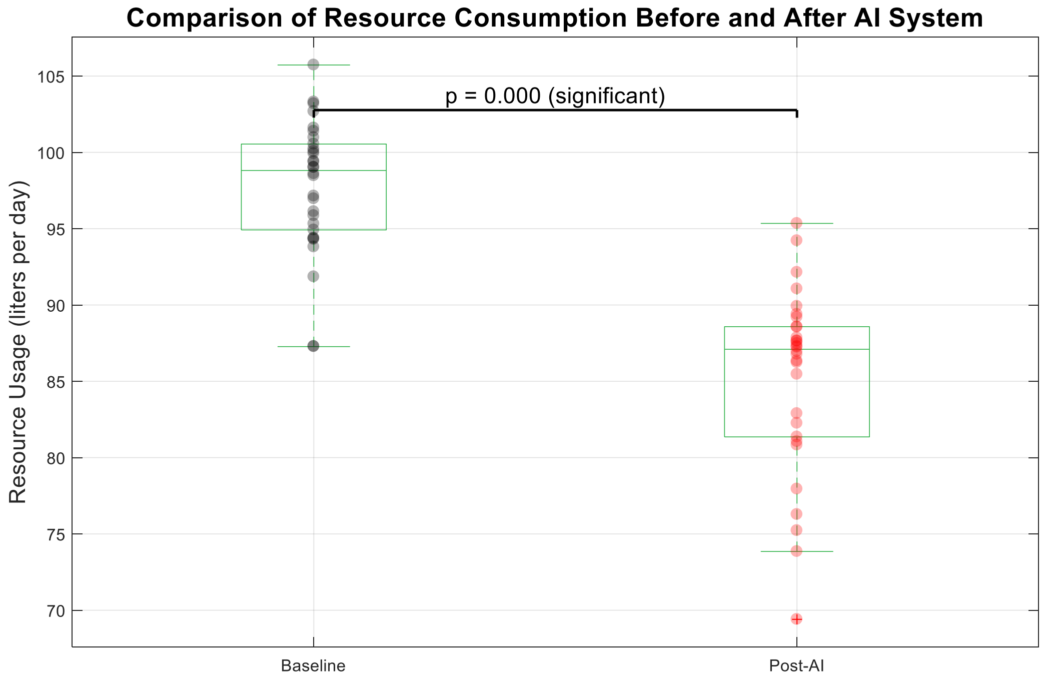

Figure (4. 16): Comparison of resource consumption in two cases before and after using the artificial intelligence-based method using the t-test method

Figure (4. 16) simultaneously displays the data distribution and statistical differences between groups before and after implementing the intelligent system. In this graph, the boxplot for each group shows the median, quartiles, and range of resource consumption changes, which provides a comprehensive picture of the data distribution. In addition, the scattered points represent data that help to better understand the variability and the possibility of outliers. This combination provides a deep visual analysis that goes beyond simply comparing means, and shows whether the observed differences are real and meaningful or not.

In addition, at the top of the graph, a line is drawn that connects the two groups and is labeled p-value, indicating the level of significance of the differences. If the p-value is less than the alpha level (usually 0.05), it indicates a statistically significant difference, which is the scientific argument that the reduction in resource consumption after implementing the intelligent system is observable and reliable, not only at the average level but also in the

distribution of the data. This type of analysis confirms the importance of implementing modern technologies in improving efficiency and reducing resource consumption and argues that the observed results are not the result of chance but the result of the positive impact of the intelligent system.

Ultimately, this chart, by providing a clear and understandable visual representation along with statistical evaluation, helps decision-makers and researchers to draw scientific conclusions based on real data and valid analyses. This approach increases the credibility of the results and shows that the observed changes are not only visually but also statistically reliable and valid.

Figure (4.17) shows the results of multiple comparisons between different greenhouse groups. In this graph, the horizontal and vertical lines indicate statistically significant differences between the different groups. This graph shows which groups have significant differences in resource efficiency and which groups are more similar in terms of efficiency. This type of display helps to understand whether the smart system is transferable across different types and scales of greenhouses, and whether the observed differences are simply the result of random variations or structural differences.

This diagram is based on statistical analysis that assesses the level of significance of the differences. If the lines of communication indicate significant differences (marked with asterisks or long lines), this indicates that the system has a different impact on some types and scales. However, if the differences are mostly insignificant, it can be argued that the system is generally generalizable to different levels. This analysis confirms the importance and transferability of the solution, as it shows that resource efficiency is affected by the system at different types and scales and that there are no or few statistically significant differences in the results. Therefore, this diagram shows that the system can be efficient under different operational conditions.

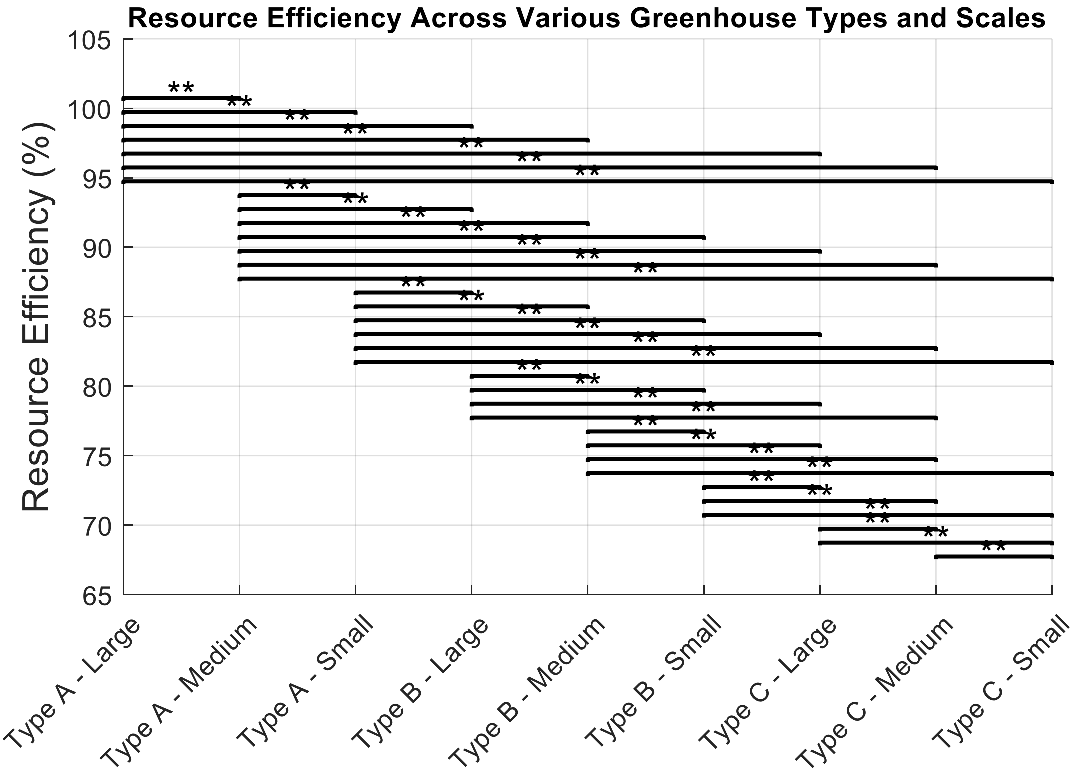

Figure (4. 17): Greenhouse resource efficiency according to different scales

The impact of the AI-based method on water savings, energy savings, cost reduction, and productivity increases is summarized in Table (4. 2).

Table (4. 2): Impact of AI on Quantitative Metrics

Metric	AI-Based Method Improvement	Source
Water Savings	11.33%	Figure 4.7: AI method shows reduced fluctuations and lower consumption
Energy Savings	6.3%	Figure 4.8: AI method reduces energy consumption
Productivity Increase	11.22%	Figure 4.10: AI method maintains optimal conditions, improving production
Cost Reduction	13.8%	Figure 4.9: Costs become lower than traditional methods after 10 years

As can be seen, using the proposed method has led to improvements in all quantitative indicators, including technical and economic indicators.

The findings of this study show that the proposed AI-based system has had a significant impact on achieving the sustainability goals defined in the conceptual model of the research. In the following, each of the system's achievements is examined separately for sustainability indicators.

The results show that the proposed system, using advanced algorithms, was able to reduce water consumption by 11.33%. The system optimized the irrigation pattern by analyzing real-time data from soil moisture sensors and environmental parameters. Specifically, during periods when soil moisture reaches a threshold, the system irrigates only when the plant actually needs it, instead of providing fixed scheduled irrigation. This approach, in addition to preventing water waste, can also improve plant health.

Smart management of energy-intensive equipment in this study resulted in a 3.6 percent reduction in energy consumption. The system prevents unnecessary equipment operation by predicting temperature fluctuations and optimally adjusting the performance of cooling and heating devices. For example, during cooler hours of the day, the system uses passive cooling methods instead of keeping devices constantly active. This smart approach, in addition to reducing costs, has a significant impact on reducing greenhouse gas emissions.

The stability of the environmental conditions created by the system has resulted in an 11.22% increase in production. By carefully controlling effective parameters such as temperature, humidity and light, plants are placed in ideal growing conditions. Studies show that this environmental stability reduces plant stress and shortens the growing period.

The cost-benefit analysis shows that the proposed system breaks even after four years, resulting in a long-term cost reduction of 13.8%. This saving is mainly due to reduced water and energy costs, as well as increased revenue from higher production. Calculations show that even after

taking into account the initial installation and start-up costs, the system will be completely cost-effective within a 10-year period. This finding could be very helpful for greenhouse owners looking to invest in smart technologies.

Therefore, the results of this study show that AI technology can simultaneously contribute to environmental, economic, and social goals in the agricultural sector. The proposed system provides a practical model for digital transformation in greenhouses by balancing productivity and sustainability. These findings can be a good basis for future policymaking to achieve sustainability in the field of smart agriculture.

4. 4. SUMMARY

In this chapter, the results of implementing an AI-based resource management system in a smart greenhouse in Taiwan were analyzed. The results showed that the proposed approach was able to achieve acceptable performance in controlling temperature, humidity, and energy consumption, and maintained its stability and accuracy even in the face of environmental changes and random noise. Also, the analysis showed that the system effectively reduced water and energy consumption and increased productivity, while also reducing long-term management costs. Compared with traditional methods, the smart system had significant advantages in all indicators, including crop production, efficiency, sustainability and costs, and the results indicated its high efficiency in improving sustainable agricultural processes. Therefore, this study showed that utilizing smart technologies and artificial intelligence-based algorithms can be an effective solution for improving productivity and sustainability in greenhouse systems.

Chapter Five

Conclusion and Suggestions

5. 1. CONCLUSION

The results of implementing an AI-based resource-management system in a smart greenhouse in Taiwan showed that this technology was able to control environmental parameters, including temperature and humidity, very effectively and accurately. The system, using intelligent and controllable algorithms, was able to significantly reduce the fluctuations of these parameters even in the face of environmental noise and sudden weather changes, and, as a result, kept the internal conditions of the greenhouse within optimal ranges for plant growth. This achievement shows that adaptive feedback-control systems, by responding quickly and intelligently to dynamic changes in the environment, can provide a stable and suitable environment for plant growth, thereby improving crop productivity and health. In fact, by accurately detecting fluctuations and automatically adjusting heating, cooling, ventilation and irrigation systems, this system has played a key role in improving growing conditions and reducing environmental stresses, which results in an increase in the quantity and quality of crops during the cultivation period.

One of the most important achievements of this study was the significant reduction in water and energy consumption. Comparing the results obtained from the smart system with traditional methods showed that this approach, in managing water and electricity consumption, was able to significantly reduce consumption fluctuations. Smart irrigation management, which was based on accurate sensors and advanced algorithms, minimised the amount of water consumed and prevented resource waste. In addition, automatic adjustment of heating and ventilation systems improved energy consumption and, as a result, reduced operating costs.

These achievements not only helped reduce economic costs, but also played an important role in realising sustainable agriculture and reducing negative impacts on the environment, because reducing resource consumption also reduces environmental impacts and is associated with reducing greenhouse-gas emissions. Precise and stable control of environmental parameters led to an increase in the quantity and quality of crop production. Data analysis showed that maintaining temperature and humidity within optimal ranges prevented environmental stress on plants and accelerated their growth. This precise control, especially in reducing control errors and the system's rapid response to changes, played an important role in improving growth processes and increasing crop yields. The results showed that plants under such controlled conditions were healthier and their growth and production rates were significant compared to traditional methods, which directly contributes to the profitability and economic efficiency of the greenhouse. In addition, reducing control errors played a key role in ensuring the final quality of the products, and thus, the quality and marketability of the final products were improved.

In the economic area, financial and cost analyses showed that although the initial investment to set up the smart system is higher, in the long term, the economic benefits of this technology are clearly visible. The results showed that over time, and with the reduction of resource-consumption costs, operational and management costs decreased and the overall profitability of the greenhouse improved. Over the ten-year period, the overall costs of the smart system decreased compared with traditional methods and this investment became more economically justifiable in the long term. These analyses showed the importance of investing in new technologies in order to reduce costs, increase productivity and profitability, and showed that the use of smart technologies allows for more economical and sustainable agriculture.

A comprehensive evaluation of the system in four different scenarios—efficiency, production, sustainability and cost—showed that this system outperforms traditional methods in all four dimensions. The greatest differences were observed in the field of energy-consumption optimisation and operational-cost reduction, which indicates the ability of the smart system to align economic and environmental goals. Also, the stability and reliability of the system in the face of diverse weather conditions and in the presence of random noise were proven; this feature is of great importance for greenhouses operating in areas with uncertain climate and requiring robust and reliable technologies. Therefore, the results showed that the designed system has reliable and stable performance not only in controlled environments but also in variable environmental conditions and can be used as a practical and effective solution for the development of smart and sustainable agriculture on a larger scale.

The key results of this research show that the proposed AI-based system can effectively improve operational stability and productivity in smart greenhouses. Under normal conditions, the system automatically adjusts environmental parameters to provide optimal stability for plant growth. When faced with challenges such as sensor failures or extreme weather conditions, the system uses alternative solutions such as safe default modes or adaptive settings to prevent crop damage and maintain stable performance. From a technical perspective, the smart system has shown significant reductions in water and energy consumption by optimising resource usage. These improvements have not only reduced operating costs, but also significantly increased crop production by maintaining optimal growing conditions. Statistical analyses confirm that these changes are statistically significant and generalisable across different types of greenhouses and for different crops.

Finally, this research shows that implementing smart solutions can simultaneously achieve environmental, economic and social sustainability goals. Reduced resource consumption, increased production and good long-term financial returns make this system an attractive option for digital transformation in agriculture. These findings can be a valuable basis for macro-decisions in the development of smart and sustainable agriculture.

5.2 Limitations

The evaluation was performed in a single commercial greenhouse in Taiwan; results may differ in other climatic regions, with other crop varieties or alternative greenhouse designs.

Effective operation depends on continuous, accurate sensor data. Prolonged sensor failures or communication interruptions, while mitigated by safe-default modes, could still reduce control accuracy.

The system entails a higher initial capital investment, which may limit adoption by smaller growers despite the demonstrated long-term economic benefits.

5.3 Future Work

Development of a reinforcement-learning-based model that can respond in real time to environmental changes (such as temperature, humidity and light fluctuations) and optimise resource consumption (water, energy, fertiliser) with minimal human intervention.

Presentation of an adaptive control method for optimising and managing resources in smart greenhouses and comparison of its results with the artificial-intelligence-based method.

Testing the system's performance in real greenhouses with different climatic conditions (dry, temperate and humid) to evaluate the resistance of artificial-intelligence algorithms to noisy data and non-ideal conditions.

Testing the system's performance in real greenhouses with different climatic conditions (dry, temperate and humid) to evaluate the resistance of artificial-intelligence algorithms to noisy data and non-ideal conditions.

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ANEXO I. RELACIÓN DEL TRABAJO CON LOS OBJETIVOS DE DESARROLLO SOSTENIBLE DE LA AGENDA 2030

Anexo al Trabajo de Fin de Grado y Trabajo de Fin de Máster: Relación del trabajo con los Objetivos de Desarrollo Sostenible de la agenda 2030.

Grado de relación del trabajo con los Objetivos de Desarrollo Sostenible (ODS).

Objetivos de Desarrollo Sostenibles	Alto	Medio	Bajo	No Procede
ODS 1. **Fin de la pobreza.**				*
ODS 2. **Hambre cero.**		*		
ODS 3. **Salud y bienestar.**			*	
ODS 4. **Educación de calidad.**				*
ODS 5. **Igualdad de género.**				*
ODS 6. **Agua limpia y saneamiento.**	*			
ODS 7. **Energía asequible y no contaminante.**		*		
ODS 8. **Trabajo decente y crecimiento económico.**		*		
ODS 9. **Industria, innovación e infraestructuras.**	*			
ODS 10. **Reducción de las desigualdades**.				*
ODS 11. **Ciudades y comunidades sostenibles**.			*	
ODS 12. **Producción y consumo responsables.**	*			
ODS 13. **Acción por el clima.**	*			
ODS 14. **Vida submarina.**				*
ODS 15. **Vida de ecosistemas terrestres.**			*	
ODS 16. **Paz, justicia e instituciones sólidas.**				*
ODS 17. **Alianzas para lograr objetivos.**		*		

Descripción de la alineación del TFG/TFM con los ODS con un grado de relación más alto.

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Anexo al Trabajo de Fin de Grado y Trabajo de Fin de Máster: Relación del trabajo con los Objetivos de Desarrollo Sostenible de la agenda 2030. (Numere la página)

The thesis makes a high contribution to SDGs 6, 9, 12 and 13 by designing and validating an AI-based resource-management system that reduces water consumption, introduces industry-leading innovation, enables responsible production and supports climate-action targets in smart greenhouses. It shows medium relevance to SDGs 2, 7, 8 and 17 through increased agricultural productivity, optimised energy use, new economic opportunities and the need for multi-stakeholder partnerships. All other SDGs are of low relevance or not applicable because of the project ’ s specific, applied focus

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