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Publication Date
2009-02-01

Peer reviewed

A Receding Horizon Control Algorithm for Adaptive Management of Soil Moisture and Chemical Levels during Irrigation

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Accepted for publication in

Environmental Modelling & Software

February 2009

Abstract

The capacity to adaptively manage irrigation and associated contaminant transport is desirable from the perspectives of water conservation, groundwater quality protection, and other concerns. This paper introduces the application of a feedback-control strategy known as Receding Horizon Control (RHC) to the problem of irrigation management. The RHC method incorporates sensor measurements, predictive models, and optimization algorithms to maintain soil moisture at certain levels or prevent contaminant propagation beyond desirable thresholds. Theoretical test cases are first presented to examine the RHC scheme performance for the control of soil moisture and nitrate levels in a soil irrigation problem. Then, soil moisture control is successfully demonstrated for a center-pivot system in Palmdale, CA where reclaimed water is used for agricultural irrigation. Real-time soil moisture, temperature, and meteorological data are streamed wirelessly to a field computer to enable autonomous execution of the RHC algorithm. The RHC scheme is demonstrated to be a viable strategy for achieving water reuse and agricultural objectives while minimizing negative impacts on environmental quality.

1. Introduction

Irrigation management typically strives to achieve a balance between water conservation and plant requirements. Other contexts, such as fertilization or irrigation with reclaimed water, shift focus toward protecting human health and avoiding resource degradation. Population growth and climate change place increasing stress on clean water supplies and point to the need for robust technologies supporting safe water reuse that is at the same time protective of soil and groundwater resources. This work introduces a well-known method from industrial control theory to the problem of adaptively managing soil irrigation with reclaimed water.

The largest current demand for reclaimed water is agricultural irrigation (Metcalf and Eddy, 2003; Solley et al., 1998). The three main risks associated with reclaimed water reuse for irrigation are (1) human exposure to pathogens and endocrine disruptors (e.g., Oron, 1996), (2) soil salinization, and (3) groundwater quality degradation by the various reclaimed water contaminants. Human risk of oral ingestion has prompted some regulators to prohibit the use of reclaimed water for food crop irrigation, while others allow it only if the crop is to be processed prior to being available to consumers (EPA, 2004). Hence, the transport and fate of pathogens (e.g., Gerba et al., 1975; Schäfer et al., 1998; Chu et al., 2003) and endocrine-disrupting chemicals (e.g., Ying and Kookana, 2005; Burnison et al., 2006) in soils and groundwater remain active research areas.

From an agronomic perspective, salinity is a problem associated with irrigation in arid and semi-arid environments; even more so when reclaimed water is applied. Salinity conveyed by the irrigation water tends to accumulate in the soil, and can necessitate transitioning to more salt-tolerant crops. Left unchecked, soil salinization will eventually render the soil non-arable. (e.g., El-Ashry et al. 1985; Brady and Weil, 1999; Schoups et al., 2005). The leaching of salts and other contaminants from the vadose zone to underlying groundwater is another potential problem with water reuse (Bond, 1998; Bouwer, 2000), or the over-application of natural or synthetic fertilizers (Hoyer et al., 1987; NRC, 1993; Wylie et al., 1994; Farid et al., 1993; Harter et al., 2002). Using more precise irrigation and fertilization methods can lessen the potential for soil salinization and groundwater degradation. Regarding specific salts, large-scale efforts aimed at assessing nitrate leaching in the Midwest U.S., for example, have documented spatially variable crop growth and yield due primarily to local microclimate and soil nutrient variations (Power et al., 2000; 2001), suggesting the potential for tailoring fertilizer applications to local conditions.

Feedback control for real-time irrigation scheduling has been investigated previously (Clemmens, 1992; Clemmens and Keats 1992a; 1992b, Phene et al., 1989; Shani et al., 2004), and several researchers have employed optimization schemes (Chao, 1979; Yaron et al., 1980; Naadimuthu et al., 1999) or near real-time adaptive scheduling to maximize crop yield given weather observations (Rao et al., 1992). To date, however, none of these efforts have coupled process-based simulators with optimization algorithms, using real-time sensor feedback on soil column states to enable autonomous, variable rate irrigation scheduling and chemical (e.g., nitrogen) management.

This paper examines the use of the receding horizon control (RHC) strategy for controlling time-variable irrigation application rates to manage soil moisture content and chemical concentrations within the soil profile. Here, the RHC method uses feedback from an embedded sensor system to parameterize an unsaturated zone flow and transport model and forecast soil moisture and nitrate levels several management time steps into the future. With the realization of the each management time step, simulation parameters are refined and the management horizon advances. The RHC is first formulated for a known irrigation site and tested for several typical soil moisture control problems and a hypothetical soil nitrate control case. This is followed by a field test of the algorithm for the case of moisture control only (due to the unavailability of reliable in situ nitrate sensors).

2. Irrigation Scheduling by Receding Horizon Control

Model Predictive or Receding Horizon Control (RHC) is a class of control algorithms that utilizes explicit process models to predict the future response of a system and command a system to a desired output using optimization as an intermediate step (Clarke, 1994; Kouvaritakis and Cannon, 2001). The expression receding horizon is intended to convey the concept that the optimization horizon is moving away from the present (into the future) by multiple management time steps. The algorithm class is so named because its optimization is executed to estimate a vector of control actions over multiple management time steps spanning the optimization horizon. After the first optimal control is applied for the current management time step, the optimization process is repeated with the same optimization horizon advancing one management period forward as illustrated in Figure 1 (Kwon and Han, 2005).

The RHC procedure is first described here for a general nonlinear model, which can be expressed by:

$$\dot{x} = f(x) + g(u) \tag{1}$$

where the function *u* is the control input, *x* is the state, *f(x)* is a nonlinear function of *x*, and *g(u)* is a nonlinear function of *u*. The objective of a control system is to maintain the outputs (states) at desired values by manipulating control inputs. To explain RHC, we first assign an arbitrary objective function to minimize the cost of state and control vectors as follows:

$$V = \int_0^{T_f} (x^2 + u^2)\, dt \tag{2}$$

where V is an objective function and T_f is final time of a prediction horizon for optimization. Then RHC proceeds by first identifying a finite set of parameters, ($p_0, \ldots, p_N$), to generate the function for control vectors $u(t)$ over the prediction horizon. This function can be any type, such as a discrete piecewise constant or spline function, as long as it can be expressed as assigned values (u_k) and derivatives ($\dot{u}_k$) where k is management time step or control step. Knowing $x(0)$, the second step is to use the initial system state (determined by measurement or estimation) to calculate the function for the state $x(t)$ or the state vector, $x(1), \ldots, x(N)$ by plugging the function $u(t)$ with initial parameter estimates, ($p_0, \ldots, p_N$), and initial condition $x(0)$ into the nonlinear model, where N is total number of management time steps in one optimization horizon. The third step is to determine the optimal parameter values for the function, $u(t)$, by nonlinear optimization of the objective function:

$$\min_{p_0,\ldots,p_N} V = \min_{p_0,\ldots,p_N} \int_0^{T_f} (x^2 + u^2)\, dt \,. \tag{3}$$

This procedure demonstrates that if one knows the initial state and a specified function for u, then the unknowns ($x(t)$ and $u(t)$) are obtainable by simulation models and optimization. The fourth step is to determine the function u using the optimal parameters ($p^*_0, \ldots, p^*_N$) and update the nonlinear model using only the first control vector, $u^*(0)$ and $x(0)$ or in general at time k as illustrated in Figure 2. $u^*(k) \ldots u^*(N-1+k)$ are obtained with the initial state information $x(k)$ using a nonlinear programming optimization algorithm and $u^*(k)$ is then used to calculate the state $x(k+1)$ for the next management time step. This new state is used as the initial condition from which to obtain $u^*(k+1) \ldots u^*(N+k)$ as the optimization horizon recedes. Finally, the system is advanced by δ (a management time step), and employs $x(t+\delta)$ as the updated initial condition, and the RHC procedure is repeated with new state information obtained from simulated values or sensor-based observations.

When applied in real-time, $u^*(k)$ must be actuated at time k, but $u^*(k)$ is calculated based on the initial condition, $x(k)$, which is not available until time k. Therefore, either a predicted $x(k)$ or measured $x(k-1)$ can be used for the initial condition, unless $u(k)$ can be obtained instantaneously at time k. If large changes are likely to occur during a management time step, then the use of a predicted $x(k)$ is recommended. If a system is poorly identified, then a measured $x(k-1)$ is preferable. When the state estimation schemes and measurements (i.e., feedback) are robust, the RHC facilitates periodic assimilation of observations, improving the parameterization process for simulation models. From this perspective, the RHC is well-suited for adaptive management of processes subject to uncontrollable perturbations (e.g., sudden weather changes).

In this work, the RHC algorithm is applied to the problem of irrigation with reclaimed water. The management problem is posed here in terms of two objectives and one constraint: (a) maintaining soil moisture levels or nitrate concentrations near or below a threshold value at a certain depth, (b) supporting crop water needs and/or maximizing the amount of water being recycled by the farmer (as in effluent disposal through reuse), and (c) maintaining application rates below the maximum infiltration rate (avoiding potential human exposure associated water runoff). The state vectors are soil moisture content, θ, temperature, T, and nitrate concentration, C, and the control vector is reclaimed water input q. For a center-pivot irrigation system (described further below) where one of two control vectors can be chosen: application rate and irrigation system speed (irrigation duration). The objectives and constraint can be addressed using the following function:

$$\begin{aligned}&\min_{q_1,\ldots,q_N} \int_0^{T_f} \left| C(t) - C_{threshold} \right|^2 dt \\ &\quad s.t. \quad q < K_s\end{aligned} \tag{4}$$

where K_s is the saturated hydraulic conductivity, $q_1, \ldots, q_N$ are the application rates at each management time step in one optimization horizon, T_f is the prediction (optimization) horizon, $C(t)$ is the nitrate concentration at a depth of interest, and $C_{threshold}$ is a threshold for the nitrate concentration. This formulation permits nitrate concentrations up to the threshold value while allowing the reclaimed water input to be maximized. Then, by bounding possible irrigation rates from zero to the maximum soil infiltration rate, surface runoff can be prevented. Other constraints, such as those pertaining to water availability or restraints on irrigation rate changes could be added to this optimization algorithm by providing stopping criteria or lower and upper bounds for application rates. If the management objective is to maintain a certain soil moisture level, then the objective function is instead

$$\begin{aligned}&\min_{q_1,\ldots,q_N} \int_0^{T_f} \left| \theta(t) - \theta_{threshold} \right|^2 dt \\ &\quad s.t. \quad q < K_s\end{aligned} \tag{5}$$

where $\theta(t)$ is soil moisture at a depth of interest, and $\theta_{threshold}$ is threshold for soil moisture.

These least squares objective functions are straightforward and simple to use, but must be used with some caution as they equally penalize $C(t)$ and $\theta(t)$ values less than and greater than the threshold. When the initial nitrate concentration or soil moisture is sufficiently removed from the threshold value, then this approach is sufficient to avoid violations. However, when the system response is relatively insensitive to control vector changes, such that there exists a lag time between control actuation and system response, then incorporating a margin of error in the threshold selection or a penalty function may be necessary. The objectives, constraints, and thresholds employed in this work were intended to demonstrate those associated with an experimental irrigation site in Palmdale, California, and are not intended to be representative of all irrigation scenarios.

Optimization schemes from the MATLAB^{TM} toolbox, a trust region-based interior-reflective Newton method (Coleman and Li, 1994; 1996) and a genetic algorithm developed (Joines et al. 1995) were coupled to the simulation models described below. Both the gradient method and genetic algorithm were used for soil moisture, but only the genetic algorithm was employed for nitrate control because the gradient method often led to convergence on local optima in the chemical transport case.

A one-dimensional (1D) coupled unsaturated flow, solute, and energy transport model was used to drive the RHC algorithm (details in Park, 2008). This level of model complexity was determined to adequately describe irrigation dynamics for the field site discussed below. While a 1D model cannot represent horizontal variability of soil and crops, it is useful for relatively homogeneous soils dominated by vertical flows, or can be invoked at multiple locations in more heterogeneous soils, where optimal application rates could be determined and applied locally using variable rate irrigation systems (Camp et al., 1998; King et al., 2005). However, where geospatial variation is great and horizontal flow is significant, more complex simulators are necessary for successful moisture and nutrient management.

In the unsaturated flow model, the water retention function $h(\theta)$ and hydraulic conductivity function $K(\theta)$ were assumed to be nonhysteretic and parameterized by the models of Mualem (1976) and van Genuchten (1980) (see Table 1 for parameter details). A plant water uptake term was included as a sink term (Feddes et al., 1976, 1988). The parameter values used to test the RHC algorithm are specific to an experimental pivot irrigation site in Palmdale, CA, which is described below in the context of the RHC field test. Hence, management schemes arrived at in this work cannot be applied to other sites without re-parameterization of the simulation models.

The boundary condition at the ground surface for the center-pivot irrigation system was modeled using a periodically applied sinusoidal pattern (Figure 3):

$$-K(\theta)\left[\frac{\partial h(\theta)}{\partial z}-1\right]=q\ \sin wt-ET \qquad 0\leq\ t<10\text{ min} \qquad (6)$$

$$\frac{\partial\theta(0,t)}{\partial z}=-ET \qquad 10\text{ min}\ \leq\ t<6\text{ hr} \qquad (7)$$

where z is the vertical depth, w is the angular frequency ($\frac{\pi}{t_1}$), t_1 is 10 min which is the duration of irrigation, q is reclaimed water application rate (control vector) to be optimized [cm/hr] in one management time step, ET is evapotranspiration rate [cm/hr] which is based on site meteorology and crop types, and 6 h is the length of one management time step (typical pivot revolution time at the Palmdale site). At the lower boundary of the simulated soil column ($z = L$), free drainage is numerically stipulated using a zero pressure gradient.

The 1D energy transport equation was employed to estimate the soil surface temperature and evapotranspiration rate. In this study, the evaporative flux affected the moisture and solute concentrations in the top section of the profile. Below this, the modeled effect of temperature on soil moisture contents and nitrate concentration were negligible. The soil surface temperature $T_s(t)$ was calculated based on meteorological data according to an energy balance and used as the boundary condition at the ground surface ($z = 0$). Penman-Monteith potential evapotranspiration (Allen et al., 1998) was then estimated to provide the negative influx at the soil surface as a boundary condition based on energy balance equation and meteorological data. At the lower boundary of the domain, a zero temperature gradient was assumed. If a more explicit nitrogen cycling model were to be used (see below), where even modest temperature changes might impact biogeochemical rates, then the implications of the energy transport model to this work would probably be more significant.

An advection-dispersion-reaction equation was used to simulate nitrate transport in the unsaturated zone. A lumped first-order nitrate removal rate was used to represent the net results of plant uptake, denitrification, nitrification, and immobilization. This over-simplification is intended as a first-approximation of the nitrogen cycling processes for the purpose of illustrating the proposed optimization strategy. At the soil surface, a solute flux-type boundary condition was used. At the lower boundary ($z = L$), a zero concentration gradient was employed.

Process simulation models were numerically solved using a Crank-Nicholson finite difference scheme (Gerald and Wheatley, 1970) in MATLAB™. Parameter values used for simulated results are summarized in Table 1.

3. RHC Algorithm Testing for Soil Moisture and Nitrate Control

The RHC algorithm was tested for soil moisture and nitrate control with variable application rates at a fixed duration, and variable application frequency and duration at a fixed rate. The RHC was also tested for soil moisture and nitrate control at a fixed depth and maximum soil moisture and nitrate concentration throughout the vertical depth. The RHC scheme successfully controlled all the aforementioned cases by maintaining soil moisture and nitrate level below the threshold value over the total control steps (Park, 2008). In this paper, two example cases, soil moisture control with variable application rate and nitrate control subject to varying initial condition are demonstrated.

3.1 Soil Moisture Control: Variable Application Rate of Fixed Frequency and Duration

The RHC was first tested as a strategy for controlling the maximum soil moisture level throughout the soil profile using variable application rates at a fixed interval and duration (Figure 4). In this case, the gradient method was used to drive the optimization aspect of the RHC algorithm. The initial soil moisture content was uniformly set to 0.2 [cm^3/cm^3] throughout a 300cm domain. As noted previously, selection of the management time step and the optimization horizon requires knowledge of the timescale of the physical processes involved. Fewer management time steps (e.g., four or less in the current problem) predict only near term systems behavior, yielding a relatively short-sighted optimal solution. This can necessitate abrupt application rate changes as the algorithm may be unable to foresee future violations sufficiently early to avoid them more gradually. In this study, different numbers of management time steps were tested, and 10 steps was determined to provide optimal solutions without requiring sudden changes in the application rate. Each management time step has one control variable, thus there were 10 control variables for this optimization scenario. The management time step for this problem was selected as 6 h and the duration of each irrigation event was fixed as 10 minutes, conditions characteristic of the irrigation system at the Palmdale test site. Optimization was executed over the 60-hr period and the first optimal value (the irrigation rate of the first management time step) was applied. The state vector (soil moisture) was then updated and used as the initial condition for the next optimization horizon. The system was updated 50 times (totaling 300 h).

Results summarized in Figure 4a-d demonstrate that the RHC algorithm successfully controlled the soil moisture throughout the profile. At early times, the algorithm prescribed the maximum application rate (4a) until the maximum moisture content in the column began to approach the threshold value (4d). At this point, the RHC prescribes decreasing application rates, rapid at first followed by incremental decreases as the soil column approaches a steady state. The maximum soil moisture level throughout the depth (4c) was consistently maintained below 0.25 [cm^3/cm^3]. The value of the objective function appears to be monotonically approaching a minimum value at the end of 50 management time steps (4b).

3.2. Nitrate control subject to varying initial conditions

This case employed the same application dynamics as the first case while adding a constant nitrate concentration to the irrigation water. A threshold value for nitrate control was chosen as 44ppm which is just below the U.S. EPA's maximum contaminant level (45ppm as nitrate). The coupled flow and transport model was used for simulating and controlling nitrate concentration in the soil moisture. The gradient method and the genetic algorithm were employed as an optimization algorithm for soil moisture control, but only the genetic algorithm was performed for nitrate control to obtain optimal irrigation rates (q_i) since the gradient method failed to find global minima in the objective space. When simulation models are highly nonlinear (e.g. solute transport in unsaturated zone) global optimization scheme should be implemented, or the genetic algorithm can be combined with the gradient method to improve the optimization solutions (Sciortino, *et al*., 2000).

Previous nitrate control trials indicated that nitrate concentration in the soil column responded slowly to the changes in application rate, thus big changes in application rate occurred at the interval of several management time steps (Figure 5a-c). When the system response is relatively insensitive to optimal control vectors such that there is a lag between control actuation and system response and the initial nitrate concentration is too close to the threshold value (Figure 5c), violations can occur. Penalty or multi-objective functions can be used to prevent such violations. For example, an application rate term can be added to the objective function to maximize the rate, thus rendering it directly sensitive to the control variable:

$$\min_{q_1,\ldots,q_N} \int_0^{T_f} \left\{ \left| C_{threshold} - C(t) \right| - \alpha \cdot q_1 \right\}^2 dt \qquad (8)$$

where α is a constant for weighting and unit matching. The other terms are the same as those in equation (4). The rationale behind this multi-objective function is balancing the decrement of the concentration difference and the application rate change. By setting the weighting factor to a small value, the objective of minimization remains tractable when the concentration difference is decreasing while the application rate is increasing. In this example, an α value of 10^{-8} was chosen (placing more weight on the concentration threshold term). This value was based on several simulations comparing the effects of the relative magnitude of the concentration difference and q_1 , the first application rate. Three initial conditions of increasing severity, initial surface concentrations of 5, 30, and 40 ppm nitrate, were used to test the multi-objective function. Initial conditions for lower boundary soil moisture, temperature, nitrate are assumed linearly distributed between surface (varying) and 0.11 (lower boundary), 20°C (surface) and 5°C (lower boundary), 5 ppm nitrate (surface) and 0 ppm (lower boundary) respectively. Nitrate concentration in the applied water was set as a constant 40ppm. The management time step for this simulation was 6h and there were 8 management time steps in one optimization horizon.

Figures 5(a-c) demonstrate that the prior objective function suffices for the lowest initial surface concentration, but fails to manage 40 ppm cases. In contrast, even the most severe case is well-managed by the multi-objective function (Figure 5(d)) through 40 management time steps. In addition, more water was applied using the multi-objective function 35.5 cm compared to 29.9 cm using the prior objective function. The results of this example are encouraging, and merit further investigation in terms of linking the most useful objective function to the site-specific objectives, constraints, input/output/control vector relationships.

4. Field Test of RHC for Soil Moisture Control

To test the RHC under real conditions, a field site was identified in Palmdale, California (longitude 118° W, latitude 34° N) which is in the Mojave Desert area. Reclaimed water is being used for agricultural irrigation there with application by a center-pivot irrigation system equipped with a 200 m (≈ 650 ft) pivot arm rotating over an area of 12.67 ha (≈ 31.3 acres). Given the current system, it was impossible to manage the pivot flow rate precisely, and instead applications were regulated by the application duration (based on the rotational speed of the pivot arm) with a fixed application rate (0.5mm/min). For simplicity, three speeds--low (8 min duration with 4mm of water), medium (6 min; 3 mm), and high (4 min; 2mm)--were employed. The main soil types in this area are characterized as loamy fine sand to fine sandy loam in terms of hydraulic conductivity and moisture retention parameters of soil sample test.

The field test was performed at a single location in the southeast quadrant of the Palmdale pivot circle, where fine sandy loam is the main soil type. The objective of the test was to prevent the moisture content at a depth of 5cm from surpassing a threshold value of 0.22 [cm^3/cm^3]. This depth was selected to enable the application rates to impact the sensors within the timeframe of the experiment (12 h). However, additional sensors were deployed in order to capture data for future offline algorithm testing. Soil moisture sensors (S-SMC-M005, Onset Computer Corporation, Bourne, MA) were installed at 5cm, 10cm, 20cm, 40cm, and 60cm. Temperature sensors (S-TMB-M002, Onset) were installed at 5cm, 10cm, 20cm, and 40cm. Data loggers (H21-001 logger with C-002 radio modem, Onset) were used to collect and wirelessly transmit soil moisture, temperature, and meteorological data, including air temperature and relative humidity (S-THA-M002, Onset), and wind speed and direction (S-WCA-M003, Onset). Atmospheric pressure and solar radiation data were downloaded from CIMIS website (California Irrigation Management Information System, www.cimis.water.ca.gov).

The 1D unsaturated flow and energy transport models for this case were coupled to a bare-soil evaporation model for the ground surface boundary condition (no crops were growing). To expedite the model parameterization process, a simplistic approach to modeling vertical heterogeneity was adopted in which a sandy soil profile was assumed to consist of two layers (0-30cm and 30-60cm) with respect to hydraulic properties, while energy transport properties were assume to be homogeneous throughout the entire soil profile. Model parameter-fitting in the RHC scheme was performed using the 5cm depth moisture content sensor data for the first 30min of each management time step. Using only the first 30min of sensor data afforded the balance of the management time step time for the optimization portion of the RHC scheme discussed below.

The model was fitted to the moisture time series by adjusting eight parameters, four of these for each layer: saturated hydraulic conductivity, saturated moisture content, residual moisture content, and an empirical moisture retention parameter (α, see Mualem, 1976; van Genuchten, 1980). Another empirical moisture retention parameter, n was fixed at 2. The need to re-estimate simulation model parameters at each management time step merits further discussion. In theory, a constant set of these material properties should be obtained from the fitting procedure, but such was not the case (Table 1). There are several reasons for this result. First, the unsaturated flow model in this study failed to account for flow patterns associated with preferential pathways, hysteresis, and other real features of flow and transport in unsaturated soil. Complexities such these probably played a significant role in the test bed, and would result in different optimal parameters under different moisture regimes. This problem was exacerbated by necessarily limiting the parameter identification procedure to a single depth (5 cm) and allotting a maximum of 30min for the fitting. These restrictions resulted in parameters that were not globally optimal, but which were nonetheless adequate for the purposes of driving the RHC algorithm. The tradeoff between model structure, model parameterization, and the sensor observations network is clearly a critical part of controlling environmental processes like irrigation and merits further research.

The genetic algorithm-based RHC scheme was configured to control soil moisture as described in Figure 6. The RHC scheme updated pivot speeds at each management time step, which were immediately actuated. The high speed (shortest irrigation duration) was arbitrarily selected as the initial setting. When the RHC started, the data from sensors were collected for 30 min to estimate parameters. Then the updated parameters were used to forecast future states to determine the next vector of pivot speeds. Because the next optimal duration should be achieved before the arrival of next management decision, initial conditions (sensor data) from the current step were used for initial conditions in calculating the next step optimal duration in the genetic algorithm. In general, however, it is recommended to use predicted initial conditions for the next management time step if the discrepancy between measured data and estimated data is determined to be minor. In this experiment, we decided to use initial data from the current step since we were uncertain that the parameter estimation, which was performed in real-time, would produce acceptable predictions. In hindsight, the predictions did appear to be sufficiently accurate (Figure 7). The management time step for this field study was 2 h (the pivot arm was driven over the sensors every 2 h) with pivot speed as the sole control vector. There were 6 management time steps in a single optimization horizon. At each management time step, model parameters were updated using the least squares method by minimizing the difference between the current sensor data and model estimates.

Comparison between the best-fitting simulations and sensor-based observations at the 5cm depth are plotted for each of the five management time steps (Figure 7). The residual norm of the least squares oscillated, but tended to improve over time and the resulting parameter adjustments remained consistent with the soil type at Palmdale over the entire management period (results not shown). Based on results obtained off-line for other soil depths, it was clear that some bias was introduced by estimating parameters using time series from a single depth (5cm). This was unavoidable due to the need to execute the parameter identification and RHC optimization steps within the 2h timeframe of the management time step. The implications of such biasing merit further investigation and suggest the need for incorporating data assimilation approaches to integrate sensor and model error into the RHC algorithm. Of course such strategies would add to the computational challenges associated with advancing the RHC algorithm in near real-time.

The results from the RHC field test are presented in Figures 8 through 10. Initially, the moisture content at 5cm was less than the threshold value, thus the RHC's initial updates called for slowing the pivot speed (increasing the duration), enabling more water to be applied to the profile (management time steps 1, 2, and 3 in Figure 9). As the estimated 5cm moisture content approaches the threshold value, the RHC called for increased pivot speeds in an attempt to stay near the threshold value (management time steps 4, 5, and 6 in Figure 9). During the field test, we accidentally executed the wrong speed at management time step 3, and a 4 min duration (high speed) was applied instead of the prescribed 8 min duration (low speed). However, RHC scheme adapted to this unexpected change and again prescribed an 8 min duration for the subsequent management time step to compensate for the inadequate water application during the previous step.

The threshold was briefly violated after the fourth management time step (Figure 9). Because of limited number of control options offered by in this scenario (3 speeds), slight over-watering was possible. For example, at management time step 4, the optimal duration value was about 5 min, but 6 min was applied, resulting in over-watering. Another reason for the violations was the previously mentioned usage of current observations as the initial conditions for the subsequent management time step. If these presumed values are sufficiently different from the actual values, this might cause a lag between optimal duration and the soil moisture response. Violations could be avoided in a number of ways, including (1) enabling better refinement of the water application speed (more precise addition of water), (2) using simulator predictions to update soil profile conditions (assuming valid parameterization), (3) using shorter management time steps to enable more frequent speed adaptation, or (4) simply allowing for some margin of error or safety factor when setting the threshold value.

A more complete view of the 5cm moisture sensor data (Figure 10) reveals that the threshold for the Palmdale test was actually violated multiple times during the test (i.e., including times between management time steps), however, the RHC controls the soil moisture by maintaining it at the end of each management time step near the threshold. Figure 10 demonstrated that the estimated soil moisture data generally matched well with the measured soil moisture data, which opens a possibility to use predicted initial conditions to calculate optimal vectors in RHC.

5. Summary and Conclusions

Irrigation scheduling has evolved toward automated systems that integrate meteorological and soil sensor measurements with simulation models. This technology development facilitates more precise management of soil and plant status in time and space, thereby enabling agriculturalists to minimize negative impacts on the environment (e.g., when reclaimed water is applied for irrigation). In this study, a receding horizon control (RHC) was proposed and tested for the control of water content and contaminants in soil with the dual objectives of maximizing reclaimed water reuse while protecting groundwater from degradation by nitrate. By integrating observations from embedded sensors, predictive models, and optimization algorithms in the RHC scheme, water and/or nitrate levels in soil were continuously maintained near threshold levels while maximizing the reclaimed water applied. Results from different cases demonstrated that various optimization schemes, control vectors, and soil profile depths to be monitored can be implemented in RHC as dictated by site-specific conditions.

While these initial results are encouraging, several near-term modifications of the RHC irrigation algorithm should be undertaken to render more robust results. First, in many cases, it is desirable to control the moisture content throughout the root zone instead of at a specific depth. Second, since we are concerned about chemical leaching into the underlying groundwater, it may be preferable to control the chemical flux or total percolated nitrate below a root zone (in anticipation of the development of reliable chemical sensors are available, such as for salinity). Third, the previously noted lag-time between adjustment of the control variable (irrigation application rate) and feedback from the nitrate concentration levels suggests that multi-objective problem formulations addressing moisture and nitrate thresholds simultaneously may be more appropriate. Finally, because management decisions stemming from the RHC approach depend strongly on site-specific conditions (soil and crop type, meteorology, initial conditions, and limitations on control vectors), these factors need to be examined in a more comprehensive manner to identify the spectra of potential benefits and limitations of the approach. For example, the resilience of the RHC algorithm to random storm events and its stability for long-term operation should be tested extensively for a variety of soil and crop conditions.

In most instances there are multiple solutes and particulates (e.g. pathogens) other than nitrate that are of concern in the reclaimed water. Multi-component control is possible using the RHC scheme if the sensors and models are available to measure and predict the state of these chemical or biological agents. Modified multi-objective functions similar to (8), for example, would need to be employed in such cases.

Longer term development should focus on increasing the error resiliency of the RHC irrigation approach. For example, network design strategies for identifying the optimal number and placement of sensors in the context of geospatial heterogeneity will be needed to scale-up the technique. Furthermore, errors stemming from sensors, model structure, and model parameters need to be propagated throughout the RHC scheme to quantify uncertainty associated with management decisions.

Acknowledgements

We gratefully acknowledge the financial support of UCLA's Center for Embedded Networked Sensing under cooperative agreement #CCR-0120778 with the National Science Foundation, and the staff support and access to the Palmdale experimental irrigation site granted by the Los Angeles County Sanitation Districts. We also thank Drs. Juyoul Kim and Steve Margulis for their MATLAB™ codes of process simulation models, and Drs. Alexander Rat'ko and Jose Saez for their assistance at the Palmdale site.

References

Allen, R.G., Pereira, L.S., Raes, D., and Smith, M., 1998. Crop evapotranspiration. Guidelines for computing crop water requirements. In: FOA Irrigation and Drainage Paper 56. Food and Agriculture Organization of the United Nations, Rome, Italy, pp. 300.

Bond, W.J, 1998. Effluent irrigation – an environmental challenge for soil science. Australian Journal of Soil Research 36 (4) 543-555

Bouwer, H., 2000. Integrated water management: emerging issues and challenges. Agricultural water management 45 (3) 217-228.

Brady, N.C. and Weil, R.R., 1999. The nature and properties of soils. 12th Ed. Prentice Hall: Upper Saddle River, New Jersey.

Burnison, K., Servos, M., Lorenzen, A., and Topp, E., 2006. Persistence of endocrine-disrupting chemicals in agricultural soils. Journal of Environmental Engineering and Science 5 (3) 211-219.

Camp C.R., Sadler, E.J., Evans, D.E., Usrey, L.J., and Omary, M., 1998. Modified center pivot system for precision management of water and nutrients. Applied Engineering in Agriculture 14 (1) 23-31.

Chao, J.C., 1979. Irrigation scheduling for a corn response model by dynamic programming. Master's Thesis, Kansas State University, Manhattan, KS.

Chu, Y., Yan, J., Baumannb, T., and Yates, M.V., 2003. Effect of Soil Properties on Saturated and Unsaturated Virus Transport through Columns. Journal of Environmental Quality. 32:2017-2025

Clarke, D., (Ed.) 1994. Advances in Model-based Predictive Control. Oxford University Press

Clemmens, A.J., 1992. Feedback-control of basin-irrigation system. Journal of irrigation and drainage engineering. 118 (3) 480-497

Clemmens, A.J. and Keats, J.B., 1992a. Bayesian-inference for feedback-control I. Theory. Journal of irrigation and drainage engineering. 118 (3) 397-415.

Clemmens, A.J. and Keats, J.B., 1992b. Bayesian-inference for feedback-control II. Surface irrigation example. Journal of irrigation and drainage engineering. 118 (3) 416-432.

Coleman, T.F. and Li, Y., 1994. On the Convergence of Reflective Newton Methods for Large-Scale Nonlinear Minimization Subject to Bounds. Mathematical Programming. 67 (2) 189-224.

Coleman, T.F. and Li, Y., 1996. An Interior, Trust Region Approach for Nonlinear Minimization Subject to Bounds. SIAM Journal on Optimization. 6: 418-445.

El-Ashry, M.T., Van Schilfgaarde, J., and Schiffman, S., 1985. Salinity pollution from irrigated agriculture. Journal of Soil and Water Conservation. 40 (1) 48-52

Environmental Protection Agency, 2004. Guidelines for Water Reuse. EPA/625/R-04/108

Farid, M.S.M., Atta, S., Rashid, M., Munnink, J.O., and Platenburg, R., 1993. Impact of the reuse of domestic waste-water for irrigation on groundwater quality. Water science and technology. 27 (9) 147-157.

Feddes, R.A., Kowalik, P., Kolinskamalinka, K., and Zaradny, H., 1976. Simulation of field water uptake by plants using a soil water dependent root extraction function. Journal of hydrology 31 (1-2) 13-26.

Feddes, R.A., Kabat, P., Vanbakel, P.J.T., Bronswijk, J.J.B., and Harbertsma, J., 1988. Modeling soil water dynamics in the unsaturated zone – state of the art. Journal of hydrology 100 (1-3) 69-111.

Gerald, C.F. and Wheatley, P.O., 1970. Applied numerical analysis. 4th Ed. Addison-Wesley Publishing Company: Reading, MA.

Gerba, C.P., Wallis, C., and Melnick, J.L., 1975. Fate of wastewater bacteria and viruses in soil. Journal of Irrigation and Drainage Division 101 (3) 157–174.

Harter, T., Davis, H., Mathews, M.C., and Meyer, R.D., 2002. Shallow groundwater quality on dairy farms with irrigated forage crops. Journal of contaminant hydrology 55 (3-4) 287-315.

Hillel, D., 1998. Environmental Soil Physics. Academic Press: Sandiego, CA.

Hoyer, B.E., Combs, J.E., Kelley, R.D., Cousins-Leatherman, C., and Seyb, J.H., 1987. Iowa Ground water Protection Strategy. Des Moines: Iowa Department of Natural Resources.

Joines, J.A., Houck, C.R., and Kay, M.G., 1995. A genetic algorithm for function optimization: A Matlab implementation. Technical Report NCSU-IE Technical Report 95--09, North Carolina State University.

King, B.A., Wall, R.W., and Wall, L.R., 2005. Distributed control and data acquisition system for closed-loop site-specific irrigation management with center pivots. Applied Engineering in Agriculture 21 (5) 871-878

Kouvaritakis B. and Cannon. M., 2001. Nonlinear Predictive Control: theory and practice. Institution of Electrical Engineers: London

Kwon, K.H. and Han, S., 2005. Receding Horizon Control: model predictive control for state models. Springer: London.

Metcalf and Eddy, Inc., 2003. Wastewater Engineering: Treatment and reuse. 4th Ed. McGraw Hill

Mualem, Y., 1976. A new model predicting the hydraulic conductivity of unsaturated porous media. Water Resources and Research 12:513–522.

Naadimuthu, G., Raju, K.S., and Lee, E.S., 1999. A Heuristic Dynamic Optimization Algorithm for Irrigation Scheduling. Mathematical and Computer Modeling 30: 169-183

National Research Council., 1993. Ground Water Vulnerability Assessment, Predicting relative contamination potential under conditions of uncertainty. Committee on Techniques for Assessing Ground Water Vulnerability, Armando Carbonell, Chair. National Academy of Sciences. National Academy Press, Washington, DC.

Oron, G., 1996. Soil as a complementary treatment component for simultaneous wastewater disposal and reuse. Water Science and Technology 34 (11) 243-252

Park, Y., 2008. Managing Irrigation with Reclaimed Water: Minimizing Negative Impacts on Soil and Groundwater Quality. Ph.D. Dissertation, University of California, Los Angeles

Phene, C.J, McCormick, R.L., Davis, K.R., Pierro, J.D., and Meek, D.W., 1989. A Lysimeter Feedback Irrigation Controller System for Evapotranspiration Measurements and Real Time Irrigation Scheduling. Transactions of the ASAE 32 (2) 477-484

Power, J.F., Wiese, R., and Flowerday, D., 2000. Managing nitrogen for water quality-lessons from Management Systems Evaluation Area. Journal of Environmental Quality 29 (2) 355-366

Power, J.F., Wiese, R., and Flowerday, D., 2001. Managing farming systems for nitrate control: A research review from management systems evaluation areas. Journal of Environmental Quality 30 (6) 1866-1880

Rao, N.H, Sarma, P.B.S., and Chander, S., 1992. Real-time adaptive irrigation scheduling under a limited water-supply. Agricultural water management 20 (4) 267-279.

Schoups. G, Hopmans, J.W., Young, C.A., Vrugt, J.A., Wallender W.W., Tanji, K.K., and Panday, S., 2005. Sustainability of irrigated agriculture in the San Joaquin Valley, California. Proceedings of the National Academy of Sciences of the United States of America 102 (43) 15352-15356.

Schäfer, A., Ustohal, P., Harms, H., Stauffer, F., Dracos, T., and Zehnder, A.J.B., 1998. Transport of bacteria in unsaturated porous media. Journal of Contaminant Hydrology 33:149–169.

Sciortino, A. Harmon, T.C., Yeh, W-G. W. (2000). Inverse modeling for locating dense nonaqueous pools in groundwater under steady flow conditions. Water resources research, WATER RESOURCES RESEARCH. 36(7), 1723-1735.

Shami, U., Tsur, Y., and Zemel, A., 2004. Optimal dynamic irrigation schemes. Optimal Control Applications and Methods 25 (2) 91-106

Solley, W.B., Pierce, R.R., and Perlman, H.A., 1998. U.S. Geological Survey Circular 1200: Estimated Use of Water in the United States in 1995. Denver, Colorado.

van Genuchten, M.Th. (1980). A closed form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Science Society of America Journal 44:892–898

Wylie, B.K., Shaffer, M.J., Brodahl, M.K., Dubois, D., and Wagner, D.G., 1994. Predicting spatial distributions of nitrate leaching in northeastern Colorado. Journal of Soil and Water Conservation 49 (3) 288-293.

Yaron, D., Bresler, E., Bielorai, H., and Harpinist, B., 1980. A model for Optimal Irrigation Scheduling with Saline Water. Water Resources Research 16 (2) 257-262

Ying, G-G. and Kookana, R.S., 2005. Sorption and degradation of estrogen-like-endocrine disrupting chemicals in soil. Environmental Toxicology and Chemistry 24 (10) 2640-2645.

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Figure 1. The optimization procedure for Receding Horizon Control (RHC) where *k, k+1, k+2* are management time steps for irrigation control. $q_{k+1|k}$ represents the optimal control vector, *q* (the irrigation application rate) at management time step, *k+1* when optimization is executed at time *k*. The first optimal values ($q_{k|k}$, $q_{k+1|k+1}$, and $q_{k+2|k+2}$) are applied to control the system (adapted from Kwon and Han, 2005).

Figure 2. Illustration of the state and control vectors before and after optimization algorithm: $u^*(k) \sim u^*(N-1+k)$ are obtained with the initial state information $x(k)$ and the first control $u^*(k)$ is then used to calculate the state $x(k+1)$ for next management time step. *N* is the total number of management time steps in one optimization horizon, *k* is current control (management) step number, thus, *1, 2, …, k, k+1, …, N* are management time step numbers.

Figure 3. An illustration of management and optimization time step. The magnitudes, q_i, is control vector (reclaimed water application rate) for optimization, where i is 1,2, …, 6. In this case, there are 6 management time steps in one optimization horizon.

Figure 4. Soil moisture control using RHC (gradient optimization method): (a) water application rate at each management time step (b) objective function value when the optimal application rate is applied at each management time step, (c) soil moisture profile at the end of 50 management time steps, (d) maximum soil moisture content in the soil profile at the end of each management time step (not necessarily at the same location).

Figure 5. Soil nitrate level control results for different nitrate initial concentrations at the surface were tried. (a) 5ppm, (b) 30ppm, (c) 40ppm, and (d) 40ppm with multi-objective function. The labels for each result are the same as Figure 8.

Figure 6. RHC scheme for soil moisture control in Palmdale, CA (arrow indicates input to the next step of the scheme)

Figure 7. Simulated and measured soil moisture data from the Palmdale RHC field test (model parameters were updated each management time step using the 5cm sensor data for the first 30min of each step).

Figure 8. Optimal water application duration (determined by pivot speed) results for the Palmdale RHC field test; the sequence for management time steps is high (4 min, initial value), medium (6 min), low (8 min), low, medium, medium, and high speed.

Figure 9. Palmdale RHC field test estimated 5 cm depth soil moisture at the end of each management time step after optimal duration was actuated. The text above and below each graph denotes the optimal duration applied at that management time step; when the soil moisture approaches to the threshold value, it tries to maintain the level by reducing irrigation duration.

Figure 10. Simulated (line) and observed (symbols) 5cm depth soil moisture from the Palmdale RHC field test (model parameters were updated each management time step using the 5cm sensor data for the first 30min of each step).

Table 1. Parameter values in models for simulated results