ARTIFICIAL INTELLIGENCE LEADING TO AN LOW-COST IRRIGATION MANAGEMENT SYSTEM

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ABSTRACT

Management can be defined as the judicious use of the resources to achieve a certain goal. In irrigation, management aims maximizing crop production at the lowest possible cost without compromising the quality of natural resources, using less water and minimizing the water loses. Between management-irrigation techniques, the most used are based on water balance, which consists of determining the amount of water that has been lost to the atmosphere in order to reestablishing it. However, it is necessary to determine culture evapotranspiration and this requires a weather station close to the site of interest. Analyzing the costs of meteorological stations it is clear that this approach is not feasible for small producers. Even for bigger planters, it requires a professional to calculate hydric balance and to periodically check soil water content. The problem with that is the elapsed time between system changes and correction actions, being the second greater than the first. As many times seen, changes in the frequency of irrigation lead to gains or losses in crop production. For this, a technologically efficient system with reduced cost, easy installation and maintenance is needed. Thus, a network of intelligent sensors, capable of monitoring environment in real-time, adapting to different crop development stages, different soils and crops and to communicating with each other, and to a server becomes an interesting solution to manage an irrigation system. This work aims to elucidate the development of a low-cost wireless sensor/controllers network to determine the soil water content for efficient irrigation management. Electronic modules were developed with low power microcontrollers since they were powered by batteries and solar panels, capable of performing the inference algorithms of the measured variables, calibration and correction of such measures, communication with other network elements and running the irrigation controller, based on Fuzzy Logic. The approach of artificial intelligence that was used has the ability to learn, to estimate parameters from their knowledge base and from the conditions around and to use imprecise data - commonly present in low-cost sensors. In addition to microcontroller capabilities, the sensor module is endowed with elements to measure soil and environmental temperatures, air relative humidity (RH), ambient lighting, soil water content, and with a wireless communication module. With the deployment of this system, an efficient and effective irrigation management can be achieved; and, by system cost, it can easily be accessed by familiar agricultures, as by small and medium farmers. Thus, this system can expand the sustainable use of available water resources and even reduce pollution of soil and water with agrochemicals, leading to the maintenance of future generations.

Keywords: Irrigation management, Fuzzy inference system, low-cost sensors.

1. INTRODUCTION

Irrigation is the human activity that has one of the biggest water footprint (WF) (Lovarelli \textit{et al.} 2016), over available hydric resources, even in global or local aspects (Pfister\& Bayer 2014). Nevertheless, as stated by many authors (Katsoulas \textit{et al.} 2006; Monaghan \textit{et al.} 2013; Kang \& Zhang 2004), irrigation leads to crop production

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gains and it is an important technology used to reach efficiency and stability in agricultural production. Therefore, it is underlying that irrigation management should intend to increase crop production and also reduce water use and water losses.

Between existing irrigation-management techniques, the most used are based on water-balance. It consists of determining the amount of water that has been lost to the atmosphere, in order to reestablish it. Consequently, equipment that can measure that amount of water is needed; usually weather stations and applying Penman-Monteith (PM) equation (Monteith 1965), recommended by FAO Irrigation and drainage paper 56 (Allen et al. 1998).

The PM equation calculates the reference evapotranspiration ($ET_0$) based on net radiation, soil heat flux, air temperature, air relative humidity and wind speed at two meters from the soil. After the calculation of $ET_0$, to determine the amount of water that the system (soil plus crop) has lost to the atmosphere it is necessary to multiply $ET_0$ by a crop coefficient ($K_c$), which varies along crop phonological stages.

Two basic problems came along with this overture. The first one refers to the necessity of specialized or at least well-trained personnel to compute $ET_0$ and to judge the culture phonological stage to determine $K_c$. The second problem refers to the need for a weather station near to the crop area, which implies to the producer a financial burden commonly not supported.

To ward off those handicaps, the irrigation management should be easy to be done and have low financial cost. Only that way, an efficient use of water could be done by a large number of producers and so mitigation of water and environmental pollution can be achieved.

A feasible way to achieve those requirements is the adoption of an autonomous and intelligent system to manage irrigation. Such system should be based on low-cost components and it must have the ability to sense changes in the environment and in the crop.

The purpose of this paper is to elucidate the conception and the concepts of a micro weather station that automatically computes $ET_0$ e $K_c$. This micro station has low-cost sensors to measure air temperature, air relative humidity, luminosity, soil water content and soil temperature.

Estimation of $ET_0$ is done by a universal function approximator (Hornik et al. 1989; Kosko 1994) based on Adaptive-Network-Based Fuzzy Inference System (ANFIS) (Jang 1993). On the other hand, $K_c$ estimation is done by data fusion of the soil-water-content sensor and the other sensors of the weather station.

The ANFIS was trained within 14 years of daily weather data provided by an automatic weather station, located on Piracicaba city in the state of São Paulo, Brazil and system validation was done within data from 517 days of the same weather station.

2. METHODS

2.1 Evapotranspiration and Penman-Monteith equation

There are many acceptable methodologies to estimate crop evapotranspiration; each method having its advantages and its drawbacks. Usually, other methods require less meteorological data than PM, but they carry the disadvantage of calibration and having an unacceptable error when they are used in regions with a different climate than the locality where they were developed (Kumar et al. 2012).
Hargreaves equation (Hargreaves & Samani 1985) is able to compute $ET_0$ only with temperature measurements, being necessary mean daily, maximum and minimum temperatures. Thornthwaite method (Thornthwaite 1948) computes $ET_0$ from the temperature and the number of hours of daylight. Priestley and Taylor’s method is a simplified form of the PM method and it only requires net radiation, temperature and soil heat flux to estimate $ET_0$.

Giving the increasing number of published methods to estimate evapotranspiration since early 1940, their rigorous need of local tunes and their poor accuracy under different conditions, FAO produced a standardized method that is able to accommodate different regions of the globe and different crop types. The current methodology is described in FAO Irrigation and drainage paper 56 (Allen et al. 1998).

This method is based on PM equation (Monteith 1965) (Equation 1)

$$ET_0 = \frac{0.408\Delta (Rn - G) + 0.271(\epsilon_s - \epsilon_a)}{\Delta + y(1+0.34U_2)} \quad \text{Equation 1}$$

Where $\Delta$ is the slope of the saturation vapor pressure temperature relationship [kPa·°C$^{-1}$]; $Rn$ is the day net radiation [MJm$^{-2}$day$^{-1}$]; $G$ is the soil heat flux [MJm$^{-2}$day$^{-1}$]; $y$ is the psychrometric constant [kPa·°C$^{-1}$]; $U_2$ is the wind speed [ms$^{-1}$] at 2 m; $(\epsilon_s - \epsilon_a)$ represents the vapor pressure deficit of the air [KPa]; $T$ is mean daily air temperature at 2 m height [°C].

It is important to mention that $\Delta$ is a function of $T$, $y$ is a function of local pressure and it can be considered a function of local altitude and $(\epsilon_s - \epsilon_a)$ is a function of $T$ and air relative humidity.

2.2 Micro weather station

The micro weather station is provided with sensors to measure air temperature; air RH; luminosity; soil humidity; soil temperature. It is also provided with a planar capacitor that can measure soil water content through Time-Domain-Reflectometry (TDR) technic. To provide power to the station, a combination of solar panels and super capacitor was made. To compute and correct data, the station has an embedded temperature sensor, an ultra-low-power microcontroller, and a radio module, to communicate with the irrigation motor pump.

Air temperature and air RH are provided by a single sensor, SHT30-ARP-B (SENSIRION 2016), of SENSIRION Company. This low-cost sensor has an accuracy of ±3 %RH and ±0.3 °C and can operate from 0% to 100% RH and from -40°C to 125°C.

Soil temperature is given by a TC1046 sensor (MICROCHIP 2016), from Microchip Company; its typical accuracy is ±0.5 °C and operates from -40 °C to 125 °C.

Luminosity is provided by BH1603FVC (ROHM 2016) sensor, from Rohm Semiconductor company. This sensor measures light with a wavelength from 400 to 750 nm and with a range of intensity of 0.1 to 500.000 illuminance (lx); its maximum sensitivity is at 550 nm wavelength.

Soil moisture sensor was built as a planar interdigital capacitor on printed circuit board (PCB) (Figure 1). Being excited with a wave of 16 MHz and with an amplifier and conditioner circuit, this capacitor can measure soil volumetric moisture from 0% to 100%.
The embedded microcontroller is an MSP430F2272 device (TEXAS 2016) from Texas Instruments Company. It can operate with a current consumption of 0.7 µA, in standby mode and has the peripherals needed to make calculations and corrections of measured signals and it is also able to compute the inference algorithm of \( \text{ET}_0 \) and \( K_c \).

2.3 Moisture sensor signal
Signal output of moisture sensor circuit is proportional to effective dielectric constant ($\varepsilon_{\text{eff}}$) (Ajayan & Vinoy 1993; Igreja & Dias 2004). However, $\varepsilon_{\text{eff}}$ value is subjected to the dielectric constant of material and respective sensor area covered with this material. Equation 6 demonstrates the relation cited.

$$\varepsilon_{\text{eff}} \propto \sum_i A_i \varepsilon_i; \sum_i A_i = 100\%$$

Equation 6

As an example, it is mentioned the case where all sensor surface is subjected to air, then $\varepsilon_{\text{eff}} \propto 100\% \cdot \varepsilon_{\text{air}}$. If half of sensor surface is immersed in water and the other half is on free air, then $\varepsilon_{\text{eff}} \propto 50\% \cdot \varepsilon_{\text{air}} + 50\% \cdot \varepsilon_{\text{water}}$.

When sensor is in soil, the following relation becomes true:

$$\varepsilon_{\text{eff}} \propto A_{\text{soil}} \cdot \varepsilon_{\text{soil}} + A_{\text{air}} \cdot \varepsilon_{\text{air}} + A_{\text{water}} \cdot \varepsilon_{\text{water}}$$

$$A_{\text{soil}} + A_{\text{air}} + A_{\text{water}} = 100\%.$$ 

Equation 7

Once the sensor is buried into the soil and considering that the soil structure is not altered, $A_{\text{soil}}$ is constant and depends only on soil porosity.

This type of sensor (interdigital capacitors) can be used to measure the surroundings moisture by differences of the dielectric constant of soil, water, and air. Air dielectric constant is one ($\varepsilon_{\text{air}} = 1$), soil dielectric constant varies between 2 and 8 ($\varepsilon_{\text{soil}} \approx [2..8]$) and water dielectric constant is approximately 80 ($\varepsilon_{\text{water}} \approx 80$) (Topp et al. 1980; Wang & Schmugge 1980; Jacobsen & Schjønning 1993).

2.4 Adaptive-Network-Based Fuzzy Inference System

Modeling a system by conventional methods consists of building a mathematical model, described by differential equations to characterize the dynamics of the system. Problems arise when all process variables are not well known or when variables are subject to noise (Jang 1993). To endeavor that problematic Takagi & Sugeno (1985) presented an approach that considers system behavior as a set of fuzzy implications and reasoning. The basis of fuzzy inference system (FIS) is the imprecise models of reasoning that humans use to make decisions, FIS is modeled as IF-THEN rules, e.g. IF moisture IS high THEN do not irrigate.

Many previous works have shown the ability that FIS has to control process variables (Castaneda-Miranda et al. 2006) and to predict them (Yun et al. 2008). The main difficulty to implement an FIS is the tuning of membership functions (Berenji & Khedkar 1992). Jang (1993) proposed a hybrid system that utilizes the back propagation learning algorithm from Artificial Neural Networks (ANN) (Hecht-Nielsen 1989) to tune FIS membership functions. This method is known as Adaptive-Network-Based Fuzzy Inference System (ANFIS). An ANFIS has the ability to approximate functions, control process, pattern classification, clustering, prediction, optimization and etc.

This work employed an ANFIS to find the relation between sensor data and reference evapotranspiration ($ET_0$) based on data from the automatic weather station, located in the Piracicaba city in the state of São Paulo, Brazil. As inputs of ANFIS it was used daily means of air temperature, air RH, and net radiation; $ET_0$ as ANFIS output. Each input was fuzzified as five linguist variables (extremely low; low; medium; high; extremely high) and membership functions were described as bell-shaped functions.

2.5 Crop coefficient ($K_c$) determination
The micro weather station possesses a soil moisture sensor that is sensible to daily changes in soil water content ($\Delta \theta_s$). When irrigation is initiated, a volume of water, determined by crop evapotranspiration ($ET_c$) has to be put into the system and it should cause a soil water content variation of $\Delta \theta_s$. Initially, on the first irrigation of the micro weather station, the volume of water that will be put into the system is proportional to $ET_0$, the parameter that FIS was trained to measure and it will cause a variation in soil water content of $\alpha \Delta \theta_s$.

Been $\{\alpha, \beta, \gamma, K\} \in \mathbb{R}^+$, the following equations can be written:

\[
ET_c \propto \Delta \theta_s \rightarrow ET_c = \gamma \Delta \theta_s \quad \text{Equation 2}
\]

\[
ET_0 \propto \alpha \Delta \theta_s \rightarrow ET_0 = \beta \alpha \Delta \theta_s \quad \text{Equation 3}
\]

\[
ET_c = K_c ET_0 \quad \text{Equation 4}
\]

\[
\gamma \Delta \theta_s = K_c \beta \alpha \Delta \theta_s \rightarrow K_c = \frac{\gamma}{\beta \alpha} \quad \text{Equation 5}
\]

For example, if the micro weather station has determined, by its calculations of $ET_0$, that a volume of two liters has to be put into the system and this volume causes a variation of 70% of $\Delta \theta_s$, measured by soil-water-content sensor, it means that $K_c = \frac{1}{70\%} = 1.43$.

### 2.6 Data training

Climatic data were provided from the automatic weather station of Biosystems Engineering Department of Luiz de Queiroz College of Agriculture at University of São Paulo (22°43' S, 47°25' W; 580m). Daily data from 01/01/2001 to 31/05/2016 was used. The first fourteen years were used as training data, resulting in 5,113 training points and restating data was used to analyze system answer, 517 points.

To simulate embedded sensor data set the following algorithm was done:

1. Sensor correlation ($S_c$) = random number between 0 and 1($rand(1)$);
2. Sensor offset ($S_o$) = $rand(1) \times Maximum \ data \ variation \times S_c$;
3. Do for all available data:
   - Sensor signal ($S'_c$) = Real data ($R_d$) $\times S_c$;
   - Time-variant noise ($T_n$) = 5%*$rand(1)$*$S'_c$;
   - Sensor signal ($S_s$) = $S'_c + S_o + T_n$.

For the three variables, temperature, air RH and net radiation it was obtained a signal with a random offset and a time-variant random noise. This was done to simulate sensor noise and imprecisions as possible errors in signal conditioning.

Figure 3 represents the correlation between actual data and simulated embedded sensor data.

### 3. RESULTS AND DISCUSSION

#### 3.1 Micro weather station financial costs

As an estimation of this micro weather station financial cost, the sum of the price of all components was made. For electronic components, the price was picked from Digi-Key Electronics, from the component that meets the project criteria and that it is
possible to buy in the quantity of just one piece. Table 1 presents the list of component prices.

![Real Temperature X Sensor signal](image)

**Figure 3.** Temperature correlations for simulated sensor signal. Simulated sensor signal \((S_n) = S'_n + S_o + T_n\) on the vertical axis and day temperature on the horizontal axis.

**Table 1.** Micro Weather station financial cost. Prices and a list of components.

<table>
<thead>
<tr>
<th>Component</th>
<th>Quantity</th>
<th>Unity (US$)</th>
<th>Total (US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Resistors</td>
<td>10</td>
<td>0.15</td>
<td>1.50</td>
</tr>
<tr>
<td>Capacitors</td>
<td>26</td>
<td>0.11</td>
<td>2.82</td>
</tr>
<tr>
<td>Inductors</td>
<td>1</td>
<td>0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>SuperCap</td>
<td>1</td>
<td>3.72</td>
<td>3.72</td>
</tr>
<tr>
<td>Crystal</td>
<td>1</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>Diodes</td>
<td>2</td>
<td>0.14</td>
<td>0.28</td>
</tr>
<tr>
<td>Connectors</td>
<td>4</td>
<td>0.30</td>
<td>1.20</td>
</tr>
<tr>
<td>Microcontroller</td>
<td>1</td>
<td>4.91</td>
<td>4.91</td>
</tr>
<tr>
<td>Op. Amplifier</td>
<td>1</td>
<td>1.67</td>
<td>1.67</td>
</tr>
<tr>
<td>Voltage Reg.</td>
<td>2</td>
<td>1.31</td>
<td>2.61</td>
</tr>
<tr>
<td>Radio</td>
<td>1</td>
<td>19.00</td>
<td>19.00</td>
</tr>
<tr>
<td>Temperature Sensor</td>
<td>1</td>
<td>5.83</td>
<td>5.83</td>
</tr>
<tr>
<td>Solar Panel</td>
<td>1</td>
<td>6.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Luminosity Sem.</td>
<td>1</td>
<td>1.12</td>
<td>1.12</td>
</tr>
<tr>
<td>PCBs</td>
<td>2</td>
<td>7.30</td>
<td>14.60</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td><strong>65.79</strong></td>
</tr>
</tbody>
</table>

As can be seen, it is possible to make this micro weather station with less than a hundred dollars. Thinking of large scale production, surely, costs can be minimized.

### 3.2 Simulations

FIS inputs had its signals degraded by an addition of a time variant random noise of 5% plus a fixed offset. Even with that degradation and without wind speed data FIS
was able to compute $ET_0$ with an $R^2 = 0.98$ and a P-value < 0.001. Figure 4, shows the dispersion of FIS response versus real evapotranspiration, computed by PM equation using Piracicaba’s-weather-station data.

![Evapotranspiration correlations](image)

**Figure 4.** FIS answer versus actual $ET_0$ computed by PM equation. PM $ET_0$ was computed with all data available from the weather station. Micro weather station $ET_0$ was computed using degraded signals for temperature, RH, and solar radiation.

To demonstrate ANFIS capabilities, it was done a simulation, equal to the one described above, except by radiation signal. This new simulation utilized $\log S_n$ as radiation sensor signal. Second simulation results were similar to first simulation results; even though coefficient of determination was greater than in the first case ($R^2 = 0.99$) it was shown that FIS answers were not statistically different. In Figure 5 is shown second simulation dispersion.

![Evapotranspiration correlations](image)

**Figure 5.** FIS answer versus actual $ET_0$ computed by PM equation. In this simulation, it was utilized sensor-signal solar radiation as $\log S_n$, where $S_n$ is sensor signal for solar radiation from the first simulation.

Simulation results show that ANFIS is a suitable inference system to deal with imprecise and noisy data and that if only signals correlated with temperature, air RH, and solar radiation are available, FIS still been able to compute $ET_0$.

### 3.2 Moisture sensor validation

To validate moisture sensor signal, after conditioning, an experiment was arranged. In this experiment, moisture sensor was immersed in water, within a velocity of $0.5 \text{[mms}^{-1}]$, until its complete surface was covered and then, movement direction was inverted and moisture sensor was withdrawn of water. Figure 6 shows
experimental results. There are 2,000 collected points, representing the sensor output with an interval of 0.5 mm depth.

![Figure 6. Moisture sensor signal after conditioning. This case represents sensor PCB being immersed and then withdrawn from the water. Vertical axes represent moisture sensor circuit output [V] and horizontal axes represent the depth of immersion in water of sensor [mm].](image)

3.3 Field experimentation

Now days, data from embedded sensors are being collected and its correlation with automatic weather station data is being done. This, to elaborate a correlation model that allows data set from 2001 to be used to train embedded FIS. After that, experimentation will be conducted with vases placed over a load cell and system will be validated.

CONCLUSIONS

Preliminary results showed system potentialities and system capabilities. ANFIS has proved itself an excellent inference system to deal with imprecise and noisy signals. Today, research is focused on field experimentation and data is being collected to potentiate use of weather data, previously collected by Piracicaba’s automated weather station, to train embedded FIS. It is strongly believed that the micro weather station in combination with soil moisture sensor will be able to operate autonomously. If more than one micro station is employed, it will be possible to map micro clime heterogeneity as well soil heterogeneity. First investigations concerning micro station costs have indicated that it will be possible to fabricate this irrigation management system with financial ballast that will be supported by many producers, even small ones. Thus, irrigation could be done efficiently, without wasting water and with crop productions gains.

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