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DYNAMIC CONTROL SWITCHING APPLIED TO WATER RESOURCE MANAGEMENT SIMULATION[1]

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ABSTRACT: Simulation of water resource management in hydrological numerical models is often limited to simple expressions such as rulecurves. More complex management requires additional layers of abstraction. Rulecurves tend to be simplistic, while abstraction implies expertise to convert management policies to a form which may not be recognizable by operators. The Regional Simulation Model (RSM) attempts to bridge this gap with the Management Simulation Engine (MSE). MSE allows dynamic switching of control algorithms facilitating hybrid control of modeled structures, even though the individual controllers are widely different. Use of hybrid controllers can simplify expression of complex management controls. This article details the architecture of the MSE that enables hybrid control. A model application is examined in which a set of tuned fuzzy controllers are dynamically switched with piecewise linear flood controllers to simulate a hybrid control scheme. The application models a Florida water conservation area and demonstrates effective flood control without sacrificing the tuned performance of the fuzzy controllers.

(KEY TERMS: water resources management; planning; watershed management; modeling; simulation.)

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INTRODUCTION

Hydrological numerical models are routinely employed to provide guidance in water resource managerial decisions, consequently, there has been considerable progress in the development of water resource control and optimization applied to hydrological numerical models. An examination of the hydrological literature reveals a wealth of advanced management techniques (Brdys and Ulanicki, 1994; Mays and Tung, 1991). For example, linear programming (Eschenbach *et al.*, 2001), artificial neural networks (Sivakumar *et al.*, 2002, Lambrakis *et al.*, 2000) fuzzy control (Dubrovin *et al.*, 2002; Shrestha *et al.*, 1996), dynamic programming (Foufoula-Georgiou and Kitandis, 1988), simulated annealing (da Conceicao Cunha *et al.*, 1999), genetic algorithms (Wardlaw and Sharif, 1999.), heuristics, and hybrids (Nayak *et al.*, 2005, Chang *et al.*, 2005, Michael *et al.*, 2005). However, these hydrological models tend to be specialized, require nonstandard input formats, and are limited in scope to either reservoir routing or local hydraulic control. Indeed, it has been recognized that the need exists for comprehensive integration of management features in

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streamflow-ground water coupled hydrological models (Belaineh *et al.*, 1999).

Coupled models commonly employed for water resource management typically contain limited resources for comprehensive management simulation. For example, all coupled management models known to the authors support water control simulation through the application of rulecurves, while only a few provide generalized control algorithms that can be completely designed by the modeler. The Regional Simulation Model (RSM), developed at the South Florida Water Management District attempts to reduce this limitation with the introduction of a multi-layer control hierarchy. This approach allows for considerable flexibility in the expression, coupling, and effective control of complex management schemes such as those imposed on regional South Florida basins.

In particular, RSM allows the use of hybrid controllers through dynamic switching of control algorithms based on state or decision variables. The focus of this paper is to describe and exemplify the RSM design applied to a regional hydrological model employing hybrid controllers. The objective of the hybrid control is to regulate water levels in a subregional basin during normal conditions with tuned fuzzy controllers, while minimizing excessive water levels with flood controllers during wet periods.

The article is organized as follows: a general description of the RSM, architecture of the Management Simulation Engine (MSE) component of RSM and how it facilitates hybrid control, presentation of a simulation model demonstrating the control, specifics of the hybrid controller, and simulation results of the hybrid controllers.

REGIONAL SIMULATION MODEL

The RSM simulates the natural and anthropogenically influenced flow of an integrated aquifer-stream system. The RSM consists of two interoperative computational modules, the Hydrologic Simulation Engine (HSE) (South Florida Water Management District, 2005a, Lal *et al.*, 2005, Lal, 1998) and the MSE (South Florida Water Management District, 2005b).

Hydrologic Simulation Engine

The hydrologic simulation engine is a fully integrated hydrological model supporting overland flow, ground-water flow, and canal flow. The overland and ground-water flow domains are discretized in the horizontal 2-D domain using unstructured triangular cells. The ground-water aquifer layers may consist of any number of variable depth layers, each of which can span an arbitrary extent of horizontal 2D cells. The stream flow network is discretized using piecewise linear canal segments, each of which can be assigned rectangular or trapezoidal cross sections. The 2D mesh and 1D stream network are independent, and may overlap partially, fully, or not at all. A wide variety of local hydrologic functions associated with urban and natural land use, agricultural management, irrigation, and local routing are handled with hydrologic process modules. These modules also control evapotranspiration and rain interactions, as well as unsaturated flow distributions.

Management Simulation Engine

The management simulation engine is based on the principle that managerial decisions applied to water control structures can be viewed as information processing algorithms distinct from the hydrological state information on which they operate. Essentially, HSE provides hydrological state information (Σ), external policies dictate managerial constraints and objectives (Λ), and MSE appropriately processes the (optionally filtered, or assessed) state and policy information to produce water management control signals (χ, μ). These control signals are applied to the hydraulic structures in HSE to satisfy the desired constraints and objectives. Figure 1 illustrates this overall cyclic flow of state and management information in the RSM.

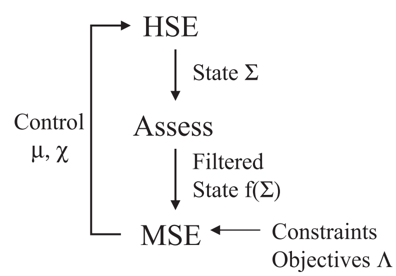

FIGURE 1. RSM State and Management Information Flow.

Multilayer Control

Specifically, the MSE architecture is based on a multilayered hierarchy, with watermovers (W) simulating water control structures, controllers (C) regulating the flow of watermovers, while the coordination and behavior of controllers are determined by supervisors (S). A schematic depiction of the

HSE-MSE layered hierarchy is shown in Figure 2. A complete description and details of the available controllers and supervisors can be found in the MSE users manual (South Florida Water Management District, 2005b).

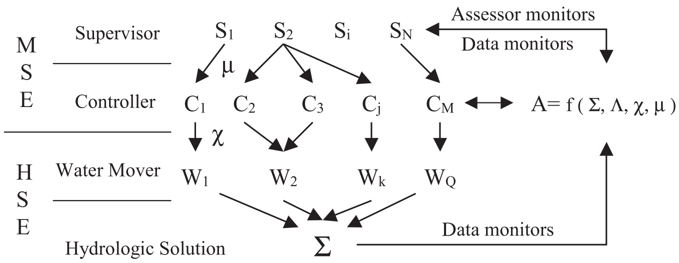

FIGURE 2. HSE-MSE Schematic Illustrating the Multilayer Control Architecture.

At the lowest layer is the hydrological state information (Σ) computed by HSE. This information includes water stages, flow values, rainfall, ET, hydrologic boundary conditions, or any other state variable used as input or computed as output by the HSE. All such variables are made available to the MSE through a data monitor interface and the optional use of assessors (A). An assessor is a data filter capable of computing spatio-temporal expectations, accumulation, or other suitable data filtering operations as indicated by the functional $A = f(\Sigma, \Lambda, \chi, \mu)$. Data monitors extend naturally to the MSE input/output variables. Therefore, the input state information available to a controller or supervisor through a monitor is not limited to water levels or flow values, but can include control information, decision variables, constraints or any other management variable.

The top level of the MSE is the supervisory layer. The function of a supervisor is to produce a supervisory signal (μ) which can change the behavior of a controller, for example, change a control setpoint value. Supervisors are designed to control multiple controllers, providing a natural way to coordinate operation of multiple controllers and their watermovers. In the case where multiple controllers are attached to a single watermover, a supervisor can dynamically select and activate a specific controller.

The intermediate layer consists of the watermover controllers. The purpose of a controller is to regulate the maximum available flow through a watermover to satisfy a local constraint. For example, a controller might be a rulecurve, a proportional-integral-derivative (PID) feedback controller, or a fuzzy controller. The MSE allows controller outputs in the range of $\chi \in [0, 1]$. The value of χ is multiplied by the watermover flow capacity (under current headwater-tailwater conditions) to compute the controlled structure flow. A value of $\chi = 0$ means no flow, $\chi = 1$ results in full flow capacity, and in general a fractional value of χ provides an equivalent fractional flow capacity.

An important feature of the MSE is the uniform interface between layers: the interface is equivalent between any supervisor and controller, and between any controller and watermover. As a result supervisors and controllers can be easily switched, even while the model is executing. This aspect is demonstrated below where fuzzy controllers optimized for standard operations are dynamically replaced with proportional and discrete flood controllers in response to significant rain events and water level conditions. This modular approach simplifies evaluation of alternative management policies, and reduces the overhead associated with reformulating and maintaining complex control modules in simulation models.

It should be noted that the implementation of specific controllers is not crucial to the demonstration of hybrid control. Similar results could be obtained with PID controllers as the default switched with fuzzy flood controllers, or other combinations of controllers which best suit the individual control requirements.

DYNAMIC CONTROL APPLICATION

South Florida Simulation Model

To illustrate a hybrid control scheme based on dynamic switching of control processors in an integrated RSM application, a model which represents the Florida lower east coast is used. This model covers roughly the area from Lake Okeechobee in the northwest to southern Miami-Dade county in the southeast. The HSE model consists of 1,124 mesh cells representing a single layer aquifer and ground surface, coupled with a canal network consisting of 455 segments. Figure 3 illustrates the HSE mesh and canal network.

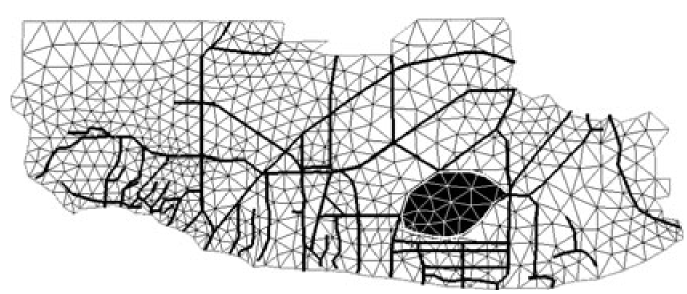

FIGURE 3. Example of RSM Application Mesh and Canal Network, Basin WCA1, Is Highlighted.

Environmental boundary conditions including aquifer hydraulic conductivity, rainfall and evapotranspiration were obtained from SFWMD datasets compiled for, and used by the South Florida Water Management Model (SFWMM). Details on the collection and processing of these data can be found in the SFWMM documentation (SFWMD, 2005c). Hydraulic boundary conditions such as mesh cell water stage along the edge of the model domain, and canal segment water stages at Lake Okeechobee inlets were also obtained from the SFWMM datasets. The complete set of model input data are available by request from the authors.

MSE Implementation

The MSE implementation incorporates 192 hydraulic structure watermovers, with a controller assigned to each watermover. There are 12 supervisors which control coordination of the controllers, however, this article is concerned with a single supervisor that coordinates flood control operations within a single basin of the model. The highlighted area in Figure 3 is a basin which corresponds to the northernmost extent of the Everglades. It is a federally protected wetland, the Arthur R. Marshall Loxahatchee National Wildlife Refuge, and is commonly referred to as Water Conservation Area 1 (WCA1). The refuge is surrounded by a canal and levee system which effectively isolates it from the adjacent lands. Water levels inside WCA1 are controlled through a series of inlet and outlet hydraulic structures located on the perimeter canals of the basin. Figure 4 depicts a schematic representation of WCA1 with the major control structures and their flow paths indicated as arrows.

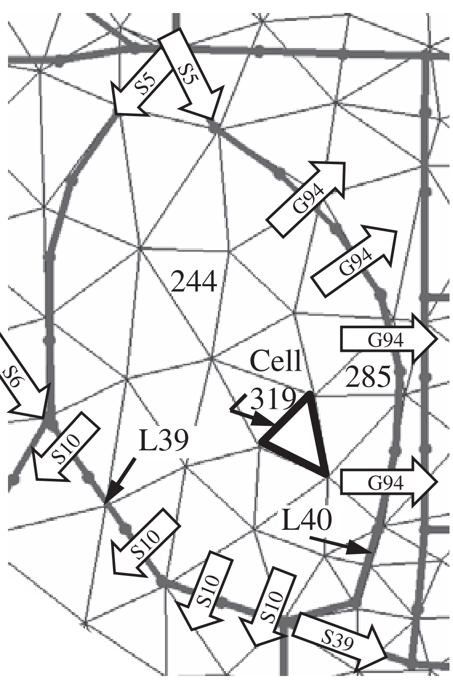

FIGURE 4. WCA1 Model Conceptualization.

The primary outlet flow structures from WCA1 are the series of S10 structures along the lower left canal rim (L39 canal). These structures discharge into an adjacent Everglades basin. The hydraulic structure S39 controls flow from the southern WCA1 rim canal (confluence of L39 and L40) into a coastal outlet canal. Additionally, the series of G94 structures are capable of discharging from the WCA1 L40 canal into an adjacent drainage district. These outlet structures will be controlled with the hybrid scheme described in the following section in order to achieve the objective specified in the Introduction.

HYBRID CONTROL

Hybrid control of structures S10, G94, and S39 is simulated by dynamically switching a default fuzzy controller with a piecewise linear flood controller in response to antecedent rainfall and water levels in WCA1. The individual controllers are described below, followed by details of the hybrid supervisor, which directs the dynamic switching.

Default Controllers

The default controllers for the S10, G94, and S39 structures are fuzzy controllers designed to maintain water levels in the WCA1 wetlands and perimeter canals. The S10 and G94 controllers are based on headwater inputs from the L39 and L40 canals, respectively, while S39 controller input is based on a tailwater constraint at a coastal structure downstream of S39. The input terms and rules for these controllers are shown in Figure 5. For example, consider input to the S10 fuzzy controller (L39 Canal Stage) with a value of 4.0 m. Referring to the center of Figure 5, this input will be classified as "medium" with a membership value of 1 (the input is fully "medium"). In this case, only RULE 2 will be activated for output. The output will be "S10 Control IS tenth open," corresponding to $\chi = 0.1$ resulting in a flow at 10% of watermover capacity. Had the input value been 4.5 m, it would have been classified as both 'medium' and 'high' to some fractional degree, with the result that RULE 2 and RULE 3 would have both been activated to some degree.

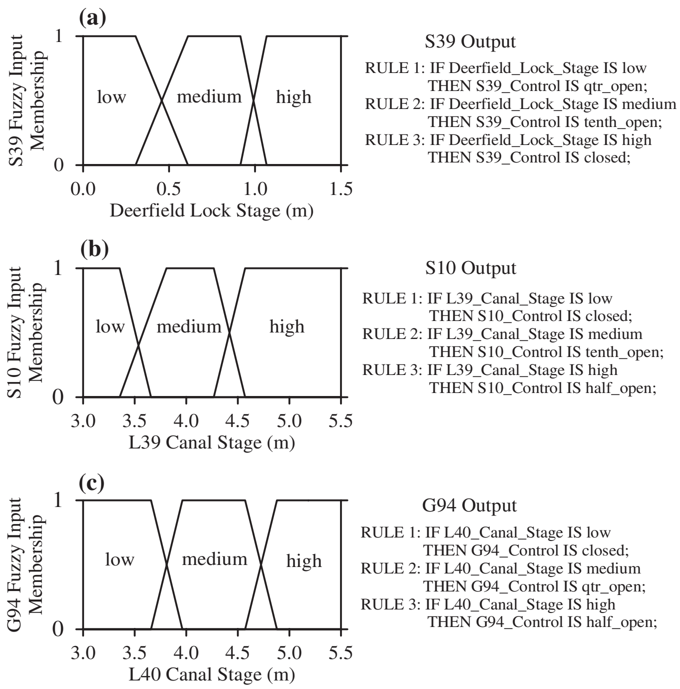

FIGURE 5. Default Fuzzy Controller Input Terms and Output Rules.

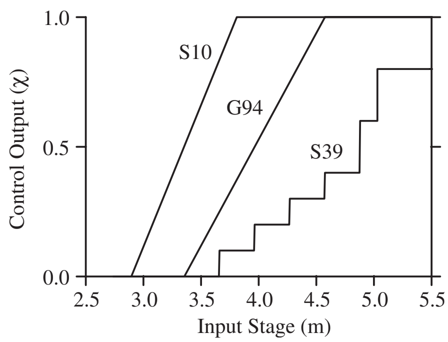

FIGURE 6. Flood Controller Functions.

Flood Controllers

The flood control functions are shown in Figure 6. The S10 and G94 flood controllers monitor the same input canal levels as the default controllers, but provide larger structure flows for equivalent canal levels. For example, if the S10 headwater has a value of 4.0 m, then the controller output for S10 is $\chi = 1$. The structure will flow at full capacity. These control functions are simple proportional controllers.

The S39 flood controller input is the watertable level at Cell 319 (Figure 4) inside the WCA1 basin. Flood control gate openings for S39 are set according to the "staircase" function shown in Figure 6 that is a discrete mapping limited to a small set of control values or gate openings. This situation is commonly encountered in the manual operation of structure flow control gates.

Dynamic Control Switching

Dynamic switching of controllers is governed by a supervisor defined in a C++ module using a standard MSE interface (see User Defined Supervisors in SFWMD, 2005b). A schematic of the MSE components associated with this supervisor is presented in Figure 7. Fuzzy controllers are labeled FS10, FG94, FS39, and flood controllers are denoted LS10, LG94, and LS39. The watermovers S10, G94, and S39, correspond to the structures shown in Figure 4. At each simulation timestep, the Hybrid Supervisor can select one of the LS10, LG94, and LS39 controllers to replace the fuzzy controller for each watermover. For example, the supervisor may direct that two of the S10 watermovers are switched to flood control, while two remain under fuzzy control, or, it might command that all four S10 watermovers are switched to flood control. At any point in time, only one controller is activated for each watermover.

Supervisory decisions are based upon state information input through an assessor and data monitors. Data monitors provide raw hydrologic state information, such as L39 and L40 canal water levels, while the assessor monitor inputs processed state information from the Assessor. The Assessor of Figure 7 computes an average watertable level (WCA1 Avg) from the three WCA1 mesh cells 244, 285, and 319 (see Figure 4); and a spatio-temporal moving average of rainfall from the same three cells (WCA1 Rain). The assessed rain is computed by first applying a moving

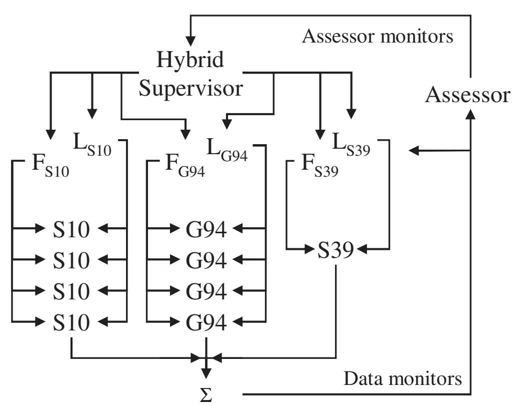

FIGURE 7. Schematic MSE Implementation for WCA1 Hybrid Control.

average to the rainfall over a 3-day period, then averaging these values over the three cells. The assessed and raw state information input to the supervisor are shown in Figure 8.

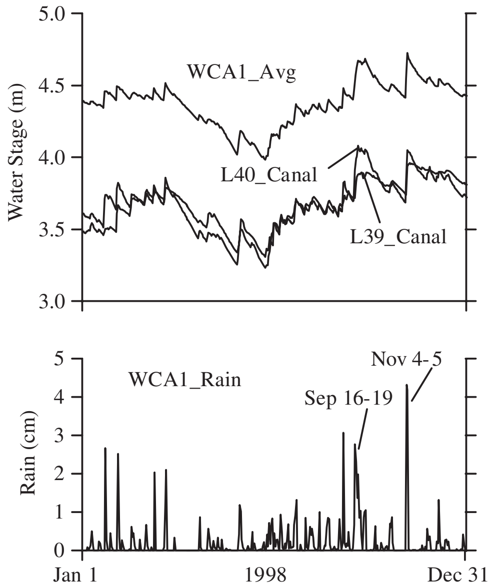

FIGURE 8. Inputs to WCA1 Hybrid Supervisor: Assessed Stage and Rainfall From WCA1; Raw L40 and L39 Canal Water Levels.

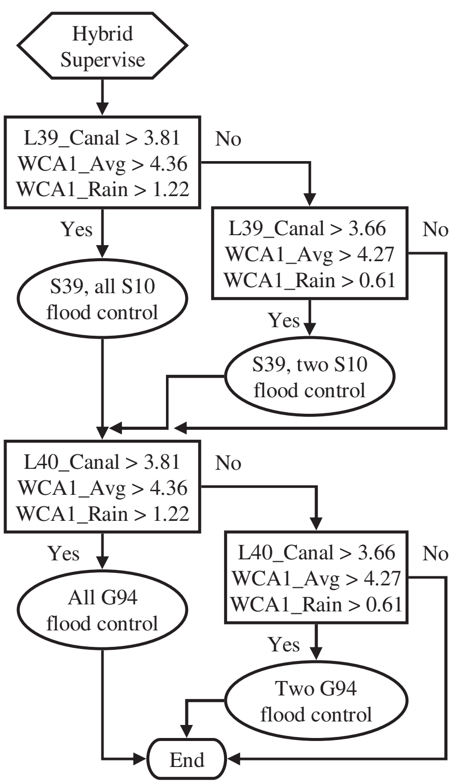

FIGURE 9. Flowchart of Dynamic Control Switching Hybrid Supervisor. Decisions are represented by boxes, all conditions in a box must be true to produce a "yes" decision. Actions are represented with ovals.

The Hybrid Supervisor is a simple decision tree which has five possible supervisory actions as shown in Figure 9:

1. No action.
2. Switch S39, four S10 to flood control.
3. Switch S39, two S10 to flood control.
4. Switch four G94 to flood control.
5. Switch two G94 to flood control.

The second and third supervisory actions are mutually exclusive, as are the fourth and fifth. Simulation results from this hybrid control are presented below.

SIMULATION MODEL RESULTS

The RSM model was executed for the period of January 1, 1998 to December 31, 1998. This period encompasses the May-September rainy season, as well as several exceptional rain events, including tropical storm Mitch, which passed over the area on November 5, 1998.

Controller Outputs

Figure 10a plots controller outputs from the G94 fuzzy and flood controllers in response to the L40 canal levels shown in Figure 8. The proportional nature of the flood controller is clear based on the L40 canal stage input.

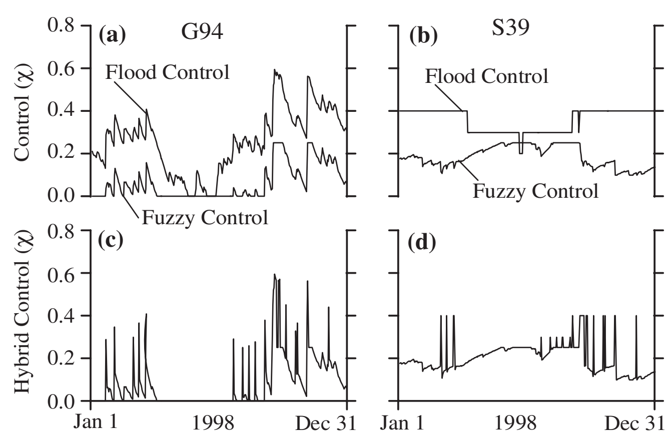

FIGURE 10. Comparison of Control Outputs. (a) Flood and default controller responses for G94. (b) Flood and default responses for S39. (c) Hybrid control of G94. (d) Hybrid control of S39.

The default and flood controller responses for S39 are presented in Figure 10b. It is clear that the flood controller is limited to a discrete set of outputs similar to a manual gate operating procedure.

The hybrid control responses are a selective superposition of the default and flood controllers as decided by the supervisory algorithm. The resultant control outputs for the G94 and S39 structures are plotted in Figures 10c and d. These are the final control signals applied to the G94 and S39 watermovers. It can be seen that the hybrid control is stable and bounded. The effect of these flows on the water levels in WCA1 canals and interior lands are examined below.

Flow and Stage Comparison

Simulation flows for the S39, and one of the S10 and G94 structures are depicted in Figure 11. The plots on the left side (a, c, e) are model results with the hybrid supervisor deactivated, flows are dictated by the default fuzzy controllers. The plots on the right side (b, d, f) correspond to flows produced by the hybrid control signals created from supervisory dynamic control switching. It is clear that the hybrid control affords flood control reactions to rain and stage states which are ignored by the default controllers. The hybrid control has effectively combined the desired features of two distinct controllers, without a change required to either one.

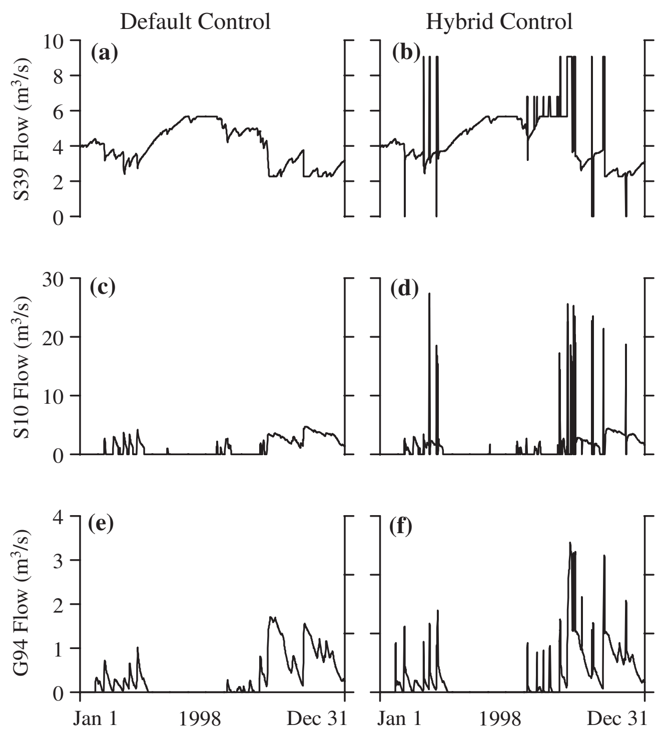

FIGURE 11. Comparison of Supervised and Unsupervised Structure Flows. (a) S39 flow with no supervision. (b) S39 flow with supervised (hybrid) control. (c) S10 flow with no supervision. (d) S10 flow with hybrid control. (e) G94 flow with no supervision. (f) G94 flow with hybrid control.

A comparison of canal stage in response to the default and hybrid control schemes over the September-December timeframe is shown in Figure 12. In response to the significant rain events in mid September, the hybrid control is responsible for maintaining the L40 canal approximately 20 cm lower than the unsupervised control. A similar suppression of canal stage is observed in response to the tropical storm of early November. The L39 canal stage reductions are smaller in amplitude, but still indicate the effectiveness of the hybrid control.

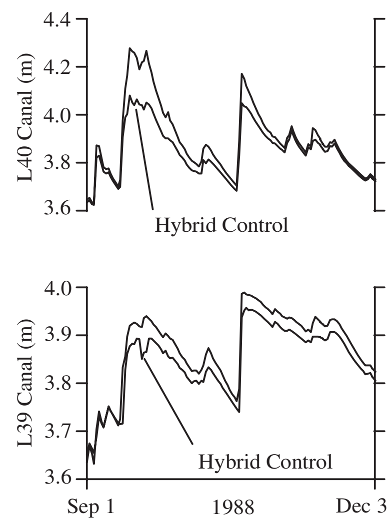

FIGURE 12. Comparison of L39 and L40 Canal Stages With Default and Hybrid Control.

CONCLUSION

Numerical hydrological models provide important guidance in the planning and activation of water resource management. As the scope and complexity of the modeled systems grow, it is useful for the management simulation of the models to allow expressions of control policies that are congruent with the actual operational policies. Such transparency between the modeled and field implemented control expressions allows nontechnical operators to easily understand the control implementation. Conversely, the operators can feedback their management approaches directly to the model implementors. One way to implement simplified control expressions is through dynamic switching of well-known process controllers. This is similar to the manner in which some experienced operators manually change control behaviors in response to variable hydrological forcing.

In the RSM, hybrid control functions are enabled through the implementation of a multilayer control hierarchy with uniform interfaces between the supervisory-controller, and controller-watermover layers. The multilayer architecture allows supervisors to change the behavior of hydraulic controllers in a natural way, for example by dynamically switching controllers, or by changing the operating parameters of a controller in response to hydrological or managerial state information.

To demonstrate this capability, a set of tuned fuzzy controllers were dynamically switched with piecewise-linear flood controllers in response to synoptic rainfall and water stage information in order to control water levels in a subregional basin. The hybrid performance of these controllers was effective in lowering canal water levels in response to rainfall events without sacrificing the overall behavior of the tuned fuzzy controllers. Such a hybrid approach may simplify the design and implementation of complex water management simulations, while retaining relatively simple expressions of the hybrid control. This modular approach lends itself naturally to evaluation of a wide range of control schemes without the need to reformulate the controllers as required in other approaches.

It is also recognized that utility of a layered control hierarchy is not limited to hydrological simulation. Indeed, this approach can be generally applied to operational control management practices since the source of the state and process information is not inherent to the control hierarchy. For example, if the hydrological state information is input from a suite of real-time field monitoring stations, and process control information is monitored and activated through a real-time command and control communication network, the multilayered control system depicted in Figure 2 can still be applied. The hydrological information, Σ, is input from the field monitoring data, while Controller to Watermover control commands are propagated over the command and control communication network. Thus the opportunity exists for nearly equivalent representations of field implemented and numerically modeled control systems.

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