

## DESIGNING A FUZZY CONTROLLER FOR THE AUTOMATION OF AN IRRIGATION SYSTEM

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*The paper presents a solution for an irrigation controller based on the fuzzy-logic methodology. First, it describes the general problem of irrigation. Then, it discusses the physical control model. The precious irrigation is great significance for arid and semiarid area. In this paper, a fuzzy control algorithm was proposed to make an optimal irrigation strategy based on the actual measured soil humidity. In this paper, the fuzzy control algorithm was introduced in detail which included the setting of input and output, the selection of membership function and the setting of fuzzy rules. Following the discussion and the formal presentation of the fuzzy controller, the paper provide examples that will show the simplicity in designing and constructing such a system and other advantages of using fuzzy logic in the feedback control problem.*

**Keywords:** irrigation; control; fuzzy logic;

### 1. Introduction

Precision farming is sometimes known as "smart farming", a term used for an easier comparison with other M2M-based implementations, such as smart metering, smart cities, and so on.

For all the M2M implementations, IT systems collect, collaborate, analyze data and present it in such a way as to initiate an appropriate response by the end user to the information received. For farmers and cultivators, depending on the type of agriculture involved, special sensors collect data on soil and crop behavior [14]. It is transmitted to the IT systems for tracking and analysis. The results of the analysis are recorded and used to respond to what is happening in the field by making the most appropriate decisions and future actions.

The smart farming solution refers to precision farming, greenhouse automation, environmental monitoring and control [13]. The use of sensors helps to properly exploit all available resources and to make moderate use of natural water resources. The weather station is an installation with tools and equipment

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for observing the weather conditions to provide information on weather forecasts and to study the weather and climate [15].

## **2. State of the art**

In the paper [2] the authors present a decision system for predicting the water content of the soil based on local climatic data. It has been proposed to use unsupervised artificial neural networks to estimate evapotranspiration based only on weather information. The authors used modeling to estimate the minimum threshold temperature required to calculate the water stress index.

In the paper [6] the authors presented a new algorithm designed to estimate the total water available in the root zone of the soil of a vine crop, using only sensors that are highly dependent on location. Taking advantage of the information about the soil, they incorporate the volumetric water content of the soil, collected manually with a probe, in the agrometeorological data. The information is then entered into a fuzzy logic system to estimate the potential of the water. Other approaches in the literature also use machine learning techniques - such as main component analysis, unsupervised agglomeration to estimate crop irrigation requirements. However, it does not specify the amount of water required, reduces the prediction to true or false, and relies on open-loop structures, taking into account only weather information and therefore unable to correct deviations from their predictions.

The paper [7] proposes an automatic decision support system for smart irrigation to manage irrigation in agriculture. The system estimates the weekly irrigation needs of a plantation, based on both soil measurements and climatic variables gathered by several autonomous nodes developed in the field. This allows for a closed loop control scheme to adapt the decision support system to local disruptions and estimation errors. Performance is tested based on decisions made by a human expert. The authors of the scientific paper [10] propose an automated decision-making system for irrigation management in a given crop field, based on both climatic and soil variables provided by weather stations and soil sensors. As discussed, the use of machine learning techniques with weather and soil variables is of particular importance and can help to achieve a fully automatic system capable of accurately predicting the irrigation needs of a crop. The system presented is evaluated by comparing it with the irrigation reports provided by an agronomist during a full season in different fields.

## **3. Methodology**

The fuzzy control methods represent a major development in conventional control technology, with an important aspect for the development of control applications by offering hybrid solutions. There are four basic structures:

1. PI / PD / PID fuzzy control

2. Sugeno and Takagi fuzzy control
3. Fuzzy model predictive control (FMPC)
4. Sliding mode fuzzy control (SMFC)

Fuzzy PID and SMFC controllers are Mamdani type. SMFC is an extension of fuzzy PID controllers. Their field of application usually refers to large nonlinear systems with considerable perturbations and modeling uncertainties.

The fuzzy PID controller is mostly used for second-order systems, which have linear or non-linear characteristic.

The fuzzy controller after Sugeno and Takagi is applied in the case of processes with nonlinear characteristic where the control law is described locally by means of linear or nonlinear control sequences. This method allows the modeling of nonlinear processes by the Sugeno-Takagi fuzzy modeling methodology. The method does not require much computational effort for optimization, being feasible in the case of online applications.

Predictive fuzzy control is applied to nonlinear systems that are characterized by perturbations and uncertainties. The design objective for FMPC is to minimize the prediction error between the measure and a reference trajectory specified in the following steps. For the implementation of the controller, a two-level structured architecture is followed. At the lower level, local optimal strategies are implemented by minimizing the prediction error in each subsystem. The design of the controller and its performance are dependent on the accuracy of the mathematical model used in describing the process. For greater accuracy, the complexity of the mathematical model increases, leading to difficulties in projecting the controller.

The model predictive control (MPC) comprises the following execution steps:

- Prediction of the output (of the process): in the process is chosen a model used in the prediction of the behavior of the output (of the process) based on the data known at time  $t$ . This stage is determined in an open loop.
- Calculation of the next command: the command is calculated in the next step so that we obtain a predicted output as close as possible to the required reference trajectory. This step is determined in an open loop.
- Closing the loop: The loop is closed by applying the value of the command, calculated in the previous stage of the process.

The sliding control method is used in nonlinear systems. This method is applied when we have modeling uncertainties, parameter changes, and perturbations. The only condition is that the upper edges of the absolute values be known. The method has a major disadvantage: drastic changes in control that lead to high stress and vibration in the control process. This can be avoided by inserting a boundary zone (saturation zone) near the switch line. In the case of

nonlinear processes, the use of linear predictive control algorithms is not recommended because they have unsatisfactory results in terms of achieved dynamic performance. The development of a nonlinear predictive control algorithm (NMPC) based on a nonlinear model requires optimization. Predictive controller design can be simplified by breaking down the nonlinear process into several linear submodels.

Takagi and Sugeno proposed a new control methodology based on the decomposition of the nonlinear feature system into several linear systems. An empirical model is developed based on fuzzy logic assigned to each subsystem. The behavior of the nonlinear process is determined by summing the outputs for each linear subprocess. The weights obtained by the degrees of belonging of the variables to all fuzzy sets are taken into account. The predictive control algorithm can be used with a fuzzy T-S (Takagi-Sugeno) model. In the fuzzy implication, the premise is composed of a lot of symbolic antecedents and the conclusion is determined by a numerical expression with a linear characteristic. Fuzzy implications are obtained based on the system's response to the step signal. What matters in fuzzy is the basic set of rules that mimic human reasoning. The most commonly used fuzzy inference technique is the Mamdani method. Fuzzy runs the inference system to produce fuzzy outputs that are defuzzified to get system outputs.

#### 4. Fuzzy controller architecture design

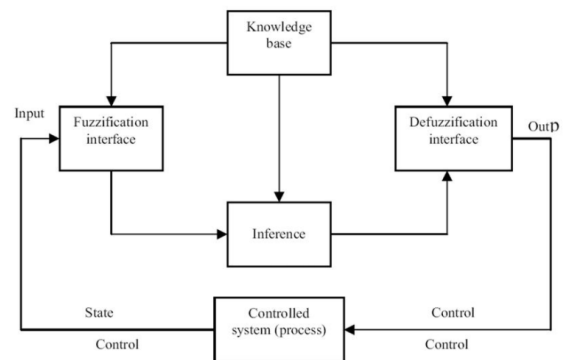


Fig.1. Fuzzy Controller Architecture

The fuzzy controller develops an operating module through the decision rules that are implemented as the human operator acts. The main components of a fuzzy controller are as it follows:

##### Input interface

- Determine which are the input variables
- Transforms input variables in relation to a range of possible values

- Performs fuzzification which has the role of converting input variables into linguistic data

The knowledge base includes:

- The database needed to define the transformation into linguistic data
- The rule base that describes the mode of action with the help of linguistic control rules applied to the database

The decision logic is the meaning of the fuzzy controller core and realizes based on fuzzy concepts a process of human decision, a process of involvement and rules of inference in fuzzy logic.

Output interface

- Performs a transposition of the input data in relation to the corresponding rule base in the output value
- Transforms the fuzzy size into a command size, this process is called defuzzification

The fuzzy controller has a knowledge base that contains the database and the rules for the data. The fuzzy data and fuzzy control rules in the controller are the necessary information stored in the database. However, the main component of a fuzzy controller is the rule base according to which all operations are performed and are expressed through linguistic variables. In the fuzzy system, the rules are of the IF-THEN type and are implemented as conditional sentences. Fuzzy inference is implemented by the decision module, based on the rules in the database.

Within the database, the main function is to provide all the information for a proper operation in the fuzzification module, the rule base and the defuzzification mode. The required information is:

- membership functions and fuzzy sets
- scaling factors and physical domain

The design parameters in the database include the following actions:

- choosing the membership functions
- choosing scaling factors for variables

In order to allow an analysis of closed-loop stability, it is necessary to know the linguistic values associated with the variables within the rules, as well as the symbolic representation of the rules. If a quantitative description for the behavior of the closed loop system is desired, it is necessary to make the quantitative interpretation for the linguistic values. In order to obtain an efficient calculation in terms of time, minimizing the memory space used, it is necessary to make the uniform representation for the membership functions.

The stability and performance of the controller depend on the scaling factors, which play a very important role similar to the role of constants in conventional control.

In order to automate an irrigation system, the following input parameters can be considered:

- temperature and atmospheric humidity
- soil temperature
- radiation and sunlight
- soil moisture
- wind speed and direction
- precipitation

➤ **Atmospheric temperature and humidity**

The relative humidity sensors and temperature sensors integrate elements and signal processing on a small footprint and provide a fully calibrated digital output. A single capacitive sensor element is used to measure relative humidity, while temperature is measured by a band sensor. The applied technology guarantees excellent reliability and long-term stability. Both sensors are seamlessly connected to a 14-bit digital-to-digital converter and a serial interface circuit. This results in superior signal quality, fast response time, and insensitivity to external disturbances. Humidity is a term for the amount of water vapor in the air and can refer to any of several. Officially, humid air is not "humid air", but a mixture of water vapor and other constituents of air, and humidity is defined by the water content of that mixture, called absolute humidity. The specific humidity is the ratio of water vapor in the contents of the mixture to the total air content (based on mass).

➤ **Soil temperature**

It is a measure of the temperature at different levels of the Earth's atmosphere. It is governed by several factors, including solar radiation, humidity and altitude. This variable should be defined as a continuous signal (normally a sine wave that simulates day and night temperature changes). An analogue temperature sensor is a chip that tells us what the ambient temperature is. These sensors use a solid technique to determine the temperature. That is, they do not use mercury (such as old thermometers), bimetallic strips (such as in some thermometers or stoves), nor do they use thermistors (temperature sensitive resistors). Instead, they use this fact as the temperature rises, the voltage on a diode increases at a known rate. From a technical point of view, this is actually the voltage drop between the base and the emitter of a transistor. By precisely amplifying the voltage change, it is easy to generate an analog signal directly proportional to the temperature.

➤ **Radiation and sunlight**

The solar radiation sensor or the solar pyramometer measures the global radiation, the sum at the point of measurement of the direct and diffuse components of the solar radiation. The sensor transducer, which converts incident

radiation into electric current, is a silicon photodiode with a broad spectral response. From the sensor output voltage, the console calculates and displays the solar radiation. It also integrates the irradiation values and displays the total incident energy within a set time period. The outer casing protects the sensor body from thermal radiation and provides airflow for convective cooling of the body, minimizing heating inside the sensor.

#### ➤ **Soil moisture**

The health of a plant is influenced by many factors, one of the most important being the rapid availability of moisture in the soil. Soil moisture is an important component in the atmospheric water cycle, both on a small agricultural scale and in the large-scale modeling of the interaction between soil and atmosphere. Vegetation and crops always depend more on the moisture available at the root than on precipitation.

In the control stage we want the soil moisture to be compared to the measured soil moisture, and a dynamic decision is made on the amount of water added to the soil and requires local information on soil moisture. The control stage interfaces with the desired soil moisture and the measured soil moisture (from the "soil" stage). This stage aims to keep the actual soil moisture as close as possible to the desired humidity. Its output is the control value of the valve, which is the amount of water that must be added continuously to the soil to maintain a minimum deviation.

#### ➤ **Wind speed and direction**

Common conventions for airspeed rating include: indicated airspeed, calibrated airspeed, actual airspeed, equivalent airspeed, and air density. The anemometre measures the direction and speed of the wind.

#### ➤ **Precipitations**

The precipitation value is classified according to the precipitation rate:

- Light rain: when the precipitation speed is  $< 2.5$  mm per hour
- Moderate rainfall: when the precipitation speed is between 2.5 mm and 7.6 mm
- Heavy rain: when the precipitation speed is  $> 7.6$  mm per hour or between 10 mm and 50 mm per hour
- Heavy rain: when the precipitation speed is  $> 50$  mm per hour [4]

Solution in choosing the membership functions and the scaling factors:

- Temperature variable (Table 1):
  - sinus function with amplitude of  $15^{\circ}\text{C}$
  - evenly distributed in the range [0 50]

Table 1

Input “Temperature”		
Temperature [°C]	Linguistic variable	Numerical range
Ambient temperature expressed in degrees Celsius	very cold	[0 0 10 15]
	cold	[10 15 20 25]
	normal	[20 25 30 35]
	hot	[30 35 40 45]
	very hot	[40 45 50 50]

- Air humidity variable (Table 2):
  - Sinus function with amplitude of 25%;
  - constant distribution
  - RH 100% means extremely humid condition, and for 50% instantly indicates very dry air conditions.

Table 2

Input “Air humidity”		
Air humidity [%]	Linguistic variable	Numerical range
Relative humidity (RH) of the environment expressed as a percentage [0 100]	low	[0 0 15 30]
	average	[15 30 45 60]
	high	[45 60 75 90]
	very high	[75 90 100 100]

The microcontroller accepts data from the sensors and compares the data with the set points, generating the corresponding signal. This stage converts water flow, temperature, air humidity, wind speed and light intensity to well-balanced actual readings.

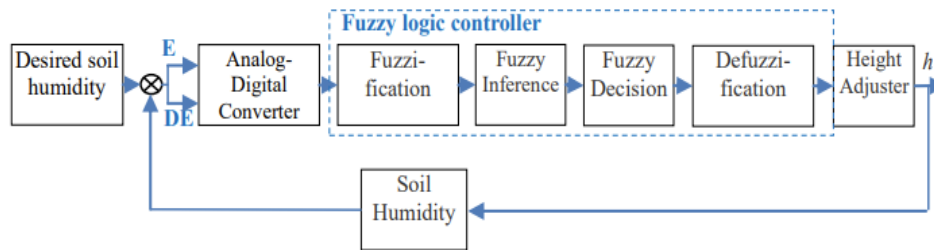


Fig. 2. The principle diagram of fuzzy controller

All the sensors will determine the humidity level and radiation, temperature, wind speed and rain. The microcontroller should get the sensor data per minute. It analyzes the data, takes the right steps and records the data. The soil moisture sensor is a sensor connected to an irrigation system controller that measures the soil moisture content in the active root zone before each scheduled irrigation event and bypasses the cycle if the soil moisture exceeds the user-set value. Soil moisture sensors, such as rain sensors, are considered to stop rain



devices, but while rain sensors measure evapotranspiration rates, the soil moisture sensor measures real-time humidity.

When connected to conventional system irrigation clocks, soil moisture sensors can override scheduled watering events by interrupting the irrigation controller circuit when adequate soil moisture is detected. The sensors have user-adjustable humidity sets that allow unique watering regimes based on plant species, soil type and / or seasonal rainfall. By using this automation technique we can reduce water consumption. It can be set at lower and upper thresholds to maintain optimal soil moisture saturation and to favor the evolution of plants. It can contribute to a deeper growth of plant roots. It is also possible to control nutrition levels as a whole so as to reduce nutrition costs. No nutrient pollution is released into the environment due to the controlled system. Therefore, it will have great savings in irrigation water, healthier plants.

## 5. Simulation

### Choice of variables and content of rules

To design a fuzzy PID controller we need to choose both the status variables and the output variables of the controller (it is equivalent to entering the process).

There are three types of state variables:

- error ( $e$ )
- error deviation ( $\Delta e$ )
- sum of errors ( $\delta e$ )

Controller output variables can be represented by:

- command ( $u$ )
- command deviation ( $\Delta u$ )

By analogy with conventional control, we obtain the following three relations:

$$\begin{aligned} e(k) &= y_{sp} - y(k) \\ \Delta e(k) &= e(k) - e(k-1) \\ \Delta u(k) &= u(k) - u(k-1) \end{aligned} \tag{1}$$

where:

- $y_{sp}$  – represents reference
- $y$  - represents the measurement variable (exit from the process)
- $k$  - represents the sampling period.

### • PID type fuzzy control

By analogy with conventional control we obtain the equation that describes a PID controller:

$$u = K_P \cdot e + K_D \cdot \dot{e} + K_I \cdot \int e dt \quad (2)$$

where:

$K_P$  - represents constant of proportionality

$K_I$  - represents constant integration

$K_D$  - represents derivation constant

By analogy with conventional control we obtain the equation that describes a PID controller:

$$\delta e(k) = \sum_{i=1}^{k-1} e(i) \quad (3)$$

### Choice of scaling factors

The stability and performance of the controller depend on the scaling factors, which play a very important role similar to the role of constants in conventional control.

For example a fuzzy PI type controller we can choose the following representation with scaling factors:

$$N_u \cdot \Delta u(k) = F(N_e \cdot e(k), N_{\Delta e} \cdot \Delta e(k)) \quad (4)$$

where:

$N_e$  - is a *scaling factor* for  $e$

$N_{\Delta e}$  - is a *scaling factor* for  $\Delta e$

$N_u$  - is a *scaling factor* for  $\Delta u$

$F$  - is a nonlinear function representing the fuzzy controller.

In this context, we can make an analogy for the conventional PI controller with the coefficients  $K_P$  si  $K_I$  in which  $F$  is a linear function that depends on  $e$ ,  $\Delta e$ ,  $\Delta u$ . There are two approaches to determining *scaling factors*: formal (or analytical) and heuristic. In Figure 3, we have the inputs in the system: relative humidity, leaf humidity, precipitation and temperature.

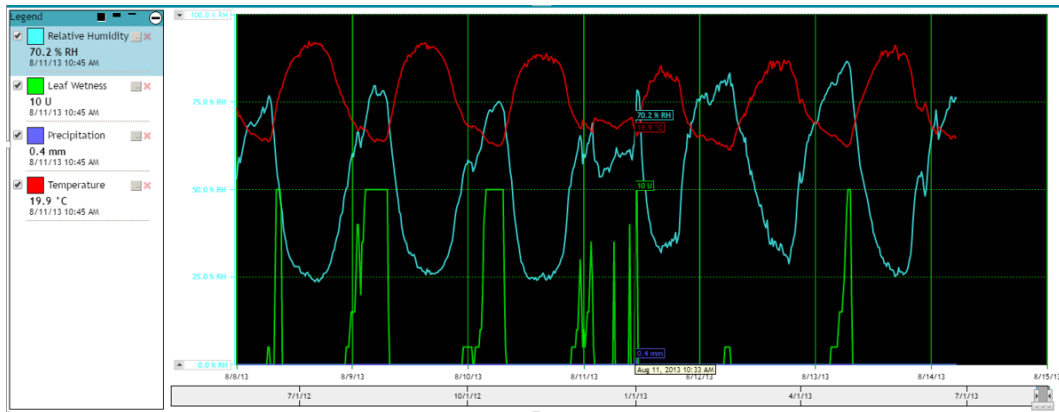


Fig. 3. Graphic with inputs for Fuzzy system

## 6. Conclusions

Crop irrigation is the most important concern in agriculture. The global water deficit puts pressure on the development of systems that not only control crop irrigation, but also provide a smart way to supply the required amount of water, taking into account external environmental factors. The implementation of an automatic system involves monitoring the weather conditions: temperature, precipitation, humidity, radiation and wind speed, sending all these details to a main station. Measurements are usually made regularly and are systematically recorded so as to improve irrigation scheduling and water management decisions. The main factor influencing plant production is the determination of soil moisture. Soil moisture is an important factor that causes crop growth. We presented the comparative analysis of the performance of control algorithms with Fuzzy Logic Control (FLC) techniques for an irrigation system. By monitoring the system inputs: precipitation, soil moisture, leaf moisture, temperature and air humidity, the aim was to reduce the water consumption required for irrigation. Process control involves mastering all information: acquiring process data, processing data, storing information, transmitting information to a control center, establishing orders to the process.

Fuzzy concepts make it possible to encode linguistic information structured in a numerical framework. Fuzzy control is considered to be one of the most attractive strategies in solving system control, particularly for nonlinear systems with inaccuracies and / or uncertainties regarding system information and system behavior. Fuzzy control developed in the Matlab simulation environment guarantees a granularity of data over time. Fuzzy controllers have a number of advantages such as robustness to modeling uncertainties or time variation of parameters as well as a simple implementation that gives an increased speed of order processing. Aspects of fuzzy control techniques that offer a multitude of hybrid solutions that contribute to the development of control applications were presented. Our contribution describes the development of an automatic decision support system for irrigation management in agriculture. The main feature of the system is the use of continuous soil measurements to complete the climatic parameters to accurately predict the irrigation needs of crops, unlike previous work which is based only on weather variables or does not specify the amount of water needed for crops. The use of real-time information from soil parameters in a closed-loop control scheme allows the decision support system to be adapted to the operation of a valve. The system performance analysis is performed by comparing the decisions made by a human expert and the decision-making component based on the Fuzzy system created.

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