Regulation of soil moisture using zone model predictive control

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Abstract: This paper concerns the input-output model identification and zone model predictive control of an agro-hydrological system modeled by a partial differential equation. The primary control objective is to maintain the soil moisture within a desired range which is suitable for grass grow. There is also a secondary control objective which is to reduce the total irrigation amount. First, a linear parameter varying (LPV) model is identified for controller design purpose using a maximum likelihood gradient-based iterative estimation method. Then, based on the LPV model, a zone model predictive control (MPC) is designed which uses an output disturbance and state observer to reduce model-plant mismatch and an asymmetric target zone to reduce irrigation amount under weather uncertainties while maintaining the soil moisture within the target range. Simulation studies show that the LPV model is a good approximation of the original nonlinear model and effectively reduces the online computational load of the MPC, and that the proposed zone MPC can lead to significant water conservation.

Keywords: Agro-hydrological system; Linear parameter varying model; Model predictive control; Zone control

1. INTRODUCTION

The increasing population and adverse climate change are escalating fresh water scarcity globally. Since irrigated agriculture consumes a large portion of fresh water, it is important to improve the efficiency in irrigation [1]. It is well recognized that if irrigators made more efficient use of water then there would be more water for environmental uses and for cities [2]. Among different approaches to improve the water usage efficiency in irrigation, one important approach is to close the loop in irrigation control systems to have closed-loop irrigation. In closed-loop irrigation, the amount of water supplied to the field is determined based on real-time field feedback signals comprising of measured soil water content, evapotranspiration rate and other on-line sensors.

Though most of the irrigation worldwide still operates under open-loop conditions, there are more and more research results on closed-loop irrigation [3, 4, 5]. In [3], an irrigation controller based on the fuzzy-logic methodology was presented to decide on how far to open the water valve and how much water to be added to the soil, by considering the temperature, air humidity, wind speed and water budget as the fuzzy variables. In [4], a constrained integral proportional-integral-derivative (PID) controller was proposed. In [5], an automated closed-loop irrigation control system was developed and tested with a selfRecently, model predictive model (MPC) has also been used in the control of irrigation systems. MPC is a very flexible optimal control framework based on solving constrained optimal control problem online repeatedly, and has been widely used in modern manufacturing industries due to its abilities to handle multivariate processes and to address state and input constraints [9, 10]. In [11, 12], Park and co-workers used MPC to incorporate sensor measurements, predictive models and optimization algorithms to drive field conditions to a desired environmental state (e.g. soil moisture, salt levels or contaminant propagation). In [13], McCarthy and co-workers implemented MPC to determine irrigation timing and site-specific irrigation volumes based on the crop production models. In [14], Delgoda and co-workers proposed to use MPC for irrigation control to minimize both root zone soil moisture deficit and irrigation amount under limited water supply. In the above MPC-based studies, due to the use of a prediction model in the controller, it is possible to incorporate the weather forecast along with other environmental and crop factors and hence control irrigation amount more accurately without hampering crop yields. The main objective in all these studies was to maintain the soil moisture in the root zone at a pre-determined set-point considering different factors such as weather forecast, irrigation type and crop types.

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propelled lateral-move sprinkler irrigation system that was set up for site-specific variable-rate water applications. Besides the above results, closed-loop irrigation results were also reported in [6, 7, 8].

However, a more natural control target in irrigation should be to maintain the soil moisture of the root zone within a range instead of a point. It will be demonstrated later in this work that a zone target can lead to further significant water conservation.

In this work, we propose a zone MPC framework for irrigation control. In zone MPC, the target is to track a target set (zone) instead of a point. Zone MPC may be used when the aim is to maintain the system outputs within specified ranges or zones, or when multiple control objectives or process uncertainty (e.g. plant-model mismatches or noises) exist. Interested readers may refer to [15, 16, 17, 18, 19] for some existing results on zone MPC theory and applications. Specifically, we consider a field represented by an agro-hydrological model that describes the water movements between soil, atmosphere and the crop (grass in this work). Since the agro-hydrological model is nonlinear and complex, the direct use of such a model in MPC poses substantial computational difficulties. To address the computational difficulties, we propose to identify a simpler input-output model to approximate the water dynamics for controller design purpose. Based on the identified model, a zone MPC algorithm is developed accounting for explicitly model-plant mismatch. The main contributions of this paper lie in:

- A systematic approach to identify a linear parameter varying (LPV) model to describe the dynamics between the irrigation amount and the root zone soil moisture.
- An approach to overcome the model-plant mismatch through an output disturbance and state observer.
- A zone MPC algorithm with asymmetric cost function for effective root zone soil moisture management.
- Extensive simulations comparing the proposed zone MPC with a set-point tracking MPC which indicates significant irrigation water saving by the proposed zone MPC design.

The rest of this paper is organized as follows. Section 2 introduces the agro-hydrological system and gives the problem formulation. Section 3 identifies an LPV model for the agro-hydrological model. Section 4 describes the proposed zone MPC algorithm for the agro-hydrological system including model transformation, output disurbance observer design and objective function design. In Section 5, simulation results are given to demonstrate the effective-ness of the proposed methods under two irrigation scenarios. Finally, concluding remarks are given in Section 6.

2. MODEL DESCRIPTION AND PROBLEM FORMULATION

2.1 Model description

We consider an agro-hydrological system that characterizes the hydrological cycle between the soil, the atmosphere and the crop (see Fig. 1). The inputs considered are the water flow to the soil by the means of rain, irrigation, drainage, evaporation and root water extraction by the crop. The crop considered in this work is grass. Moreover, only vertical hydrological dynamics are considered and horizontal homogeneity is assumed.



Fig. 1. A schematic of the agro-hydrological system.

In this system, the soil water flux is computed using the Darcy's law $\left[20\right]$

$$q = -K(h)\frac{\partial(h+z)}{\partial z} \tag{1}$$

where q (cm/hour) is soil water flux density, K(h) (cm/hour) is hydraulic conductivity, h (cm) is soil water pressure head , z (cm) is the vertical coordinate inside soil matrix. Under the assumption of continuity and using the above Darcy's equation, the soil moisture movement in variably saturated soil can be described by the following Richards' equation [21]:

$$\frac{\partial\vartheta}{\partial t} = \frac{\partial \left[K(h)(\frac{\partial h}{\partial z} + 1)\right]}{\partial z} - S(h) \tag{2}$$

where ϑ (cm^3/cm^3) is soil moisture content, S(h) ($hour^{-1}$) is a sink term which characterizes the root water extraction.

The Richards' equation is discretized in both time and space. The time is discretized with equally spaced nodes and the length is discretized with unequally spaced nodes. At the top much finer discretization relative to the bottom is used to capture the faster dynamics at the top. The implicit backward, finite difference method with explicit linearization of hydraulic conductivities will be used to discretize the Richards' equation at each node.

2.2 Model parameters and control problem formulation

In this paper, the soil type we considered is Coachella, which is a combination of mainly sand and small amount of loam. The field capacity of this type of soil is $0.35 \ cm^3/cm^3$ and permanent wilting point is $0.15 \ cm^3/cm^3$. The plant available water is $0.20 \ cm^3/cm^3$.

The soil is covered by grass whose roots usually lie between 10 cm and 15 cm below the soil surface. We assume that the primary water intake by grass takes place around 13 cm below the surface and it corresponds to the 6th discretization node. The agro-hydrological model will be used as a simulator of the actual field. The external inputs to the agro-hydrological system include irrigation and weather conditions (precipitation, temperature, humidity, solar radiation and wind speed). Some of the important parameters are listed below:

Soil layer	$K_{\rm sat}$	$\vartheta_{\rm res}$	$\vartheta_{\rm sat}$	α	n
1	8	0.03	0.50	0.016	2.68
2	10	0.02	0.47	0.016	2.68
3	10	0.01	0.47	0.016	2.68
4	8	0.01	0.50	0.016	2.68

For irrigation management, a natural control target is to maintain the soil moisture in the root zone within the range in which the root water uptake is maximal (0.20 $cm^3/cm^3 \sim 0.35 \ cm^3/cm^3$), instead of maintaining the soil moisture at a constant set-point. The primary control objective of this work is to design a control system to maintain the soil moisture at the center of the root zone in the desired range considering model-plant mismatch and different operation constraints. The secondary control objective is to minimize the use of irrigation water.

3. LPV MODEL IDENTIFICATION AND VALIDATION

In this section, we propose to identify an input-output LPV model to approximate the dynamics between the irrigation amount (the manipulated input) and the soil moisture at the center of the root zone (the controlled output) for control design purpose.

3.1 LPV model for the agro-hydrological system

It is found through extensive simulation that using only one linear time invariant (LTI) model cannot adequately describe the its dynamics of the agro-hydrological system. Therefore, we choose to use an LPV model.

For the agro-hydrological model, the soil moisture at the 6th node (the center of the root zone) is picked as the scheduling variable, and an LPV model is built to approximate the soil moisture dynamic of the 6th node in the operating region. Let us assume that M working points are selected in the operating region. For each working point, the soil moisture at the 6th node is approximated by a local LTI model. The global LPV model that describe the soil moisture at the 6th node can be expressed as:

$$y(k) = \sum_{i=1}^{M} \alpha_i (s(k-1)) x_i(k)$$
 (3)

where y(k) is the output (soil moisture) of the LPV model, s(k) := y(k) is the measurement of the scheduling variable at the *kth* sampling instant, α_i is the associated weighting coefficient of $x_i(k)$. Specifically, the output at *ith* working point is described as follows:

$$x_i(k) = -\sum_{j=1}^{n_a} a_j^i x_i(k-j) + \sum_{j=1}^{n_b} b_j^i u(k-j) + d^i =: \varphi_i^{\mathrm{T}}(k)\beta_i$$

where u(k) is the input (irrigation amount) of the model, a_j^i , b_j^i and d^i are the parameters of the *ith* local model, β_i and φ_i are the parameter vector and information vector and defined as $\varphi_i(k) := [-x_i(k-1), \cdots, -x_i(k-n_a), u(k-1), \cdots, u(k-n_b), 1]^{\mathrm{T}} \in \mathbb{R}^{n_a+n_b+1}$ and $\beta_i := [a_1^i, \cdots, a_{n_a}^i, b_1^i, \cdots, b_{n_b}^i, d^i]^{\mathrm{T}} \in \mathbb{R}^{n_a+n_b+1}$.

To achieve smooth transitions between operating regions of the M local models, exponential weighting functions are

employed and the normalized weighting factor for the *ith* local model is calculated by the following equations:

$$\alpha_i(s(k)) = \frac{\omega_i(s(k))}{\sum_{i=1}^M \omega_i(s(k))} \tag{4}$$

$$\omega_i(s(k)) = \exp\left(\frac{-(s(k) - S_i)^2}{2\sigma_i^2}\right) \tag{5}$$

where σ_i denotes the validity width of the *ith* local model, S_i denotes the *ith* pre-specified working point.

3.2 Model identification and validation

The identification of the LPV system is to estimate all the unknown parameters $\theta := [\beta_i, \sigma_i^2]$, $(i = 1, 2, \dots, M)$ based on the input-output data and scheduling variable data. There are many ways to estimate the global LPV model [22, 23, 24], In this paper, the maximum likelihood optimization approach introduced in [24] will be used to estimate the parameters. In the model identification, the precipitation is also treated as irrigation. Other weather factors such as temperature, humidity, solar radiation and wind are treated as disturbances. By simulating the agro-hydrological model with varying weather conditions and changing irrigation input, input-output data can be collected for model identification.

To determine the optimal number of working points M, different numbers of working points are tested. Specifically, M = 2, 3, 4 and 5 are considered. In the simulations, the sampling time is 1 hour, the input signal is the binary input signal with average switching time of 15 hours. During the transition period between two different operating points, the irrigation amount changes as ramp signals.

After obtaining the input-output data of each case, we identify LPV models based on the input-output data sets. By performing the residual analysis, the orders n_a and n_b of the local ARX models were both determined to be 1. We compare the prediction performance of these LPV models (M = 2, 3, 4 and 5) using the training data set (self-validation) and a new data set generated using a stochastic input signal (cross-validation). Table 3.2 shows the root mean square errors of self-validation (SV RMSE) and cross-validation (CV RMSE) of the identified LPV and LTI models. From Table 3.2, we can see that both

Table 3.2 The prediction performance of the identified LTI and LPV models

Model type	SV RMSE	CV RMSE
LTI $(M=1)$	0.0222	0.0397
LPV $(M=2)$	0.0086	0.0163
LPV $(M=3)$	0.0078	0.0135
LPV $(M = 4)$	0.0054	0.0056
LPV $(M=5)$	0.0053	0.0056

the SV RMSE and the CV RMSE of the LPV models are much smaller than those of the LTI model and decrease as the working points M increases. However, the performance improvement from M = 4 to M = 5 is negligible. Therefore, we choose the LPV model with M = 4. Fig. 2 shows the cross-validation of the identified LPV model with M = 4. Further, we investigated the steady-state diagram of the LPV model and compared it with the steady-state diagram characterized by Richards' equation. The results are shown in Fig. 3. It is seen that the identified LPV model with M = 4 effectively captures the dynamic and steady state characteristics of the agro-hydrological model.



Fig. 2. The corss-validation of the identified LPV model with M = 4. The dashed line is the output of the agro-hydrological system, the solid line is the output of the identified LPV model.



Fig. 3. Steady-state diagram of the Richard's equation (dashed line), the LPV model with M = 4 (solid line) and LTI model with M = 1 (dash-dotted line)

4. ZONE MODEL PREDICTIVE CONTROL DESIGN

In this section, we present the proposed zone MPC design based on the identified LPV model. First, an augmented state observer is designed which estimates submodel states of the LPV system as well as an augmented output disturbance state. The output disturbance state is introduced to account for model mismatch (between the LPV model and the original model) and unknown external disturbances due to changing weather condition. Then, based on the estimated states and disturbance, a zone MPC with asymmetric cost function is designed to maintain the soil moisture within a target zone. The asymmetry in the cost reflects a more urgent need to avoid the soil moisture falling below the withering point than the need to save irrigation water when the soil moisture is high.

4.1 Augmented state observer design

To proceed, we rewrite the LPV model in the following state-space form:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) + d \\ y(k) &= C(s(k-1))x(k) \end{aligned} (6)$$

where $x(k) \in \mathbb{R}^4$, $u(k) \in \mathbb{R}$ and $y(k) \in \mathbb{R}$ are the system state, input and output respectively. A, B, d and C are matrices and vectors of appropriate forms based on the LPV model in (3) - (5). Specifically, $A = \text{diag}(-a_1^1, -a_1^2, -a_1^3, -a_1^4), B = [b_1^1, b_1^2, b_1^3, b_1^4]^T, d =$ $[d_1^1, d_1^2, d_1^3, d_1^4]^T, C(s(k-1)) = [\alpha_1(s(k-1)), \alpha_2(s(k-1)), \alpha_3(s(k-1)), \alpha_4(s(k-1))]$. To account for model mismatch and unknown disturbances, we introduce an output disturbance state p(k) to the above state-space model. Similar approaches has been used in [25, 26, 27, 28] to result in the so-called offset free MPC. The augmented state-space model is expressed as follows:

$$x(k+1) = Ax(k) + Bu(k) + d
 p(k+1) = p(k)
 y(k) = C(s(k-1))x(k) + p(k)$$
(7)

The proposed observer for the above augmented system has the following form:

$$\hat{x}(k|k) = \hat{x}(k|k-1) + L_x(k)(y(k) - \hat{y}(k|k-1)) \quad (8)$$

$$\hat{p}(k|k) = \hat{p}(k|k-1) + L_p(k)(y(k) - \dot{y}(k|k-1))$$
(9)

$$\hat{x}(k+1|k) = A\hat{x}(k|k) + Bu(k) + d,$$
 (10)

$$\hat{p}(k+1|k) = \hat{p}(k|k)$$
 (11)

$$\hat{s}(k) = y(k) \tag{12}$$

$$\hat{y}(k+1|k) = C(s(k))\hat{x}(k+1|k) + \hat{p}(k+1|k)$$
(13)

where \hat{x} , \hat{p} and \hat{y} denotes the predicted state, output disturbance and output respectively. The filter gain L_x , L_p can be computed using Kalman filtering techniques [28].

4.2 Zone MPC design

In the zone MPC design, the primary control objective is to maintain the soil moisture in a range which is ideal for grass grow. There is also a secondary objective to save irrigation water. Due to the uncertainties in the changing weather condition (precipitation, humidity, etc.), the target zone employed in the zone MPC is made smaller than the actual ideal soil moisture range. This leaves a margin for handling the uncertainties of the system. Moreover, since the risk cost of the soil moisture dropping below the withering point is higher than the risk cost of wasting irrigation water, we introduce asymmetric penalties on the output trajectories that violate the zone tracing objective. The target zone and asymmetric tracking penalty is illustrated in Fig. 4. The proposed zone MPC is based on the augmented system model in (7). At a sampling time k, the following optimization is solved:

$$\min_{u(i),\bar{\epsilon}(i),\underline{\epsilon}(i)} \sum_{i=1}^{N} \left(\bar{Q}\bar{\epsilon}(i)^2 + \underline{Q}\underline{\epsilon}(i)^2 \right) + \sum_{i=0}^{N-1} Ru(i)^2 \quad (14a)$$

s.t.
$$x(i+1) = Ax(i) + Bu(i) + d$$
 (14b)
 $p(i+1) = p(i)$ (14c)

y(i) = C(s(i-1))x(i) + p(i)(110) (114)

$$x(0) = \hat{x}(k|k), \quad p(0) = \hat{p}(k|k)$$
 (14e)

$$\underline{W}_3 - \underline{\epsilon}(i) < y(i) < \overline{W}_3 + \overline{\epsilon}(i) \tag{14f}$$

$$u(i) \in \mathbb{U} \tag{14g}$$

$$\underline{\epsilon}(i) \ge 0, \quad \overline{\epsilon}(i) \ge 0 \tag{14h}$$



Fig. 4. Proposed target zone and asymmetric tracking cost: the target zone enclosed by the dotted line indicates the desired soil moisture range. The tracking cost is 0 in the zone W_3 which is in the interior of the target zone, and is positive and asymmetric around W_3 in W_2 and W_1

In the above zone MPC design, the objective function (14a) consists of two parts. The first part corresponds to the asymmetric soil moisture zone tracking penalty and the second part corresponds to penalty on the irrigation amount. The asymmetric zone tracking penalty is realized by introducing slack variables $\bar{\epsilon}$ and $\underline{\epsilon}$ to relax the target zone in (14f). \underline{W}_3 and \overline{W}_3 correspond to the lower and upper bound of the tracking zone respectively. Q and \bar{Q} are the cost associated with violating the lower and upper bound of the target zone respectively, with $Q > \bar{Q} > 0$. (14e) specifies the initial condition where the initial system state x and disturbance p are obtained by the augmented observer in Section 4.1. The input constraint set \mathbb{U} specifies the allowed irrigation amount within one sampling time.

5. RESULTS AND DISCUSSION

In this section, the performance of the state and disturbance observers will be tested and the performance of the proposed zone MPC will be compared with a setpoint tracking MPC under different irrigation cases. The sampling time is 1 hour, We choose a control horizon N = 5. The weighting matrices are $\bar{Q} = 50$, $\bar{Q} = 4000$ and R = 20.

To ensure that the grass has enough moisture supply, the ideal range is set as $\mathbb{Z} = [0.20 \ cm^3/cm^3, 0.35 \ cm^3/cm^3]$. The zone MPC tracks a target zone of $W_3 = [0.22 \ cm^3/cm^3, 0.34 \ cm^3/cm^3]$, and the set-point tracking target is $0.28 \ cm^3/cm^3$.

5.1 Unrestricted irrigation time

First, we compare the performance of the set-point tracking MPC with the zone-MPC in the case without restriction on irrigation time. Here, a logistic function $1/(1 + \exp(-u))$ is added to the cost function to reduce the number of on-off switches. The output trajectories of the set-point tracking MPC and the zone MPC are shown in Fig. 5. The total irrigation amount of the two MPC configurations are 169 cm and 136.3 cm. It is seen that the zone MPC leads to significant irrigation water savings compared to setpoint tracking MPC while maintaining the soil moisture within the target zone. This is because the proposed zone-MPC provides larger admissible output range than the setpoint tracking MPC, so that more degrees of freedom in the controller can be released to minimize the irrigation amount.

5.2 Restricted irrigation time

Second, we compare the performance of the set-point tracking MPC with the zone-MPC in the case with restriction on irrigation time. Specifically, the irrigation is restricted to take place only the following time of the day: 4:00am-6:00am, 12:00am-14:00pm and 18:00pm-20:00pm. The simulation results are shown in Fig. 6. The total irrigation amount of the two MPC configurations are 211.7 cm and 144.0 cm. From these results, we can see that zone MPC results in less irrigation amount and zone tracking violation compared with the set-point MPC in different irrigation cases.



Fig. 5. Closed-loop soil moisture trajectories under the setpoint tracking MPC (dash-dotted line) and the zone-MPC (solid line): unrestricted irrigation time.



Fig. 6. Closed-loop soil moisture trajectories under the setpoint tracking MPC (dash-dotted line) and the zone-MPC (solid line): restricted irrigation time.

6. CONCLUSIONS

This work aims at control system design for agrohydrological systems. First, an LPV model was identified based on the first-principle agro-hydrological model. Then, a zone MPC was designed based on the LPV model. An augmented state and output disturbance observer was employed to account for the model mismatch and uncertainties in the changing weather condition. The proposed zone MPC minimizes an asymmetric cost to lay heavier penalty on the soil moisture dropping below the withering point than on water consumption. Simulation results show that the proposed zone MPC may lead to considerable irrigation water saving as compared to the conventional set-point tracking MPC.

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