Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.11 n.52, p. 266-275. March./April., 2025.
DOI: https://doi.org/10.5935/jetia. v11i52.1926

RESEARCH ARTICLE OPEN ACCESS

FUZZY IRRIGATION MODEL IN PROTECTED CROP BASED ON EXPERT KNOWLEDGE

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ARTICLE INFO

Article History
Received: March 13, 2025
Revised: March 20, 2025
Accepted: March 15, 2025
Published: April 30, 2025

Keywords:
Irrigation model,
Protected crop,
Artificial intelligence,
Fuzzy system,
Expert knowledge.

ABSTRACT

Fuzzy logic is a subfield of Artificial Intelligence that allows human knowledge to be expressed naturally, through linguistic variables and values, and an inference process very similar to the one it uses daily. The present research uses expert criteria to design and evaluate a model based on a fuzzy system to predict the irrigation time of the protected crop of cucumber (Cucumis sativus L.). The variables temperature, soil moisture and lighting are used for the model construction, which is coupled to an existing IoT technology in the various crops company "Valle del Yabú", serving as a support system for decision making. The prototype is created and simulated in MATLAB, then transferred to a Raspberry Pi 4 Model B, using the Python programming language. Tests using a database collected during one crop cycle show a 10.07% reduction in water usage compared to the standard irrigation currently implemented by the company.

I. INTRODUCTION

Agriculture is the main food source in all world countries [1]. The global demand for food means greater pressure on water resources [2], and agriculture is by far the largest consumer of water, accounting for around 70 % of all water withdrawals for irrigation, with a figure that can be as high as 95 % in some developing countries [3].

The agriculture industry is becoming more data-centric and requires more advanced and accurate information and technologies [4]. The difference between the demand and supply of water in agriculture is considered a problem that must be solved through advanced technologies to optimize resource use [5]. A precision or smart irrigation system is a sustainable method of saving water to maximize crop yields and reduce the unwanted environmental impacts of irrigation [6].

Worldwide there are numerous advances in terms of different technologies applied to agriculture for better performance in general, through the use of the Internet of Things (IoT) [7], robotics [8], or Artificial Intelligence (AI) techniques [9], to cite just a few examples.

The various crops company "Valle del Yabú", is the main productive center of the province of Villa Clara, there is the base business unit (UEB, acronym in Spanish) for protected and semi-protected crops, which has several of these premises to produce vegetables, which have a semi-automated irrigation system.

Despite the good results obtained today in greenhouses, the institution's experts indicate that better resource optimization can be achieved [10], either in favor of reducing consumption or increasing production. Taking the best of previous related works [11],[12], this research aims to contribute to this scientific problem in search of a viable solution, which only requires the knowledge of experts.

For this purpose, fuzzy logic is among the most widely used AI tools in current agriculture [13] when it is necessary to raise production results and optimize resources, especially in processes that require a knowledge base that is normally only available to experts on the subject, but that through the simple use of everyday language can be collected and put in a position to be improved and expanded. Numerous recent uses in the literature show the potential of this technique in a general way [14-17] and more attached to the topic of intelligent irrigation specifically [18-21].

The case study, cucumbers (Cucumis sativus L.), are among the most cultivated vegetables in the world, and due to their widespread use, there is a rich variety of these fruits [22].

Regardless of its genotype, there is a general trend of this crop (and of most plantations) towards certain conditions necessary for favorable growth, the most influential variables are ambient temperature, relative humidity, soil moisture, lighting, pH, and electrical conductivity [22],[23]. Only a few variants modified for certain climates escape generality [22].

The created model interacts in a deployed IoT system, using the ThingBoard platform, which is open-source software for the collection, processing, visualization, and management of data from devices [24],[25]. The communication protocol used is MQTT, developed by the OASIS organization, which is a standard communication protocol designed for the IoT [26],[27].

The programming languages MATLAB and Python are used in favor of building the model. MATLAB is an environment highly used by the scientific community, and Python is one of the favorite programming languages for AI development due to its syntactic simplicity and versatility. Both have an extensive amount of tools for AI development [28-31].

II. LOGIC AND FUZZY SYSTEM FOR IRRIGATION MODEL

The fuzzy system (FS) designed has four fundamental standard functional blocks Figure 1 [32]. Intentionally, from the first stage, the design was made in MATLAB due to the great potential of the Fuzzy Logic Toolbox, and because the prototype is achieved in a highly visual, fast, and efficient way. The version used was MATLAB 2022a.

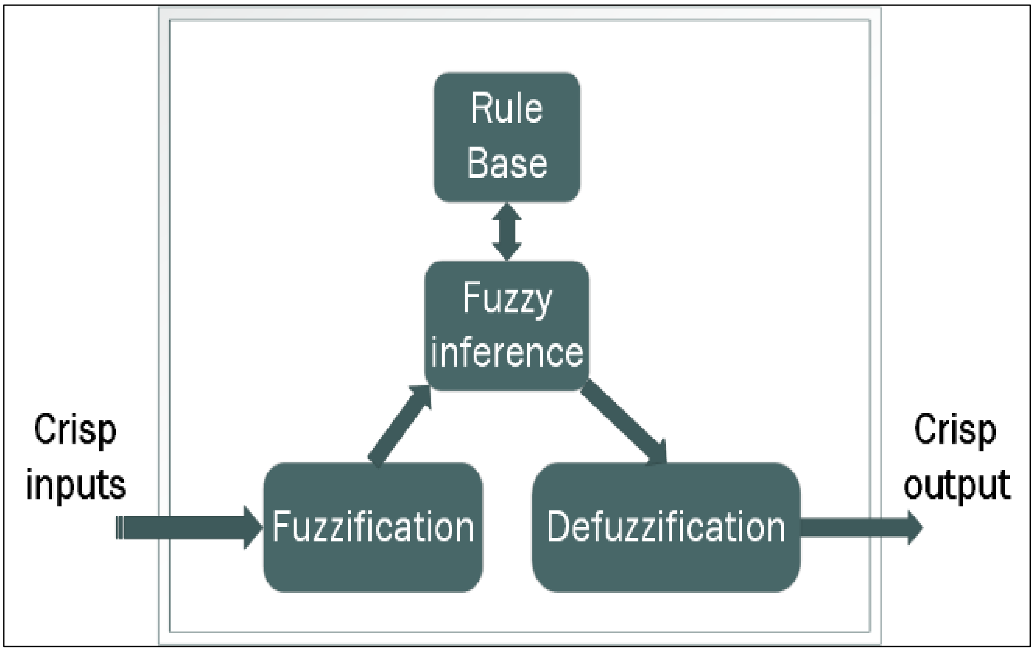

Figure 1: Fundamental functional blocks of a fuzzy system of quantitative input and output.
Source: Authors, (2025).

A fundamental point in the FS is the definition of both the input and output variables. To select the inputs used in cucumber (Cucumis sativus L.) production, the environmental variables that have the most influence and are available in the IoT system installed in the greenhouses were chosen.

The selected input variables were: ambient temperature, soil moisture, and lighting. The only output variable needed was: irrigation time, which corresponds to the duration of the suggestion given to the operator at the time of the irrigation schedule. Was only modified the time and not the frequency of irrigation because it is expected that the crops have a fixed daily frequency of four times.

II.1 DESIGN OF THE FUZZY LOGIC

II.1.1 MEMBERSHIP FUNCTIONS

The memberships proposed here consist of triangular and trapezoidal functions for the FS inputs and output, respectively. The figure below shows the independent value (x) versus the degree of membership (μ) for both.

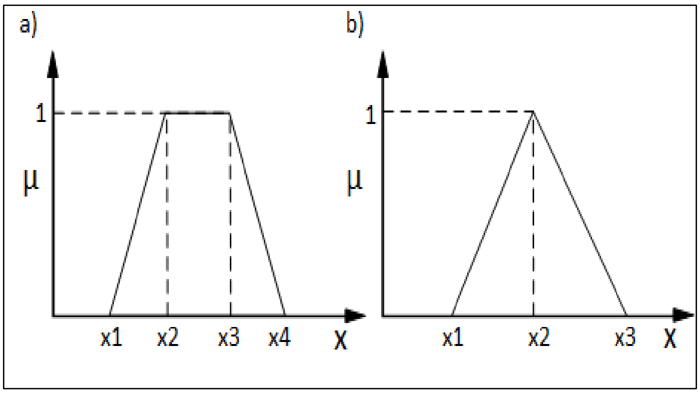

Figure 2: Membership functions: a) trapezoidal b) triangular.
Source: Authors, (2025).

As can be seen in Figure 2 a) due to its shape, the trapezoid is determined by four critical points. The universe of discourse was partitioned using this function into three subspaces, and it was applied in a general way to the variables: temperature, soil moisture, and lighting (input variables). In this way, each linguistic variable is associated with a value as shown in the following table:

Table 1: Variables and linguistic values of system inputs.

	Linguistic value		
Temperature	Cold	Favorable	Hot
Soil Moisture	Dry	Favorable	Wet
Lighting	Dark	Medium	High

Source: Authors, (2025).

As can be seen in Figure 2 b) due to its shape, the triangle is determined by three critical points. The universe of discourse was partitioned using this function into five subspaces, and it was applied to the only output variable: irrigation time. In this way, each linguistic variable is associated with a value as shown in the following Table 2:

Table 2: Variables and linguistic values of system output.

	Linguistic value				
Irrigation Time	Zero (Z)	Short (S)	Medium (M)	Long (L)	Very Long (VL)

Source: Authors, (2025).

II.1.2 FUZZY RULE SET

To build the knowledge base of the system, Mamdani's rules were used [32]:

$$\textbf{IF } x_1 \text{ is } \tilde{A}_1{}^k,\ x_2 \text{ is } \tilde{A}_2{}^k \text{ and } x_3 \text{ is } \tilde{A}_3{}^k\ \textbf{THEN } y^k \text{ es } \tilde{B}^k \quad (1)$$
$$k = 1,2,3\ldots r$$

Where $\tilde{A}_1{}^k$ and $\tilde{A}_2{}^k$ are the representation of the fuzzy set for the k-th antecedent and $\tilde{B}^k$ is the fuzzy set of the k-th consequence.

A system of three inputs and three linguistic values, as is the case, to be fully expressed with only conjunction operators, must have, according to the multiplication rule, $3 * 3 * 3 = 27$ rules. Fuzzy standard operations were selected as connectors, (2) as a conjunction operator, and (3) for the aggregation of the rules. Let $\tilde{A}$ and $\tilde{B}$ be two fuzzy sets:

$$\mu_{\tilde{A}\cup\tilde{B}}(x) = \mu_{\tilde{A}}(x) \vee \mu_{\tilde{B}}(x) = max\big(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\big) \quad (2)$$

$$\mu_{\tilde{A}\cap\tilde{B}} = \mu_{\tilde{A}}(x) \wedge \mu_{\tilde{B}}(x) = min\big(\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\big) \quad (3)$$

Tables 3, 4, and 5 express the set of rules used for the system, based on one of the three possible linguistic values of the soil moisture variable.

Table 3: Rules for the duration of irrigation at dry soil moisture.

	Lighting		
Temperature	*Dark*	*Medium*	*High*
Cold	VL	VL	VL
Favorable	M	L	L
Hot	Z	S	S

Source: Authors, (2025).

Table 4: Rules for the duration of irrigation at favorable soil moisture.

	Lighting		
Temperature	*Dark*	*Medium*	*High*
Cold	M	M	M
Favorable	P	M	M
Hot	Z	P	M

Source: Authors, (2025).

Table 5: Rules for the duration of irrigation at favorable wet moisture.

	Lighting		
Temperature	*Dark*	*Medium*	*High*
Cold	Z	Z	Z
Favorable	Z	Z	Z
Hot	Z	Z	Z

Source: Authors, (2025).

II.1.3 INFERENCE AND DEFUZZIFICATION METHOD

The implication mechanism used is also standard and responds to operation (3). The system is of the Mamdani type, so operator (2) was used for the aggregations. The method used for defuzzification is the centroid method. The center of gravity of the resulting set is the final output of the system, this is the estimated irrigation time, finally expressed as a numerical value.

II.2 DESIGN OF THE FUZZY SYSTEM FOR EMBEDDED HARDWARE

The device selected to deploy the system was a Raspberry Pi 4 Model B. The board is part of the IoT system mounted in the greenhouses of the "Valle del Yabú", where its function is precisely to receive data from sensors, process them and output the estimated irrigation time, which acts as an Agricultural Decision System Support (ADSS). The deployed sensors Figure 3 measure a variety of environmental variables, but of these, they are only inputs to the system, the three necessaries for its operation.

Figure 3: Sensor node.
Source: Authors, (2025).

The sensor readings come to the Raspberry Pi by sending packets using the MQTT protocol, and once the prediction is made, the result is transmitted using the same protocol. The ThingsBoard platform oversees establishing the necessary broker for communication and allows the visualization of both the behavior of the variables involved, as well as the suggested irrigation time in real-time, which the operator must consider when scheduling the time. The platform resides in another Raspberry Pi of the same model, exclusively dedicated to serving as a server for the IoT system.

Each node or sensing device has a publication topic called "Node". Under this topic, and with the use of a dictionary of six variables, the information is transmitted to the broker. The Raspberry Pi is subscribed to that topic, and after using the necessary variables as inputs to the FS, it returns another one that contains only the output of the model. The architecture shown in Figure 4 describes the data flow in a general way.

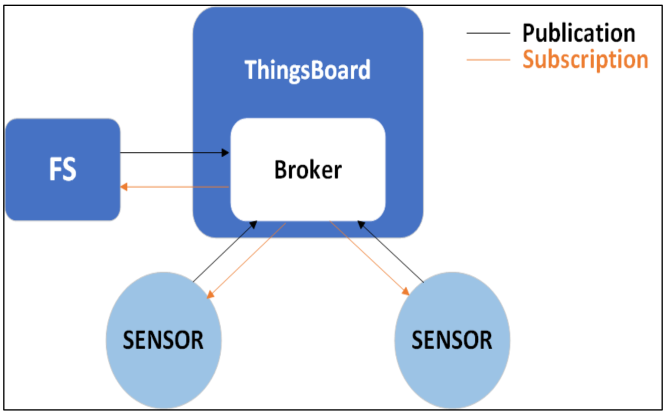

Figure 4: Architecture for the coupling to the IoT system. The FS is isolated from the coordinator node.
Source: Authors, (2025).

II.2.1 FUZZY SYSTEM PROGRAMMING

To program the FS scripts in the embedded hardware, the Python programming language in its version 3.11 was used and the Anaconda distribution was used as a work environment, due to its ease in managing packages in the field of data science. The third-party modules used were: scikit-fuzzy and paho-mqtt. As a complement, the pandas and matplotlib modules were also needed to manage data structures and visualize the results respectively.

III. GETTING THE IRRIGATION SYSTEM

The model obtained is an FS 3-1, it has three inputs and a single output. The system was built in MATLAB, using Fuzzy Logic Toolbox, and named: “FSystem”. Its general configuration is shown in Figure 5.

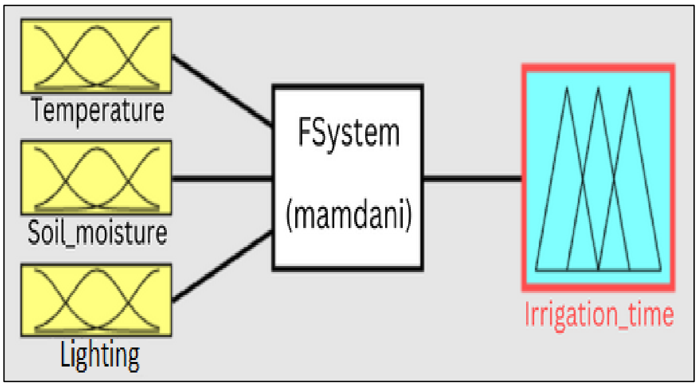

Figure 5: Obtaining fuzzy logic in MATLAB.
Source: Authors, (2025).

The membership functions were conceived from the reviewed literature and the criteria of the UEB experts of protected and semi-protected crops of the "Valle del Yabú".

Due to the use of only trapezoidal and triangular membership functions, the assignment of critical points was determined in a highly relational and intuitive way. Each input variable in Tables 6 and 7 presented a "Favorable" or "Normal" range that describes the set of fuzzy values that favor plant growth, with a plateau of unitary membership value, which alludes to the possible threshold or tolerance that exists in the quantitative description of the range, which by nature presents uncertainty.

The other two extreme ranges, with consistent linguistic values, describe the limit conditions for the variable to which analysis is made, presenting in the same way, a plateau of unitary membership value to compensate for the diffuse character of said limits.

On the other hand, the output variable Table 8, when representing fixed amounts of irrigation of a practical nature, could be eliminated from uncertainty plateaus, and therefore the triangular function remained as a result of its description.

The input variables are expressed in Celsius degrees (°C), percentage ratio (%), and luminous flux per unit area (lux) correspondingly. The output variable "Irrigation_time" is expressed in minutes (min).

Table 6: Critical points of the “Temperature” membership function.

	Cold	Favorable	Hot
Critic points	[0 0 14 20]	[14 20 30 40]	[30 40 50 50]

Source: Authors, (2025).

Table 7: Critical points of the “Soil_moisture” membership function.

	Dry	Favorable	Wet
Critic points	[0 0 17 22]	[17 22 26 50]	[26 50 60 60]

Source: Authors, (2025).

Table 8: Critical points of the “Lighting” membership function.

	Dark	Medium	High
Critic points	[0 0 0.45 1]	[0.45 1 13000 175000]	[13000 175000 21000 21000]

Source: Authors, (2025).

Table 9: Critical points of the “Irrigation_time” membership function.

	Z	S	M	V	VL
Critic points	[0 0 7.5]	[0 7.5 15]	[7.5 15 22.5]	[15 22.5 30]	[22.5 30 30]

Source: Authors, (2025).

III.1 FUZZY RULE SET

The rules described for the FS are analyzed in Tables 3, 4 and 5. Of the set of 27 total rules, many of these presented logical redundancy, therefore, taking advantage of the idempotent nature of the conjunction operator, the existing rules were reduced to 15, making use of the property expressed in equation (3).

$$\text{IF } B_1 = B_2 = B_3 = \cdots B_n$$

$$A \cup B_1 \cup B_2 \cup B_3 \cup \ldots B_n = A \qquad (3)$$

In this way, the rules that express the system become more coherent and attached to natural language, for example, Table 10 summarizes a simple expression: "If Soil_moisture is wet then Irrigation_time is zero" (Rule 1). Table 5 shows the rules obtained. The symbol "x" means "don't care" the value of the linguistic variable.

Table 10: Reduced rules for the FIS.

Rule	Input			Output
	Temperature	*Soil Moisture*	*Lighting*	*Irrigation time*
1	x	Wet	x	Z
2	Cold	Favorable	x	M
3	Favorable	Favorable	High	S
4	Favorable	Favorable	Medium	M
5	Favorable	Favorable	Dark	M
6	Hot	Favorable	High	Z
7	Hot	Favorable	Medium	S
8	Hot	Favorable	Dark	L
9	Cold	Dry	x	VL
10	Favorable	Dry	High	M
11	Favorable	Dry	Medium	L
12	Favorable	Dry	Dark	L
13	Hot	Dry	High	Z
14	Hot	Dry	Medium	S
15	Hot	Dry	Dark	VL

Source: Authors, (2025).

III.2 INFERENCE AND DEFUZZIFICATION METHOD

By using the proposed inference and defuzzification methods, the FS responded as shown in Figure 6. An example is observed for the intermediate values of the universe of discourse, activating rules 1 and 4, unifying the sets obtained employing the operator (1), and quantifying the response by the centroid method, to obtain an estimated irrigation time of 13.4 min.

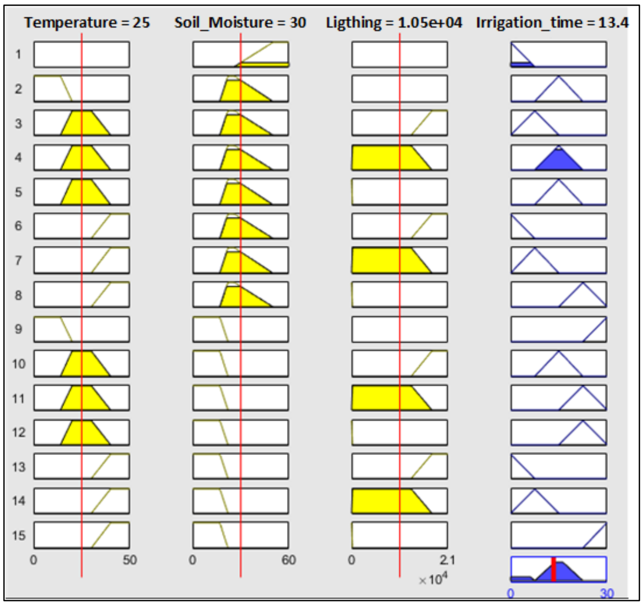

Figure 6: Simulation of the FS in Fuzzy Logic Toolbox.
Source: Authors, (2025).

Given the configuration of the system and its defuzzification method, the minimum possible time that the FS can suggest is 2.4 min, and a maximum of 27.5 min.

The behavior of the output, concerning temperature and lighting, is complex, and as expected, highly dependent on soil moisture. There is a natural gradient to the increase in irrigation time with the decrease in soil moisture, for the same surface level. Figure 7 shows these two variables compared, for different soil moisture references.The first of these graphs a), shows visually and in a more evident way, the maximum point of 27.5 min, which is between the temperature values of 0 and 10, and which is independent of lighting, which is expected behavior. On the other hand, the last graph d) shows rule number two of the FS obtained, in which regardless of the variations of the remaining parameters, the irrigation time is 2.4 min, which corresponds to the minimum point of our system.

The valleys or plateaus presented by the levels are coherent with those existing in the membership functions because describe the range of uncertainty or error rate of the linguistic values.

III.3 INFERENCE AND DEFUZZIFICATION METHOD

After a prototype, the FS was embedded in the Raspberry Pi 4 Model B, which serves as a data analysis server in the mentioned IoT system (Figure 4). The script that integrates the model was transferred to the SD card, and it was configured as a process to be executed in an infinite loop at each boot of the device.

To verify the correct rewriting between both languages, graphs of the membership functions of both the input and output variables of the system were generated, using the matplotlib module.

To verify the correct transfer of the rules, as well as the inference and defuzzification methods, a random test database with 3000 points was generated, which were compared to those returned by the FS created in MATLAB using a script that made use of the Python random module. The test presented 100% compatibility between the datasets.

The verification of the FS obtained for the embedded hardware was preceded by the verification of its correct coupling to the IoT technology. In the ThingsBoard platform of the main node, a new device named "Raspberry AI" was created in charge of the administration of the Raspberry Pi of this project. Random test data was sent to it, and upon verification of receipt, the dashboard was configured for the final consumer. The window that the operator can observe is shown in Figure 8.

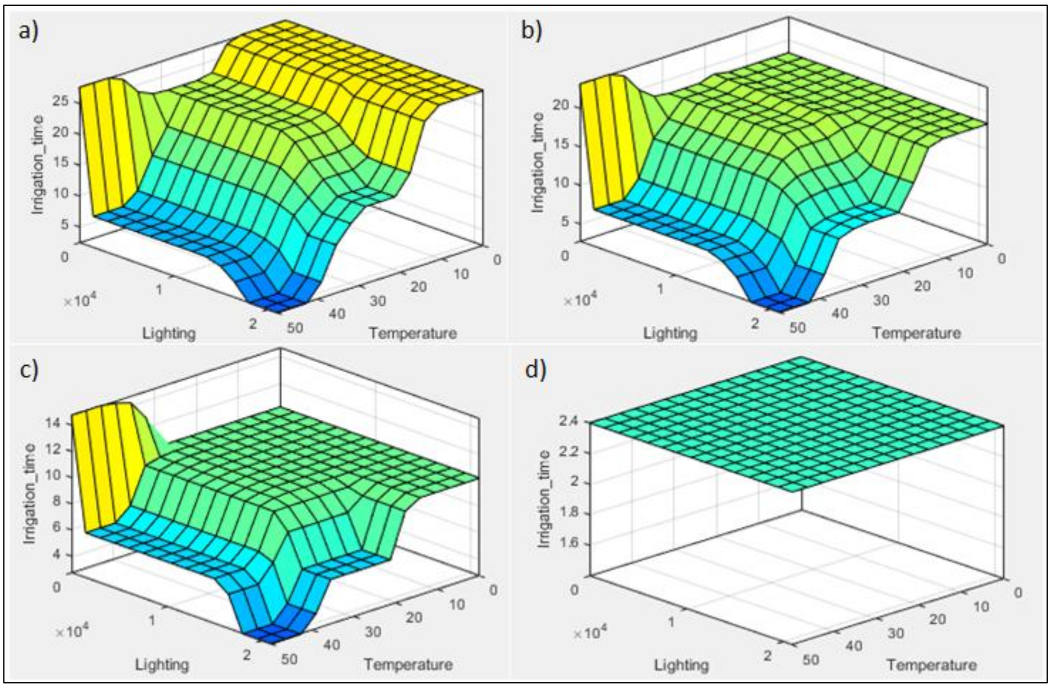

Figure 7: Surfaces in the Fuzzy Logic Toolbox. References of soil moisture: a) 0%, b) 20%, c) 40%, d) 60 %.
Source: Authors, (2025).

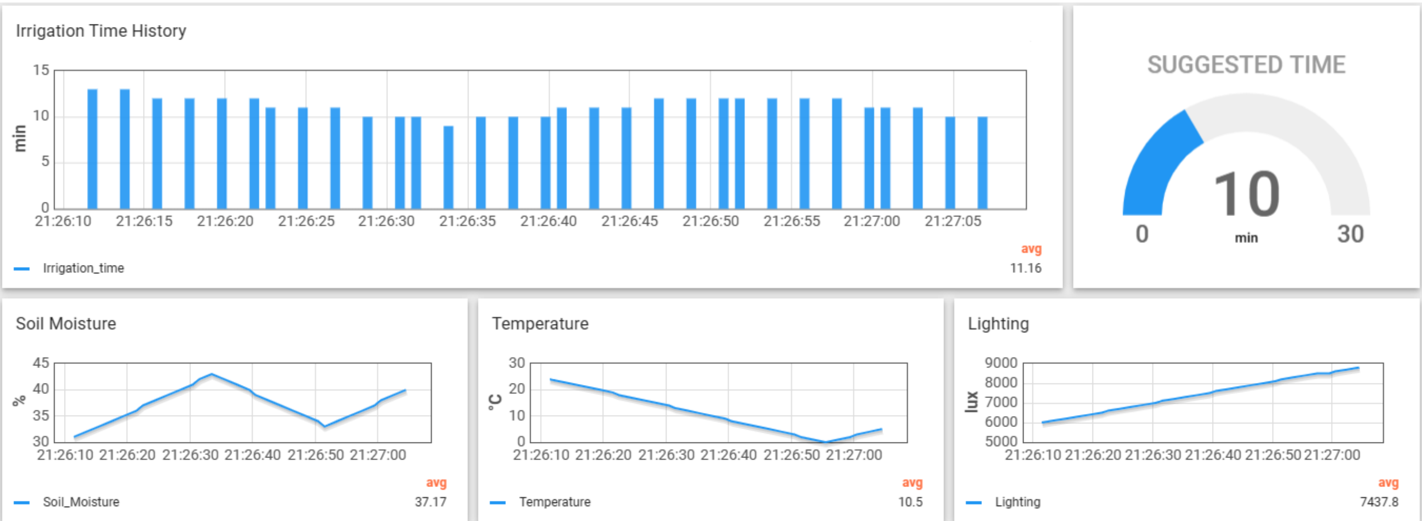

Figure 8: ThingsBoard visualization dashboard.
Source: Authors, (2025).

History charts are configurable in the sample range and interval they can display. These serve to provide a notion of the behavior of variables over time. As additional data, each one shows in the lower right part the average behavior of the variable. In the upper right part of the entire window, there is a widget to show the FS irrigation prediction in real-time.

The display panel is displayed on a Kuman 7" 1280x800 screen, connected to the central Raspberry Pi that the ThingsBoard platform server has. When programming the watering time of the pumping, the operator must make use of it, and based on your experience and the suggestion given, set the end time. One of the last tests carried out on the embedded FS was the measurement of the time it took the Raspberry Pi to process and send a single data packet with the required information. After using the time module and measuring the execution time interval of 1000 sends, the average delay was 1.71 seconds. This period is much lower than the data collection rate of the IoT deployment, which is 15 min.

IV. EVALUATION

In a lapse of time of a month, the IoT network was installed in one greenhouse. During this period, samples of the input variables of the system were taken.

Table 11 shows an analysis of the stored data, specifically for the center's irrigation schedules. Four data packets are received every hour since the nodes are transmitted with a frequency of 15 min. The number of samples is not uniform, nor does it correspond to the 112 that do not exist in total, this is due to possible losses, either due to transmission problems of the sensing nodes or reception of the platform, disconnection of the devices due to lack of power supply or other inconveniences.

The range of the variables, minimum and maximum possible value, is framed in the universe of discourse of the membership functions of the designed FS. Even if the sensing of a variable exceeds these limits, no error will occur, since the embedded FS was built so that any of these values can be interpreted by extreme linguistic values.

Beyond the irrigation schedules, it is interesting to explore the behavior of the variables globally, that is, of the entire sample. When observing the standard deviations in Table 12, these present a significantly small value compared to the values in which the variable in question oscillates.

This fact is typical of greenhouses, given their controlled environment. On the other hand, the mode and the mean represent two indicators of great interest for our FS. These are a measure of the trend of environmental conditions in the crop cycle, which are little fluctuating as previously shown by the standard deviation. The fact that the mode for illumination is 0 lux, for the sample data set, indicates that most of the IoT system operation occurred at nighttime.

By substituting these points of interest in the FS using the Fuzzy Logic Toolbox, the results of Figure 9 are obtained. The model estimates the same irrigation time currently made by the operators: 15 minutes. This indicates that, on average, the FS expresses the same level of knowledge as the experts, resulting from their accumulated experience. Outside the threshold close to the trend of the variables, the FS expresses "new experiences".

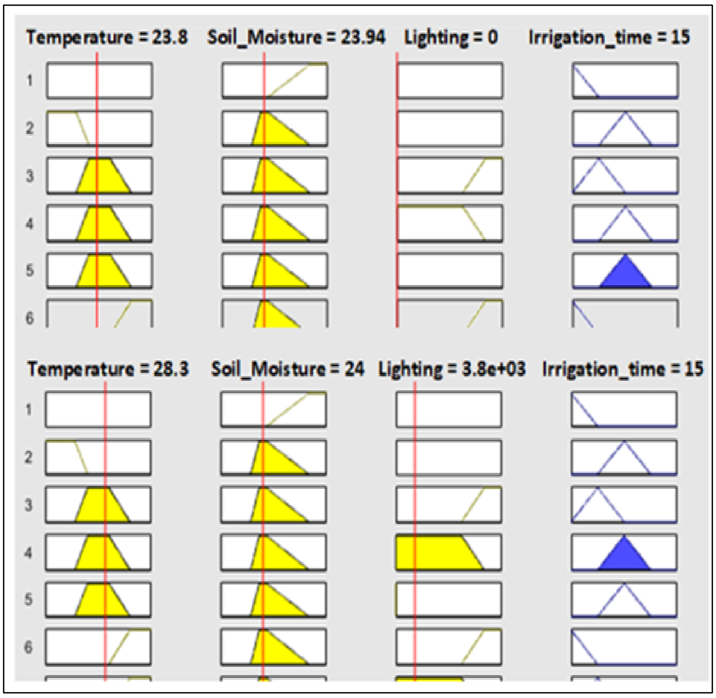

Figure 9: Evaluation of central tendency values in Fuzzy Logic Toolbox.
Source: Authors, (2025).

Table 11: The extreme behavior of the input variables during the sample period for irrigation schedules.

Schedules	Temperature (°C) (Min-Max)	Soil Moisture (%) (Min-Max)	Lighting (lux) (Min-Max)	Samples
8 AM	22.6 – 30.1	1.72 – 37.52	1309 -	109
10 AM	27.2 – 36.9	11.78 –	4391 –	108
1 PM	32.2 – 42.5	12.45 –	410 -	56
3 PM	28.9 – 46.1	13.75 –	591 -	44

Source: Authors, (2025).

Table 12: General behavior of the input variables during the sample period.

	Temperature (°C)	Soil Moisture (%)	Lighting (lux)
Min - Max	21.6 – 47.8	0.32 – 40.61	0 - 20723
Variance	29.97	44.98	29408484.7
Standard	5.47	6.71	5422.96
Mode	23.8	23.94	0
Mean	28.27	24.0	3800.07

Source: Authors, (2025).

The 2182 samples collected, without discriminating hours, were processed by the FSystem module, and the prediction was obtained for each triad of values. The Pearson correlation matrix is plotted in Figure 10. Irrigation time is inversely proportional to the three FS inputs. Although the correlation is not necessarily indicative of a cause-effect, it shows that to a greater extent, the achieved model is dependent on soil temperature and moisture, and to a lesser extent on lighting.

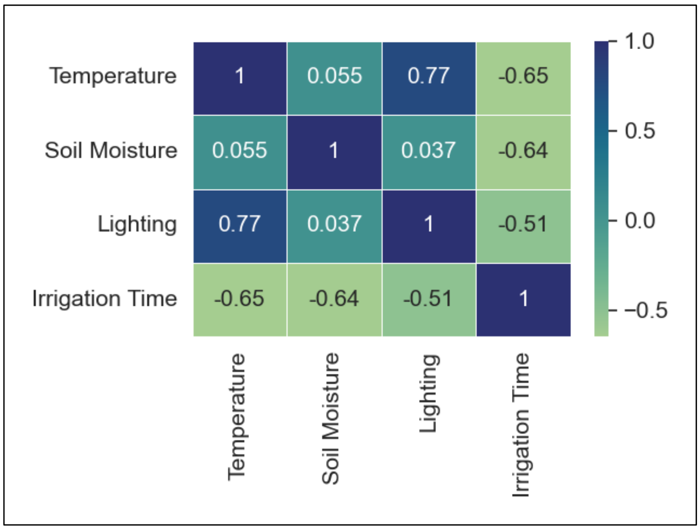

Figure 10: Pearson correlation of the processed samples.
Source: Authors, (2025).

With the use of the processed data the graph of the behavior of the inputs and the output of the FS for the irrigation schedules are constructed (Figure 11). The notable correlation between temperature and lighting in the greenhouse can be qualitatively observed, which can be related quantitatively to the results obtained in Figure 10 (0.77 units of Pearson correlation).

Since the soil moisture has a lower range of oscillation, the changes in the FS predictions move around according to the other conditions: the temperature and lighting, because both are the most fluctuating and time-dependent variables. These fluctuating variables are highly dependent on the time of day. From all this information it can be concluded that, despite having built the FS giving greater weight to the soil moisture variable, in practice, for our case study, the most determining variable so far is temperature.

It is observed that the general tendency of the suggested time is to decrease as the day progresses, which is evident quantitatively in the averages of Table 13, except in the last hour. The FS decreases its output and limits the minimum and maximum values to the pair. The model notices a greater need for irrigation in the first shift, and then the prediction of all the others falls below what the standard time establishes. The final result is that in accumulation, the model reduces resource use from 4755 to 4276 min, meaning 10.07%.

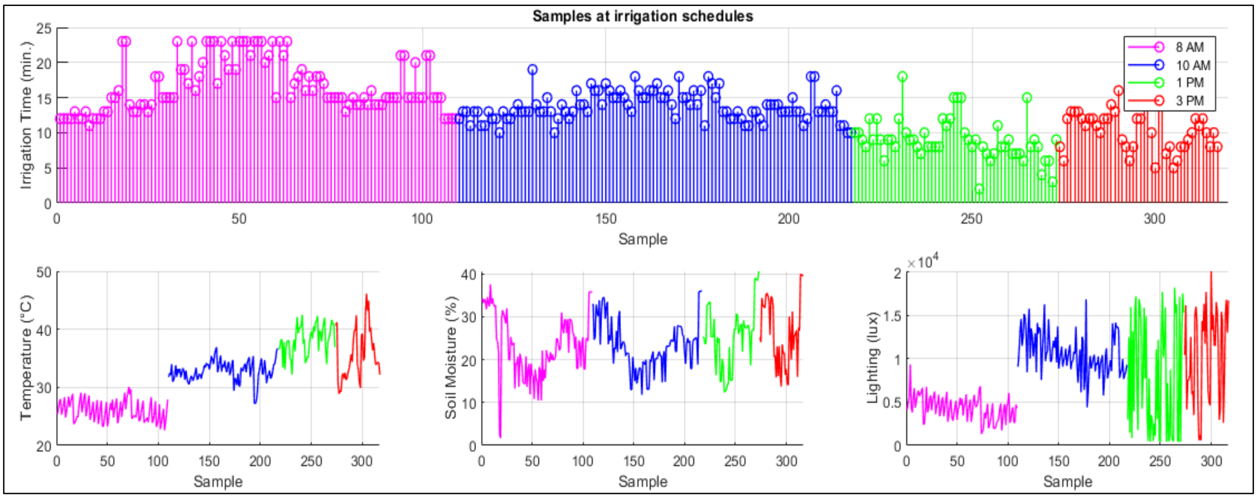

Figure 11: Graph of the inputs and output of the FS of the samples for the irrigation schedules.
Source: Authors, (2025).

Table 13: Irrigation times in study hours.

	Schedules			
	8 AM	**10 AM**	**1 PM**	**3 PM**
Minimum time (FS)	11 min	10 min	2 min	5 min
Maximum time (FS)	23 min	19 min	18 min	16 min
Mean time (FS)	16.75 min	13.75 min	8.98 min	10.5 min
Standard time	15 min	15 min	15 min	15 min
Total time (FS)	1826 min	1485 min	503 min	462 min
Standard total time	1635 min	1620 min	840 min	660 min
Accumulated time (FS)	**4276 min**			
Standard accumulated	**4755 min**			

Source: Authors, (2025).

V. DISCUSSION

The use of an FS as a solution to the modeling of the irrigation system is a more manageable and interpretable alternative in contrast to the methods of Fuzzy Cognitive Maps in previous works made for the institution [11],[12]. The main knowledge engine of the system, the membership function and fuzzy rules are obtained directly from the knowledge of experts. The model built from the use of fuzzy logic is not specific, nor exclusive, for the case study, but rather the proposed methodology allows the same procedures to be applied to any other variety in protected cultivation at the center.

Much of the reviewed literature makes use of an FLC, as a solution to the problem of the intelligent irrigation system, controlling the irrigation system either by closing or opening a valve or by continuously establishing the irrigation time using timers. Faced with this, the FS designed as ADSS has the disadvantage of having a delayed action. The final action element, the irrigation system, is activated by the operator, and once the process is started its interruption is manual. In the time frame of the programmed irrigation, the climatic conditions can have abrupt changes, such as those caused by a sudden rain, which affects the system variables, and although the prediction changes accordingly, the FS cannot impose the new state.

The computational cost of the FS is negligible concerning other AI techniques, and this is evidenced by the short average response time for receiving, processing, and sending data. This feature makes it versatile and less dependent on large hardware resources. The IoT architecture where the model is coupled presents great modularity, since by isolating a node for data processing, the main node that serves as server and orchestrator is not saturated by the execution of algorithms. From the reviewed literature, the implementation of the model in architectures such as those presented in [18],[20] would entail a computational overload, since the UEB has a total of 42 cultivation houses, a considerable number of threads to be processed by the node coordinator.

VI. CONCLUSIONS

In this research, an irrigation model based on fuzzy logic was designed, specifically a fuzzy system, for embedded hardware, for the optimization of water resources. Based on the work carried out, the following conclusions were reached:

- The interpretability of the FS makes the model practical. The selection of trapezoidal membership functions and their consequent unit plateaus in the fuzzification process of the FS entries allowed the expression of the error presented by the linguistic values according to expert criteria:
- The model obtained is computationally light, with an average response time between reception, processing and sending of 1.71 seconds, making it suitable for the chosen hardware.
- The FS shows satisfactory behavior, taking the same standard decision as the operators for the trend of the samples collected, and suggesting, in general, a reduction of 10.07% of the irrigation time, that is, a proportional saving of resources.

VII. AUTHOR'S CONTRIBUTION

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VIII. ACKNOWLEDGMENTS

Special thanks to the Internet of Things and Artificial Intelligence for Automation Group from the University "Marta Abreu" of Las Villas (UCLV) and the workers and specialists at the various crops company "Valle del Yabú".

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