REAL–TIME CONTROL OF AN OPEN CHANNEL GATE BY USE OF SELF–TUNING CONTROLLER

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ABSTRACT: This study demonstrates the application of a stochastic adaptive controller, the self-tuning controller (STC) of Clarke and Gawthrop (1975), for the real-time control of a gate opening to maintain a certain water level in the reservoir dammed by a gate. The Kalman filter is used to estimate, in real time, the parameters needed to compute the optimal control strategy. To demonstrate the effectiveness and to study the characteristics of the STC to control the gate opening, it is applied to an experimental open channel sluice gate. This study shows some detailed characteristics of the use of the STC specifically in order to control weir gate openings.

INTRODUCTION

In Japan, many weir gate structures are located in tidal inlets (river mouths) because feasible sites for reservoir constructions upstream are limited. The water of an estuarial reservoir dammed by weir gates is extracted for domestic, agricultural and industrial water uses. Water level variations are expected especially during flood periods, therefore water is released to maintain a certain water level. Maintaining a certain water level is required to prevent sea water from entering the reservoir and to avoid drainage problems due to the hydraulic connection between reservoirs and aquifers in the agricultural land close to the reservoir. Automatic feedback control can greatly enhance the efficiency of the operation of gates and increase the benefits associated with their use, as well as not allowing the water upstream to rise above a certain height. With automatic controllers, gate openings are optimally determined so that the energy consumed in operating the gates is minimized and unnecessary depletion of the reservoir is avoided.

A commonly used automatic controller receives the on-line data of upstream and downstream water levels, present gate openings, and river discharge at a nearby upstream station. These data determine the gate openings according to a control strategy and commands are then carried out to operate the gates. However, the control strategy is not very efficient in treating the stochastic nature of the system. It requires that the inflow is accurately measured or forecasted and that the system can be accurately modelled, because the deviation between actual reservoir water level and the required one is not used to correct any modelling errors. Also, it is not adaptive, i.e., if there are changes in the system, the control strategy will be incorrect. Failure to take into account the stochastic and dynamic properties of the system in designing the control strategies has resulted in largely unsatisfactory and sometimes even unable control. An alternate procedure for designing the control strategy is therefore needed.

Adaptive control systems automatically adjust controller parameters on-line in response to changes in the system dynamics, or noise characteristics, or both. This study demonstrates the application of a stochastic adaptive controller, the self-tuning controller (STC) of Clarke and Gawthrop (1975), for the real-time control of weir gate openings.

The same gate opening control problem for lock and dam gate openings has been discussed by Duong et al. (1978) using one type of self-tuning regulator reported by Wieslander and Wittenmark (1971) . A summary of self-tuning regulators is given by Astrom and Wittenmark

(1973). Although the application of the STC to optimal control of groundwater abstraction for river flow augmentation has already been discussed by O'Connell (1980), as far as we know, its application to flood control problems has not yet been investigated.

An experimental channel gate is chosen to demonstrate the effectiveness and to study the characteristics of the STC for controlling the gate opening. This study shows some interesting characteristics of specifically the STC in order to control weir gate openings.

SELF-TUNING CONTROLLER

When applying the STC for an open channel gate operation as well as a typical weir gate operation, the system model considered is expressed by

$$y(k+1) = h_0\, y(k) + b_0'\, Q(k) + c_0\, I(k) + d_0\, L(k) + v(k+1) \tag{1}$$

based on the reservoir continuity equation, where k is the sampling interval, y is the reservoir water level (system output or uncontrolled variable), Q is the gate release (system input or controllable variable), I is the inflow, L is the abstraction, v is an uncorrelated zero-mean random noise, and h_0, b_0', c_0, and d_0 are the unknown system parameters.

The objective of the STC is to control the input Q(k) so that the cost function given by Eq. (2) is minimized. The cost function consists of the expectation of the sum of squares for the deviation of the reservoir water level from a target value or 'set point' and the change in the control variable from one time step to the next.

$$J(k) = E[\,\{y(k+1) - y^*(k+1)\}^2 + \lambda'\{Q(k) - Q(k-1)\}^2\,] \tag{2}$$

Here E is the expectation operator, $y^*(k+1)$ is the set point which is the target reservoir water level, and the factor λ' is the weight for change in the control variable from one time step to the next, and is used to stabilize the controller by hampering the control effort (O'Connell, 1980).

Using the measured data for y(k), the optimal 1-step ahead predictor $\hat{y}(k+1 \mid k)$ is given as

$$\hat{y}(k+1 \mid k) = h_0\, y(k) + b_0'\, Q(k) + c_0\, I(k) + d_0\, L(k) \tag{3}$$

By substituting Eq. (3) into Eq. (1), Eq. (1) is transformed as :

$$y(k+1) = \hat{y}(k+1 \mid k) + v(k+1) \tag{4}$$

Substituting Eq. (4) into Eq. (2), taking the expectation, and setting the derivative of J(k) with respect to Q(k) equal to zero to obtain the minimum cost give:

$$\{\hat{y}(k+1 \mid k) - y^*(k+1)\}\frac{\partial \hat{y}(k+1 \mid k)}{\partial Q(k)} + \lambda'\{Q(k) - Q(k-1)\} = 0 \tag{5}$$

Using $\partial \hat{y}(k+1 \mid k) / \partial Q(k) = b_0'$ (from Eq. (3)), the control law is given by:

$$\{\hat{y}(k+1 \mid k) - y^*(k+1)\} + \lambda\{Q(k) - Q(k-1)\} \tag{6}$$

where $\lambda = \lambda' / b_0'$ (7)

Define a generalized output function ψ so that

$$\psi(k+1) = y(k+1) - y^*(k+1) + \lambda\{Q(k) - Q(k-1)\} \quad (8)$$

The prediction of $\psi(k+1)$ at time k is then obtained by replacing $y(k+1)$ with $\hat{y}(k+1 \mid k)$;

$$\hat{\psi}(k+1 \mid k) = \hat{y}(k+1 \mid k) - y^*(k+1) + \lambda\{Q(k) - Q(k-1)\} \quad (9)$$

Therefore the output function is expressed by

$$\psi(k+1) = \hat{\psi}(k+1 \mid k) + v(k+1) \quad (10)$$

Hence the minimization of J is equivalent to minimize the square of the error in the prediction of ψ by the control law (Eq. (6)) at time k. In order to implement the self-tuning scheme, Eq. (3) is substituted into Eq. (9) to obtain

$$\hat{\psi}(k+1 \mid k) = h_0\, y(k) + b_0\, Q(k) + b_1\, Q(k-1) + c_0\, I(k) + d_0\, L(k) - y^*(k+1) \quad (11)$$

where

$$b_0 = b_0' + \lambda \quad (12)$$

$$b_1 = -\lambda \quad (13)$$

Since $\hat{\psi}(k+1 \mid k)$ needs to be controlled to remain zero at every time step, Q(k) is determined from Eq. (11) as:

$$Q(k) = -\{h_0\, y(k) + b_1\, Q(k-1) + c_0\, I(k) + d_0\, L(k) - y^*(k+1)\} / b_0 \quad (14)$$

Again this control law minimizes the variance of $\psi(k)$. The substitution of Eq. (11) into Eq. (10) yields

$$\psi(k+1) = h_0\, y(k) + b_0\, Q(k) + c_0\, I(k) + d_0\, L(k) - y^*(k+1) + v(k+1) \quad (15)$$

Expressing the first four terms by the product of the so-called state vector and observation vector defined below, Eq. (15) becomes

$$\psi(k+1) = M(k+1)x(k+1) - y^*(k+1) + v(k+1) \quad (16)$$

where the state and observation vectors are

$$x(k) = [\, h_0, b_0, b_1, c_0, d_0 \,]^T \quad (17)$$

$$M(k) = [\, y(k-1), Q(k-1), Q(k-2), I(k-1), L(k-1) \,] \quad (18)$$

In order to implement the feedback control (Eq. (14)), the coefficients h_0, b_0, b_1, c_0, and d_0 are to estimated. The Kalman filtering technique is applied for the on-line identification of these coefficients and the following set of equations is recursively used:

$$x(k + 1) = x(k) + u(k) \tag{19}$$

$$\psi(k) = M(k)x(k) - y^*(k) + v(k) \tag{20}$$

In order to update the parameters, ψ needs to be measured at every time step k. Since $\psi(k)$ is defined by Eq. (8), k+1 is replaced with k and $\psi(k)$ is calculated after y(k) is measured. After this the control law (14) is again determined using the estimated parameters $\hat{x}(k|k)$ at time k. Therefore, Eq. (20) is the observation equation in the Kalman filtering formulation.

APPLICATION OF THE STC IN AN EXPERIMENTAL OPEN CHANNEL

In Fig. 1, an experimental open channel and the controlling system used in this study are shown. The experiments have been carried out following the four operational rules below;
1. A personal computer generates the time-varying inflow I which is recorded scaled-down flood flow at the Onga River in Fukuoka, Japan.
2. The personal computer receives the measured water level from the gauges installed at the up- and downstream in the channel simultaneously.
3. The STC algorithm calculates the optimal gate release after estimating the system parameters of Eq. (14).
4. A signal in volts is transmitted to a gate operation motor to facilitate the gate handling.
The four operational rules above represent one cycle. In the present experiment, 333 cycles ofthe operation were repeated until the end of the synthetically generated flood. The sampling time for measuring the water level and controlling the weir gate were equally set to 6 seconds

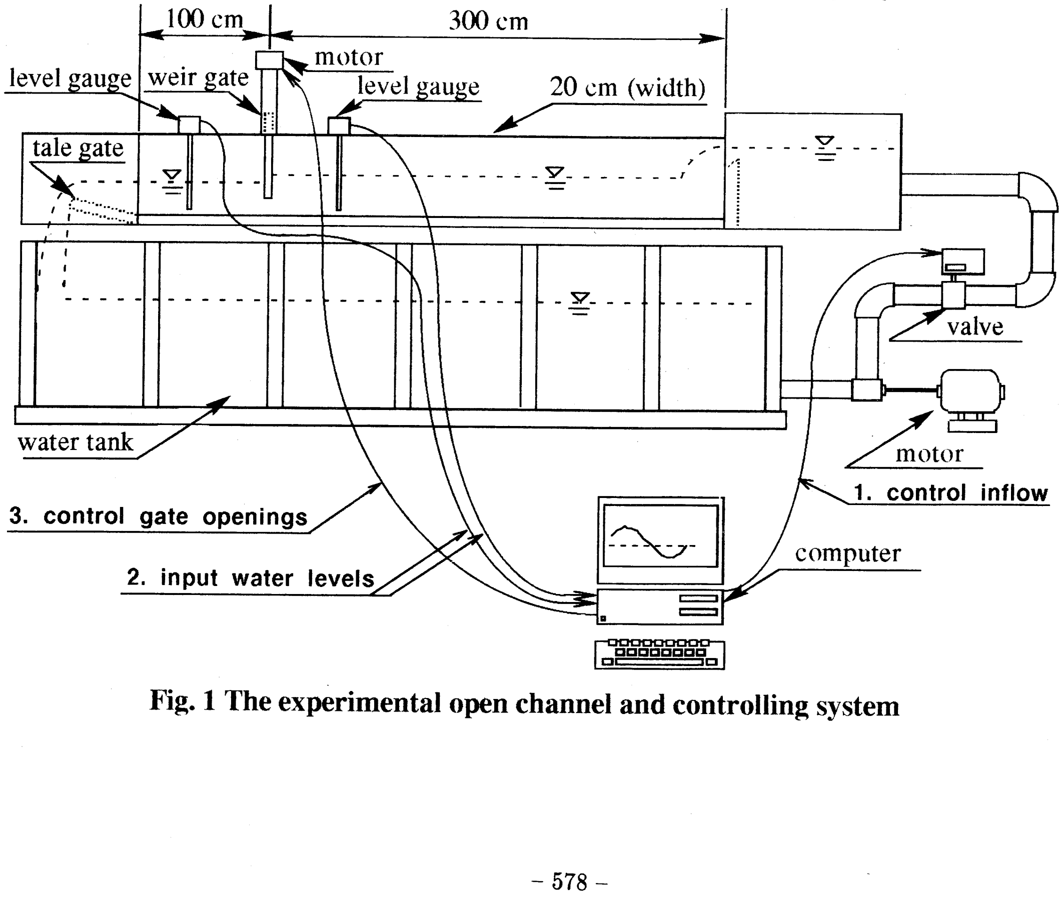

Fig. 1 The experimental open channel and controlling system

in the experiment. The target water level can be arbitrarily varied. In the present study, two cases of target water levels were tested; a constant water level and a sinusoidal change with time to check the capability of the control against the target. The weight value λ' in Eq. (2) and the initial values required for the Kalman filtering are listed in Table 1. The system noise vector u(k) in Eq. (19) was set to the state vector x(k) multiplied by 0.5% except for Examples 2 and 5. In case of Examples 2 and 5, the initial values of the system parameters were set as half of the values of those in Examples 1 and 4. This caused the system to behave poorly and the gate could not be operated well when setting the system noise level to 0.5%. Therefore, u(k) was set to be equal to x(k) multiplied by 5% in these cases. The standard deviation of the observation noise v(k) was set to 0.5cm.

Table 1 Experimental conditions

	target water level y*	weight value λ' $(\times 10^{-6})$	initial parameters $[h_0, b_0, b_1, c_0, d_0]$	system noise level
Example 1 (Fig. 2a-4a)	constant	1	[1.0, -0.002, 0.001, 0.002, -0.002]	0.5%
Example 2 (Fig. 2b-4b)	constant	1	[0.5, -0.001, 0.0005, 0.001, -0.001]	5%
Example 3 (Fig. 2c-3c)	constant	0	[1.0, -0.001, 0, 0.001, -0.001]	0.5%
Example 4 (Fig. 5)	sine curve	1	[1.0, -0.002, 0.001, 0.002, -0.002]	0.5%
Example 5 (Fig. 6)	sine curve	1	[0.5, -0.001, 0.0005, 0.001, -0.001]	5%

RESULTS AND DISCUSSIONS

Figs. 2a to 2c show the variation of the inflow I (full line) and the gate release Q (broken line) depending on the different combinations of the parameters listed in Table 1. Figs. 3a to 3c show the time series plots of observed water level y (full line) and target water level y* (broken line). Figs. 4a to 4b show the behavior of the estimates of the controller parameters. Further, as additional examples, Figs. 5 to 6 show the variation of I and Q, and the time series of y and y* where y* was set to a sine curve.

Figs. 2a to 2c indicate that the optimal gate release Q calculated from Eq. (14) follows the pattern of inflow I with some small fluctuations. These fluctuations are caused by the converting of gate discharge into gate openings. The discrepancies are mainly a result of uncertain gate discharge coefficient. If this coefficient can be determined exactly less errors can be obtained. Especially at the initial stage in Fig. 2b, the optimally determined gate release tends to fluctuate more compared with the other two cases because large values of λ' and system noise level and poor initial estimates for the state variables were used.

The plot of observed water levels y in Fig. 3 is a direct translation of the gate release Q in Fig. 2, i.e., the deviation between the observed y and target y* is large when the difference between I and Q is large. When comparing Figs. 3a and 3b it is seen that the behavior of y in Fig. 3a follows better the pattern of y* without big deviations as in Fig. 3b. However, it is noteworthy that even if the system can not be mathematically specified, the STC can automatically update

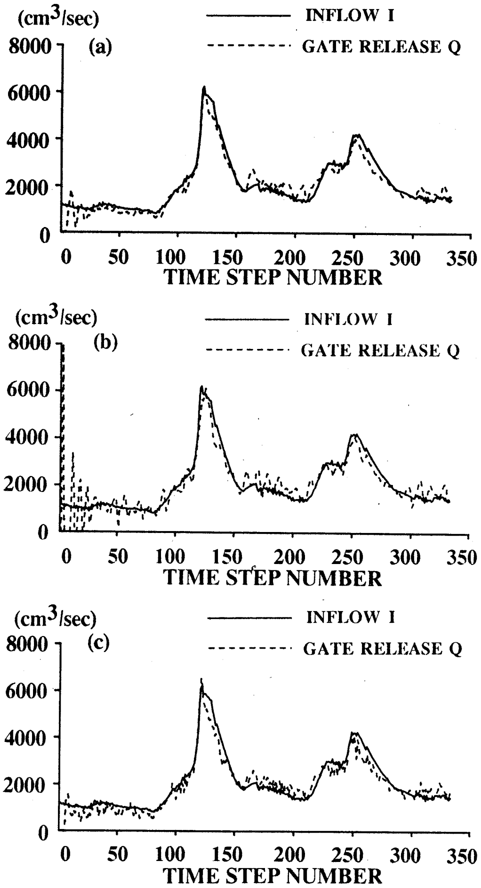

Fig. 2 Time series of inflow I and gate discharge Q

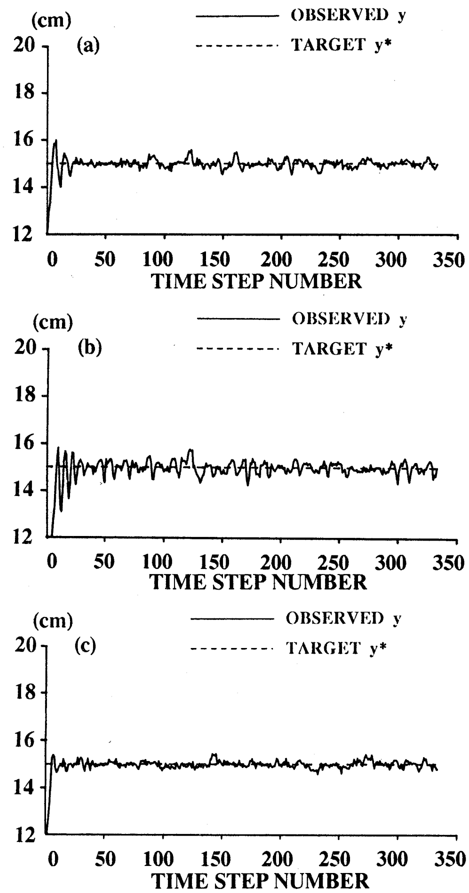

Fig. 3 Time series of observed water level y and target water level y*

to compensate itself to a natural stochastic system. In the same way, when comparing Fig. 3a with Fig. 3c it is seen that the behavior of y in the former follows better the pattern of y* than in the latter. This is due to that the weight coefficient for the change of Q from one time step to the next, in the cost function Eq. (2), equals 0. Due to this the STC algorithm neglects the change of Q and just aims at minimizing the deviation between y and y*.

The behavior of the estimates of the system parameters for Examples 1 and 2 are show in Figs. 4a and 4b. Here, the behavior of the system parameters in Example 3 has been omitted but is similar to Fig. 4a. The variation of the parameter estimates is typical for a self-tuning algorithm. During the two flood periods (see Fig. 2), the estimation process by the Kalman filter continues, but yields unstable parameter estimates as shown in both Figs. 4a and 4b. Except for these flood periods, the variation of the parameter estimates are more stable in Fig. 4a than in Fig. 4b. This is due to the difficulty in giving the initial values of the system parameters and system noise levels.

In Examples 4 and 5, the experiments were operated under the same condition regarding the weight value and the initial values for system parameters in as Examples 1 and 2, respectively. Only y* was set differently (see Table 1). Figs. 5 and 6 show that the behavior of Q and the deviation between y and y* in Examples 4 and 5 are similar to those in Examples 1 and 2. In other words, the STC can control well the weir gate system of the experimental open channel independently of the y* pattern.

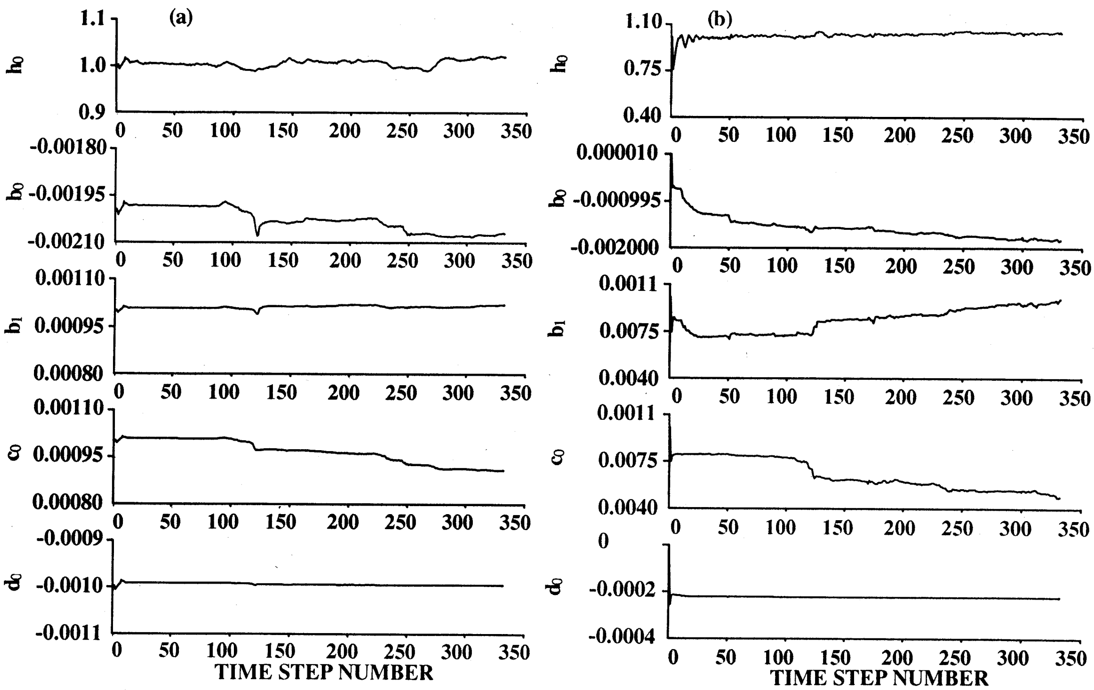

Fig. 4 Variation of the controller parameter estimates.

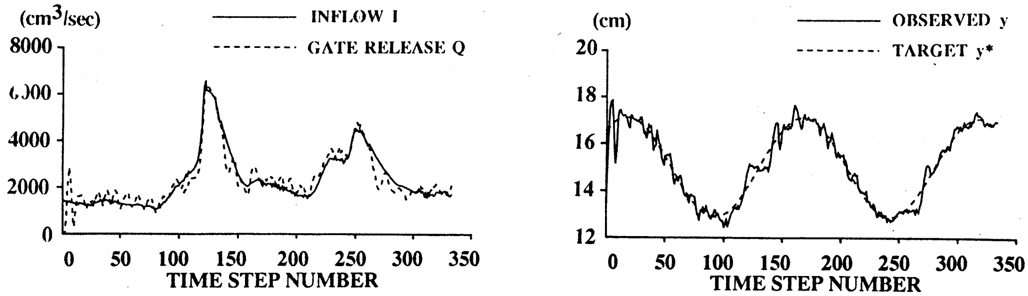

Fig. 5 Time series of I, Q, y, and y*

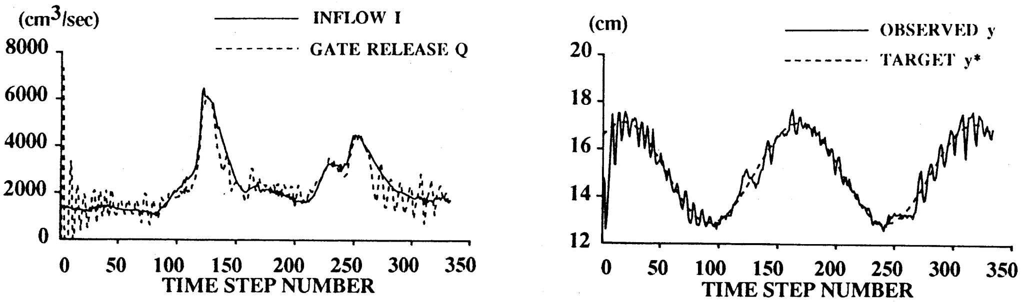

Fig. 6 Time series of I, Q, y, and y*

From the above it is concluded that the behavior of the STC is in accordance with setting the weight value for the change of Q in Eq. (2), initial values of system parameters, and the system noise level. If the observed water level y is to be more close to the target water level y*, the weight λ' and the system noise level should be small. The more close the initial values of the system parameters are to true values, the more effective is the STC. Moreover, the STC can control the weir gate openings effectively also if the target water level y* is not constant.

CONCLUSION

The STC strategy has been found to be well suited for the optimal control of a channel gate opening. The results shown in this study can serve as a basis for more extended applications of the STC to actual water flow and water level control problems arising in flood control systems, water resources systems, water distribution networks, and sewer control systems.

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