IoT

Article

Utilizing an Internet of Things (IoT) Device, Intelligent Control Design, and Simulation for an Agricultural System

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Abstract: In an agricultural system, finding suitable watering, pesticides, and soil content to provide the right nutrients for the right plant remains challenging. Plants cannot speak and cannot ask for the food they require. These problems can be addressed by applying intelligent (fuzzy logic) controllers to IoT devices in order to enhance communication between crops, ground mobile robots, aerial robots, and the entire farm system. The application of fuzzy logic in agriculture is a promising technology that can be used to optimize crop yields and reduce water usage. It was developed based on language and the air properties in agricultural fields. The entire system was simulated in the MATLAB/SIMULINK environment with Cisco Packet Tracer integration. The inputs for the system were soil moisture sensors, temperature sensors, and humidity sensors, and the outputs were pump flow, valve opening, water level, and moisture in the sounding. The obtained results were the output of the valve opening, moisture in the sounding, pump flow rate, outflow, water level, and ADH values, which are 10.00000013 rad/s, 34.72%, 4.494%, 0.025 m^3/s, 73.31 cm^3, and 750 values, respectively. The outflow rate increase indicates that water is being released from the tanks, and the control signal fluctuates, indicating that the valve is opening.

Keywords: multi robot system; IOT device; smart agriculture system; intelligent controller

Citation: Amertet Finecomess, S.; Gebresenbet, G.; Alwan, H.M. Utilizing an Internet of Things (IoT) Device, Intelligent Control Design, and Simulation for an Agricultural System. *IoT* **2024**, *5*, 58–78. https://doi.org/10.3390/iot5010004

Academic Editor: Amiya Nayak

Received: 10 December 2023
Revised: 18 January 2024
Accepted: 24 January 2024
Published: 31 January 2024

1. Introduction

Farmers need to adapt to the shifting demands of the environment as well as those of regulators, consumers, food processors, and retailers. The effects of soil erosion, biodiversity loss, and climate change are all becoming more and more of a burden, as are consumer preferences for food and worries about its production. Furthermore, the natural world, in which farming interacts with plants, pests, and diseases, continues to provide difficulties. Even if there are many solutions available in modern agriculture, the results vary because every farm is different in terms of the amount of water needed, the kind of soil, the temperature, and the humidity [1]. For these reasons, farmers are looking for technology that can solve the issues facing agriculture today. For farmers, a highly promising solution is to integrate Internet of Things devices with intelligent controller algorithms in agricultural systems. The Internet of Things (IoT) has revolutionized the agricultural sector by providing farmers with real-time data on crop health, soil moisture, and nutrient levels. These data can be used to optimize crop yield, reduce water usage, and minimize the use of pesticides and fertilizers. IoT sensors can be used to monitor the health and well-being of livestock, optimize feeding schedules, detect illness, and improve breeding programs. Automated irrigation systems can be used to monitor soil moisture levels and weather patterns to optimize irrigation schedules, which can help reduce water usage and improve crop yield [2].

Many researchers have spent their time on the application of IoT devices in agriculture without considering the application of different controllers in agriculture to date. Furthermore, to sustain the health of the farm and maintain mass productivity, it is necessary to implement intelligent controller algorithms such as fuzzy logic, adaptive, model predictive, and so on into an agriculture system in order to enhancement the communication between faming system. The nature of agriculture structure requires flexibility, ease of implementation, robustness, and interpretability. Among the intelligent controllers, a fuzzy logic controller is the best fit to address the nature of agriculture structure requirements. The reason is that it works with imprecise inputs, does not require an accurate mathematical model, and can handle nonlinearity. It enables advanced fuzzy logic to control a pump's switching time according to user-defined variables, whereby sensors are the main aspect of and contributor to the system [3]. It introduces an innovative irrigation time control system for smart farming that leverages fuzzy logic to regulate the timing of irrigation in crop fields, effectively curbing water wastage while ensuring that crops receive neither too little nor too much water. A smart greenhouse system based on an IoT and fuzzy inference system can create an automatic microclimatic condition that optimizes the conditions of plant growth through the use of IoT sensors and actuators that automate the controlling of weather factors to enhance the plant growing process. A smart farm system can optimize water usage for agriculture. The system implements an open loop fuzzy logic control system using a Mamdani control system. The inputs to the fuzzy logic control system are adapted from a humidity sensor, temperature sensor, and the flux sensor in the field [4,5].

The purpose of this research is to improve automation systems in the agricultural industries by integrating intelligent controllers with Cisco Packet Tracer. As a result of Internet of Things devices being integrated into the system, farmers can now easily determine their current farming situation. The rest of this paper is organized as follows: Section 2 carries out a literature review, and Section 3 presents mathematical models of the system. The results and a discussion are presented in Section 4, and conclusions are drawn in Section 5.

2. Literature Review

Smart agriculture systems can be traced back to the mid-1980s, when research into automated fruit harvesting systems began in Japan, Europe, and the United States. Impressive advances have been made since then in developing systems for use in modern agriculture. To date, agriculture systems have utilized different technologies such as precision farming, hydroponics, aquaponics, robots, temperature and moisture sensors, aerial images, GPS technology, and vertical farming [6]. The most popular applications of artificial intelligence in the agriculture industry are in three major categories: agricultural robots, predictive analytics, and crop and soil monitoring. Computer vision and deep-learning algorithms are used to process data captured by drones and/or software-based technology to monitor crops. Farmers use technology daily. Automated drones already monitor fields and collect data on crops. Agricultural robots are being developed to carry out the fieldwork. Robots have successfully planted, tended, and harvested crops. In order to realize the full potential of the IoT, there is a need to integrate ubiquitous smart devices and cloud-based applications [7,8]; a combined IoT framework with a cloud at the center gives the flexibility of dividing associated costs in the most logical manner and is also highly scalable. In the combined framework, sensing service providers can join the network and offer their data using a storage cloud; analytic tool developers can provide their software tools; artificial intelligence experts can provide their data mining and machine learning tools useful in converting information to knowledge; and computer graphics designers can offer a variety of visualization tools [9–12]. An agricultural management method supported by technology monitors, assesses, and evaluates the requirements of specific fields and crops. The focus of these efforts is on robotics, which includes sensors, aerial images, and sophisticated local weather forecasts, as well as Big Data and advanced analytics capabilities. This results in reduced environmental impact, financial savings, and optimized fertilizer utilization.

Using data and information technologies to optimize intricate farming systems is known as smart farming. Smart farming does not place as much emphasis on exact measuring or differentiating between or within individual animals, as it does with PA. The emphasis is more on data application and access—that is, how to make intelligent use of the information gathered. Farmers can obtain real-time data regarding the state of the soil and plants, the terrain, the climate, the weather, the utilization of resources, labor, and funding [13,14]. By using mobile devices like smartphones and tablets, farmers now possess the knowledge necessary to base their judgments on factual information rather than gut feeling. Regular use of web-based data platforms in conjunction with Big Data analysis, internal and external farm networking, and precision and smart farming techniques is common. Products for IoT-enabled smart agriculture are made to automate irrigation systems and use sensors to monitor crop areas. Consequently, farmers and related brands may conveniently and remotely check agricultural conditions. Agriculture currently uses a variety of technologies. Therefore, to determine the degree of technology employed in the system, it is necessary to identify and compare the various technologies. For simplicity, this is compared in Table 1.

Table 1. Smart flatform comparison to date [15,16].

Technologies	Goals	Business Processing Module	Alarm Notification Module	Data Control	Communication Protocol	Posting On Social Networks and Public Data
APOLLO	Controlling crop growth and conditions	Applicable, VRI estimation module	Applicable	Applicable, crop growth monitoring and crop yield estimation	Not applicable	Not applicable
SMART AKIS	Management Information	Not applicable	Not applicable	Applicable, flexible and adaptive platform of smart farming technologies	Not applicable	Applicable
SIG AGRO ASESOR	Crop SIG Manager	Applicable, VRF and VRI modules	Applicable	Applicable	Not applicable	Applicable
Agrivi	Applicable, Plan, monitor and analyze crop activities	Applicable, crop seasons and pest monitor alert	Applicable	Applicable, crop data and inputs cost management	Not applicable	Not applicable
Smart Water-Saving	Intelligent irrigation programmer with sensory connectivity	Not applicable	Not applicable	Applicable, soil moisture data acquisition	Applicable, private protocol	Not applicable
PLATEM PA	Applicable, Management Information with an intelligent VRF and VRI Open Data, Farmers/Providers and Social network	Applicable, business rule engine based on data acquisition and historical data	Applicable, notification module in multimedia platform	Applicable, historical data acquisition is represented in graphs and downloaded files	Communication protocol Implemented based on open standard protocol in VRF and VRI devices	Farmers and providers access on-line forums to post results, crop failures, alerts, crop yield,

Researchers are using a variety of technologies in agriculture systems, including machine learning, remote sensing, image processing, sensor networks, and so on, to boost agricultural productivity. In order to gain insights, it is necessary to compare the controller algorithms used in agricultural systems. The comparison is based on how easily it can be automatically tuned during operation, as demonstrated in Table 2.

Table 2. Comparison of control algorithms in smart agriculture applications [15–17].

Controller Algorithms	Advantages	Disadvantages	Applicable in Smart Agriculture?
PID	Simplicity, applicability, and reliability	Long tuning time	Yes, recommended
P	Easy to implement	Long settling time, steady state error	Partially, recommended
PD	Easy to stabilize, faster response than just P controller	Can amplify high frequency noise	Partially, recommended
PI	No steady state error	Narrower range of stability	Partially, recommended
MPC	Works effectively within constraints of the real actuator which are relatively narrow	Depends on complex algorithm that needs longer time than the other controller	Recommended
LQR	Simplicity, robustness, and flexibility	Only requires the knowledge of the system dynamics and the desired cost function. It does not depend on the initial conditions, disturbances, or uncertainties of the system	Recommended
Fuzzy logic	Flexibility, ease of implementation, robustness, and interpretability	Dependence on human expertise, difficulty in tuning, limited accuracy and computational complexity	Best recommended
Slide mode	Fast dynamic response, insensitivity to variations in plant parameters and external disturbance.	Chattering, which is a very high-frequency oscillation of the sliding variable around the sliding manifold	Recommended
Backstepping	Can accurately track the desired trajectory or setpoint, ensuring that the system behaves as intended	The high gain observed is needed to avoid full state measurement	Recommended
Adaptive	Improves performance and robustness	High cost is produced and the process is very complex.	Recommended
Machine learning	Improved accuracy, cost reduction, scalability, increased efficiency, data dependency, computational resources, sampling	Needs high training	Recommended

3. Mathematical Models of the System

Figure 1 demonstrates how the overview of the present work begins with the collection of related works and the identification of issues. Following accurate problem acquisition, mathematical models of the agricultural tanks are created. Appropriate control algorithms are developed based on the mathematical models. The complete system is then be tested and simulated. After integrating the models with Cisco Packet Tracers and simulating again, if the test result validates the requirements, the findings are received and discussed. The procedure is repeated until the intended outcome is achieved. If the tested results are not validated by the requirements, which are checked against the mathematical model, the procedure is repeated.

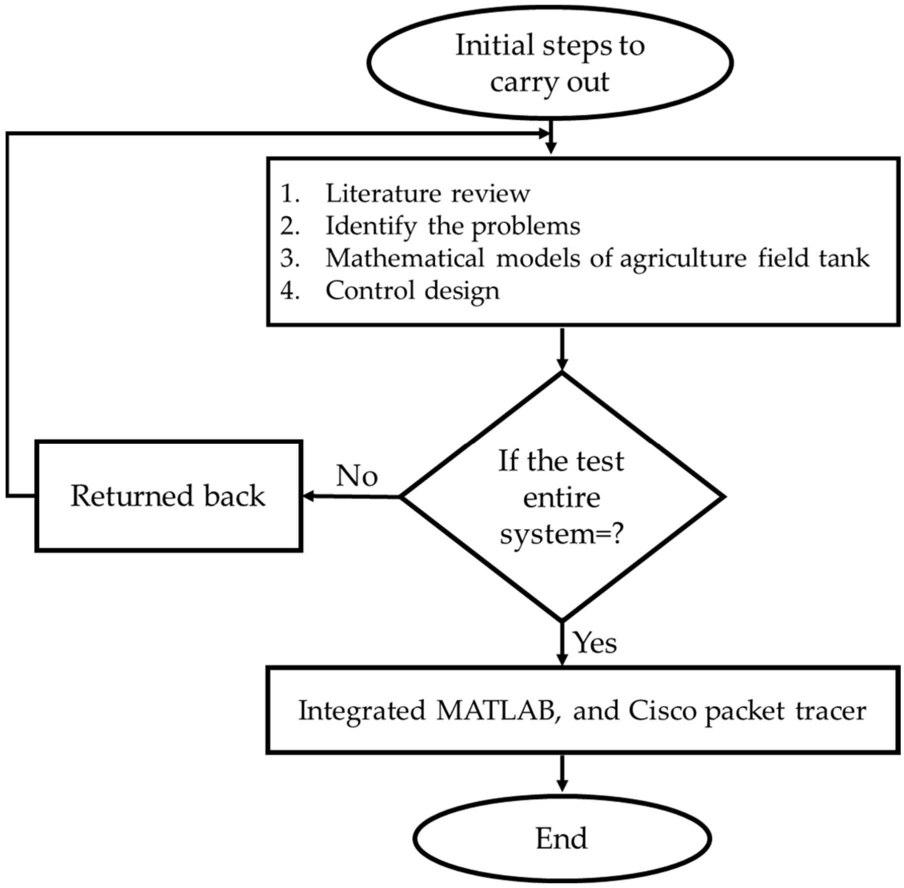


Figure 1. Flow chart of the current work.

3.1. Working Principles of Smart Agriculture

From Figure 2, it can be understood that agriculture can be a field as suitable as industry for the application of automation. Addressing the issues in the agricultural sector is challenging because crops are unable to communicate their emotions. Furthermore, humans are unaware of all the requirements that plants have. Farmers' extensive and protracted experience offers partial, but not complete, comprehension. The use of the Internet of Things in smart agriculture would help with issues like industry 4.0 agriculture using artificial intelligence and machine learning concepts, and IOT smart farming [18]. It aids in issue solving, goal keeping, improvement, categorization, and disease prediction in agricultural systems. Intelligent controllers (fuzzy logic controllers) would receive reference parameters (input) such as temperature, humidity, and soil moisture. The controller would then estimate the necessary specification and send it to the agricultural system. The Internet of Things is integrated into the agricultural system, allowing farmers to receive messages and quickly understand any issues. The reference settings would be modified for the farmer based on the need [19,20]. Fuzzy logic controller algorithms would be used to make the decision and carry out the action itself if the farmers were not given the proper system parameters. On the other hand, industrial processes can be designed by modules to apply specific robots to specific tasks, whereas the complex tasks of agriculture sometimes cannot be split into simple actions.

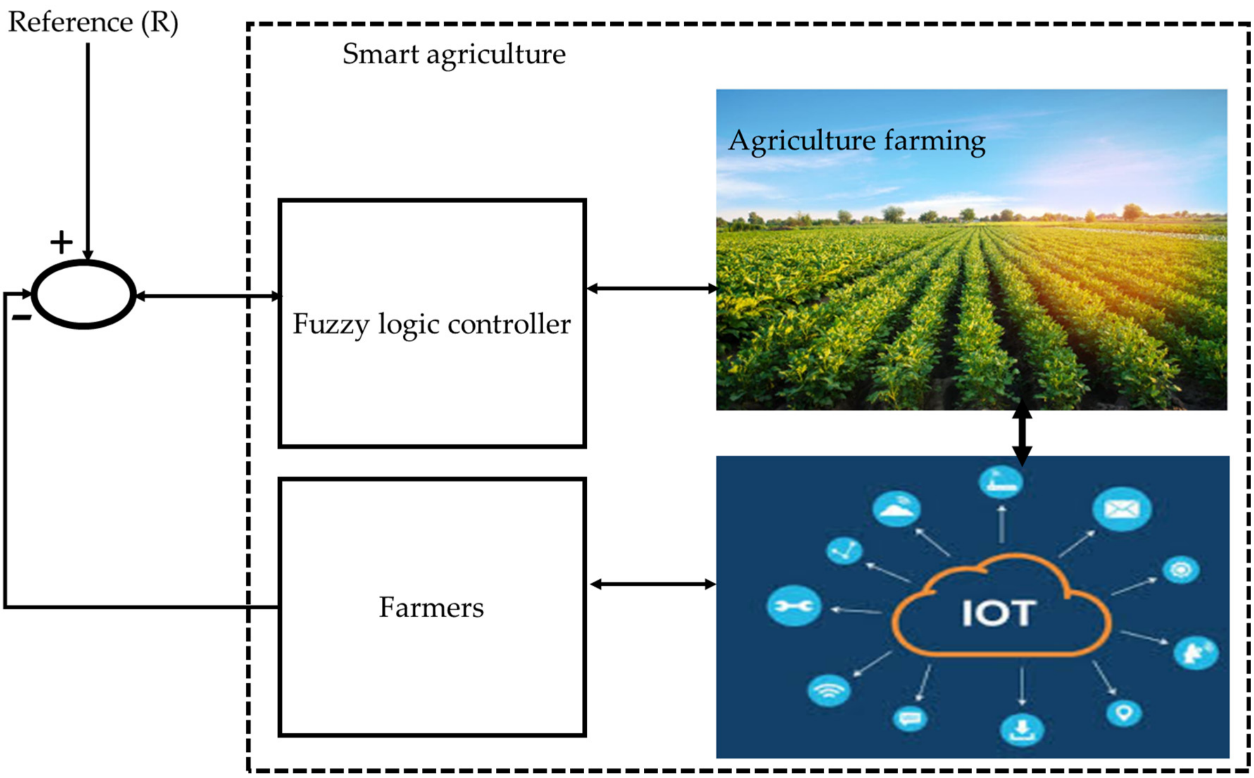


Figure 2. Smart agriculture system.

3.2. Mathematical Models of the Water Reservoir Tank Level, and Its Opening Valve

As shown in Figure 3, when considering a tank that has fluid flowing in (input) and fluid flowing out, we define the output as depth in the tank. Now, the research questions could be:

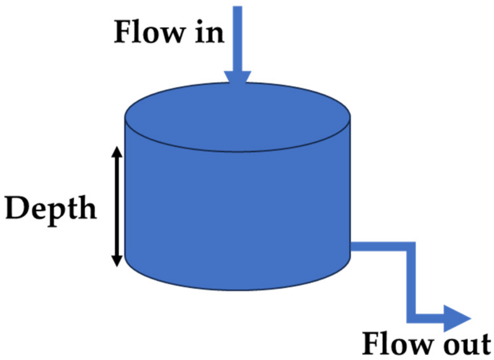


Figure 3. Water tank level for smart agriculture system.

How does the depth depend upon the inflow and outflow?

How does the outflow depend upon the depth?

In order to answer the questions, it must be understood that the outflow will depend upon the pressure in the tank (which depends upon the depth and density) and a constant linked to the pipe shape [21].

$$f_{out} = R\rho g h \tag{1}$$

Equation (1) represents the outflow models; the rate of the change of the depth will depend on the cross-sectional area, the difference between flow in and out.

$$\frac{dV}{dt} = A\frac{dh}{dt} = f_{in} - f_{out} \tag{2}$$

$$A\frac{dh}{dt} + R\rho g h = f_{in} \tag{3}$$

Observations from inflow Equation (3) show that the time constant depends on the resistance (pipe opening) of the outlet pipe and the cross-sectional area.

$$\frac{A}{R\rho g}\frac{dh}{dt} + h = \frac{1}{R\rho g} f_{in} \tag{4}$$

Gain depends on the resistance (pipe opening) of the outlet pipe:

$$T = \begin{cases} \frac{A}{R\rho g} \\ K = \frac{1}{R\rho g} \end{cases} \tag{5}$$

It was noted that the resistance to flow is actually $\frac{1}{R\rho g}$. If the cross-sectional area is increased, the time constant increases. If the resistance to flow K is increased, the time constant and steady state gain also increase. We ignore the impact of density and gravity. This marks the end of the mathematical models for inflow and outflow models. To adjust the system automatically and fulfill the objective, it is necessary to look at the control strategy.

This model works with inaccurate and hazy data. This is based on degrees of truth and is a glaring oversimplification of the real-world issues, as it includes only water tanks, which are a component of an agricultural system. For the time being, fuzzy logic control works well because some parameters are unknown.

3.3. Fuzzy Logic Control Design

Fuzzy logic is a mathematical method for representing vagueness and uncertainty in decision making. It allows for partial truths, where a statement can be partially true or false, rather than fully true or false. Fuzzy membership is a concept in fuzzy logic that assigns a degree of membership to an element in a set. The degree of membership is a value between 0 and 1, where 0 indicates that the element is not a member of the set, and 1 indicates that the element is a full member of the set [15]. There are different types of membership functions that can be used to model fuzzy sets, as represented in Table 3. While fuzzy logic has many advantages, there are also some disadvantages to using it. One of the main disadvantages is that it can be difficult to design a fuzzy system that accurately models a complex system. Fuzzy systems can also be computationally expensive to run, especially if they involve a large number of rules or membership functions. Additionally, fuzzy systems can be difficult to interpret, especially if they involve a large number of rules or membership functions [22].

Table 3. Comparison of fuzzy memberships.

Specification of the Membership	Comparisons of the Memberships	Level of Estimating Probability
Singleton membership function	This assigns a membership value of 1 to a specific value of x. It is useful when the set has a single element [15].	Good
Triangular membership function	This is one of the most widely used membership functions. It is used to model sets that have a triangular shape. The membership value increases linearly from 0 to 1 and then decreases linearly from 1 to 0 [16].	Better
Trapezoidal membership function	This is similar to the triangular membership function, but it has a flat top. It is used to model sets that have a trapezoidal shape [17].	Better
Gaussian membership function	This is used to model sets that have a bell-shaped curve. It is often used in statistics to model normal distributions [18].	Excellent

Table 3. *Cont.*

Specification of the Membership	Comparisons of the Memberships	Level of Estimating Probability
Sigmoidal membership function	This is used to model sets that have an S-shaped curve. It is often used in artificial neural networks [19].	Better
Generalized bell membership function	This is a generalization of the Gaussian membership function. It is used to model sets that have a bell-shaped curve, but with more flexibility [17].	Best
Z-shaped membership function	This is used to model sets that have a Z-shaped curve. It is often used in control systems [18]	Better

Based on the comparison hits, a Gaussian membership function was selected for this work [23].

$$F(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (6)$$

Figure 4 depicts the conventional layout of a fuzzy logic controller. Before going into the main control block, the inputs which were crisp values produced by the feedback error and change in error were conditioned by multiplying by constant gains using a preprocessor. The fuzzification block matches data with criteria of rules and transforms input data into degrees of membership functions. The Mamdani-type inference engine took the rule-based commands as input, calculated the degree of capability of the used rules, and produced a fuzzy set for the defuzzification block, which took the fuzzy output data and produced crisp values. Through the use of the centroid defuzzification approach, the outputs of the fuzzy sets were transformed into crisp values [24,25].

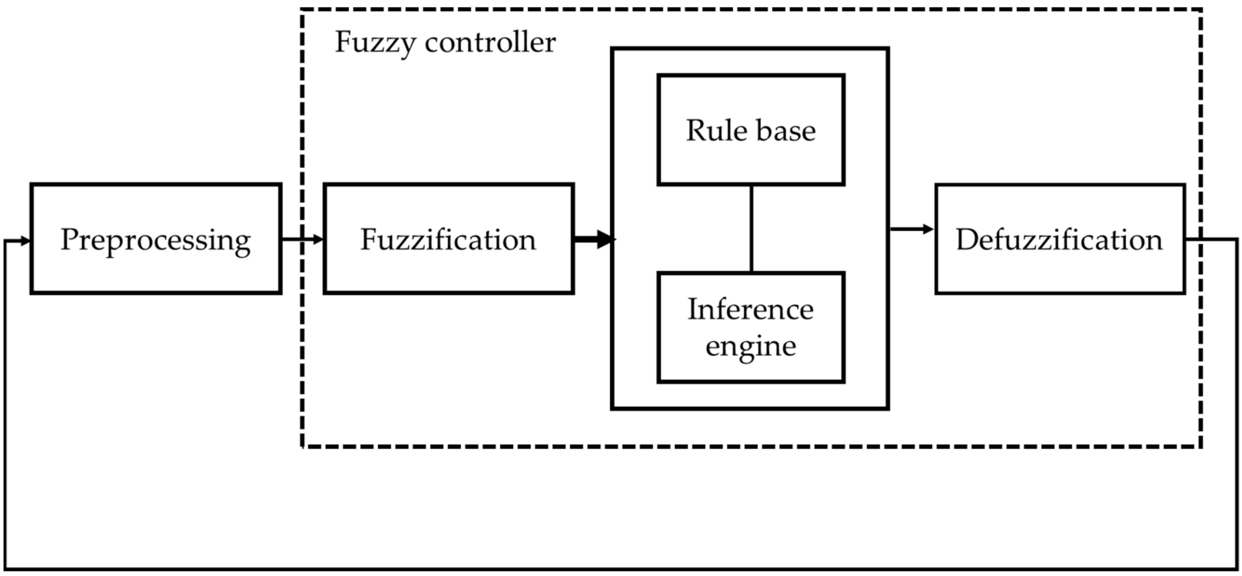


Figure 4. Fuzzy logic controller scheme.

3.3.1. Membership Function Assignments

The membership assignment for temperature is displayed in Figure 5. Temperature regulation would be based on function. Low is represented in black, normal is presented in red, and high is represented by blue, which have been assigned to the values. The Gaussian function is used to represent the function. While probability was represented by the vertical axis, the horizontal axis was expressed in degrees Celsius.

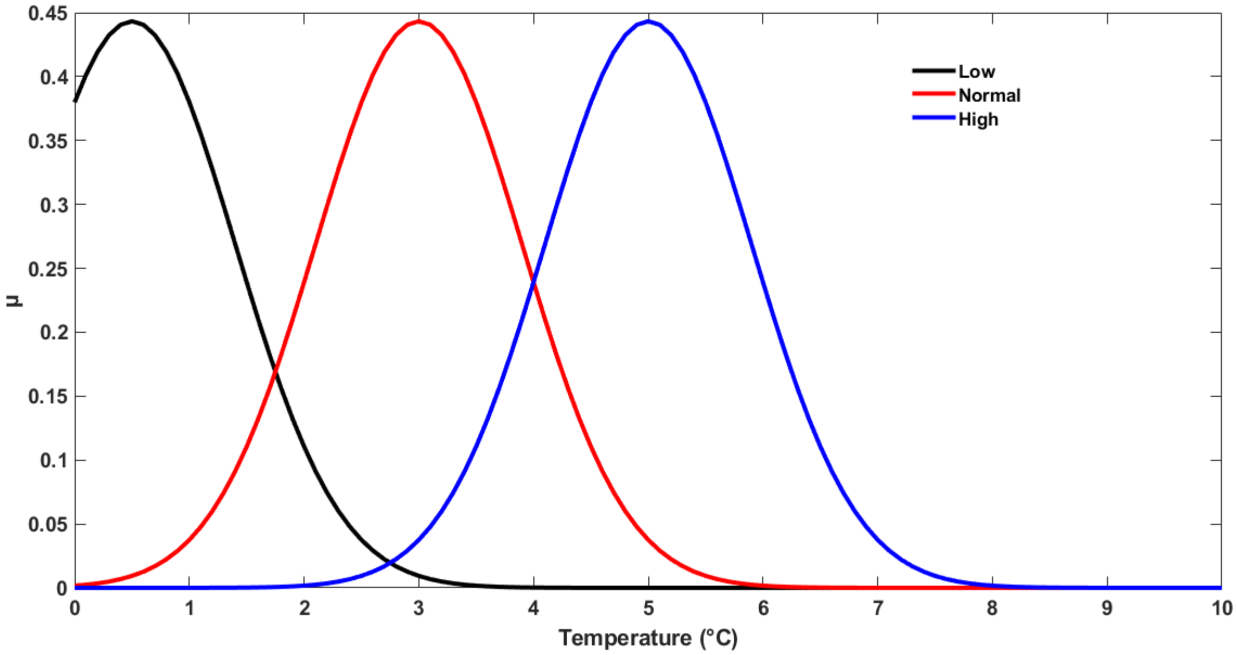


Figure 5. Fuzzy membership function for temperature.

Figure 6 shows the membership assignment for humidity. Function would be the basis for controlling humidity. The values have been given as low, represented in black, normal, presented in red, and high, represented in blue. The function is represented by the Gaussian function. The horizontal axis was given in mass per cubic meter, whilst the vertical axis denoted probability.

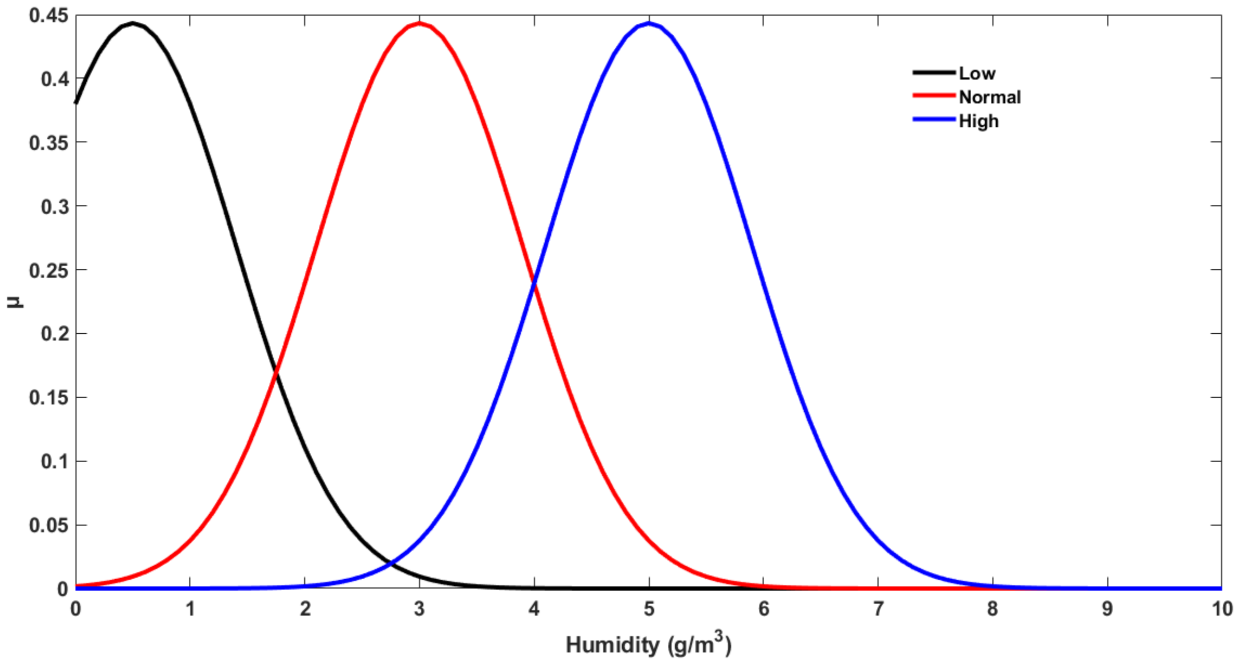


Figure 6. Fuzzy membership function for humidity.

The membership assignment for humidity is displayed in Figure 7. The foundation for regulating soil moisture would be function. Three values have been assigned to the values: low, which is represented in black, normal, which is presented in red, and high, which is represented by blue. The Gaussian function is used to represent the function. The vertical axis represented probability, and the horizontal axis was expressed in mass per cubic meter.

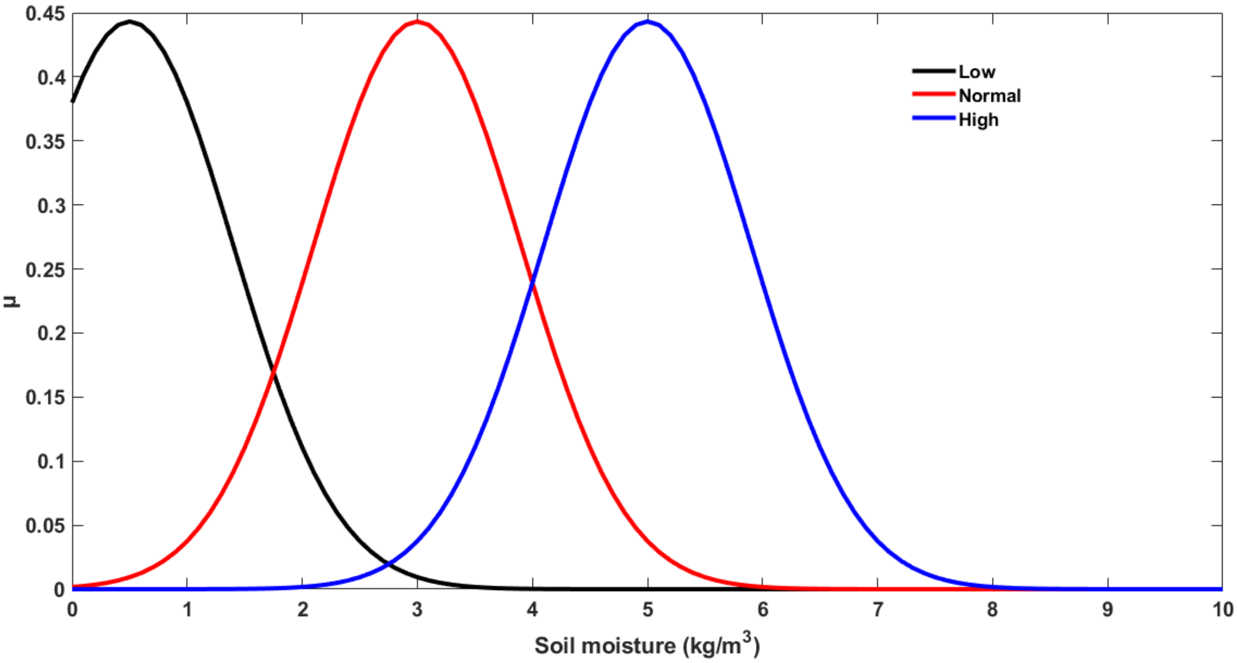


Figure 7. Fuzzy membership function for soil moisture.

Figure 8 shows the membership assignment for opening the valve. Function would be the cornerstone for controlling the valve's opening. Wet is represented by blue, cold is shown in red, moderate is presented in black, hot is demonstrated in purple, and dry is presented in green. The function is represented by the Gaussian function. Probability was represented by the vertical axis, while degrees were shown by the horizontal axis.

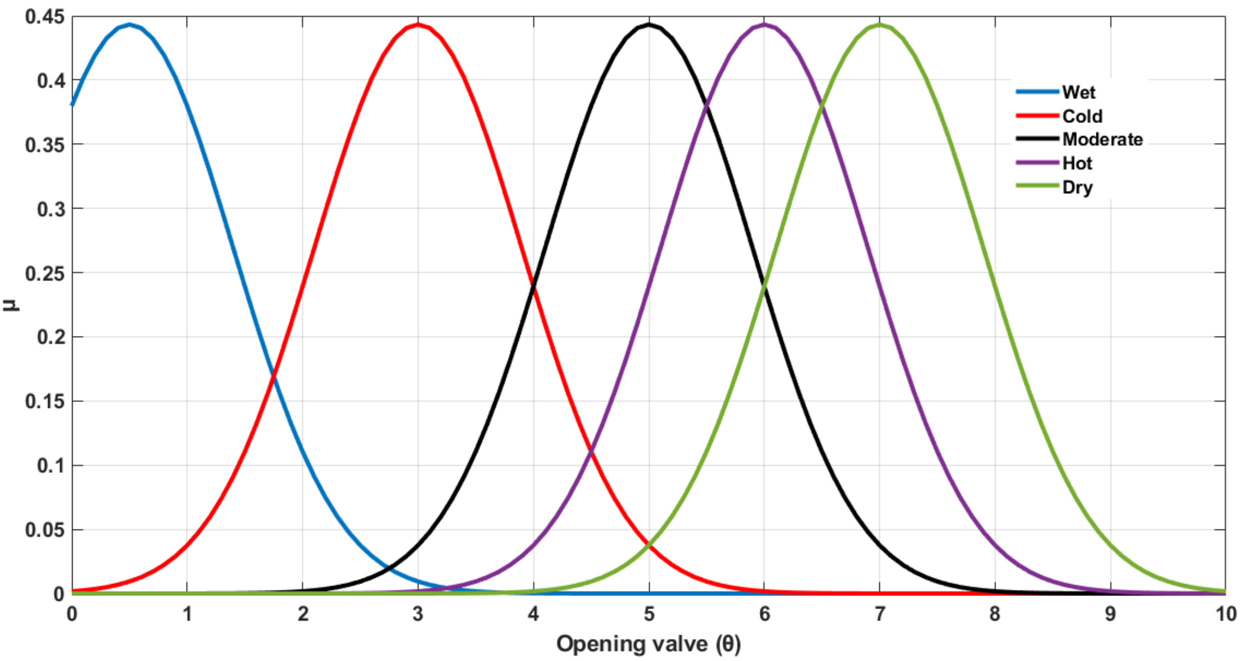


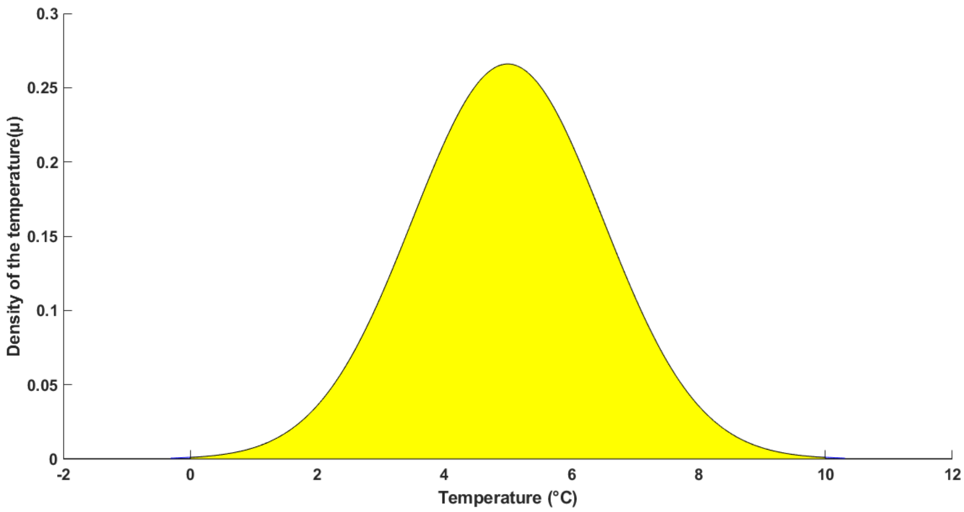
Figure 8. Fuzzy membership function for opening valve.

As shown in Table 4, the fuzzy logic designs were determined by the language rules. Z stands for zero response, P1 shows positive small, which means the valve would be open slightly, N2 signifies negative large, which means the valve is completely closed, and P2 indicates positive large, which means the valve is fully opened and the water is discharging.

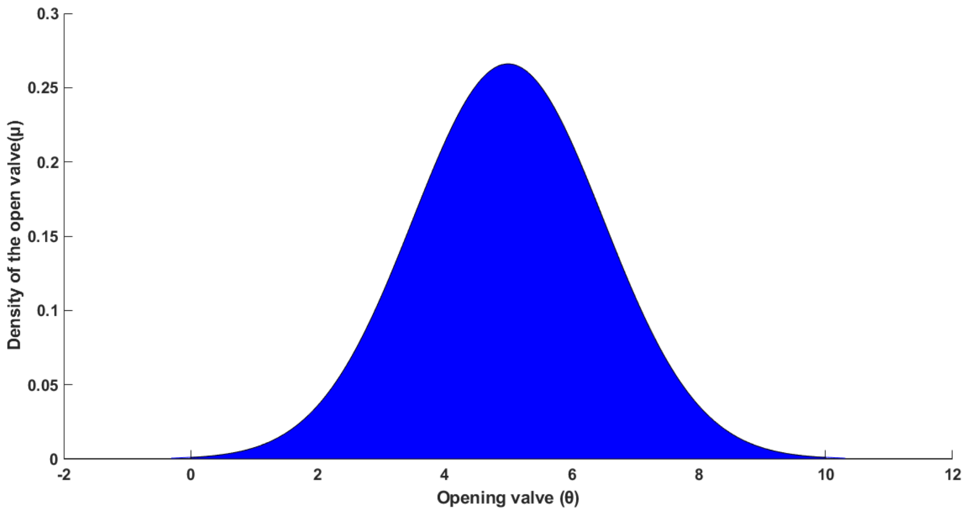
Table 4. Rule design for IOT device.

Temperature	Opening Valve			
	Wet	**Cold**	**Moderate**	**Dry**
Low	N2	Z	P1	P2
Normal	Z	Z	P1	P2
High	P2	P1	Z	P2

Figure 9a,b demonstrate how these rules base their control efforts on a number of if–then statements regarding (e) and (De). Specifically, if the error is equivalent to the values for temperature (TV), humidity (HV), and soil moisture, then control (c) is changed to open the valve (OV). The system was tuned and experiments were conducted to identify the number of these if–then statements. It is simple to repeat the procedure by adjusting the input numbers with the aid of the vertically positioned red line. It adjusts itself prudently. The yellow color in Figure 9a indicates the face of the input parameters, while the blue color in Figure 9b shows the output parameters.



(**a**) input density probability for rules of the fuzzy interface system



(**b**) output density probability for rules of the fuzzy interface system

Figure 9. Density probability for rules of the fuzzy interface system.

Plotting the first output variable against the first two input variables, the fuzzy logic rule surface provides the output surface for the fuzzy inference system. The midpoints of each input variable's corresponding range are used as reference values for the other input variables in fuzzy systems with three inputs. As a result, Figure 10 shows the smoothness of the control signal change and offers the rule surface that corresponds to the rules. Figure 10 shows the fuzzy numbers with the lightness change caption and colors representing the least and greatest uncertainty levels. and was greatly impacted by the work, which offered approaches for visualizing data with uncertainty based on variations in saturation, brightness, and/or intensity. The hue of the map indicates the degree of uncertainty with respect to the lower values. The color-coded map illustrates the degree of uncertainty towards the higher numbers.

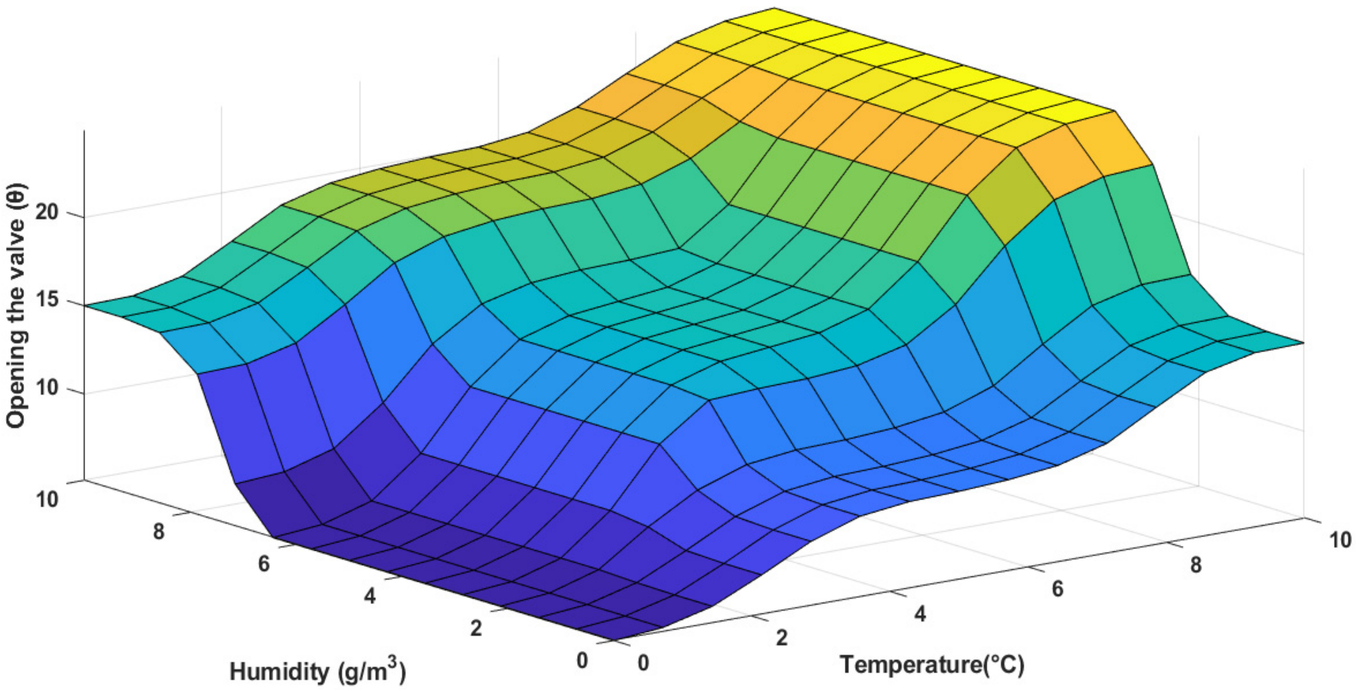


Figure 10. Fuzzy logic rule surface.

The aim of this controller design is to enhance communication between ground mobile robots, aerial vehicles (quadcopters), and farming fields. In order to achieve the goals of this work, this section provides a case study for the intelligent fuzzy logic controller and formulations of air properties in agricultural fields. Figure 11 shows that the components consist of three inputs: soil moisture sensors, temperature sensors, and humidity sensors. The fuzzy logic controller then receives signals from the three inputs in order to control the pumps and valve opening conditions. As the valve opens, input fills the water tank. The filled water levels are measured by water level sensors and flow rate sensors, which send feedback to the fuzzy logic controller. Based on the feedback signals, the fuzzy logic controller automatically adjusts the input signals and then sends them to the respective outputs.

Figure 12 shows the working principles of the IoT implementation in the agriculture system. The system starts up and initializes, then collects data from the agricultural fields. It then prints whether the soil moisture (SM) is less than 27%, in which case the sprinkler turns on, or if the soil moisture (SM) is greater than 27%, in which case the sprinkler turns off.

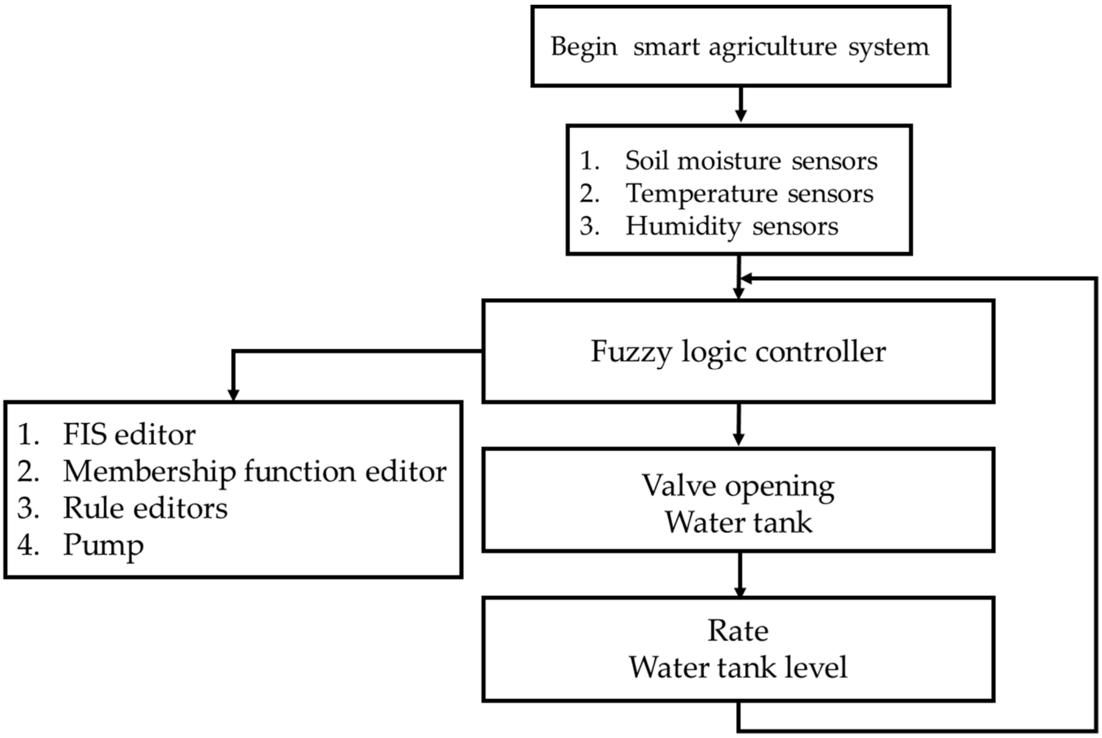


Figure 11. Block diagram of smart agriculture system.

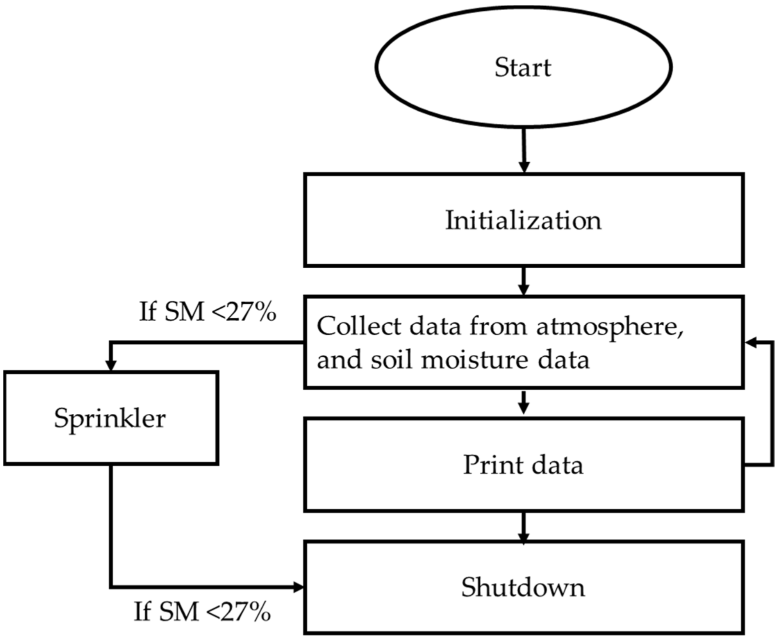


Figure 12. Schematics of the model.

3.3.2. Case Study for the Intelligent Fuzzy Logic Model

These rules can be used to create a fuzzy logic-based system that can control a pump's switching time according to user-defined variables, whereby sensors are the main aspect of and contributor to the system. The proposed system can help automate irrigation and reduce water consumption and watering time [15–19]. Here are some fuzzy rules for temperature, humidity, soil moisture, and soil acidity as input and output in a smart agriculture system:

- Temperature:

 - If the temperature is low, then the output is cold;
 - If the temperature is normal, then the output is moderate;
 - If the temperature is high, then the output is hot.
- Humidity:
 - If the humidity is low, then the output is dry;
 - If the humidity is normal, then the output is moderate;
 - If the humidity is high, then the output is wet.
- Soil Moisture:
 - If the soil moisture is low, then the output is dry;
 - If the soil moisture is normal, then the output is moderate;
 - If the soil moisture is high, then the output is wet.
- Soil Acidity:
 - If the soil acidity is low, then the output is basic;
 - If the soil acidity is normal, then the output is neutral;
 - If the soil acidity is high, then the output is acidic.

These rules can be used to create a fuzzy logic-based system that can control a pump's switching time according to user-defined variables, whereby sensors are the main aspect of and contributor to the system. The proposed system can help automate farms and reduce water consumption and watering time.

3.3.3. Formulation of the Air Properties in the Agricultural Field

It was assumed that the opening of the valve, moisture in the sounding, pump flow rate, and water levels during the valve's operation would be taken into account. However, other factors were not considered in the work. Based on this assumption, the following parameters would be formulated as follows [20]:

$$\text{Moisture in sounding } (\%) = \sqrt{\frac{\gamma p}{\rho}} * 100 \tag{7}$$

where γ is the constant ideal ratio, p is the pressure sound in the system, and ρ is the specific density of the air.

$$\text{Outflows(Q)} = \frac{\pi * \mathrm{D}^2 * n * H}{4 * g} \tag{8}$$

where D is the diameter of the reservoirs, n is the number of moles, H is the head of the water in the field.

$$\text{Pumps flow (rpm)} = \text{GPM} \tag{9}$$

where gallons per minute (GPM) is the flow rate.

$$\text{Valve opening} = \text{Q proportional to Area} \times \text{Sqrt of DP} \tag{10}$$

where DP is the pressure drop across the valve.

4. Results and Discussion

The purpose of this research article was to create an Internet of Things (IoT) weather station that also incorporated a soil moisture monitoring component. The device is intended to notify the user when the moisture content of the soil drops below a certain value. To notify the user that the moisture content of the soil is too low, sprinklers, which correspond to the three soil moisture sensors, will turn on. The initial idea was to feed all of these data onto a server designed to handle IoT projects and then plot the data continuously. From Table 5, it was understood that IoT devices (temperature sensors, ADH sensors, and water vapor per kg) are used as inputs for the fuzzy logic control. The outputs are rotations of the pumps, moisture in the sounding, water level sensors, outflow, and valve opening. Of these output parameters, valve opening is constant throughout the process, while the input parameters vary.

Table 5. Simulation results of the IOT application in smart agriculture system.

Input Parameters			Output Parameters				
Temperature (Celsius)	**Water Vapor per Kg**	**ADH Values**	**Water Level Sensors (cm^3)**	**Moisture in Sounding (%)**	**Pump Flow (%)**	**Outflow (Q/s)**	**Valve Opening (rad/s)**
27	10	750	73.31	34.72	4.494	0.025	0.5
20	10	500	48.88	45.87	3.275	0.025	0.5
10	10	300	29.33	84.75	1.424	0.025	0.5
0	0	50	4.888	555.5	6.718	0.025	0.5
0	20	50	4.888	1111	6.718	0.03082	0.5
40	10	1000	97.75	23.92	4.008	0.025	0.5

Table 6 presents the comparison between the previous results [2–4] and the current results.

Table 6. Comparison of previous work and current work.

Specification Parameters	Current Work	Previous Work [2–4]	Change (%) (Current Work over Previous Work)
Rise time (s)	0.8	1.2	33.3
Settling time (s)	0.012	1.04	98.8
Peak time (s)	0.13	1.2	89.2
Temperature (Celsius)	27	27	0
ADH values	750	750	0
Moisture in sounding (%)	34.72	30	15.7
Pump flow (%)	4.494	3.5	28.4
Outflow (Q/s)	0.025	0.025	0
Valve opening (rad/s)	0.5	0.33	51.51

Figure 13 demonstrates the water levels in the fields. The vertical axis indicated the water level in mega metric cube (Mm^3), whereas the horizontal axis showed the time in hours. At the beginning, it slowly increases since the amount of water required by the field was not much. It increases slowly until about 9.8 h, after which it dramatically increases, indicating that the field requires more water. Too much water in agricultural areas can affect how the soil functions, hinder plant growth, and increase the risk of nutrient runoff. Too little water, on the other hand, can have devastating effects on crops and their ability to take up nutrients from the soil. Intensive groundwater pumping for irrigation depletes aquifers and can lead to negative environmental externalities, causing significant economic impact on the sector and beyond.

As seen in Figure 14, valve opening is a term used in irrigation to describe the degree to which a valve is open or closed. It is typically expressed as a percentage, with 0% indicating that the valve is completely closed and 100% indicating that the valve is completely open. The valve opening determines the amount of water that flows through the valve and into the irrigation system. By adjusting the valve opening, the controller can control the amount of water that is delivered to their crops. For this case, its opening slowly increases, because the level of the water discharge flow rate is directly proportional to the product area and the drop in pressure. The water level has a minimum of 10 m^3, meaning that when the valve is opened, the water level will likewise gradually rise from 10 m^3.

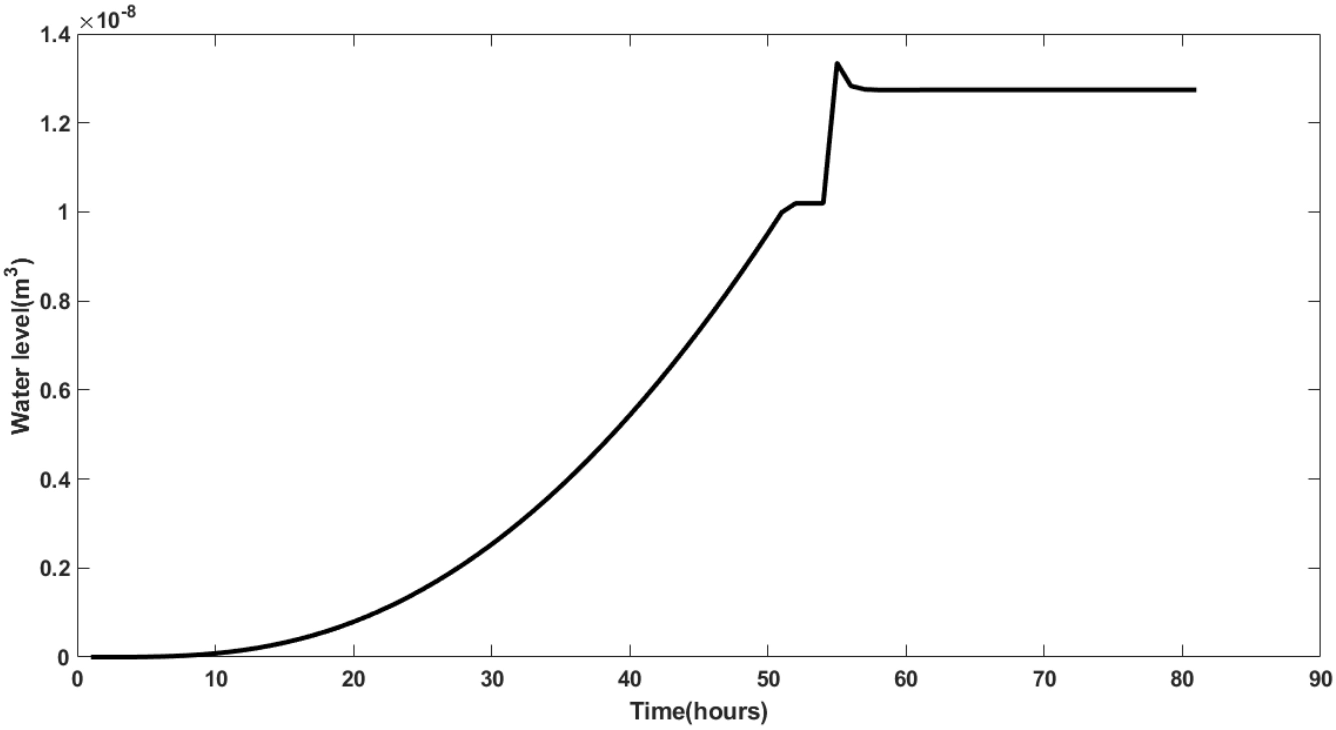


Figure 13. Measurements of water level in agricultural fields.

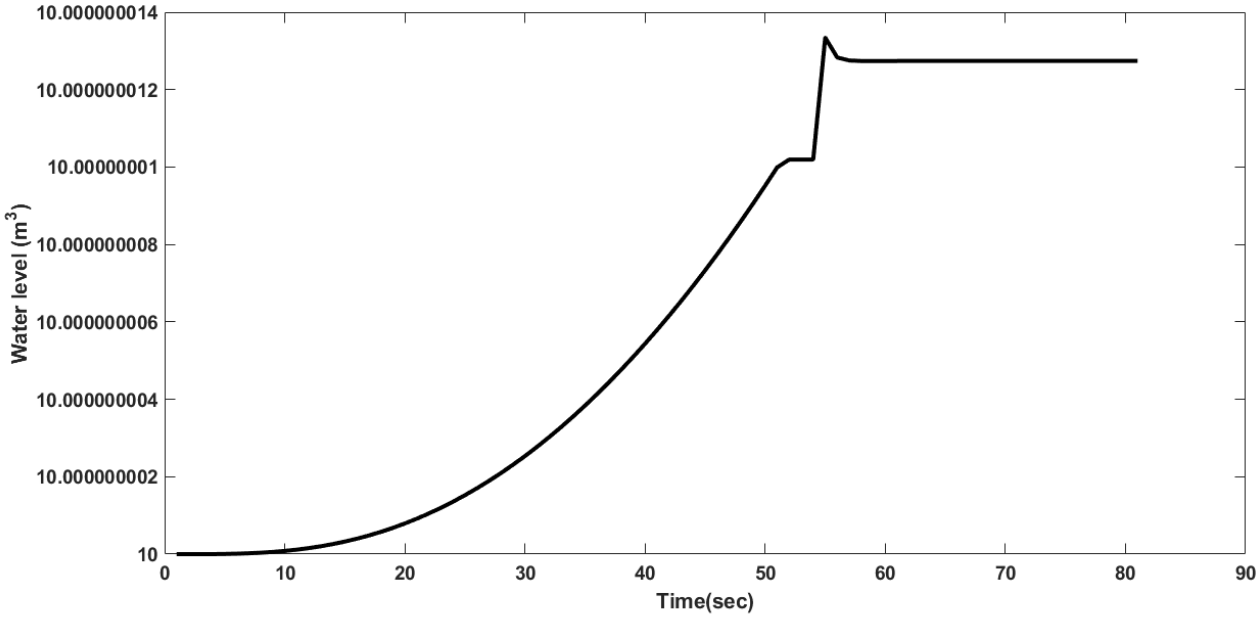


Figure 14. Valve opening mechanism.

As shown in Figure 15, in the IoT, a controller effort is a term used to describe the amount of torque or force that is applied to a pump and valves in order to achieve a desired performance. Controllers are defined by the type of control input and the type of output they use to drive the pump and valves. For example, a flow rate controller accepts flow rate commands as input and produces torque (effort) commands as output.

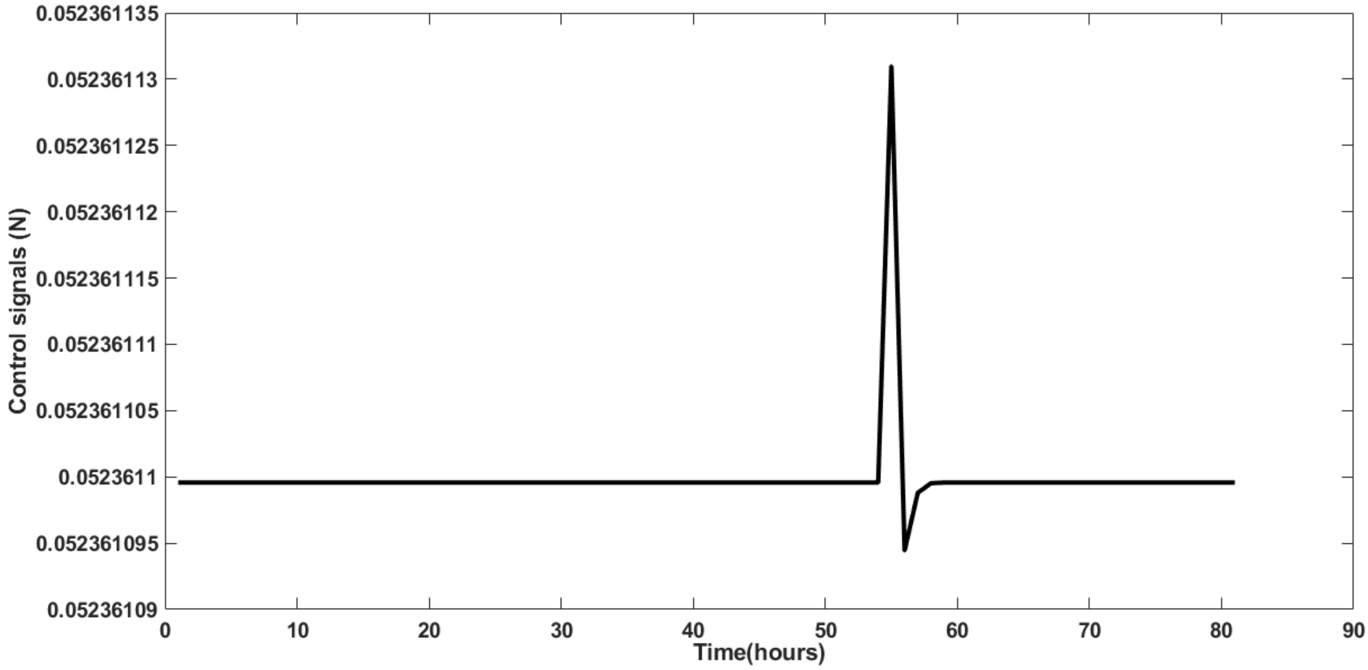


Figure 15. Controller effort.

Figure 16 represents the discharge of water in the agricultural fields. It means that flow rate discharge is the volume of water that flows through a pipe or channel per unit of time. In the agricultural sector, flow rate discharge is an important parameter for irrigation systems. It is used to determine the amount of water that is delivered to crops automatically, and to ensure that the farm system is operating properly.

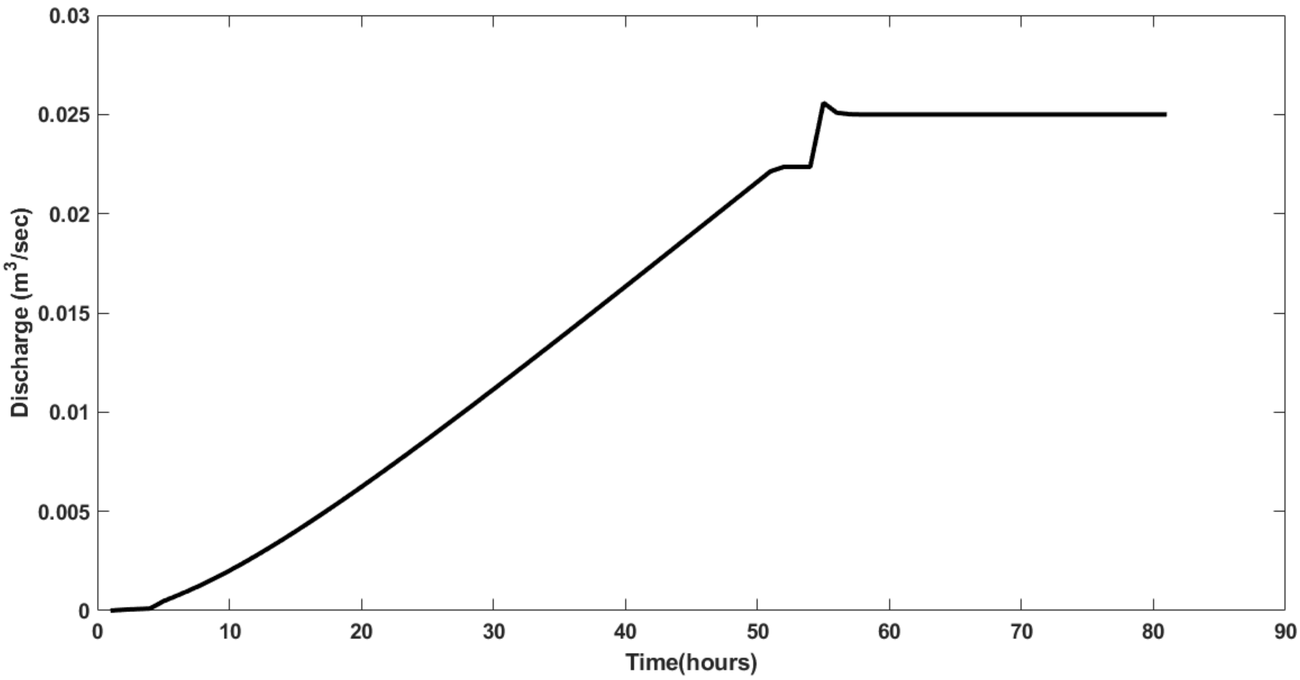


Figure 16. The discharge rates.

As shown in Figure 17, errors related to water level grow proportionately. An inaccuracy characterized as a proportional error depends on how much the water level variable changes. Thus, the relationship between the change in water level and the change in time (hours) is straightforward. Time (hours) divided by water level always equals the same constant, since this change is always of an equally quantifiable quantity. A statistic that shows how much a water levels sample percentage is expected to deviate from the proportion in the overall proportion that constitutes the standard error of a proportion.

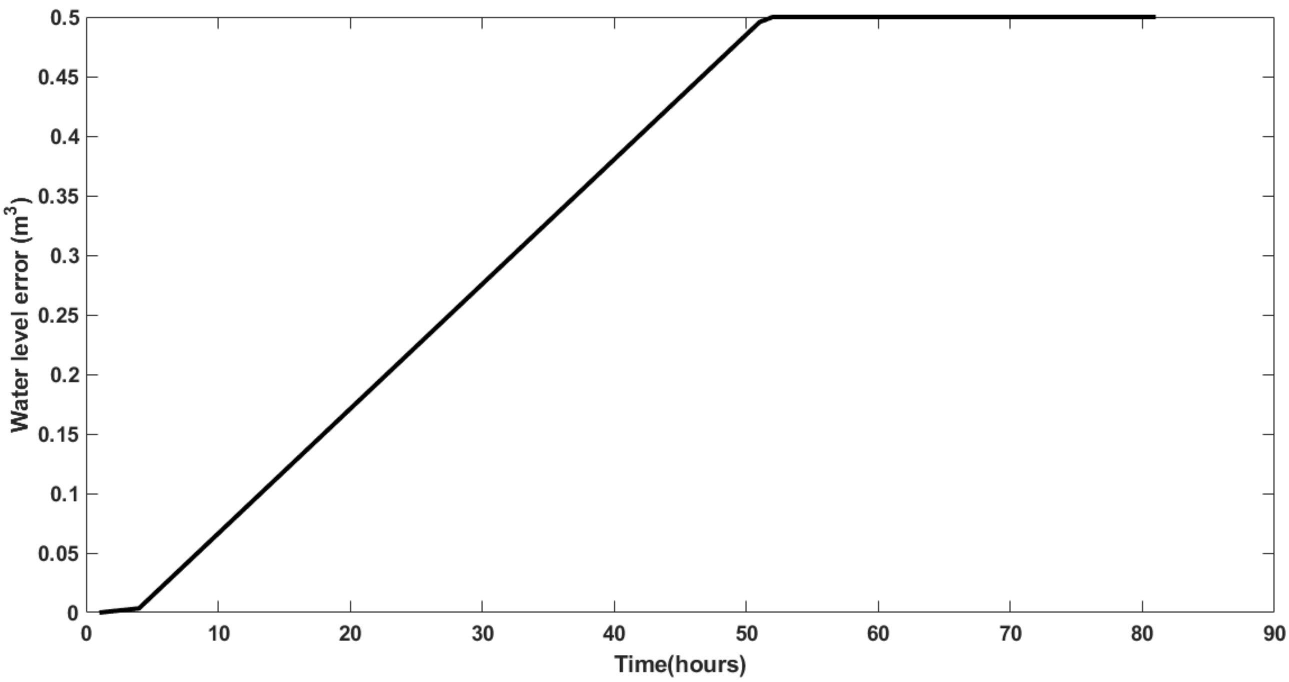


Figure 17. Water level error.

After the controller design was finished, it was implemented in Cisco Packet Tracer with integrated MATLAB/SIMULINK environments. Figure 18 shows the real-time flow of data packets during the simulation. The fuzzy logic intelligent controller is the home gate connected to the IoT backend server. The IoT connection enables users to check the status of the IoT parameters such as temperature, humidity, and soil moisture from an IoT browser homepage. The IoT browser homepage shows a list of the smart devices, allows visualization of their status, and permits remote interaction with the devices. Logical interaction between smart devices can be set while connected to the IoT main homepage. Interactions between devices are based on set conditions, such as starting a chiller when the temperature of a particular unit needs to be lowered or reducing oxygen supply to a boiler in order to reduce fire tube temperatures. The central control PC, manager smartphones, and tablets, which are connected to the local central office wireless LAN (WLAN), can connect to the dedicated IoT homepage via a browser in order to monitor all connected IoT devices. Cisco Packet Tracer has a feature with the possibility to switch from real-time to simulation mode. The first mode enables the possibility to create the underlying network, connect IoT devices, and define IoT backend logic. However, only in the simulation mode, it was possible to validate that the network communication layer really happened between the devices. In the simulation mode, it was possible to simulate packet traffic between nodes and devices in order to check the connectivity, routing protocols, and other network logic. This mode helped to physically visualize and troubleshoot any kind of network, for example, setting up pings or more complex packages between nodes.

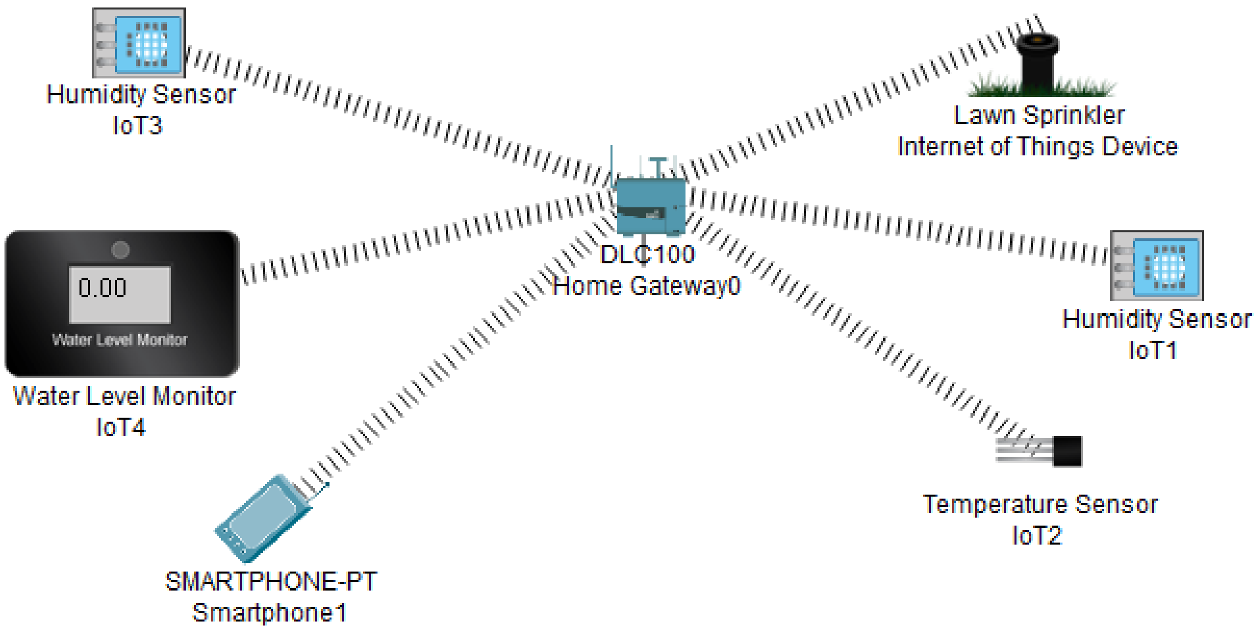


Figure 18. Real-time flow of data packet.

5. Conclusions

This study aimed to incorporate an Internet of Things (IoT) agricultural system that monitors soil moisture, temperature, and humidity as input parameters and automatically opens the valve as an output. In order to achieve these goals, a wide range of pertinent research papers were looked into to determine the current problems. One of the problems was the difficulty of having valves in agricultural fields that open automatically. Based on well-founded concerns, mathematical models of agricultural tanks were created. Fuzzy logic controllers were designed using the mathematical models that were provided. It was determined to create fuzzy logic controllers by utilizing the language-based membership function. Fuzzification of fuzzy language started next, and was followed by rule evaluation and defuzzification. Next, a fuzzy logic surface and fuzzy logic rules were created. When the fuzzy logic system was complete, it was all transferred to a mathematical model of a water tank to watch how the controller functioned. After that, Cisco Packet Tracers were used to integrate the entire system within the MATLAB environment. Sprinklers that correspond to the three soil moisture sensors activate, and the gadget notifies the user when the soil moisture content falls below a predetermined threshold. After being loaded onto a server built to handle IoT devices, the data are continually plotted. The field's water requirement rises gradually for approximately 9.8 h before sharply increasing, suggesting that the field needs more water. In agricultural settings, an excess of water can disrupt soil structure, impede plant development, and raise the possibility of nutrient runoff. Crops and their capacity to absorb nutrients from the soil can suffer greatly from inadequate watering. Aquifers are depleted, and adverse environmental externalities may result from intensive groundwater pumping for agriculture, which has a substantial financial impact on the industry and beyond. In agriculture, "valve opening" refers to the extent to which a valve is open or closed. A percentage is usually used to represent it, where 0% denotes a fully closed valve, and 100% denotes a fully opened valve. The amount of water that passes through the valve and enters the agricultural system is determined by the valve opening. Farmers can regulate how much water is applied to their crops by changing the opening of the valve. The amount of torque or force supplied to a pump and valves to accomplish a specified performance is referred to as the controller effort in the Internet of Things. The kind of control input and output that a controller uses to operate the pump and valves characterizes the controller. For instance, a flow rate controller generates torque (effort) commands as an output after receiving flow rate commands as input. Flow rate discharge is a crucial agricultural system element in the agriculture industry. It is used to figure out how much water is automatically applied to crops and to make sure the farm system is running smoothly. Smart gadgets are linked to the IoT backend server through a house gate. Through the IoT connection, users can remotely interact with the devices and check their status from the homepage of an IoT browser. While linked into the IoT main portal, smart device interactions can be configured logically. Device interactions are dependent on predetermined parameters. For example, a chiller may be started when a certain unit needs its temperature dropped, or the oxygen supply to a boiler may be reduced to lower fire tube temperatures. All linked IoT devices may be monitored by the central control PC, management cellphones, and tablets by connecting them via a browser to the specific IoT site. One characteristic that makes integrating MATLAB/Simulink with Cisco Packet Tracer possible is the ability to transition between simulation and real-time mode. It is feasible to confirm that the network communication layer between the devices actually occurred in the simulation mode. To examine network logic, routing protocols, and connectivity between nodes and devices, a packet tracer simulation can be performed. This mode facilitates the physical visualization and troubleshooting of any type of network, including the configuration of more intricate packages or pings between nodes. It was discovered that the optimal outcome came from combining the Cisco Packet Tracer with the MATLAB environment. If agricultural temperature, humidity, and soil moisture content were all effectively controlled, as well as if water tanks could open on their own, these outcomes would occur. Farmers and crops would be in communication at the same time. Consequently, in comparison to earlier research studies, the suggested intelligent control system is the most appropriate with IoT gadgets for the implementation of smart farm systems.

Author Contributions: S.A.F.: Visualization, Writing—original draft, Writing—review & editing, Conceptualization, Data curation, Formal analysis, Investigation, Methodology, and Software; G.G.: Validation, Funding acquisition, and project management; H.M.A.S: Supervision, Writing—review & editing, checking technical parts. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in the study are included in the article.

Conflicts of Interest: The authors declare no conflict of interest.

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