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Research Article

Sensor-Based Model Driven Control Strategy for Precision Irrigation

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Improving the efficiency of the agricultural irrigation systems substantially contributes to sustainable water management. This improvement can be achieved through an automated irrigation system that includes a real-time control strategy based on the water, soil, and crop relationship. This paper presents a model driven control strategy applied to an irrigation system, in order to make an efficient use of water for large crop fields, that is, applying the correct amount of water in the correct place at the right moment. The proposed model uses a predictive algorithm that senses soil moisture and weather variables, to determine optimal amount of water required by the crop. This proposed approach is evaluated against a traditional irrigation system based on the empirical definition of time periods and against a basic soil moisture control system. Results indicate that the use of a model predictive control in an irrigation system achieves a higher efficiency and significantly reduce the water consumption.

1. Introduction

Agriculture represents the major water consumer globally; this sector uses approximately the 70% of the available fresh water resources worldwide, mostly in crop irrigation activities. The world average efficiency of agricultural irrigation is about the 50%–60%, mainly due to the inappropriate management of this natural resource [1]. A deficient water management causes not only the waste of this vital liquid, but also a significant reduction on crop productivity.

Precision irrigation refers to the management of the irrigation scheduling according to the crop requirements. The amount of water applied to the crop is based on measurements of soil, crop, and weather variables which reflects the status of the plant [2]. Among the main goals of precision irrigation are the increment of water efficiency, the reduction of energy consumption, and the maximization of crop productivity, by using technology such as wireless sensor networks, mobile devices, remote sensing, real-time control, and information systems.

Nowadays, most of the commercial automated irrigation systems offered by the market (Acclima, Rainbird, Watermark, Decagon) are programmed to irrigate at time intervals for predefined periods of time. The irrigation schedule is defined offline, and it is usually based on the user empirical knowledge on crop needs, soil characteristic, and weather factors [3]. Some farmers use crop evapotranspiration (et_c) data to determine the irrigation schedule. Evapotranspiration represents the water lost caused by soil surface evaporation and crop transpiration; therefore the amount of water applied is used to refill the water consumed by the plant and the environment. Most recently, there have appeared in the market new commercial automatic controllers that regulate the use of water, based on soil moisture measurement by implementing a closed-loop irrigation control. These controllers activate irrigation when sensors detect that soil moisture is under a predefined low limit threshold and deactivate irrigation if soil moisture is above a high limit [4, 5]. On-off control may also be implemented based on direct plant canopy measurements, such as the crop water stress index that can be obtained by measuring the air and canopy temperatures, as well as the atmospheric vapor pressure [6]. However, due to practical difficulties on obtaining real-time measurements from the canopy, it is difficult to find any commercial irrigation controllers based on direct plant measurements.

In recent years, agricultural engineers and control community have increased their attention to the analysis and implementation of real-time closed-loop irrigation control

systems, since the use of control techniques for precision irrigation has demonstrated the obtention of large amounts of water savings. Two major research approaches can be observed in this area: modelling and implementation.

For the first approach, the main focus is the analysis of the dynamics of soil, crop, and weather conditions in order to properly model the irrigation process. Reference [7] implements a wireless sensor network to automate a viticulture irrigation system; the work focuses on modelling the process dynamics using the water balance model proposed by [8]. In [2] a soil-plant-atmosphere model was developed to simulate water transport in a crop field and to design and test model-based irrigation control strategies such as PID (Proportional-Integral-Derivative) control and MPC (model predictive control). Reference [9] proposes a predictive control algorithm to schedule irrigation events and uses measured weather data to evaluate the simulation model. Reference [10] investigates how soil moisture sensors positioning and accuracy may affect the performance of soil moisture based surface drip irrigation scheduling under different conditions. However, in general those approaches do not deal with the implementation details when the systems are implemented for large crop fields.

The second research approach mainly deals with the integration of technology such as wireless sensor networks, real-time controllers, and information systems to implement automatic irrigation systems. In [11] an automated irrigation system, based on a wireless network of soil moisture and soil temperature sensors, was developed to optimize water use for agricultural crops; the system was evaluated in an organic sage greenhouse where either the moisture or the temperature activates the on-off irrigation control. In [12] different experiments on commercial plantations were conducted in order to manage the irrigation based on soil moisture measurements validating the feasibility to implement on-off control on woody and vegetable crops. In [13] a wireless sensor network was developed to acquire field soil property data (soil moisture, electrical conductivity, and soil temperature), compared to predefined thresholds, and as a result activate or deactivate the drip irrigation. In [14] an automated closed-loop irrigation control system was developed where irrigation decisions were site-specifically made based on feedback from soil water conditions, by controlling the on-off times for groups of sprinkler nozzles. Although these approaches consider detailed implementation issues, they do not include a model for the process dynamics and as a result controller design is simple and empirical.

The work presented in this paper describes the implementation of an automatic system for precision irrigation considering a model driven approach, where the process dynamics are experimentally identified and validated in order to design a predictive algorithm implemented over an embedded system platform to achieve optimization in the use of water for agricultural activities. This work extends the preliminary results obtained on [15] where a model predictive control strategy for closed-loop irrigation was simulated. In this paper, the mathematical model is refined and validated experimentally, the predictive algorithm is implemented over an embedded platform in order to automate a drip irrigation field, and the obtained results on the evaluated crop are compared against the typical commercially available approaches.

Model predictive control (MPC) is an optimal control strategy based on numerical optimization over a finite horizon, as denoted by [16]. MPC requires a heavy computational load to achieve optimization, where future control inputs and future process responses are predicted using a mathematical model and optimized according to a cost function. Model predictive control has been proposed as a suitable technique for large water distribution systems. In [17], MPC is used to generate flow control strategies from the sources of water to the consumer and irrigation areas to achieve safety volumes in dams and flow control stability. In [18], a hierarchical system to control an irrigation canal is proposed, where a centralized predictive controller controls the inflow to the canal and coordinates the local controllers by modifying their set-points. In [19], MPC is used to maintain the water level of navigation canals while reducing water levels deviations. In the proposed approach a predictive algorithm minimizes the control signal (effective irrigation) while keeping soil moisture under specific thresholds (avoiding water stress) and considers external disturbances (evapotranspiration) to predict the process dynamics.

The rest of this paper is structured as follows. Section 2 introduces the hydrological balance, the evapotranspiration, and the soil moisture concepts. Then, in Section 3 the formal definition of the process model is presented and the controller design strategy is defined. Section 4 presents the model parameter estimation based on direct measurements from soil moisture and weather conditions, and it also presents the results where the predictive model is evaluated against traditional irrigation systems based on the definition of time periods and against a basic soil moisture control system. Finally, Section 5 concludes the paper.

2. Preliminaries

2.1. Hydrological Balance. The process dynamics of an agricultural irrigation system can be described by using the hydrological balance model [8]. This model establishes that a change in water storage during a time period in a specific location is the result of water inflows (irrigation, rainfall, and capillary rise) minus the water outflows (evaporation, plant transpiration, water runoff, and deep percolation), as depicted in Figure 1.

Using soil moisture $\theta(t)$ in order to measure field water storage, then, the hydrological balance dynamics can be defined as

$$\dot{\theta}(t) = \mathrm{ir}(t) + \mathrm{rf}(t) + \mathrm{cr}(t) - \mathrm{et}_c(t) - \mathrm{dp}(t) - \mathrm{ro}(t), \quad (1)$$

where soil moisture variations in the root zone $\dot{\theta}(t)$ depends on effective irrigation $\mathrm{ir}(t)$, rainfall $\mathrm{rf}(t)$, capillary rise $\mathrm{cr}(t)$, crop evapotranspiration $\mathrm{et}_c(t)$, deep percolation $\mathrm{dp}(t)$, and water outflow due to runoff $\mathrm{ro}(t)$.

If a dry and plain land area for irrigation is considered, then $\mathrm{rf}(t)$ (assuming no rainfall), $\mathrm{cr}(t)$ (assuming no deep water available for capillary rise), and $\mathrm{ro}(t)$ (assuming no

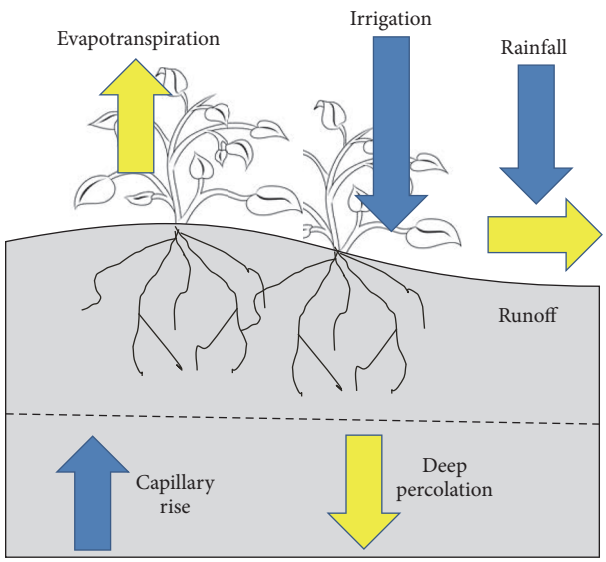

Figure 1: Components of hydrological balance for an irrigation system (figure obtained from Allen et al. [8]).

runoff due to plain land) terms can be removed from water balance, and simplified dynamics can be expressed as

$$\dot{\theta}(t) = \mathrm{ir}(t) - \mathrm{et}_c(t) - \mathrm{dp}(t), \tag{2}$$

where soil moisture variations $\dot{\theta}(t)$ depend just on the effective irrigation, crop evapotranspiration, and deep percolation.

2.2. Evapotranspiration. Crop evapotranspiration represents the water lost caused by soil surface evaporation and crop transpiration. The evapotranspiration rate is normally expressed in millimeters (mm) per unit of time (usually days). The rate expresses the amount of water lost from the cropped surface in units of water depth. An evapotranspiration of 1 mm/day is equivalent to a loss of 10,000 liters per hectare per day.

Crop evapotranspiration et_c depends on both weather factors and crop characteristics (crop type, development stage). According to [8], the water demand of any crop can be computed by multiplying the weather factors of the evapotranspiration with a coefficient that depends on the crop specific characteristics, as denoted by

$$\mathrm{et}_c(t) = K_c \mathrm{et}_o(t), \tag{3}$$

where K_c is the constant crop coefficient which depends on the crop type and its development stage; this constant is globally known and it is independent from the environmental conditions. Reference evapotranspiration $\mathrm{et}_o(t)$ depends only on weather parameters, and it can be obtained by using the FAO Penman-Monteith method [20], which requires measurements from solar radiation, wind speed, air temperature, and relative air humidity variables.

2.3. Soil Moisture. Soil moisture plays an important role in agriculture. Soil moisture refers to the amount of water in soil,

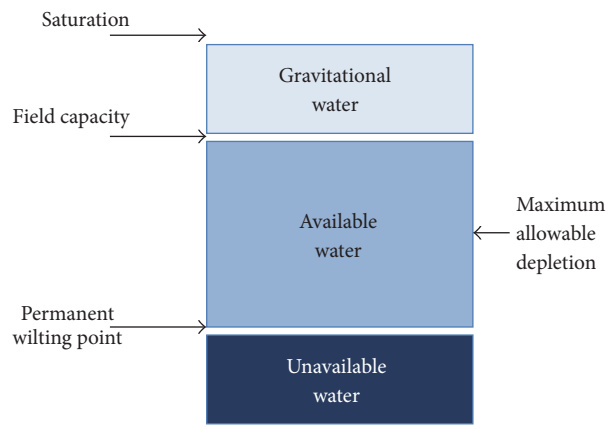

Figure 2: Volumetric water content parameters.

which is described as the volumetric water content (VWC). Volumetric water content (θ) indicates the percentage of water volume for a specific volume:

$$\theta = \frac{V_W}{V_T}, \tag{4}$$

where V_W is the water content in volume units for a specific sample and V_T is the total volume sample (soil + water + air).

In any crop, the soil moisture needs to be maintained above permanent wilting point and stay below field capacity. Permanent wilting point is the soil moisture level at which plants cannot longer absorb water from the soil. Field capacity is the quantity of water stored in a soil volume after drainage of gravitational water. The available water capacity of soil is the water that is available to the crop, and it represents the range of soil moisture values that lie above permanent wilting point and below the field capacity, as shown in Figure 2. The point below field capacity where crops become stressed is known as the maximum allowable depletion (MAD); below this level the crop is able to receive water from soil; however after a period of time it will become stressed. This value is expressed as a percent of the available water capacity and typically represents 50% for most of the crops.

Field capacity and permanent wilting point are heavily influenced by soil textural classes, [21]; for example, a silt loam type of soil (frequently used for agricultural purposes) has a typical range of values from 0.3 to 0.4 volumetric water content for the available water capacity.

3. Materials and Methods

3.1. Plant Dynamics Model. Based on the hydrological balance (2), the process dynamics for an irrigation system can be described as a block diagram with two inputs (effective irrigation and reference evapotranspiration) and one output (soil moisture), as shown in Figure 3.

Notice that reference evapotranspiration (et_o) is used instead of crop evapotranspiration (et_c), because et_o depends only on external weather parameters. On the other hand, et_c is the result of et_o that multiplies the crop coefficient (K_c) according to (3), so it is assumed that K_c is a constant that

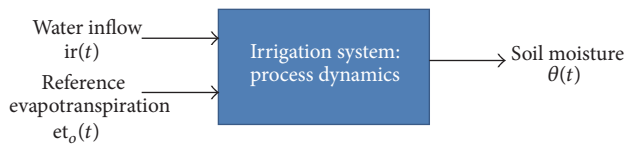

Figure 3: Irrigation system input/output definition.

belongs to the internal process dynamics of the irrigation system. Also notice that deep percolation $\mathrm{dp}(t)$ is not present in the block, since it is assumed that water percolation in an irrigation system is clearly proportional to soil moisture [7], then (2) can be rewritten as

$$\dot{\theta}(t) = \mathrm{ir}(t-\tau) - K_c \mathrm{et}_o(t) - c_0\theta(t), \tag{5}$$

where c_0 is a constant value denoting the proportional relation between soil moisture and deep percolation and τ represents the time-delay from the start of irrigation until the sensor detects a change in the soil moisture.

Since a discrete model is required, then by using the Euler approximation on soil moisture variations

$$\dot{\theta}(t) = \frac{\theta(kh+h) - \theta(kh)}{h}, \tag{6}$$

where h is the sampling interval. Using (6) in (5), the discrete time dynamics is given by

$$\theta(kh+h) = c_1\theta(kh-\tau) + c_2\mathrm{ir}(kh) - c_3\mathrm{et}_o(k); \tag{7}$$

without the loss of generality c_1, c_2, and c_3 can be used as the three discrete coefficients that absorb the previous coefficients h, K_c, and c_0. Also it is considered that τ is considerably larger than h.

Now (7) can be reformulated by using a first-order state-space representation as

$$\theta(kh+h) = [c_1][\theta(kh)] + [c_2 \quad c_3]\begin{bmatrix}\mathrm{ir}(kh-\tau)\\ -\mathrm{et}_o(kh)\end{bmatrix}, \tag{8}$$

where c_1, c_2, and c_3 are coefficients that define the dynamics of the process and can be obtained from direct measurements of the evapotranspiration, the soil moisture, and the effective irrigation.

3.2. Coefficients Estimation. Although soil moisture dynamics can be defined by a well-known stochastic differential equation (2), the estimation of soil moisture variations for large areas is highly complex, due to the large spatial variation in measurements along with the presence of processes (irrigation, percolation, evapotranspiration, etc.) that vary in space and time [22]. As a result soil moisture has a highly nonlinear behavior, since measurements of soil moisture can vary at spatial scale as small as meters. In addition, drainage rates depend on topographic variations, water movements depends on heterogeneity at scale that hardly can be quantified, and even evapotranspiration varies spatially and timely due to soil and vegetative variations. Therefore coefficients c_1, c_2, and c_3 from (8) are time-variant and difficult to estimate.

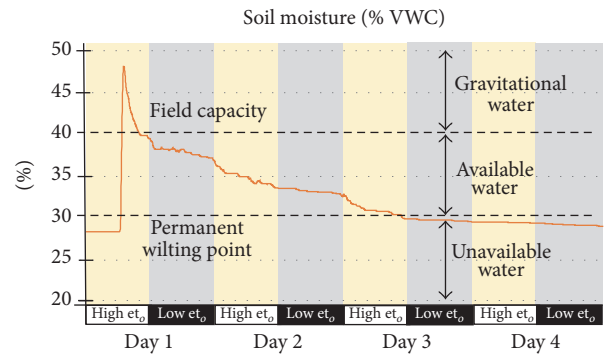

Figure 4: Soil moisture general dynamics.

However the soil moisture general dynamics is simple and intuitive; see Figure 4. Irrigation adds soil moisture up to a saturation level. Then excess water is rapidly drained until field capacity is reached. Below field capacity, moisture is withdrawn at a slower rate, depending on the crop evapotranspiration. Therefore, the soil moisture slope that represents the water depletion rate is higher during the day (high et_c) and lower during the night (low et_c). When soil moisture arrives to the wilting point, plants cannot longer extract water from soil. Below wilting point the rate of depletion is even slower and mostly depends on soil characteristics.

Therefore, in order to simplify the dynamic model, make an adequate parameter estimation, and reduce the complexity caused by the spatial and temporal variations in measurements, two considerations were carried out to conduct the model identification process:

(i) Soil moisture measurements may involve a large group of nodes distributed along a large piece of land; therefore in order to obtain a single representative soil moisture value for the irrigation area, a data aggregation method is required to summarize the information provided by a group of soil moisture sensors. According to [23] measuring accuracy is exponentially improved when increasing the number of soil moisture sensors.

(ii) Since crop-water-soil dynamics are different depending on the soil volumetric water content level specified in Figure 4, then parameter estimation for c_1, c_2, and c_3 is obtained for each level; that is, one set of parameters correspond to the level below the permanent wilting point, another to the available water level (between field capacity and permanent wilting point), and another one to the gravitational water level. Within each level parameters are considered time-invariant.

For system identification purposes (8) is rewritten as

$$\theta(kh+h) = [c_1 \quad c_2 \quad c_3]\begin{bmatrix}\theta(kh)\\ \mathrm{ir}(kh-\tau)\\ -\mathrm{et}_o(kh)\end{bmatrix}; \tag{9}$$

then (9) can be simplified as

$$\theta(kh+h) = \gamma^T\phi(kh), \tag{10}$$

where

$$\phi(kh) = \begin{bmatrix} \theta(kh) \\ \mathrm{ir}(kh-\tau) \\ -\mathrm{et}_o(kh) \end{bmatrix} \tag{11}$$

is the regressor vector that can be obtained from direct measurements, $\theta(kh+h)$ is the known output, and $\gamma^T = [c_1 \;\; c_2 \;\; c_3]$ is the parameter vector to be estimated.

Suppose there is an estimate of the parameter vector $\widehat{\gamma}$; then at time kh the estimation can be obtained by

$$\widehat{\theta}(kh+h) = \widehat{\gamma}^T(kh)\,\phi(kh), \tag{12}$$

where the least square estimate of γ minimizes the cost function defined by

$$J_k = \sum_{i=1}^{k}\left[\theta(ih) - \widehat{\gamma}^T(kh)\,\phi(ih-h)\right]^2, \tag{13}$$

expanding the quadratic term

$$J_k = \sum_{i=1}^{k}\begin{bmatrix} y(ih)^2 + \widehat{\gamma}^T(kh)\,\phi(ih-h)\,\phi^T(ih-h)\,\widehat{\gamma}(kh) \\ -2y(ih)\,\phi(ih-h)\,\widehat{\theta}(kh) \end{bmatrix}; \tag{14}$$

since on least squares $\partial J_k/\partial\widehat{\gamma}(kh) = 0$, then applying partial derivative on (14) the parameter vector can be estimated by

$$\widehat{\gamma}(kh) = F(k)\sum_{i=1}^{k}\phi(ih-h)\,y(i), \tag{15}$$

where

$$F(k) = \left[\sum_{i=1}^{k}(ih-h)\,\phi^T(ih-h)\right]^{-1}. \tag{16}$$

Now, recursive least square is used to ease the implementation into a real-time algorithm. Recursive least square is an online implementation of least squares where the estimated parameter is predicted and corrected by using the current measurement [24], in the form of

$$\widehat{\gamma}(kh+h) = \widehat{\gamma}(kh) + F(kh+h)\,\phi(kh)\,\epsilon(kh+h), \tag{17}$$

where $\epsilon(kh+h) = y(kh+h) - \widehat{\gamma}^T(kh)\phi(kh)$ is the a priori estimate error and $F(kh+h)$ is the adaptation gain that can be updated by

$$F(kh+h) = F(kh) - \frac{F(kh)\,\phi(kh)\,\phi^T(kh)\,F(kh)}{1+\phi^T(kh)\,F(kh)\,\phi(kh)}. \tag{18}$$

By using (17) and (18), an offline algorithm can be implemented in order to estimate coefficients c_1, c_2, and c_3, as shown in Algorithm 1.

This recursive algorithm is executed after a number of samples are directly obtained from the process; therefore $\theta(kh+h)$ and $\phi(kh)$ are known and available. The current estimate is equal to the previous estimate plus a correction term. The correction term is proportional to the deviation of the predicted value from what is actually observed. The adaptation gain is updated on each iteration to achieve fast convergence. At the end, coefficients are taken from the last estimation of the loop.

3.3. Model Predictive Control. To implement the controller for the closed-loop irrigation system, model predictive control (MPC) is used in order to minimize the control signal (effective irrigation) while keeping soil moisture under specific thresholds (avoiding water stress) and by considering external disturbances (reference evapotranspiration) (Algorithm 2). Figure 5 shows a feedback loop where the control objective is to keep within certain thresholds the soil water content in order to have a healthy and productive crop. Thus the process variable $y(kh)$ is the soil moisture, $r(kh)$ is the reference value (soil moisture set-point), and the error value $e(kh)$ is obtained as a result of the difference between the process value and the reference value.

The environmental factors affecting the irrigation systems are modelled as an external disturbance, so the reference evapotranspiration $\mathrm{et}_o(kh)$ represents the disturbance signal affecting the process. By knowing the disturbance model, then the system may predict the disturbance effects and react before these effects affect the process output.

Given the dynamic model of a closed-loop irrigation system defined by (8), the controller knows the process dynamics due to the online estimated internal model obtained from (17) by using recursive least squares. Within the controller, a numerical optimization algorithm is executed based on the current error and the disturbance measurements; this information is applied to the internal model and an optimal solution is found over a finite horizon T_{FH}, which minimizes the following quadratic cost function based on the error and the control signal,

$$J(kh) = \sum_{i=0}^{T_{\mathrm{FH}}-1}\begin{bmatrix} \left(e^T kh+ih \mid kh\right) Qe(kh+ih \mid kh) \\ +u^T(kh+ih \mid kh)\,Ru(kh+ih \mid kh) \end{bmatrix}, \tag{19}$$

where matrix Q is positive semidefinite and matrix R is positive definite and represents the weight given to the error and the control action, respectively, within the cost function. Also, $e(kh+ih \mid kh)$ and $u(kh+ih \mid kh)$ denote the predicted error and control effort, respectively, at time $kh+ih$ performed at kh.

The optimal input sequence for the problem of minimizing $J(kh)$ is denoted by

$$u^*(kh) = \arg\min_u J(kh), \tag{20}$$

subject to

$$\begin{aligned} u(kh) &= \{0, I_{\max}\}, \\ \theta(kh) &\geq \theta_{\min}, \\ \theta(kh) &\leq \theta_{\max}, \end{aligned} \tag{21}$$

$\widehat{\gamma}(0) = [c_1(0), c_2(0), c_3(0)]$
$F(0) = \sigma$
for $k = 0; k \leq$ number_of_samples; $k++$ **do**
  $y(kh+h) = \theta(kh+h)$
  $\epsilon(kh+h) =$ obtain_error $(y(kh+h), \widehat{\gamma}(kh), \phi(kh))$
  $F(kh+h) =$ calculate_adaptation_gain $(F(kh), \phi(kh))$
  $\widehat{\gamma}(kh+h) =$ estimate $(\widehat{\gamma}(kh), F(kh+h), \phi(kh), \epsilon(kh+h))$
end
$[c_1, c_2, c_3] = \widehat{\gamma}(kh)$

Algorithm 1: Coefficients estimation.

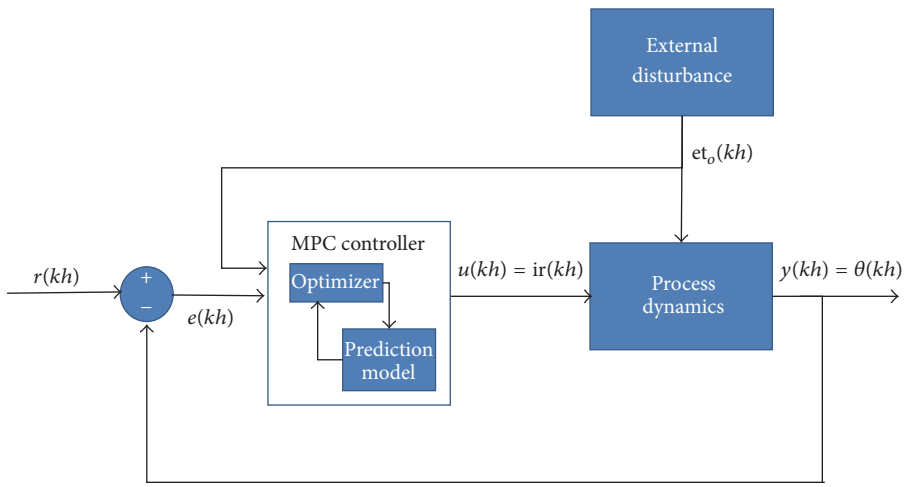

Figure 5: Model predictive control loop.

where irrigation at a specified time $u(kh)$ can only have two values; irrigation is either off (=0) or on ($=I_{\max}$). Soil moisture value $\theta(kh)$ is constrained by the measurement range provided by the sensors.

The algorithm determines "when" to start irrigating and "how much" water the crop requires. Therefore, the optimal input sequence $u^*(kh)$ is obtained by adjusting the soil moisture low threshold and the irrigation period to optimal values.

The algorithm starts at kh by reading current values for soil moisture, irrigation, and reference evapotranspiration; these are considered as initial conditions and represented by $\theta(0)$, $\mathrm{ir}(0)$, and $\mathrm{et}_o(0)$. Then, for each combination of predefined values for the soil moisture low threshold vector θ_{LT} and the irrigation period vector ir_P, the algorithm estimates the sequence of next state predictions over the finite horizon T_{FH}, while updating inputs, applying the control rules, and calculating the total cost. Finally, the algorithm finds the optimal combination of θ_x and ir_y that provides the best control rules to determine the optimal input sequence.

4. Experiments and Results

4.1. Experimental Platform Set-Up. The experimental platform consists of a data acquisition and control system described in [25], where a modular and scalable design approach is considered in order to provide different levels of access with different data contents. At the lower level, raw data from sensors is available, and at higher levels more refined and consolidated information can be obtained from the system. The experimental platform is divided in three access levels (field, data, and user) and it is capable of controlling four irrigation areas, as depicted in Figure 6.

At the field level, there are four irrigation areas that can be controlled, where each area includes two sensor nodes and one actuator node. Notice that only one weather node can be used for the four irrigation areas, since environmental variables have practically the same values for the complete field area. The actuator node controls an irrigation valve and measures the water flow; meanwhile each sensor node contains three soil moisture sensors to measure the volumetric water content at the crop root level. The sensor, weather and actuator nodes are implemented with low cost boards Arduino Mega based in the microcontroller ATmega328 (https://www.arduino.cc/). Soil measurements are conducted by using a Decagon Devices (http://www.decagon.com/) 10HS volumetric water content sensor, as shown in Figure 7. The sensors are located at the crop root level, with a measurement range from 0% to 60% of volumetric water content and a resolution of 0.1% when calibrated. In the actuator node (see Figure 7) a Rain Bird irrigation valve (Rain Bird Corporation, http://www.rainbird.com/) is used to activate

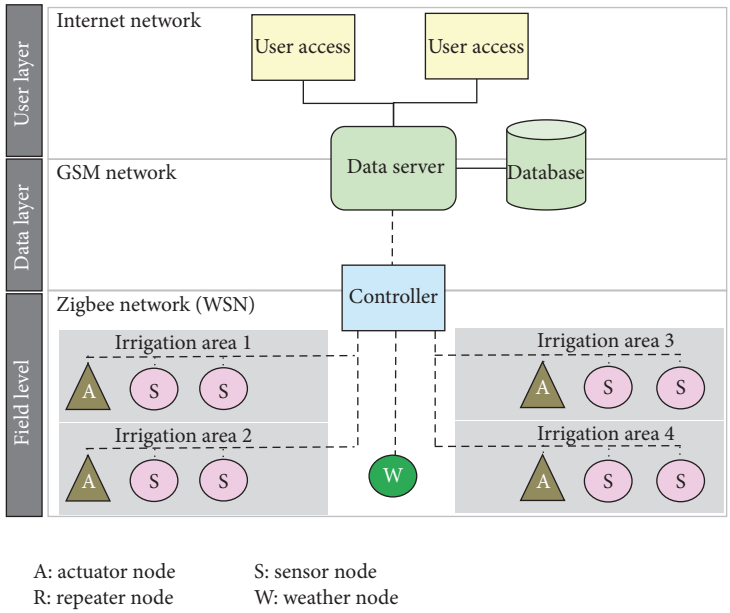

Figure 6: Data acquisition and control system architecture.

$\theta_{\mathrm{LT}} = [\theta_1, \theta_2, \theta_3, \ldots, \theta_n]$
$\mathrm{ir}_P = [\mathrm{ir}_1, \mathrm{ir}_2, \mathrm{ir}_3, \ldots, \mathrm{ir}_m]$
$[\theta(0), \mathrm{ir}(0), \mathrm{et}_o(0)] = \mathrm{read\_current\_values}\ ()$
for $x = 1;\ x \le n;\ x++$ **do**
  for $y = 1;\ y \le m;\ y++$ **do**
    $J_{\mathrm{sum}} = 0$
    for $i = 0;\ i < T_{\mathrm{FH}};\ i++$ **do**
      $\theta(ih + h) = \mathrm{next\_state}(\theta(ih), \mathrm{ir}(ih), \mathrm{et}_o(ih))$
      $\mathrm{et}_o(ih + h) = \mathrm{next\_et}_o(\mathrm{et}_o(ih))$
      $\mathrm{ir}(ih + h) = \mathrm{ir}(ih)$
      if $\theta(ih) \le \theta_x$ **then**
        $\mathrm{ir}(ih + h) = I_{\max}$
        $\mathrm{irrigation\_time} = 0$
      end
      if $\mathrm{irrigation\_time} > \mathrm{ir}_y$ **then**
      $\mathrm{ir}(ih + h) = 0$
      end
      $\mathrm{irrigation\_time} = \mathrm{irrigation\_time} + h$
      $u(ih) = \mathrm{ir}(ih)$
      $J_{\mathrm{current}} = \mathrm{current\_cost}(e(ih), u(ih))$
      $J_{\mathrm{sum}} = J_{\mathrm{sum}} + J_{\mathrm{current}}$
    end
    if $J_{\mathrm{sum}} < J_{\min}$ **then**
      $J_{\min} = J_{\mathrm{sum}}$
      $\mathrm{optimal\_}\theta_{\mathrm{LT}} = \theta_x$
      $\mathrm{optimal\_ir}_P = \mathrm{ir}_y$
    end
  end
end

Algorithm 2: Model predictive control.

or deactivate the field irrigation, and Hunter Flow Sync (http://www.hunterindustries.com/) sensor is used to measure the water flow. The weather node is used to calculate the reference evapotranspiration et_o from the environmental variables according to Penman-Monteith, a Decagon PYR Sensor measures the solar radiation, from a Decagon Davis Cup anemometer the wind speed is measured, and a Decagon VP-4 sensor is used to obtain the air temperature, the air relative humidity, and the barometric pressure, as depicted in Figure 8.

At the data level, a wireless sensor network (WSN) is implemented where the control node produces aggregated information from different sensor raw data. The WSN is implemented over the IEEE 802.15.4 standard which is the basis for the Zigbee communication protocol (http://www.zigbee.org/). Zigbee has become the de-facto standard for wireless sensor networks due to low cost, low power consumption, and small communication packet size. The wireless communication element is implemented by a radio-frequency Digi International Xbee (https://www.digi.com/) transceiver that operates at 2.4 Ghz with a data rate of 9600 bps and an open-field coverage of 1.6 kms. The controller node main element is a high performance microcontroller dsPIC33F within the Microchip Explorer 16 board (http://www.microchip.com/); see Figure 8. Control tasks are executed on the Erika real-time kernel (Erika Enterprise, http://erika.tuxfamily.org/); the real-time kernel provides to the microcontroller the capability to schedule several periodical tasks. The module has a dual network access, since it communicates with the wireless sensor network and also includes a long range communication access with the data server through the GPRS standard. The GPRS element consists of a SIMComm SIM900 (http://www.sim.com/) integrated circuit which implements the modem functionality.

At the user level, a data server module is implemented by a multicore Dell PowerEdge server (http://www.dell.com/), which includes web services, internet access, and a database in order to store historical information from the central

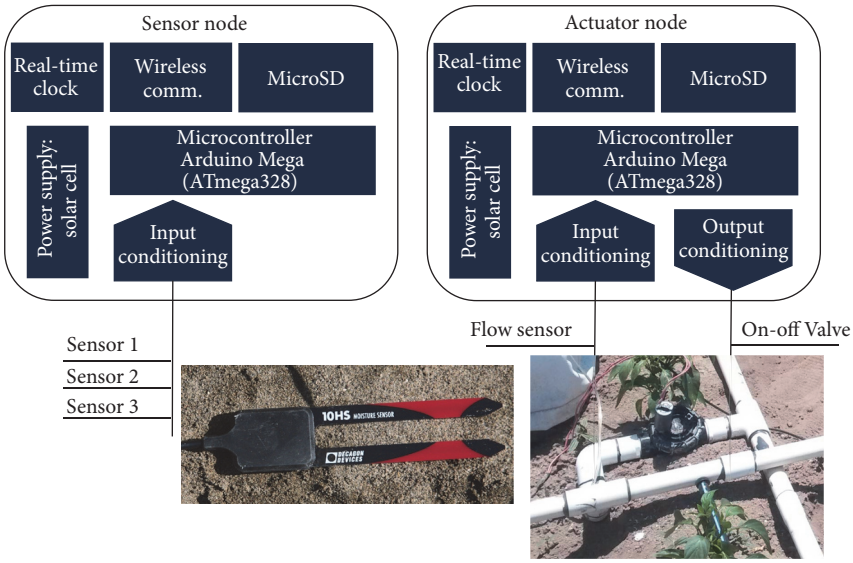

Figure 7: Sensor and actuator nodes hardware implementation.

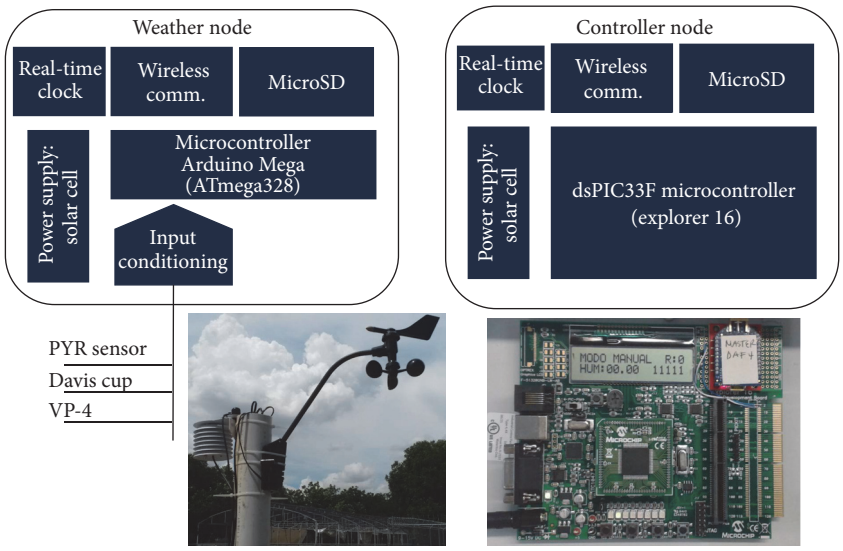

Figure 8: Weather and controller nodes hardware implementation.

modules that can be located in remote areas. The database is implemented through the open-source platform Django (https://www.djangoproject.com/). The user can access the data through web pages.

4.2. Plant Dynamics Validation. Process dynamic data (soil moisture, reference evapotranspiration, and irrigation) was captured by the data acquisition system for 21 days. The first experimental field corresponds to one irrigation area of approximate 20×10 meters; six sensor nodes were distributed along the field. Drip irrigation was used in order to water the area covered by grass; the irrigation process was manually activated at different days with different durations in order to have values from below permanent wilting point until saturation. The sensors were located in a depth of 20 cm in order to measure the soil moisture at the grass root level. For process identification grass was used instead of a specific crop, since grass $K_c = 1$; that is, $\mathrm{et}_c = \mathrm{et}_o$.

After data was captured, an offline recursive least square algorithm defined by (17) and (18) was executed on Matlab (http://www.mathworks.com/) in order to obtain the process dynamics coefficients c_1, c_2, and c_3, for each one of the three volumetric water levels:

(i) Gravitational water (above field capacity): the process dynamics depends on c_1 with a high value, while c_3 has no effect; c_2 has a great impact during irrigation instants.

(ii) Available water (below field capacity, above permanent wilting point): the process dynamics depends

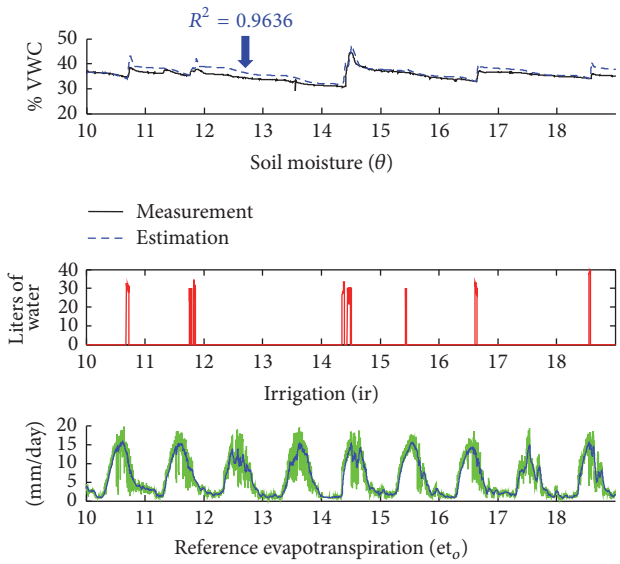

Figure 9: Model validation results.

on mostly c_3, but also c_1 has an effect; c_2 has similar impact as in the gravitational level.

(iii) Unavailable water (below permanent wilting point): the process dynamics depends on c_1 with a low value and c_3 has no effect; c_2 has a lower impact in comparison with the other levels.

Once the model coefficients were obtained, the estimated model was validated with direct measurements. In the same experimental field, a validation run was conducted with random irrigations for 10 days during each one of the months of April, May, June, July, and August. Figure 9 shows the result for the days corresponding to the month of June; as can be seen the process model produces a good estimation of the soil moisture behavior with a correlation coefficient $R^2 = 0.9636$, with an average value of $R^2 = 0.9139$ for the five months, as described in Table 1.

4.3. Evaluated Methods. The objective of the automatic irrigation systems is to make an efficient use of water and energy by applying the right amount of water, at the right time and in the right place, in order to avoid, both, crop water stress and water waste. Many different commercial and research approaches have been proposed; based on the analysis on how these approaches apply control engineering to implement an automated irrigation system, five different irrigations methods were defined for the purpose of this work.

Level 0 (Empirical Open Loop Irrigation). There are no automation elements, irrigation is manually conducted based on the experience and labor from the farmer. This method is still widely used in today's agriculture. This method is not considered for the evaluation.

Level 1 (Time Based Open Loop Irrigation). The automated systems consist of a timer that activates pumps and valves on a predefined basis; no sensing elements are used. Irrigation decision is defined offline and based on farmer empirical knowledge.

Table 1: Model validation correlation coefficient results for each month.

Evaluated month (during 10 days)	Correlation coefficient R^2
April	0.9671
May	0.8798
June	0.9636
July	0.9139
August	0.9412
Average	0.9331

Level 2 (Feed-Forward Open Loop Irrigation). In this type of strategy controller applies irrigation to refill the water consumed by the crop and the environment. The irrigation system must be capable of measuring the crop evapotranspiration by using a sensing system or acquiring the data from near public weather stations. Typically farmers conduct this process on a weekly basis.

Level 3 (Closed-Loop Irrigation). The controller applies irrigation when sensors detect that measurements are below a predefined low threshold and stops irrigation when a high threshold has been reached. Typically soil water content is used as the measured variable.

Level 4 (Model-Based Closed-Loop Irrigation). The control system contains the mathematical model that describes the process dynamics and uses feed-forward and feedback strategies to implement advanced control laws and achieve optimal solutions. A model predictive control algorithm has been implemented in order to look for an optimal irrigation input sequence based on (20) and (21).

4.4. Results and Discussion. The second experimental field corresponds to four contiguous irrigation areas of approximate 20 × 10 meters each, for a total area of 80 × 10 meters, in order to evaluate the four irrigation methods. The type of soil is the same as in the first experimental field, and both fields are in the same physical location. Drip irrigation was used to water a green pepper crop. A 3/4 HP water pump with a maximum flow rate of 170 liters per minute was used to provide water for irrigation; each area had an on-off valve to activate the irrigation. Each irrigation area contains up to 70 drippers in order to provide 560 liters per hour to the area; a total of six soil moisture sensors were located for each area, as seen in Figure 10 indicated by the red-white circles. The evaluation was conducted during the months of September and October. The experimental field is located outside the city of Delicias, Chihuahua, in Mexico (latitude: 28.169149, longitude: −105.502768).

The four evaluated irrigation methods are compared in terms of accumulated error J_{acum} and control effort $J_{control}$. In both cases, the lower the value the better the performance.

The accumulated error indicates how good the system is to maintain the soil moisture levels close to the reference

Figure 10: Experimental field with green pepper crop.

Table 2: Water consumption for the evaluated methods.

Evaluated method	Water consumption (in liters)	Level 4 water savings
Level 1	47,940	67.4%
Level 2	26,038	40.0%
Level 3	18,370	14.9%
Level 4	15,622	—

value. The maximum allowable depletion level (MAD) is considered as the process set-point or reference value, since below this level the crop becomes stressed and above it water may be wasted. The error indicates the difference between the current soil moisture value and the set-point, expressed in percentage of volumetric water content (VWC) as defined by (4). The accumulated error represents the sum of errors at the sampling instants during the evaluation period.

The control effort indicates how efficient the system is, in order to minimize the water consumption. The control effort is represented by effective irrigation and it is expressed in liters of water applied to the crop.

Accumulated error and control effort are defined as

$$J_{\text{acum}} = \sum_{i=0}^{T_{\text{eval}}-1} |e(kh)|,$$
$$J_{\text{control}} = \sum_{i=0}^{T_{\text{eval}}-1} |u(kh)|, \tag{22}$$

where T_{eval} is the evaluation time, $e(kh)$ is the difference between the soil moisture reference value and the process output (current soil moisture) at instant kh, and $u(kh)$ is the control signal (effective irrigation) at instant kh. The sampling period h for this evaluation is two minutes and the MPC finite horizon T_{FH} is one week. The time-delay τ from (8) equals 20 minutes, and the matrices Q and R from (19) have values of 0.0001 and 0.1, respectively, in order to give more weight to the control action (irrigation) rather than the error, since the main objective is to save water.

During an evaluation period of 30 days, the water consumption results for each evaluated method are shown in Table 2. The third column expresses the percentage of saved water obtained by Level 4 in comparison with the other methods.

Table 3: Irrigation error for the evaluated methods.

Evaluated method	Irrigation error	Level 4 error reduction
Level 1	100,039	71.3%
Level 2	45,958	37.5%
Level 3	36,741	21.8%
Level 4	28,719	—

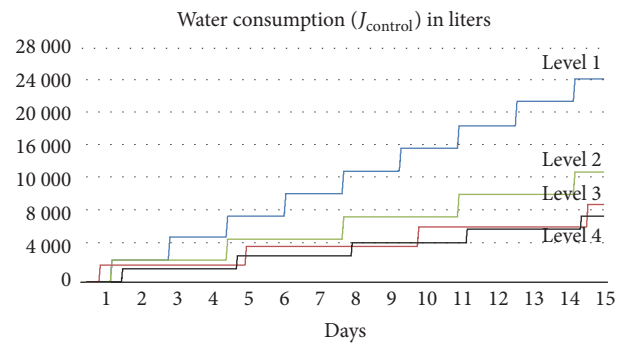

Figure 11: Water consumption evolution for the evaluated methods.

On Figure 11 the evolution of water consumption for each method is observed for the first 15 days of the evaluation period.

The irrigation error results and Level 4 error reduction percentage compared against the other methods are shown in Table 3.

On Figure 12 the evolution of irrigation error for each method is observed for the first 15 days of the evaluation period.

In general Level 4 method (MPC controller) offers the best performance considering the reference error and the control effort parameters. The implementation of the MPC controller requires an intensive computational load; however, high performance embedded devices and real-time kernels support the implementation of complex algorithms such as the required in an MPC controller. Also the relatively slow process dynamics for an irrigation system contribute to the implementation of a real-time predictive control strategy.

5. Conclusions

This paper proposes the use of a model driven control strategy for precision irrigation. Considering that the process dynamics of an irrigation system can be described with the hydrological balance model, evapotranspiration and soil moisture variables can be sensed in order to implement a model predictive control (MPC) to minimize the control signal (effective irrigation) while keeping soil moisture under specific thresholds (avoiding water stress) and considering external disturbances (reference evapotranspiration) to predict the process dynamics.

A recursive least squares algorithm has been used in order to estimate the model coefficients. These coefficients have been validated by using direct measurements from

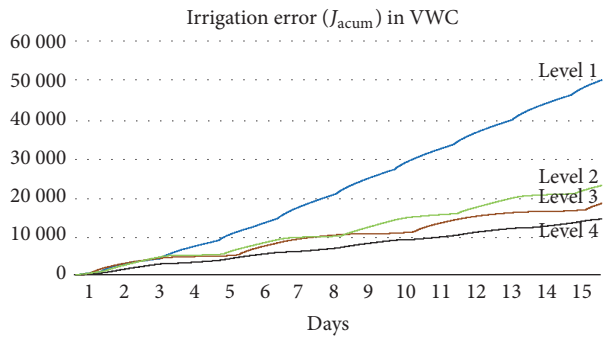

Figure 12: Irrigation error evolution for the evaluated methods.

the irrigation system. Then the proposed predictive control strategy has been implemented over an embedded platform, in order to evaluate the proposed irrigation method against the traditional methods used by the farmers. Experimental results indicate that the use of a model predictive control strategy in an irrigation system achieves a higher control efficiency and significantly reduce the control effort (water consumption).

Future work will focus on conducting the parameter estimation algorithm online and obtaining direct plant measurements by using imaging devices in order to evaluate the crop development and include this element as a variable in the MPC model.

Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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