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Temperature Compensation of pH Measurements Using a Fuzzy Inference System and Genetic Algorithms

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***Abstract*—pH is a crucial variable in hydroponic crops that indicates the solution's acidity or alkalinity. It is necessary to control and adjust the pH in the nutrient solution of the crop since it affects the transference of nutrients to the root. The pH measurement compares the solution's potential with unknown [H+] with a known reference. At the same time, the function of the pH meter is to convert the voltage ratio between a reference and a sensing half-cell into pH values. In acidic or alkaline solutions, the voltage at the outer membrane sur-face changes proportionally to changes in [H+]. However, temperature affects the pH measurement, producing inaccurate measurements. The most complex sensors integrate Automatic Temperature Compensation (ATC) since they accurately adjust the electrode calibration for pH when the temperature changes. Nevertheless, ATC cannot correct for the pH/temperature effects of samples that are unknown. This research proposes a fuzzy interference system to compensate for the effects of temperature on pH measurement through a Mamdani interference system besides genetic algorithms to tune the vertices in the output arrays.**

***Index Terms*—Fuzzy, genetic algorithms, artificial intelligence, instrumentation, pH variable.**

I. Introduction

A. Description of Problem

Hydroponics is the technique of soilless cultivation, in which the water supplied to the plants dissolves a nutrient solution. When the nutrient solution is applied, the crops are not affected in their growth and development and obtain high yield potentials. A Key factor in hydroponic crops is the control and adjustment of the pH levels of the nutrient solution since it affects the availability of nutrients in the water and therefore prevents root uptake. An element that can be found in different chemical forms depending on the pH of the solution. Soluble chemical forms will be directly assimilated by the roots, while other chemical forms will be insoluble and not assimilated, or even others may be toxic to the plant. In intensive crops, the pH of the substrate and/or nutrient solution must be within a narrow range. In addition, this pH value will increase slightly as the plants absorb the nutrients, so it should be monitored periodically and adjusted if necessary. The correct pH depends on the growing medium, the type of plant, and its age. The pH value is a measure that helps to control the nutrient dosing pumps when the pH value goes down or up. However, the pH measurement is no longer linear in behavior when the temperature changes. Automatic temperature compensation (ATC) is built into some sensors, allowing precise calibration adjustments of the pH electrode when the temperature changes. However, ATC cannot correct for unknown sample pH/temperature effects. When the behavior of a sensor is known, the ATC works adequately to perform the calibration of some sensors.

A problem to be solved with fuzzy interference systems is to find a structure and the type of rules for the implementation to reach an optimal behavior. Genetic algorithms have been implemented in the literature to optimize fuzzy systems applied to obtaining appropriate values for parameters measured in real problems.

A Fuzzy model was built based on a hybrid genetic algorithm adaptive network (GA-ANFIS) where the clustering as rule-based parameters is simultaneously optimized using Gas and Artificial Neural Networks (ANNs) [1]. Similarly, a neuro-fuzzy inference system (ANFIS) tuned by particle swarm optimization (PSO) algorithm monitors a nuclear power plant sensor [2].

Roy and Datta [3] proposed a hybrid model with a genetic algorithm and a fuzzy inference system used as a strategy in saltwater intrusion management. The genetic algorithm adjusts the parameters of the fuzzy system to obtain the optimal structure. Similarly, Genetic programming and artificial neural networks generate two nonlinear models to predict energy consumption in artificial lighting systems for closed plant production systems (CPPS) [4].

In this work, we use a fuzzy inference system to compensate for the temperature changes in pH measurements, using a genetic algorithm to tune the best vertices of the membership functions to obtain the desired behavior, specially adapted for the sensor used.

B. Theoretical Framework

The fuzzy interference systems rely on the concepts of fuzzy set theory (fuzzy if-then rules and fuzzy reasoning). Several researchers have successfully applied this theory in different area1s, such as automatic control, data classification, decision analysis, expert systems, time series prediction, robotics, and pattern recognition. A rule base integrates the selection of fuzzy rules, the database (dictionary) defines the membership functions used in the fuzzy rules and the reasoning mechanism that runs the interference procedure on the given commands and facts to derive a reasonable output or conclusion [5].

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The fuzzy set enumerates the degree of membership of an element that refers to a set. Therefore, the characteristic function of a fuzzy set can have values between 0 and 1, which denotes the degree of membership of an element to a given set [6].

If X is a collection of objects denoted generically by x, then a fuzzy set A in X is defined as a set of order pairs:

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \tag{1}$$

where $\mu A(x)$ is the membership function for the fuzzy set A. The MF assigns to each element of X a degree of membership among 0 and 1. A fuzzy set is an extension of the classical set definition in which the characteristic function is allowed to have any value between 0 and 1.

A linguistic variable is a concept that qualified in a fuzzy way. Examples are height, age, error, error variance, among others. This variable is called "linguistic" due to its features defined in spoken language.

The discourse universe contains all the possible values taken by the elements that possess a property expressed by the linguistic variable. For example, in linguistic variables "height of a human," a set of values would be given between 1.4 and 2.3 m.

The different classifications made on the linguistic variable are called linguistic values, like the case of height. Thus, the universe of discourse could match different linguistic values such as low, medium, and high.

A linguistic value (name of the fuzzy set) together with a membership function (maps the elements of the universe of discourse) is a fuzzy set.

The union operation of two fuzzy sets A and B is a fuzzy set C, denoted as C = A ∪ B or C = A OR B. The membership function is related to that of A and B defined by Jantzen [7]:

$$\mu_C(x) = max((\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x). \tag{2}$$

The intersection of fuzzy sets can be defined analogously. The intersection of two fuzzy sets A and B is a fuzzy set C, written as C = A∩B or C = A AND B, whose MF is related to those of A and B by:

$$\mu_C(x) = max((\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x). \tag{3}$$

Although in principle, any function would be valid for defining fuzzy sets. The most common functions used in practice are:

- GAMMA function,
- L function,
- LAMBDA or triangular function,
- PI or trapezoidal function,
- Smooth trapezoidal function,
- Gaussian function.

The fuzzy set theory allows us to represent vague (imprecise) facts and relations. Fuzzy reasoning is making inferences from fuzzy facts and relationships, combining fuzzy evidence, and updating the accuracy of beliefs.

Mamdani fuzzy systems mimic the performance of human operators in charge of controlling specific industrial processes. The goal was to summarize the operator's experience into a set of IF-THEN (linguistic) rules that a machine uses for automatically controlling the process. Specifically, using such a set of IF-THEN rules, a Mamdani fuzzy system defines a function f that generates numerical outputs y=f(x) from (generally numerical) input values x:

$$p \rightarrow q \equiv p \wedge q \rightarrow \mu_{p\rightarrow q}(u,v) = min(\mu_A(u), \mu_B(v). \tag{4}$$

Defuzzification refers to an operation for transforming a fuzzy set into a crisp representative value. For example, with the centroid defuzzification method, the fuzzy output is transformed into a number. This defuzzification is the most widely adopted defuzzification strategy, reminiscent of the calculation of expected values of probability distributions:

$$Z_{CG} = \frac{\sum_{k=1}^{l} z_k \mu(z_k)}{\sum_{k=1}^{l} \mu(z_k)}. \tag{5}$$

Genetic algorithms simulate the process of natural selection based on Darwin's theory of evolution. Those species that can adapt to changes in their environment can survive and reproduce and pass on to the next generation. This algorithm simulates the "survival of the fittest" among individuals of consecutive generations to solve a problem. Each generation consists of a population of individuals where each individual represents a possible solution. The name given to each individual in the population is chromosome; within each chromosome are n number of genes which are the set of bits that make up a solution.

Genetic algorithms make the analogy with the genetic structure and behavior of chromosomes in the population. The basics of GAs include the natural selection principles listed below:

1. Individuals in the population compete for resources and mates.
2. Those individuals that are successful (fittest) then mate to create more offspring than others.
3. The genes of the "fittest" parents survive throughout the generation, i.e., sometimes parents create offspring that are better than either parent.
4. Therefore, each successive generation is better suited for its environment.

The summarized algorithm is below:

1. Randomly initialize the population.
2. Determine the fitness of the population.
3. Until convergence repeat:
    a) Select the parents of the population.
    b) Crossover and generate a new population.
    c) Perform the mutation in the new population.
    d) Calculate the fitness of the new population.

II. Methodology

The fuzzy inference machine considers the voltage delivered by the electrode (AgCl) measured with five samples of known pH, 4, 6.86, 7, 9.18, 10 at different temperatures (15°C to 30°C), thus obtaining a small database with 80 readings for the genetic algorithm. These experiments define the values of the input and

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TABLE I
ELECTRODE VOLTAGE VALUES AT DIFFERENT TEMPERATURES

	pH=4	pH=6.86	pH=7	pH=9.18	pH=10
°C	**mV**	**mV**	**mV**	**mV**	**mV**
15	161.51	8	4.95	-119.63	-163.53
16	162.11	8.03	5.12	-121.06	-163.11
17	162.71	8.05	5.23	-121.5	-163.8
18	163.31	8.08	5.67	-121.99	-164.31
19	163.88	8.1	5.75	-122.63	-164.88
20	164.48	8.16	5.86	-122.78	-164.48
21	165.08	8.19	6.09	-123.01	-166.08
22	165.68	8.23	6.2	-123.22	-166.68
23	166.28	8.26	6.25	-124.09	-167.28
24	166.88	8.27	6.43	-124.53	-167.85
25	168.55	8.28	6.53	-124.96	-169.08
26	176.05	8.31	6.73	-125.38	-169.3
27	176.65	8.33	6.86	-125.78	-169.85
28	178.25	8.37	7.03	-125.24	-170.25
29	179.90	8.42	7.26	-125.7	-170.85
30	180.13	8.39	7.67	-126.12	-172.45

output universes specific to the electrode used. The rule used in the controller is the Mamdani rule. The aggregation was done through the max operation and defuzzification by a centroid of gravity.

The fuzzy models presented here have two input variables: the value of the voltage measured by the electrode V and the value of the temperature of the solution T. The output variable, pH, describes the temperature of the solution. The output variable, pH, describes the actual pH value at a given temperature. The inputs are the voltage represented by the set V with five terms:

$$\mathrm{V} = \{\mathrm{VpH10}, \mathrm{VpH9.18}, \mathrm{VpH7}, \mathrm{VpH6.86}, \mathrm{VpH4}\},$$

where each value represents the approximate pH value corresponding to the voltage levels measured by the electrode.

And the temperature represented with the set T with five terms:

$$\mathrm{T} = \{\mathrm{TVL}, \mathrm{TL}, \mathrm{TA}, \mathrm{TH}, \mathrm{TVH}\},$$

VL represents the Very low, L set as Low, A is the Average, H equal to High, VH denominated Very High.

The expected output in the experiment is a pH level between 4 to 10. Thus, we let the genetic algorithm tune the fuzzy inference system for obtaining the appropriate output sets for the centroid defuzzification.

Then, the output is given by pH with five terms:

$$\mathrm{pH} = \{\mathrm{pH4}, \mathrm{pH6.86}, \mathrm{pH7}, \mathrm{pH9.18}, \mathrm{pH10}\},$$

where each value represents the real pH value taking into account the temperature. The universe considered for the voltage ranges that the sensor can deliver is UV = $\{x \in \mathbb{Z}: -200 \leq x \leq 200\}$, for temperature is UT = $\{y \in \mathbb{Z}: 15 \leq y \leq 30\}$ and for pH value UpH= $\{z \in \mathbb{Z}: 4 \leq z \leq 10\}$.

The objective function (equation (6)) uses the genetic algorithm in the fuzzy inference machine to fit the vertices of the Gaussian functions (5 input sets, 5 output sets, and 25 rules) with the data in Tables 1 and 2:

$$y = \left(\sum_{i=1}^{80} |Ai - Bi|\right) + \frac{0.1}{|M - m|}, \tag{6}$$

where *Ai* is the value obtained with the fuzzy inference machine using the vertices tuned by the genetic algorithm, *Bi* is the desired value for the dataset values. *M* is the maximum, and *m* is the minimum of the values obtained. The objective is to minimize the function given in equation (6). As the problem to be optimized is dimension 105, we used an initial population of 500 individuals, each with 1155 alleles, where every 11 alleles form a bit string representing a real number, with a resolution of 1000 decimals. The selection method is by tournament, the tournament size applied here is 100, the number of crossover points is a random number, the mutation rate is 5%, and 30000 generations. Table 1 represents the values of the voltage (mV) at different tempures (°C), and different pH.

III. RESULTS

The fuzzy inference system developed in Python can find a value that approximates the actual pH value. Figure 1 shows the fuzzy inference machine that corresponds the target pH values with the data set's input voltage and temperature values.

Figure 2 shows the data sets for the different input voltages normalized-tuned by the genetic algorithm.

The pH measurement with 16 different temperatures (from 15°C to 30°C) was divided into sets of 5 (total 3 data sets) to validate the sensor characterization. Figure 3 shows the element of the input normalized to two, where according to the temperature, the system infers the optimum pH value.

The data set for the output universe is tuned by the generic algorithm and represented in Figure 4. The centroid defuzzification method obtained the appropriate pH value with

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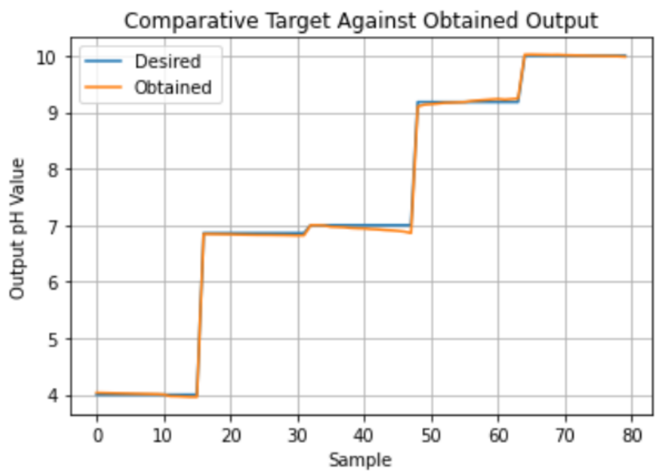

Fig. 1. Comparative graph between the output obtained and the desired output with the input data of the dataset

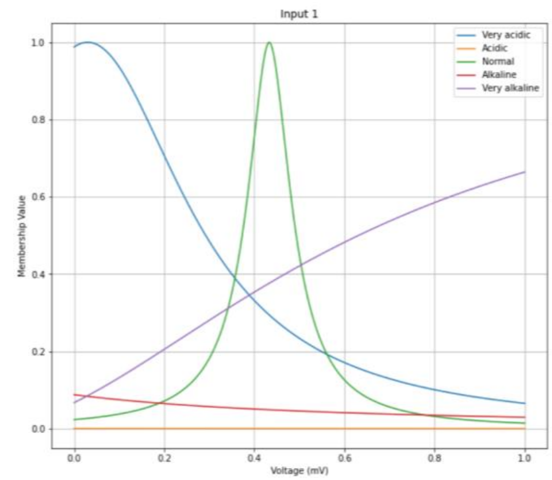

Fig. 2. Voltage (mV) input sets, tuned by the genetic algorithm

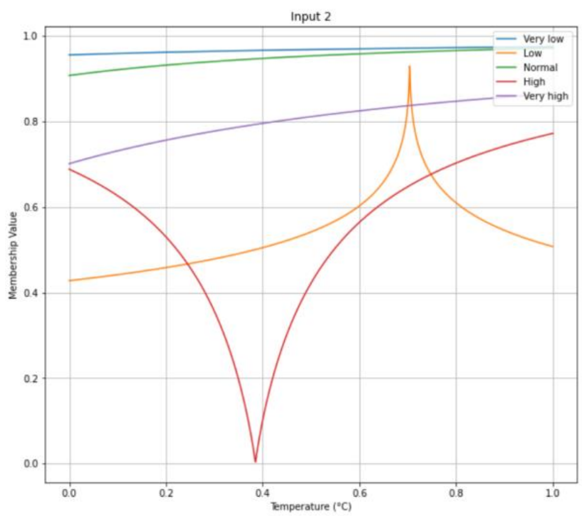

Fig. 3. Input sets for temperature (°C) tuned by the genetic algorithm

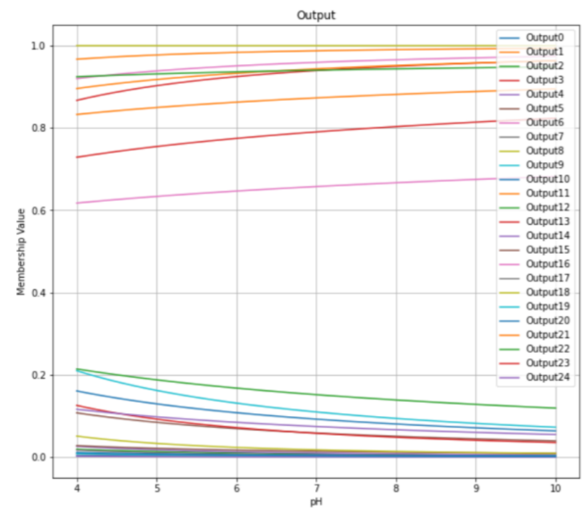

Fig. 4. Output sets tuned by the genetic algorithm

the vertices of the Gaussian functions generated by the genetic algorithm.

IV. Conclusions

The present investigation uses a Mamdani fuzzy logic system autotuned through genetic algorithms to obtain the real pH value without considering the slight variation of the temperature. The system can identify the correct pH values considering the possible changes in the voltage that can influence the electrode due to the temperature. At the same time, an important fact is that the performance of the pH electrode is deteriorated by the useful life or by external factors. With the application of the fuzzy system, it is possible to approximate a sensor's behavior to another in optimal conditions or more sophisticated with ATC. It would be enough to build a set of data with the voltage measurements given by the sensor at certain temperatures and the correct pH value that corresponds to the readings of the sensor already calibrated. The genetic algorithm function will tune the fittest vertices for the fuzzy interference system sets in the defuzzification to obtain the correct pH value. For this work, the system only works in the range of data we used (pH4 to pH10), as future work will create a more extensive data set. In addition, the incorporation of fuzzy logic in a control mechanism for monitoring nutrients in water in a multilevel hydroponic growing system considering parameters such as pH, conductivity, and temperature. By considering these variables, dosing pumps will activate for the modification of nutrients in the water.

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