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João M. LEMOS*, Luís M. RATO**, F. MACHADO*** , Nuno NOGUEIRA***,
Pedro SALGUEIRO****, Rui N. SILVA*****, Manuel RIJO******

PREDICTIVE ADAPTIVE CONTROL OF WATER LEVEL IN CANAL POOLS

A case study on the use of a predictive adaptive algorithm to control pool level in a pilot water distribuition canal is described. The algorithm is a modification of the basic MUSMAR controller that includes parallel integral action and, in the case of multiple pools, feedforward action to coordinate the gates. Experimental results in the case of a single pool and simulations for multiple pools are presented. The contributions of the paper stem from the explicitation of rules for tuning the adaptive controller in a practical situation and from the coordination of different pools using reduced complexity controllers and feedforward in a multivariable setting.

1. INTRODUCTION

The problem considered in the paper is the control of the pool level in a pilot water distribution canal. This problem has been the subject of a lot of attention, of which [1-5] are representative examples. The main difficulties are unmodelled dynamics (the plant is infinite dimensional), variable transport delays and strong interactions between the different subsystems (pools). While the generatility of existing references depart from a model that is initially identified, serving then as a basis for controller design, the approach followed in this paper relies on adaptive control and hence allows for changes of the canal dynamics due to unpredictable factors that slowly act over time. This approach has also the advantage of not requiring the expensive initial phase of modelling.

In order to control the canal the predictive adaptive MUSMAR algorithm was selected [6]. This algorithm has a number of advantageous features such as a certain degree of insensivity with respect to plant i/o transport delay and unmodelled dynamics [7]. It has been applied to several industrial or large scale plants with distributed parameter dynamics including industrial boilers [8], arc welding [9] and distributed collector solar fields [10].

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* INESC-ID/IST, R. Alves Redol 9, 1000-029 Lisboa, Portugal, jlml@inesc.pt. Corresponding author. The work reported in this paper was performed under project FLOW, POSC/EEA-SRI/61188/2004, supp. by POSC and FEDER, and NiSIS (Nature Inspired Smart Information Systems) network.
** Departamento de Informática, Universidade de Évora, 7000 Évora, Portugal, lmr@di.uevora.pt.
*** INESC-ID/IST, R. Alves Redol 9, 1000-029 Lisboa, Portugal.
**** INESC-ID/IST, R. Alves Redol 9, 1000-029 Lisboa, Portugal.
***** Departamento de Informática, Universidade de Évora, 7000 Évora, Portugal, PDS@di.uevora.pt.
****** Dep. de Eng. Electrot. e de Computadores, Fac. De Ciências e Tecnologia, Univ. Nova de Lisboa, rns@fct.unl.pt
******* Núcleo de Hidr. e Controlo de Canais, Univ. de Évora, Apartado 94, 7002-544 Évora, Portugal, rijo@uevora.pt.

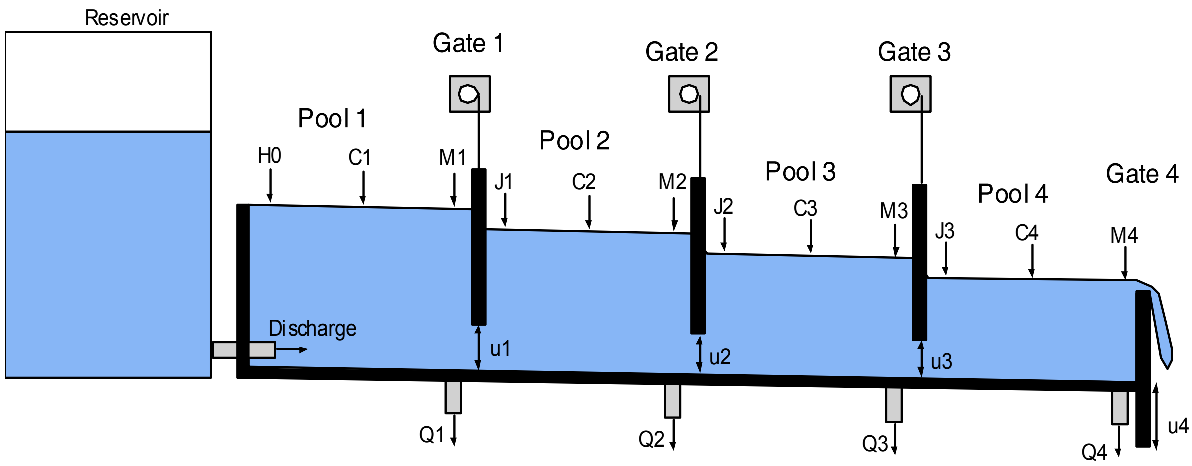
The present paper includes results for a single pool as well as for multiple pools. Both the objectives of tracking a reference and regulating the level in the presence of disturbances for each pool level are considered. The paper is organised as follows: After this introduction, the plant is described in section 2. Section 3 describes the algorithm and its adaptation to the problem at hand and section 4 presents experimental and simulation results. Conclusions are drawn in section 5.

2. PLANT DESCRIPTION

The plant to be controlled is the experimental canal of *Núcleo de Hidráulica e Controlo de Canais* of UNiversidade de Évora, located in the south of Portugal. Figs. 1 and 2 show a general view of it. It has been the subject of other studies, *e. g.* [4].

1. Overall view of the experimental canal.

2. The end of the computer controlled canal with gate 3 (foreground) and gate 4 (background) and the beginning of the returning traditional canal (feft). On the right the wells where two level sensors are installed can be seen.

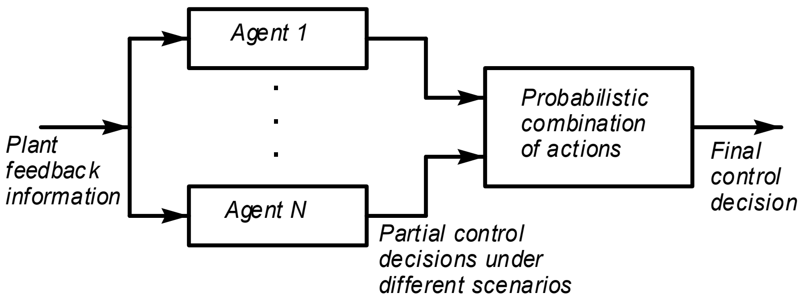


3. Schematic view of the experimental computer controlled canal.

The canal has *141 m* long and is divided in 4 pools, separated by gates. A SCADA system allows to perform computer control of the system with a sampling interval of *1 s*. From the systems point of view, this is a distributed parameter system with 4 inputs (the gate position commands), 4 outputs (the level of each pool measured just before each gate) and 4 disturbances (water flow outlets in each pool). Fig. 3 shows a schematic view of the canal, with the main variables indicated.

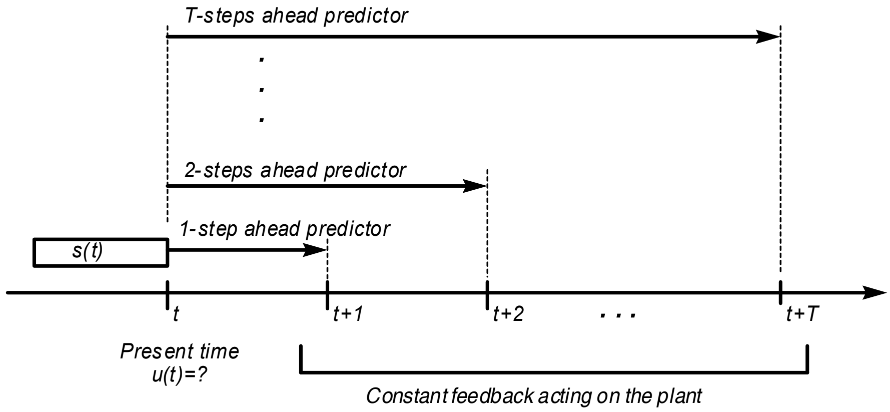
3. THE CONTROL ALGORITHM

Many natural systems rely on multiple individual actions that combine in a probabilistic way to yield the desired result. In a control framework, this inspires a structure where the control decision is based on the probabilistic merging of multiple agents, such as shown in fig. 4. Each agent receives the same plant signals but takes partial decisions assuming different scenarios. A probabilistic combination of these partial actions yields the final control decision.



3. Control decision based on the probabilistic merging of multiple agents.

In an ideal situation (perfect modelling, complete state information, no disturbances, no nonlinearities), only one agent (one controller, based on a single plant model) would be enough to achieve a high performance controller. In the presence of non-ideal factors, however, a controller based on just one agent is prone to yield incorrect control actions. If, instead, the controller is based on multiple agents (simpler controllers based on different plant models), the diversity thereby introduced leads to increased performance and robustness properties.



4. Diversity based plant description using multiple predictors sharing a common regressor build from plant data, assuming a constant feedback from $t+1$ up to $t+T$.

In order to achieve a practical control algorithm, the plant I is described (fig. 4) by multiple predictive models, sharing a common regressor. Assuming a constant feedback to act on the plant, the predictive models are described by

$$y(t+i) = \theta_i u(t) + \psi_i' s(t) + v_i(t)$$
$$u(t+i-1) = \mu_{i-1} u(t) + \phi_{i-1} s(t) + w_{i-1}(t) \qquad i = 1, \dots, T$$

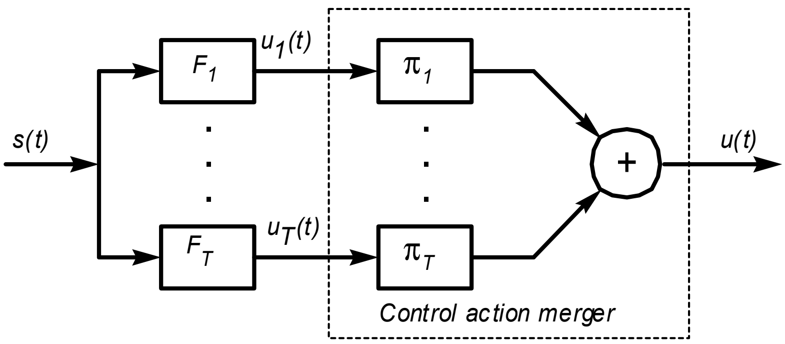
where u is the manipulated variable, y is the deviation of the output of the system to control with respect to the set-point, v and w are residues orthogonal to the data in a least squares sense and $\theta_i, \psi_i, \mu_i, \phi_i$ are parameters to be extracted from plant data using Least Squares. The pseudo-state vector $s(t)$ is made from samples of past plant data and defines the controller structure. An example is

$$s(t) := [y(t) \cdots y(t-n+1)\ u(t-1) \cdots u(t-m)\ w(t) \cdots w(t-p+1)]'$$

where w is an auxiliary signal (system's internal variable or accessible disturbance). Each of the individual agents is designed such as to minimize the single-step horizon i steps ahead cost functional given by

$$J_i(t) = E\left[y^2(t+i) + \rho u^2(t+i-1) \mid I^t\right] \qquad i = 1, \dots, T$$

where $E[\circ \mid I^t]$ is the mean conditioned on the available observations up to time t, I^t.



5. Realization of the MUSMAR control [6] law by merging T self-tuners, each matched to a single-step horizon i-steps ahead cost functional. Compare with fig. 2.

The control action generated by the partial controller (agent) i is given by a feedback from the pseudo-state $s(t)$

$$u_i(t) = F_i' s(t) \qquad i = 1, \ldots, T \qquad \text{with} \quad F_i = \frac{1}{\theta_i^2 + \rho\,\mu_{i-1}^2}\left(\theta_i\,\psi_i + \rho\,\mu_{i-1}\,\phi_{i-1}\right)$$

and the probabilistic weights for merging these actions are given by [2] (see fig. 4 for a block diagram that parallels fig. 2):

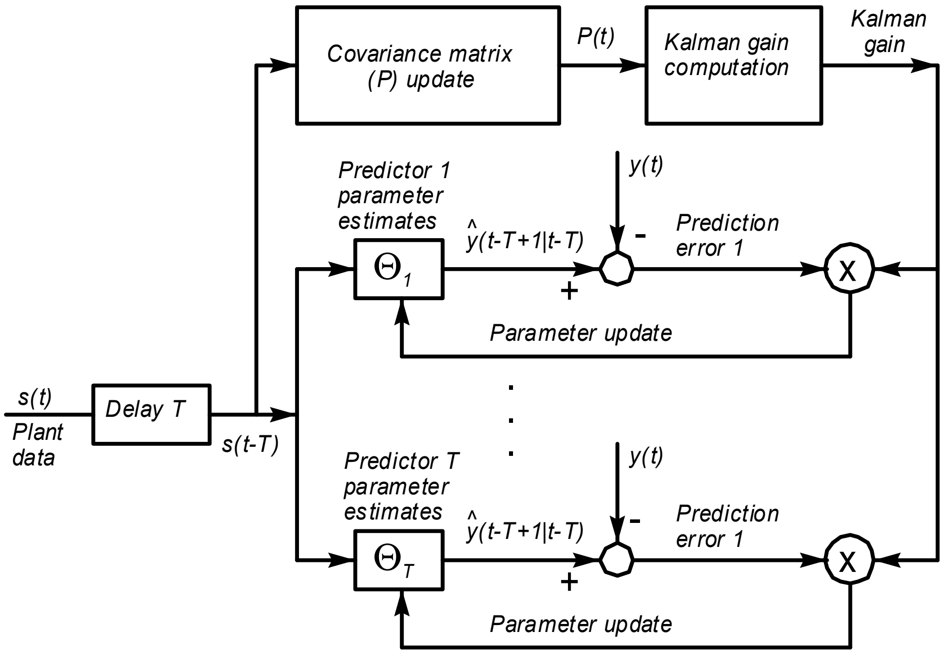
$$\pi_i = \frac{\theta_i^2 + \rho\,\mu_{i-1}^2}{\sum_{j=1}^{T}\left(\theta_j^2 + \rho\mu_{j-1}^2\right)}$$

Actually, this multiple actions merge to yield the control action simply defined by

$$u(t) = F' s(t) \qquad \text{with } F = -\frac{\sum_{i=1}^{T}\theta_i\psi_i + \rho\,\mu_i\phi_i}{\sum_{i=1}^{T}\left(\theta_i^2 + \rho\,\mu_{i-1}^2\right)}$$

This controller has a number of interesting features that are a consequence of the diversity features that it embodies. In particular, the update of the gain vector F is made suich as to minimize the steady state quadratic cost defined by

$$J^\infty = \lim_{t\to\infty} E\left[y^2(t) + \rho\,u^2(t)\right]$$



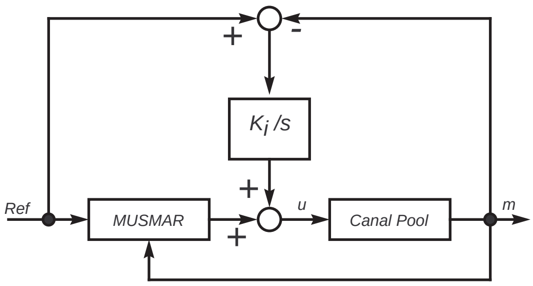
6. Multiple predictors parameter update from plant data, using a common Kalman gain and redundant estimates.

Indeed, the update of F in two consecutive time steps is given by

$$F(t) = F(t-1) - \frac{1}{\alpha} R_s^{-1} \nabla_T J^\infty(F(t-1))$$

where $\alpha = \sum_{j=1}^{T} \theta_j^2 + \rho \mu_{j-1}^2$, R_s is an approximation of the Hessian matrix of J^∞ and $\nabla_T J^\infty(F(t-1))$ is an approximation of the gradient of the steady state cost with respect to the cost. Hence, the controller acts as an approximation to a Newton type minimization algorithm that seeks the minimum of the steady state quadratic cost. Furthermore, this approximation becomes better when the number of predictive models (the diversity) increases.

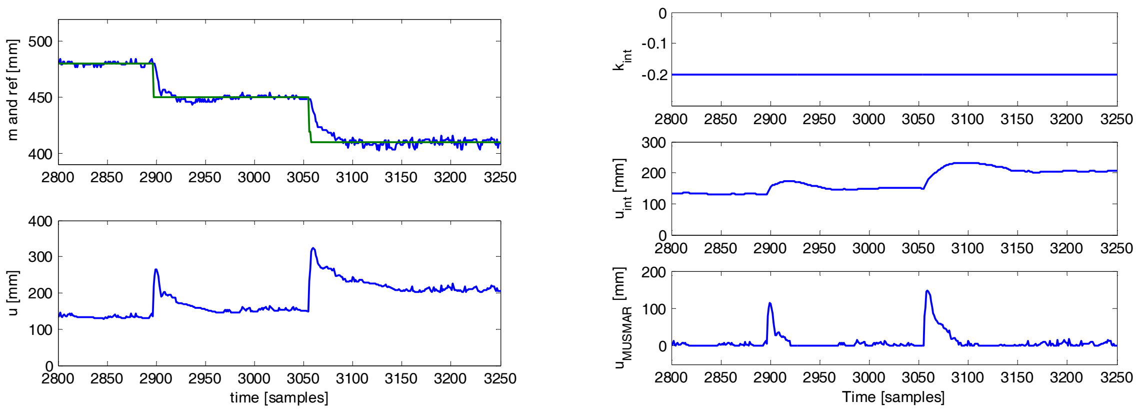
Separate MUSMAR controllers are employed for each pool, but with feedforward signals designed in such a way has to coordinate them. This is achieved by using as accessible disturbance in each controller the sum of the tracking error of the precedent pools. Furthermore, a low gain integrator is used in pareallel to eliminate stationary tracking errors (fig. 7).



7. Block diagram of the controller:MUSMAR with the parallel integrator.

4. RESULTS

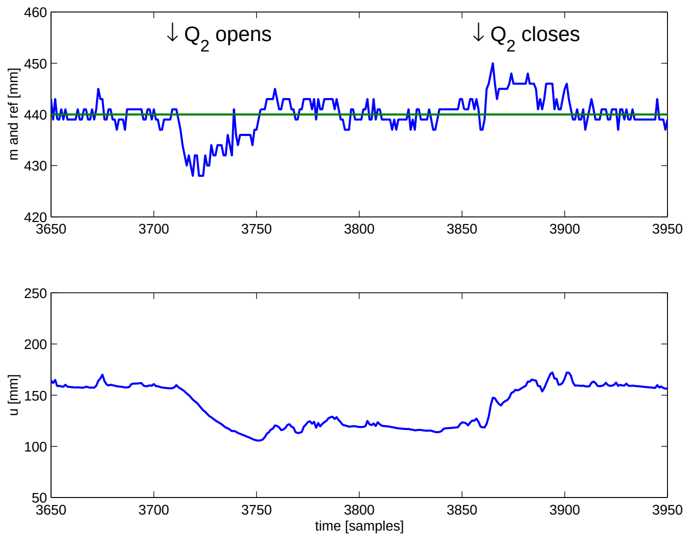
Figs. 8 and 9 show experimental results for a single pool. The configuration used was $T = 10$



8. Tracking a reference level. Left: model and reference (top) and manipulated variable (bottom). Right: Contribution of the integral effect (middle) and of MUSMAR (bottom) to the manipulated variable. Experimental results with one pool.

$n = 3$, $m = 2$, $\rho = 0.01$ and $K_I = -0.02$. Fig. 8 (right) shows how MUSMARE and the parallel integrator conjugate their control actions. MUSMAR acts essentially during the transients, providing a fast response, while the integrator adjusts the gate position during steady state to achieve zero tracking error.

Fig. 9 shows experimental results on disturbance rejection. The disturbances are induced by opening the exterior outlet to simulate the use of water for irrigation. When the outlet Q_2 opens, the gate closes to compensate the loss in water flow.



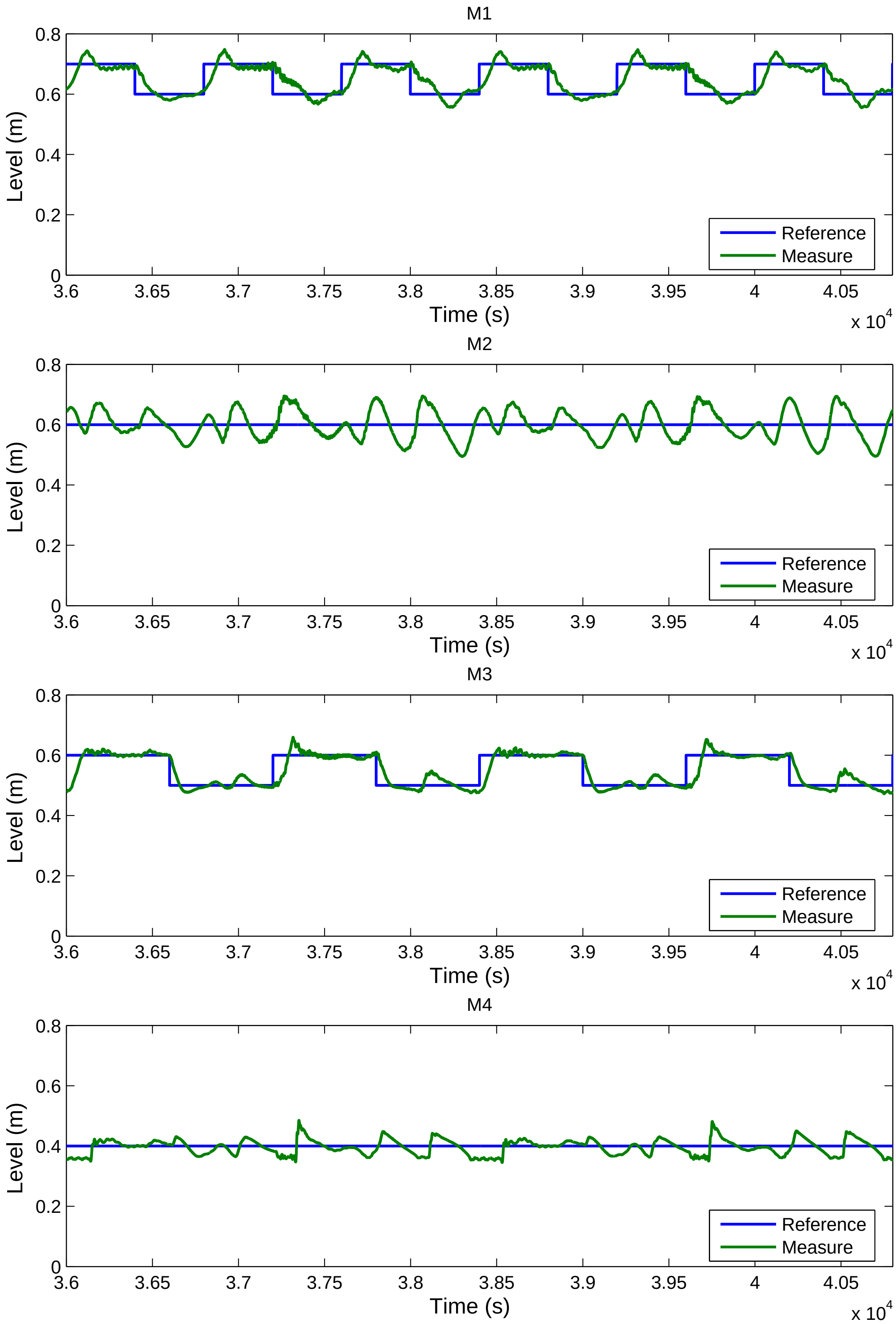
9. Rejecting disturbances due to the opening of the external outlet: Measured level and constant reference (above) and manipulated variable (below).

Figs 10 and 11 show simulation results when the four pools of the canal are controlled each with a MUSMAR controller having an integrator in parallel. The simulation was performed using a SIMULINK model based on the numeric integration of the Saint-Venant equations that has been calibrated with plant data.

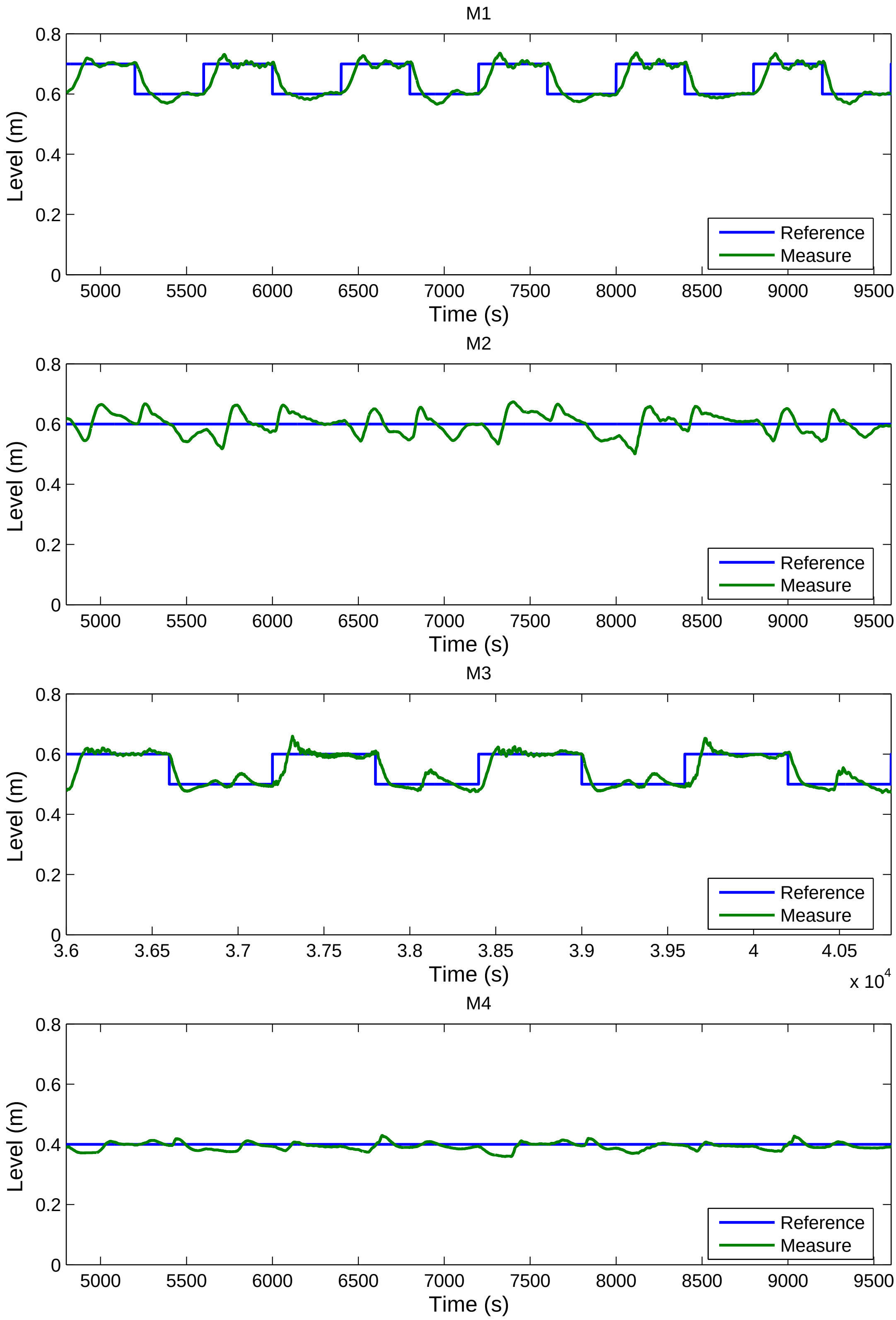
In a practical situation, a canal is usually operated with a constant reference. In this case, for the sake of testing the dynamic response of the controlled canal, the reference of pools 1 and 3 is made to vary in alternation, according to squared signals. This induces disturbances from the one pool into the others, resulting in frequent level changes.

In the case of fig. 11 there is a feedforward included in the pseudo-state made from the sum of the tracking errfors of the previous pools, while for fig. 10 this feedforward action is not used. The rationale for this consists in the fact that the controller of a pool will act to compensate the existing tracking error and this results in the retention of release of a certain quantity of water that will disturb the down-stream pools forcing their controllers, in turn, to react. The feedforward action allows a corrective action that anticipates the effect of the water expected to arrive due to the action of the upstream controllers.

As can be seen by comparying both figures, the feedforward action results in oscillations of small amplitude.



. 10. Tracking a reference level. Level and reference of the four pools when all pools are controlled with MUSMAR.



11. Tracking a reference level. Level and reference of the four pools when all pools are controlled with MUSMAR with feedforward.

5. CONCLUSIONS

The paper shows how to configure a predictive adaptive controller in a practical situation. Prediction over extended horizon is needed for tackling the difficulties associated with the variable delays associated to the transport phenomena (water displacement). The redundancy in the identification of the predictive models helps tackling unmodeled dynamics inherent to an infinite order (distributed) plant. Furthermore, this is a multivariable plant with strong interaction between the different parts. Although MUSMAR could be configured as a multivariable controller, this would yield severe identifyability problems. The results show that the feedforward scheme proposed allows to achieve a good perfcormance due to a balance between pool coordination and reducing the identifyability problems.

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