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Dynamic Model of Soil Moisture for Smart Irrigation Systems

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***Abstract*—In geographical areas subject to an arid climate, one of the most precious resources is water, which often get wasted due to inefficient irrigation systems. Automated irrigation systems which relies on closed loop control and feedback from sensors can help to closely match the water supply to the crop demand and avoid waste. In recent years, predictive control strategies were proposed for high tech watering systems which rely heavily on complex models incorporating variables such as crop water demand, soil evapotranspiration, weather conditions etc.. Through these models it is possible to anticipate the water demand of the crop, and give optimal irrigation scheduling with a significant reduction in water consumption. In this paper we developed a model of the soil moisture dynamics based on climatological data of the Kingdom of Bahrain. The model, which is based on the hydraulic balance approach, was validated by comparing its estimated output with real measurements.**

Keywords—irrigation system, model identification, soil moisture

I. INTRODUCTION

The Kingdom of Bahrain is characterized by an arid to extremely arid environment. The country experiences high temperatures, unpredictable and often scarce rainfall, high evapotranspiration rates and high humidity levels. The demand for water has significantly increased in the last forty years, leading to a depletion of renewable groundwater water sources. The government has invested heavily in desalination plants and plants for the treatment of sewage effluent to provide non-conventional water resources for agricultural uses. Nevertheless, the minimization of water losses and the reduction of irrigation water are still essential for the sustainability of water resources and irrigated agriculture [11].

According to the Water Report published by UNESCO in 2003 (Water Report, 2003), about half of the water used for irrigation is wasted due to its poor management. In geographical areas subject to an arid climate, such as the Kingdom of Bahrain, the focus of water management is on strategies that allow to conserve water supplies without compromising the quality of the vegetation.

Traditionally, irrigation tasks have been performed by farmers, which relied on their experience to determine the times and duration of crop watering. The automation of irrigation systems such as sprinkler, drip or subsurface drip, which are set to irrigate at specific times and for a specified amount of time, has made the irrigation process more efficient, since they require minimum intervention from the farmers. However, these type of open loop control systems based on timers can lead to an under- or over-watering if they are not set correctly which can result in damage of the crop and waste of water. More efficient irrigation systems able to closely match the water supply to the crop demand require some form of closed-loop control, where feedback from one or more sensors is used to determine the time of irrigation and the quantity of water [2][3].

In recent years, model-based irrigation control strategies have been presented in many papers, where complex models incorporating variables such as crop water demand, weather conditions, water saturation etc., are used to get a reliable estimation of water requirement [4] [5]. Dynamic models based on the so-called water balance approach [1] are the most commonly used in these . The models can be obtained if initial soil moisture, evapotranspiration (ET), precipitation, and the water capacity of the soil are known. In particular, having a reliable estimation of ET is crucial since it establish the quantity of water to be provided through irrigation.

The work presented in this paper is based on the research described in [4], [5] and [9], where a model which uses the soil moisture control and the climatic factors is developed and applied in a model predictive control framework. Here, a similar dynamic model is developed based on climatological data of the Kingdom of Bahrain. The rest of this paper is organized as follows. Section II describe the water balance approach and the deriving process model. Section III presents the model identification approach used to derive the model and the equipment and sensors used for process measurements. Section IV presents the results of the model validation based on cross-validation and residual analysis. Finally, section V concludes the paper.

II. SOIL MOISTURE DYNAMIC MODEL

A. Water Balance Equation

The starting point of the development of our model is the water-balance approach, exemplified in Fig. 1. This approach is based on estimating the water soil content at any given time. Rain, irrigation and capillary rise of groundwater towards the root zone increase the water content in the root zone. On the contrary, evaporation, crop transpiration and percolation reduce the water from the root zone. The water content dynamics in the root zone are described by the following water balance equation:

$$M(t+1) = M(t) + IR(t) + RAIN(t) + CR(t) - ET_c(t) - DP(t) - RO(t) \quad (1)$$

Where M is the soil water content (soil moisture), IR is the quantity of water used for irrigation, $RAIN$ is the rainfall, CR is the capillary rise, ET_c is the crop evapotranspiration, DP is the deep percolation and RO is the water runoff. Considering the flat terrain and the dry weather conditions which characterize the Kingdom of Bahrain, it is reasonable to assume that the water inflows due to rainfall and capillary

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rise as well as the water runoff are nil. Under these assumptions, (1) becomes:

$$M(t+1) = M(t) + IR(t) - ET_c(t) - DP(t) \quad (2)$$

where the soil water content depends only on the irrigation depth, the crop evapotranspiration and the deep percolation. The measurement unit of M is the Volumetric Soil Moisture Content which refers to the millimeters of water in 100 mm of soil.

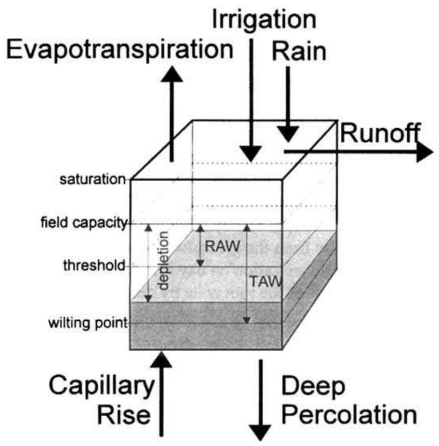

Fig. 1. Water Balance Model [6]

B. Evapotranspiration Estimation

Evapotranspiration (ET) is a process that consists of liquid vaporization of liquid water from the soil and the vaporization of liquid water contained in plant tissues to the atmosphere. The ET is affected by weather conditions (solar radiation, air temperature, air humidity and wind speed), crop factors (crop type, variety and development stage) and management and environmental conditions (soil salinity, application of fertilizers, control of diseases and pests etc.), which they have to be taken into account when assessing ET rate [12]. The ET rate, which expresses the amount of water lost from a cropped surface in units of water depth, is normally expressed in millimetres (mm) per unit time [6].

There are different approaches to estimate ET. Among them, the FAO Penman Montheith approach is recommended as a standard method for ET estimation in agriculture [6]. This method generally provides accurate ET estimation, but it is quite complex and requires extensive meteorological data such as radiation, air temperature, air humidity and wind speed, which might not be always available. For this reason, under certain climatological conditions, simpler estimation methods can be used, such as the FAO Blaney-Criddle estimation. This method, which was proposed in the early sixties, has proved to be a reliable way for estimating ET in various locations of the world with different weather conditions [7] [8].

The evapotranspiration rate from a reference surface is called the reference crop evapotranspiration ET_o, and refers to an hypothetical grass reference crop with specific characteristics, namely actively growing green grass of 8–15 cm height. ET_o, is affect only by climatic parameters. In this paper, the empirical FAO Blaney –Criddle method was used to estimate ET_o, as follows:

$$ET_o = p \cdot (0.457 \cdot T_{mean} + 8.128) \quad (3)$$

where ET_o is reference crop potential ET in mm/day-1, p is the mean annual percentage of daytime, T_{mean} is the mean daily temperature [°C] given as

$$T_{mean} = \frac{T_{\min} + T_{\max}}{2} \quad (4)$$

The crop factors and management and environmental conditions are taken into account when estimating the actual ET_c by introduction the crop coefficient K_c as follows:

$$ET_c = K_c \cdot ET_o \quad (5)$$

When operating in non-standard conditions, the parameter K_c can be adjusted for crops different from the reference grass crop or for environmental stresses such as the presence of pests and diseases, soil salinity, low soil fertility, and so on.

C. Deep Percolation

Deep percolation (DP) under irrigation occurs when water infiltrates below the crop root zone. Soil permeability as well as the water content determine the amount of water which percolate during surface irrigation. Direct measurement of DP is difficult. In this paper, we adopted the assumption formulated in [10], namely that DP depends on the soil water content M. If M is high, more water will flow to other points due to differential pressure, and vice-versa. Under this assumption, we express DP as:

$$DP(t) = K_p \cdot M(t) \quad (6)$$

where K_p is an unknown parameter to be estimated.

III. Model Identification

A. Model Structure

The system identification process requires to choose a model type and structure suitable to represent the system keeping in mind its intended purpose. For this purpose, we can utilize the knowledge and physical insight introduced in Section II when selecting the model structure [5]:

Substituting (5) and (6) in (2) we obtain:

$$M(t+1) = K_s \cdot M(t) + IR(t) - K_c ET_o(t) \quad (7)$$

where K_s=1-K_p

The mathematical model of the discrete-time system described by a linear difference equation such as (7) can be written in terms of a recursive formula as:

$$x(t+1) = Ax(t) + Bu(t) \quad (8)$$

$$y(t) = Cx(t) + Du(t) \quad (9)$$

where $x(t)$, $u(t)$ and $y(t)$ are vectors representing the state of the process, the input signal and the output variable. The matrices A, B, C and D are constant transition matrices which express the dynamics of the process. Defining the following state variable:

$$x(t) = M(t) \quad (10)$$

And the following input variables:

$$u(t) = \begin{bmatrix} IR(t) \\ ET_o(t) \end{bmatrix} \tag{11}$$

We can write (8) and (9) as:

$$M(t+1) = [K_s]M(t) + [1 \quad -K_c]\begin{bmatrix} IR(t) \\ ET_o(t) \end{bmatrix} \tag{12}$$

$$M(t) = [1]M(t) + [0]\begin{bmatrix} IR(t) \\ ET_o(t) \end{bmatrix} \tag{13}$$

The model structure expressed by (12) and (13) is adopted as a suitable model representing soil moisture dynamics in the root zone. This model structure built on physical grounds, still has a number of parameters (K_s and K_c) to be estimated from measured data.

B. Data Acquisition System

Data to be used in the system identification process have been collected using a data acquisition system implemented on an Arduino Uno microcontroller board. A temperature sensor LM35, which provides an output voltage linearly proportional to the Centigrade temperature, and a soil moisture sensor FC-28 have been used. The soil moisture sensor, which gives moisture values from 0-1023, has been calibrated against saturation, when the soil is completely soaked in water and completely dry. The system is designed as a standalone unit, which takes the reading from the two sensors and stores the data directly on an SD card.

Fig. 2 shows the measurements of the soil moisture M at 10 cm depth, irrigation IR and the temperature T in proximity of the moisture sensor. These data have been collected by uniformly sampling over a two days period with a sampling rate of one hour.

Since irrigation lasts for a short period of time but provides great amount of water, it is reasonable to model IR as a pulse signal [9]. The measured temperature T has been used to estimate ET_o using (3). For the calculation of ET_o, the mean annual percentage of daytime p has been substituted by the actual percentage of daytime for the time of the year in which the experiment is conducted. From Fig. 2, we can notice that there is no significant time delay between the start of the irrigation and the soil moisture response. This depends on the fact that the irrigation event happened shortly before the moisture sensor's sampling. Moreover, the infiltration response was immediately noticeable because of the proximity of the sensor to the water source. It is reasonable to assume that under different conditions, there would be a longer delay between the irrigation time and the soil moisture response.

C. Parameters Estimation

The data generated from the data acquisition experiments has been used for model identification and validation.

The measurements of the temperature T, the soil moisture M and the estimation of ET_o were used to estimate the parameters K_s and K_c in (12). A schematic overview of the data acquisition and system identification process is shown in Fig. 3. The identification and validation of models from data was done using the Matlab System Identification Toolbox.

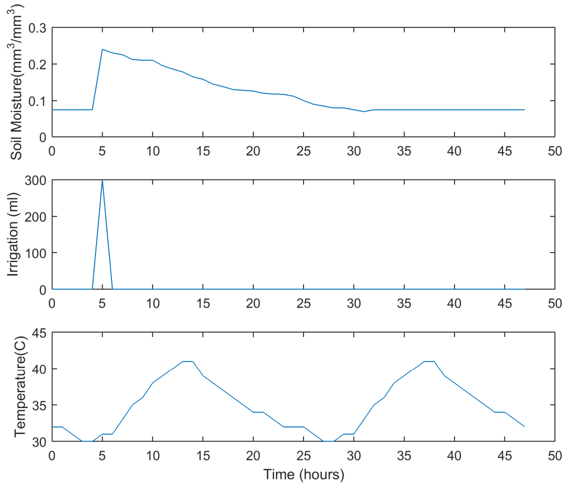

Fig. 2. Soil Moisture, Irrigation and Temperature Data

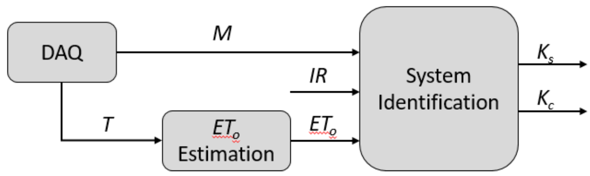

Fig. 3. Schematic of System Identification

IV. Model Validation

The quality of the parametric model obtained in previous section has been validated using cross-validation and residual analysis.

In the cross-validation experiment, the identified model response have been simulated using different measured input data to that used for identification and compared with actual soil moisture for the same input signal. The measured and simulated soil moisture are shown in Fig. 4.

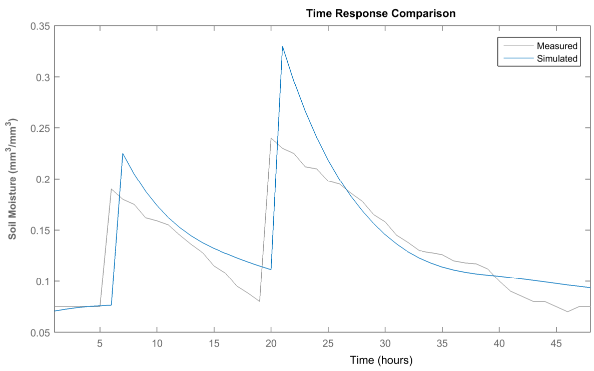

Fig. 4. Measured and Simulated Soil Moisture

Both the whiteness and independence correlation tests have been used to assess the quality of the identified model. Fig. 5 (a) illustrates the results of the whiteness correlation test. It can be noticed that the 95 percent confidence intervals are completely satisfied for all residuals. This gives an indication that the prediction errors between the model and the system are independent of each other and of past data, and therefore suggest that the identified model is a good model.

The result of the independence test confirms those of the whiteness test. Fig. 5 (b) shows how the model reveals little residual dependence on input signal. Peaks in the residual-input correlation function indicate that the some outputs are not properly described in the model, but this is not necessarily an indication of an inaccurate model, given the small number of peaks.

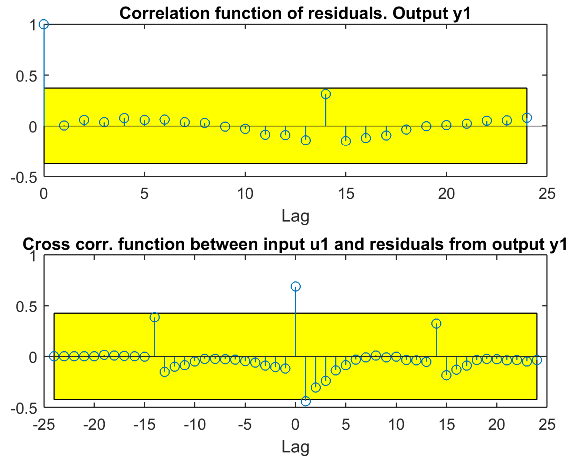

Fig. 5. Auto and Cross Correlation of Residuals

From the system validation results we can conclude that the model derived through the system identification process is suitable to describe the dynamics between soil, water and temperature. Although there are differences between the measured soil moisture and the simulated one, the model is able to describe the dynamic of the soil moisture, with a predicted mean squared error around 0.0014.

V. CONCLUSIONS

The work presented in this paper represents the first step towards the application of advance control algorithm for irrigation scheduling. Techniques such as Model Predictive Control (MPC) and Adaptive Control rely on models which have to be generated, validated and implemented in such controllers with the aim of optimising controller performances.

The simple linear model described in this paper is suitable to describe the essential dynamics between soil, water irrigation and temperature and could be used in combination with model-based control techniques for irrigation management over a short time horizon. However, the quality of the model is limited by quality of the data used in the system identification process. To improve the data several precautions could be taken, such as taking the measurements over differed operating conditions and estimate ET_o using the FAO Penman Montheith approach. Moreover, for a model closer to real operating conditions, sample data should be collected over a sparse area using sensors located at root depth.

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