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Fuzzy based Irrigation Control System for Indian Subcontinent

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Water resource usage should be optimized as there is always a scarcity. This paper aims to provide an efficient way of water using sense and weather data and implementing a fuzzy decision model. An automated intelligent watering system is proposed in this paper using the internet of things and fuzzy logic. The weather data, coupled with Temperature, Relative Humidity, and soil moisture sensor data, is used to decide whether to switch on/off the motor. In-house-created prototypes of ground-moving robots have soil moisture, digital humidity, and temperature sensors implanted in them. The soil moisture sensor is attached to the Rack and pinion mechanism. The soil moisture sensor is pushed into the soil when the pinion rotates. It minimizes the use of sensors by using a distributed sensing method. Based on data obtained from sensors and meteorological information, the system will use this information to decide whether to Switch on/off the sprinkler motor. A fuzzy logic-based system decision is implemented on the input sensor and weather data, and the model will decide to switch on/off the actuator. An accuracy of 97% is achieved. The Android app is used to visualize sensor data, based on which the farmer can manually control the motor.

Keywords: Fuzzy systems, Internet of things, Robot, Sensor systems and applications, Smart watering

Introduction

It is essential to save freshwater for agricultural purposes that are in short supply. Due to a lack of intelligent irrigation systems, rural farmers are forced to consume enormous amounts of freshwater.[1] Watering is carried out in conventional farming without regard for soil moisture, temperature, humidity, or meteorological conditions, which does not ensure the crop receives the optimal quantity of water.[2] Watering requirements vary according to the crop, and farmers may be unaware of how this affects the crop's production. Sensors are buried throughout the field to monitor agricultural field characteristics, from which data is collected via wireless sensor networks. Detecting the remote sensor is difficult. The paper's major contribution is to develop a weather-based smart irrigation system using a ground-based robot with sensors. And also to develop a Fuzzy inference model for the final decision of the output actuator (sprinkler motor). The crop sensor parameters are also displayed in the app.

Since the soil moisture sensor reports the amount of water and power being used, the motor is turned on or off automatically to limit the utilization of excessive amounts of water and electricity. Crop watering requirements alter concerning variations in the soil and atmospheric conditions. The suggested weather-based smart watering system relies on soil moisture, humidity, and temperature sensors that are compared to the optimal level for the crop. If the soil moisture, humidity, and temperature readings are not optimum, watering is done. The goal is to develop a smart watering system to increase agricultural output. This proposed approach can be applied in agricultural systems for automation to address the difficulties of traditional agricultural methods. A farming field irrigation system is created to monitor water requirements, remotely saving water and labor costs. It is done by increasing the precision of sensors that detect factors like soil moisture, temperature, humidity, the amount of water the soil can store, how much each crop requires water, and how each crop responds. Water is delivered to the agricultural field according to the data provided by the soil moisture sensor, temperature sensor, and weather data. Using WIFI, the whole system is fully automated to minimize human labor. The paper's significant contributions include, Crop parameters visualization in a mobile app using which a decision can be taken, processing the crop sensor parameters and weather information in the cloud can decide whether to switch the motor on or off.[3–5]

A Secure, intelligent water system using fuzzy logic is discussed.[6] Blockchain technology has been

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implemented to make communication secure. The model didn't consider weather information to decide the status of the motor. The smart watering system is implemented using IoT and fuzzy logic.[7] Soil moisture, temperature, and humidity information are used to decide the status of the motor. The information is communicated to the farmer using the Global system for mobile communication. A set of rules are proposed and implemented using fuzzy logic to decide when to switch on the motor. The proposed model didn't consider the forecast weather information, and it can't be used in multi-crop and multi-soil environments. A smart watering system using weather information and soil moisture sensor is proposed.[8] A low-cost Smart water system in multi-soil and crop environment is proposed.[9] The paper proposed a ground-moving robot that can be used to collect the soil moisture information using which the motor can be switched ON or OFF, based on the location of the robot. An actual prototype to use in the agriculture field is not developed. A method of monitoring the agriculture field and introducing automatic irrigation is discussed.[10] This paper proposed economical water usage using humidity and temperature sensors. The Raspberry Pi controller monitors the crop parameters and sends the values to the cloud.

The method is proposed to collect various sensor data from the agriculture field, which is used to decide the motor status.[11] An Optimization algorithm for smart farming using genetic algorithms is proposed to reduce energy consumption.[12] As it is required to place the sensor collection unit at a remote location that does not have the required power supply, batteries and solar panels need to be used. The wireless sensor network energy efficiency in smart agriculture is discussed.[13–15]

Proposed Method

A smart watering system is proposed using sensor-equipped mobile robots and meteorological information to address conventional agricultural water problems. In general, farm fields are typically located far away from farmers' homes. The sprinkler motor can be switched ON/OFF, and the soil parameters can be viewed using an Android smartphone app.

Principle of Operation

The proposed method has a ground-moving robot and is equipped with crop sensors. The Rack on the R&P mechanism is controlled using the servo motor to get the moisture sensor into the soil. Then, the information is used to decide whether to activate or deactivate the motor. In the automatic mode, the soil moisture, humidity, and temperature information are sent to the cloud server. Cloud servers process this data along with the weather information using fuzzy rules to decide output actuator action. The farmer can over-impose his decision on the automatic smart watering system and take a final call through his mobile app. The Work Flow of the proposed system is shown in Fig. 1. The Wi-Fi module is initialized when the power is switched on in the automatic mode and communicates with Arduino. The motor gets turned on when the moisture level is very dry irrespective of the weather information, humidity, and temperature. When the moisture status of the soil is dry, normal, or

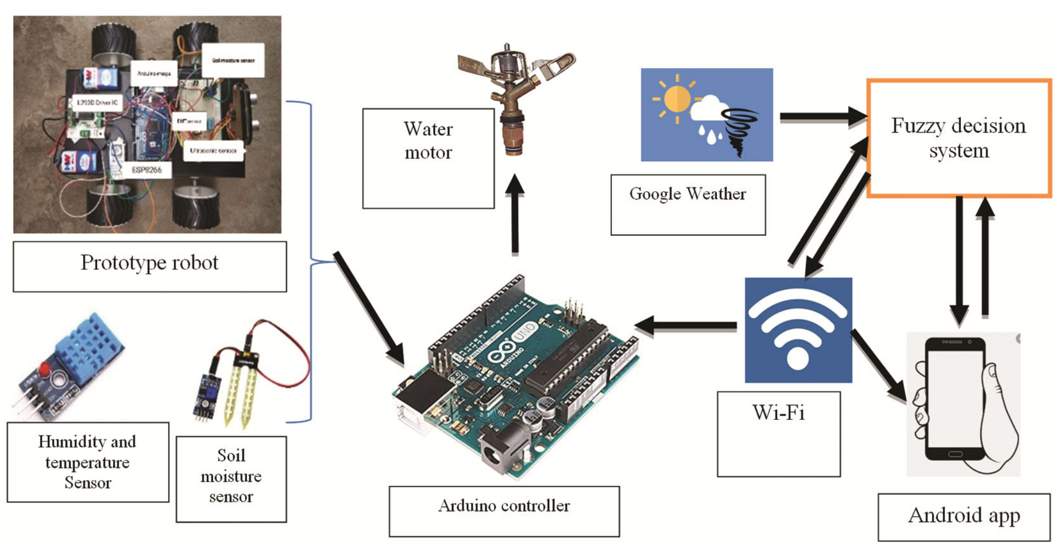

Fig. 1 — The planned system's workflow

wet, the weather information is used to check the occurrence of rain within the next 3 and 7 days, and the motor is switched ON/OFF by considering the humidity and temperature of the field using fuzzy inference system.

The soil moisture sensor is used to check the moisture content, whose value is categorized into four levels: very dry, dry, normal, and wet. Soil moisture sensor, humidity, temperature sensor, and weather information are used along with fuzzy rules to decide the motor's status, as shown in Fig. 2. The temperature sensor can be used to measure the surrounding temperature of the form field, and the humidity sensor can be used to measure the humidity in the field. The Wi-Fi module sends all the information from these sensors to the cloud server.

Smart Irrigation Decision Support System

For the proposed smart watering system, fuzzy logic is used to make the final decision by using that data from the sensors and weather data. The fuzzy logic module uses the plant knowledge database to make a choice specific to the plant. The Fuzzy Logic module is preferred in this application for decision-making problems, and this is one promising approach. It is easy and straightforward to implement in IoT applications. After taking the decision using the Fuzzy Logic module regarding the on and off of the sprinkler motor final decision is communicated to the Android app. The main components of the proposed smart watering system are shown in Fig. 3, which consists of fuzzy rules, fuzzy inference systems, defuzzification, and membership functions.

For the Fuzzy Logic-based smart irrigation decision support system to be implemented, it is required to define Input and output variables, and Every input and output has to be assigned a unique membership function. Each input and output variable has a set of rules assigned to it, and for each input value, membership functions are defined to yield a fuzzy value. Inference for the fizzy rule sets and aggregation of the inference for each rule is made to obtain the crisp output value using the resultant inference value.

Input and Output Categorizations

For the decision (output) of the SWS, the temperature, humidity, soil moisture sensor data, and weather information are taken as input. In addition, the sprinkler motor status is output.

Temperature

The temperature is obtained from the DHT sensor. It has been categorized into three levels such as low, normal, and high.

$$\text{Temperature}_{\text{low}}(x) = \begin{cases} 1, x < 10 \\ \frac{30-x}{20}, 10 \le x < 30 \end{cases} \quad \ldots (1)$$

$$\text{Temperature}_{\text{normal}}(x) = \begin{cases} \frac{x-10}{10}, 10 < x < 20 \\ 1, 20 < x < 40 \\ \frac{50-x}{10}, 40 < x < 50 \end{cases} \quad \ldots (2)$$

$$\text{Temperature}_{\text{high}}(x) = \begin{cases} \frac{x-40}{10}, 40 \le x \le 50 \\ 1, x > 50 \end{cases} \quad \ldots (3)$$

Relative Humidity

The Relative Humidity is obtained from the DHT sensor and has been categorized into three levels: low, normal, and high.

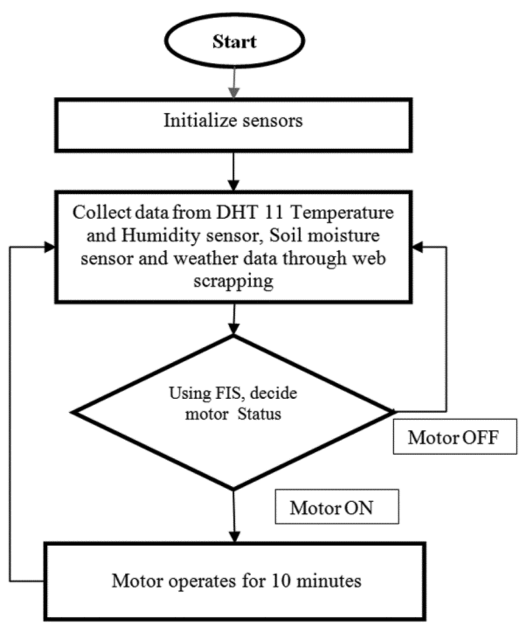

Fig. 2 — Simple flow of the proposed

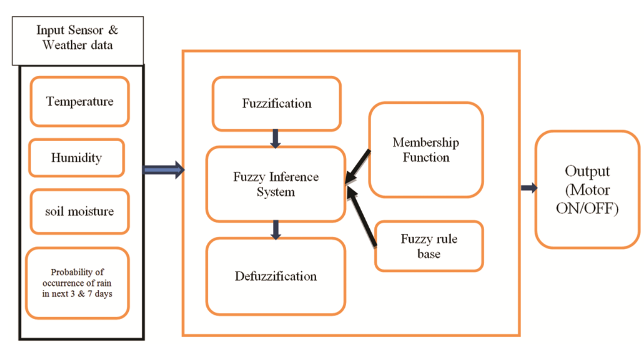

Fig. 3 — Fuzzy inference system

$$\text{Relative humidity}_{\text{low}}(\mathrm{x}) = \begin{cases} 1, \ x < 20 \\ \frac{35 - x}{15}, 20 \le x \le 35 \end{cases} \quad \ldots (4)$$

$$\text{Relative humidity}_{\text{normal}}(\mathrm{x}) = \begin{cases} \frac{x - 25}{10}, 25 \le x \le 35 \\ 1, 35 \le x \le 45 \\ \frac{50 - x}{5}, 45 \le x \le 50 \end{cases} \quad \ldots (5)$$

$$\text{Relative humidity}_{\text{high}}(\mathrm{x}) = \begin{cases} \frac{x - 45}{5}, 45 \le x \le 50 \\ 1, x > 50 \end{cases} \quad \ldots (6)$$

Soil Moisture

The soil moisture sensor is attached to the Rack in the R & P mechanism. Data collected by the soil moisture sensor has been categorized into four levels: very dry, dry, normal, and wet.

$$\text{Soil moisture}_{\text{very dry}}(\mathrm{x}) = \begin{cases} 1, x < 10 \\ \frac{15 - x}{5}, 10 \le x \le 15 \end{cases} \quad \ldots (7)$$

$$\text{Soil moisture}_{\text{dry}}(\mathrm{x}) = \begin{cases} \frac{x - 10}{50}, 10 \le x \le 15 \\ 1, 15 \le x \le 20 \\ \frac{25 - x}{5}, 20 \le x \le 25 \end{cases} \quad \ldots (8)$$

$$\text{Soil moisture}_{\text{normal}}(\mathrm{x}) = \begin{cases} \frac{x - 20}{5}, 20 \le x \le 25 \\ 1, 25 \le x \le 35 \\ \frac{35 - x}{5}, 35 \le x \le 40 \end{cases} \quad \ldots (9)$$

$$\text{Soil moisture}_{\text{wet}}(\mathrm{x}) = \begin{cases} \frac{x - 35}{5}, 35 \le x \le 40 \\ 1, x > 40 \end{cases} \quad \ldots (10)$$

The trapezoidal membership function is used to define each input and output parameter. A glimpse of each input parameter membership function is given in Fig. 4, and their ranges with category labels are given in Table 1.

Weather Information

By using the current weather information[10], rainfall is estimated. The weather information provides various keywords such as Hail, Light Rain, Scattered Thunderstorms, Showers, Scattered Showers, Rain and Snow, Chance of Rain, Chance of Storm, Rain, Cloudy, Storm, Thunderstorm, Chance of Storm, Partly Sunny, Sunny, Mostly Sunny, Snow Showers: Snow showers, Icy, Fog, Light Snow, Freezing Drizzle, Chance of Snow, Sleet, Mist, Flurries, Dust, Overcast, etc. Out of these keywords, Hail, Light Rain, Scattered Thunderstorms, Showers, Scattered Showers, Rain and Snow, Chance of Rain, Chance of Storm, Rain, Cloudy, Storm, Thunderstorm, and Chance of Storm keywords are used to determine the probability of occurrence of rain in next 3 and 7 days is in in Eqs (11 & 12).[10]

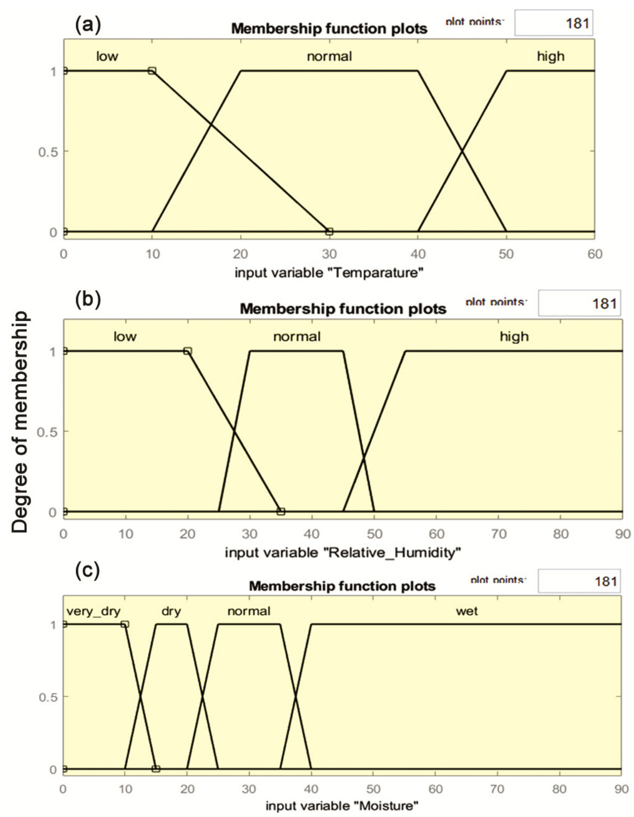

Fig. 4 — Membership function of (a) Temperature (b) Humidity (c) Soil moisture

Table 1 — Input parameters ranges with category label

Temperature	Category	Relative Humidity	Category	Soil moisture range	Category
0–27	Low	0–30	Low	0–10	Very dry
27 – 40	Normal	30–50	Normal	10–20	Dry
40 – 60 or above	High	50–100 or above	High	20–40	Normal
	—			40 100 or above	Wet

$$\text{Possibility of rain}_{\text{ in next 3 days}}(X) = \begin{matrix} no, \ x = 0 \\ yes, \ x = 1 \end{matrix} \quad \dots (11)$$

$$\text{Possibility of rain}_{\text{ in next 7 days}}(X) = \begin{matrix} no, \ x = 0 \\ yes, \ x = 1 \end{matrix} \quad \dots (12)$$

Sprinkler Motor

A binary fuzzy membership function is given for the output of the smart watering system in Eq. (13).

$$\text{Sprinkler motor status } (x) = \begin{matrix} off, x = 0 \\ on, x = 1 \end{matrix} \quad \dots (13)$$

Implementation and System Deployment

Various sensors such as soil moisture sensors, DHT temperature, and humidity sensors have been used. Arduino microcontroller is used to collect the data from sensors sent to the cloud server.

Prototype Model for Smart Watering System

A prototype ground-moving robot has been developed, which is shown in Fig. 5, where the soil moisture sensor, DHT sensor, ultrasonic sensor, Rack, and pinion mechanism has been embedded. The proposed smart watering system is used here to acquire and monitor the data from the sensors which are connected to Arduino. The soil moisture sensor is attached to the Rack in the Rack and pinion mechanism, as shown in Fig. 5. The ultrasonic sensor is used to avoid obstacles and prevent collisions. The soil moisture sensor is attached to the Rack in Rack and pinion mechanism, which penetrates the soil to collect the soil moisture values at random intervals, as shown in Fig. 6. The ground-moving robot moves to various positions in the field, and in that particular position, the moisture, humidity, and temperature values are measured along with GPS data. The ground-moving robot is embedded with an ultrasonic sensor which helps the robot to avoid collisions with obstacles.

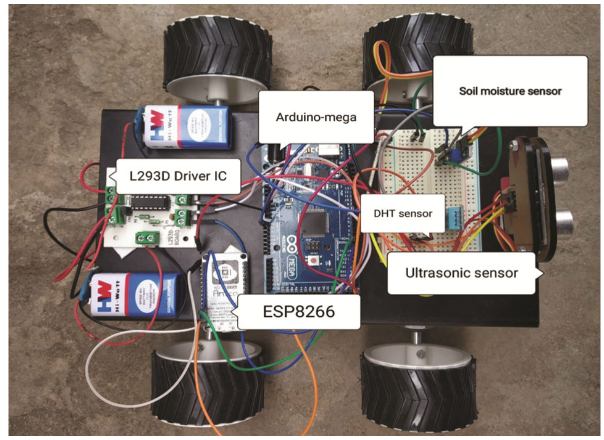

Fig. 5 — Photograph of the prototype of smart watering system

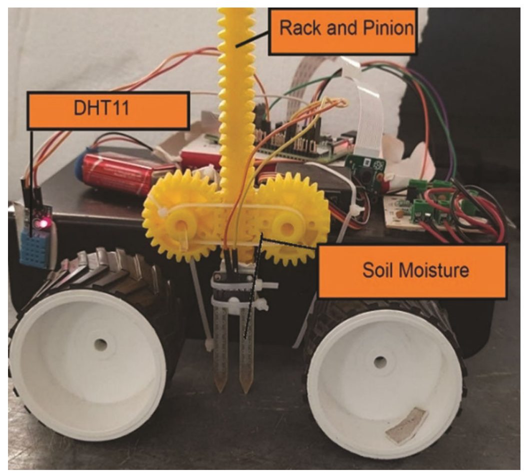

Fig. 6 — Soil moisture sensor attached to rack and pinion mechanism

Smart Watering System Mobile Application

Data from various sensors is sent to the cloud server, which also uses the weather data to check the probability of occurrence of rain in the next 3 and 7 days. With the help of a fuzzy rule knowledge base and fuzzy inference system, the cloud server computes the actuator's output (sprinkler motor on/off status). Concerning the various plants, the fuzzy rules and the input data ranges can be changed in the server. An Android mobile application is designed to allow the user to view the sensor parameters and control the smart watering system remotely. It provides absolute control to the farmer or user for controlling the actuator. Irrespective of the smart watering system, the farmer's decision is final. This app can send alerts to the farmer and provide a schedule calendar for watering the plants, as shown in Fig. 7.

Development of Fuzzy Inference System for Smart Watering

Creating a fuzzy set is one of the sub-processes of a fuzzy expert system. Matching linguistic terms to the actual values of input variables determines each rule's degree of membership. The interval [0, 1] can be used to create a fuzzy set by assigning a membership value to each item. In a fuzzy set, membership values indicate how closely an object adheres to the set. Assuming that a represents an element of the universe, we can say that A and X represent a fuzzy set. This is why the membership function $\mu_x(a)$ characterizes the fuzzy set as in Eq. (14).

$$\mu_x(a) : A \rightarrow [0, 1] \quad \ldots (14)$$

Values assigned to universal set A members must fall within a predetermined range, as stated by the membership function in Eq. (15).

$$X = a, \mu_X(a) \mid a \in A \quad \ldots (15)$$

The fact base, a subset of the knowledge base, contains both symbolic and numerical data. Fact base is a term used to describe a knowledge-based system's factual knowledge. The current state of the system notation is given as in Eq. (16).

IF x is P and y is Q THEN A = f(x,y) … (16)

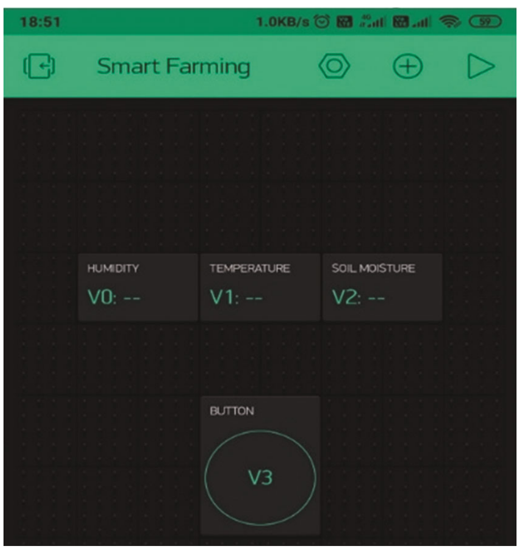

Fig. 7 — Smart farming mobile app

Here, PQ are fuzzy sets in antecedents, and A = f(x,y) is a crisp function in the consequent.

Each rule's antecedent is analyzed. Fuzzy intersections and fuzzy unions are used to obtain a single membership value when the antecedent rule has more than one part. The intersection of two fuzzy sets (X and Y) is shown as in Eq. (17).

$$\mu_{X\wedge Y}(A) = 1 - \min(1, (1-\mu_X(a))^P + (1-\mu_Y(a))^P)^{1/p} \quad \ldots (17)$$

Fuzzy union refers to OR. The union of two fuzzy sets X and Y defined on A is given as in Eq. (18).

$$\mu_{X\vee Y}(A) = \min(1, (1-\mu_X(a))^P + (1-\mu_Y(a))^P)^{1/p} \quad \ldots (18)$$

Each rule's result and antecedent value are provided as a fuzzy set. A fuzzy implication operator is used to create a new fuzzy set. Finally, each rule's outputs are combined into a single fuzzy set, which can then be used for further analysis.

Rules are formulated using the temperature, relative humidity, moisture sensor range, and the probability of rain in the next 3 and 7 days. The trapezoidal membership function given in Equations 1–10 represents the sensor data ranges. The fuzzy inference system is implemented in MATLAB in the verbal-visual rules, which can be visualized in Fig. 8. The rule viewer window can be seen in Fig. 9.

Finally, the defuzzification of a fuzzy expert system is completed. A crisp value must be created by converting the fuzzy value to a crisp one. Defuzzification is done using the Yager method here in Eq. (19).

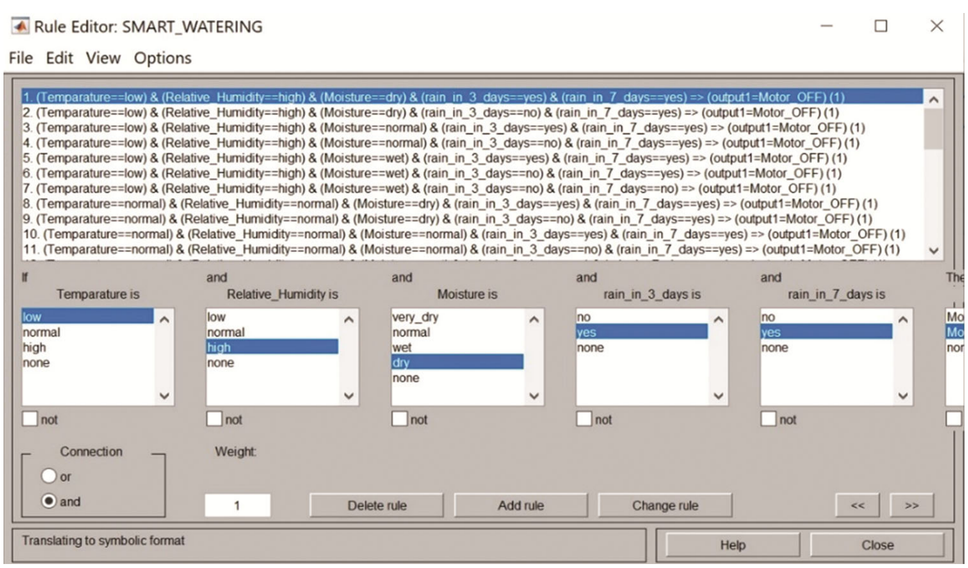

Fig. 8 — Verbal fuzzy rule window

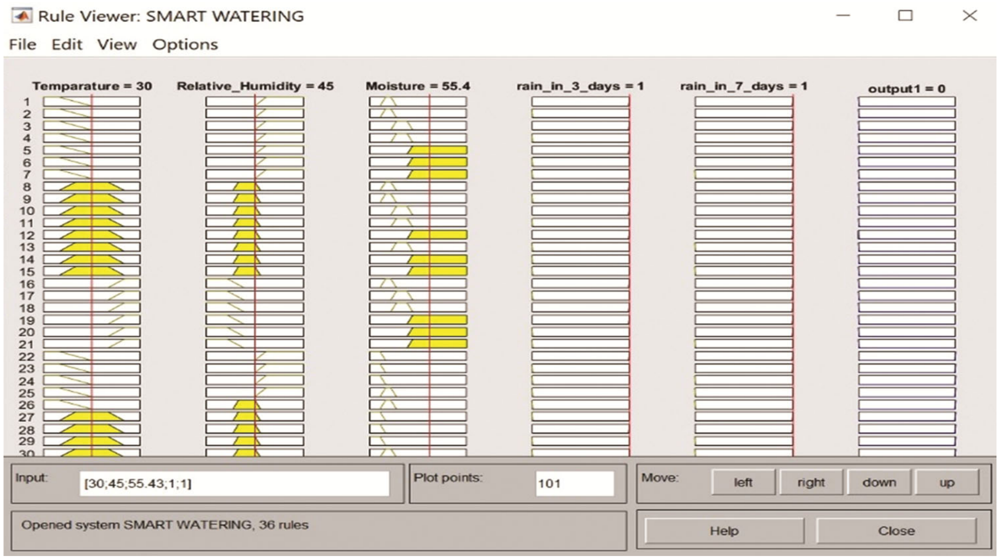

Fig. 9 — Fuzzy rule viewer Window

Table 3 — A compassion of the proposed system with currently existing systems

Specification	Proposed SWS	Fuzzy Logic Based SWS[7]	IoT Based Smart irrigation[14]	Intelligent And Secure SWS[6]
Decision System	Fuzzy Logic	Fuzzy Logic	Machine Learning	Fuzzy Logic
Sensors Used	Soil Moisture, Humidity Temperature Camera	Soil Moisture, Humidity Temperature Rain Senor, LDR	Soil Moisture, Humidity Temperature Camera	Soil Moisture, Humidity, Light Intensity
Controller	Arduino Uno	Arduino Uno	Arduino Uno	Raspberry Pi
App Used for monitoring crop parameters	Blynk	—		Garden Pi
Communication interface	WIFI	Gsm	WIFI	WIFI
Weather Abstraction	Google Weather	Rain sensor	Nil	Nil
Cost	Low	High	High	High
Multiple Crops Support	YES	No	No	No
Accuracy	97 %	—	96%	—

$$Y = \frac{\int [\mu_X(y)]^q y\,dy}{\int [\mu_X(y)]^q dy} \quad \dots (19)$$

Results and Discussion

The real-time sensor data is stored in the cloud for the final decision-making of the smart watering system. Cloud servers consist of fuzzy rules knowledge base. The rule-based fuzzy inference engine uses knowledge base entries to match the final output. The real-time values of temperature, humidity, soil moisture, and weather data are evaluated, and a recommendation about the final decision of the Actuator (Motor ON/OFF) is calculated. The fuzzy rule-based engine compares the sensor values with the threshold value stored in the knowledge base and computes the output. For smart watering, the data from sensors is collected 4 to 5 times a day and transmitted to the server, which is compared with the threshold values of temperature, humidity, and moisture to check whether the motor is ON/OFF.

A sample of 10 test cases, and the fuzzy inference system evaluated output of the actuator (sprinkler motor ON/OFF) decision has matched exactly with the test case decision (Table 2). We have evaluated the developed fuzzy inference system on a database of 1079 Samples and achieved an accuracy of 97%, which signifies that out of 1079 test cases, the fuzzy inference system has evaluated output correctly for 1046 samples. The proposed system is designed to use freshwater efficiently and to maintain the soil moisture at an optimum level. The compassion of the proposed system with currently existing systems is shown in Table 3, which shows that the proposed

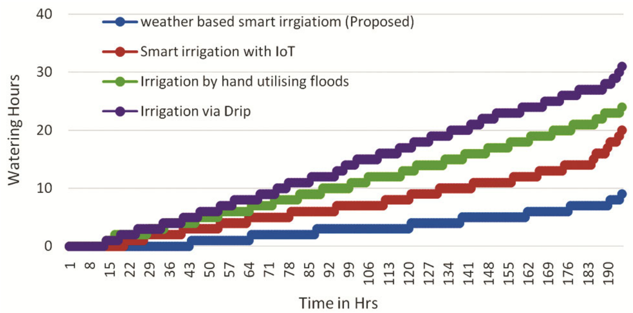

Fig. 10 — Water usage analysis for 150 hours

model performance is good in various aspects. Water usage analysis for 150 hours is given in Fig. 10.

Conclusions

This work presents a smart watering system using fuzzy logic and IoT. The prototype is designed at a low cost and with good accuracy. The rack and pinion mechanism has caused to use of a minimum number of sensors irrespective of the field size. It has also avoided the problem of tracking the buried sensors. Weather information is collected, and important keywords concerning the probability of occurrence of rain in the next 3 and 7 days are estimated. A fuzzy inference system with various fuzzy rules and membership functions was developed and tested for the input taken at various time intervals. The smart watering system has provided a final decision on the status of the output actuator, which is the sprinkler motor in the present work. A mobile app has been used to give the current readings of the remote crop sensors. It also takes the command from the user. This system is beneficial for the farmer to switch on or off the motor at odd times (especially at night).

To further develop the proposed model, it is possible to incorporate a camera into the ground-moving Robo, which can then be used to detect crop diseases through machine learning. A machine learning algorithm can identify crop diseases and recommend the appropriate pesticide to use in cases where the farmer is unaware of the diseases. In addition, a PH sensor can be used with the proposed system to measure crop soil PH values, and an external chemical substance can be used to maintain the PH value at the optimum level based on the crop.

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