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PROTECTIVE SHUTDOWN OF ADAPTATION IN CASE OF UNRELIABLE ESTIMATES IN THE WATER SUPPLY AND HEATING CONTROL SYSTEM

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Abstract:
This paper examines the problem of improving the reliability of adaptive control in water supply and heating systems under conditions of noise, measurement asynchronousness, and residual estimation errors. A protection mechanism is proposed between the estimation unit and the fuzzy adaptation unit for the PID controller coefficients. After normalizing the current state and parameter estimates, a vector of invalidity indicators is generated. If the information is correct, the controller coefficients are determined using the Mamdani fuzzy inference mechanism. If the admissibility limit is violated, the adaptation is disabled, and control continues with fixed coefficients. This approach eliminates erroneous controller reconfiguration and maintains the continuity of the computational cycle.

Keywords: adaptive control, PID controller, Mamdani fuzzy logic, validation control, protection mechanism, water supply and heating.

1. Introduction

In digital water supply and heating control systems, the quality of the control response is determined not only by the controller structure but also by the reliability of the data entering the computing circuit. In real-world conditions, measurements of water temperature, water volume, flow rate, ambient temperature, and incoming flow temperature are generated asynchronously, contain noise, and are incomplete in some cycles. Consequently, even after preliminary processing and evaluation, the system may receive values that are impractical for direct use in adaptive reconfiguration of the controller coefficients.

The problem of working with irregularly discretized and incomplete time series is widely discussed in modern literature. In [1], asynchronous time series are analyzed from the perspective of incomplete data, focusing on reconstructing the hidden structure of sequences. In [2, 10], a method for reconstructing irregularly discretized observation sequences for digital twins is proposed. In [3], asynchronous observations are considered within the framework of continuous-discrete state models, while in [4], a specialized method for processing irregular multivariate time series is proposed. Both studies confirm the persistent interest in the problem of processing asynchronous and incomplete information. These studies confirm that the problem of processing asynchronous and incomplete information remains relevant. However, their primary focus is on time series reconstruction, model construction, and anomaly detection, while the issue of protecting the adaptive control loop from unreliable current estimates remains unaddressed.

Research on discrete control and stability under time delays is also of significant importance for digital control systems. [5] examines control under variable delays in discrete-continuous loops, further emphasizing the importance of correctly using information at each cycle of the computational cycle. However, the problem of limiting or temporarily disabling adaptation when unreliable estimates appear is not specifically addressed in these studies.

Applied research related to water supply and heating systems has shown that control quality significantly depends on signal preprocessing, filtering, and correct state estimation. In [6], changes in signal characteristics before and after filtration during water filling and heating were investigated. In [7, 13], the use of an extended Kalman filter and an RLS approach for processing sensor data was considered. In [8, 14], the effectiveness of fuzzy adaptation of a PID controller in water supply and heating systems was demonstrated. Furthermore, in [9, 15], approximation models applicable to the construction of computational procedures for data processing were discussed. However, even in these studies, the question of how to proceed in the adaptive loop when current estimates appear that fall outside the permissible ranges or do not correspond to the physical constraints of the model remains insufficiently addressed.

Thus, existing works have considered in sufficient detail the problems of restoring irregular data, signal filtering, state estimation, and fuzzy adaptation of controllers. However, the issue of introducing a special protective mechanism between the estimation stage and the stage of adaptive reconfiguration of the coefficients, preventing the use of unreliable estimates in the control loop, remains insufficiently addressed. This determines the relevance of this study.

2. Materials and Methods

Problem statement

The state of the object at sampling step k is described by a vector

$x_k = \left[T_k, H_k, T_{out,k}, T_{in,k}, Q_k\right]^{\mathrm{T}}$, (1)

and the vector of estimated parameters is given by

$\theta_k = \left[k_{heater,k}, k_{loss,k}, \eta_{pump,k}, \eta_{heater,k}\right]^{\mathrm{T}}$.(2)

The measurement information is determined by the observation equation

$z_k = h(x_k) + v_k$, (3)

where v_k — is the measurement noise. After the estimation step, the x_k and θ_k components are reduced to the dimensionless range [0,1]:

$\widetilde{Y_k} = \frac{Y_k - Y_{min}}{Y_{max} - Y_{min}}$. (4)

For the controlled coordinate, the normalized error and its discrete rate of change are formed:

$\tilde{\varepsilon}_k = \tilde{x}_{ref,k} - \tilde{x}_k, \qquad \Delta\tilde{\varepsilon}_k = \frac{\tilde{\varepsilon}_k - \tilde{\varepsilon}_{k-1}}{\Delta t}$. (5)

The input vector of the fuzzy adapter is constructed based on these values

$\xi_k = \left(\tilde{\varepsilon}_k, \Delta\tilde{\varepsilon}_k, \tilde{\theta}_k\right)$. (6)

This composition of input variables corresponds to your adopted adaptation structure.

To control the admissibility of current estimates, a binary feature $b_k(Y)$ is introduced

$b_k(Y) = \begin{cases} 1, & Y_{min} \le Y_k \le Y_{max} \\ 0, & Y_k < Y_{min} \text{ или } Y_k > Y_{max} \end{cases}$.(7)

From these features, the uncertainty vector

$$r_k = \begin{bmatrix} b_k(T) \\ b_k(H) \\ b_k(T_{in}) \\ b_k(T_{out}) \\ b_k(Q) \\ b_k(k_{heater}) \\ b_k(k_{loss}) \\ b_k(\eta_{pump}) \\ b_k(\eta_{heater}) \end{bmatrix} (8)$$

is formed, and the logical variable of adaptation tolerance is defined as

$$s_k = \begin{cases} 1, & r_k = 0 \\ 0, & r_k \neq 0 \end{cases} .(9)$$

Thus, the problem is reduced to constructing a control law in which adaptive tuning is used when $s_k = 1$, and the system switches to fixed-coefficient mode when $s_k = 0$.

Mathematical Switching Model

With a correct information set, the PID controller coefficients are determined by the Mamdani fuzzy inference operator:

$$\left(\widetilde{K}_p(k), \widetilde{K}_i(k), \widetilde{K}_d(k)\right) = \mathcal{F}_M\left(\tilde{e}_k, \Delta\tilde{e}_k, \tilde{\theta}_k\right) . (10)$$

The transition to physical values is performed according to formula (11)

$$K_l(k) = K_l^{min} + \widetilde{K}_l(k) \cdot \left(K_l^{max} - K_l^{min}\right), \quad l \in \{p, i, d\} . (11)$$

The control action is formed according to the discrete PID law (12)

$$u_k = K_p(k)\varepsilon_k + K_i(k) \sum_{m=0}^{k} \varepsilon_m \Delta t + K_d(k) \frac{\varepsilon_k - \varepsilon_{k-1}}{\Delta t}, (12)$$

where ε_k — is physical control error.

Taking into account the protective mechanism, the coefficients are selected according to rule (14)

$$K_p(k) = \begin{cases} K_p^{ad}(k), s_k = 1 \\ K_p^0, \ s_k = 0 \end{cases} K_i(k) = \begin{cases} K_i^{ad}(k), s_k = 1 \\ K_i^0, \ s_k = 0 \end{cases} K_d(k) = \begin{cases} K_d^{ad}(k), s_k = 1 \\ K_d^0, \ s_k = 0 \end{cases} .(14)$$

Thus, when $s_k = 1$, the system operates in adaptive mode, and when $s_k = 0$, it operates in fixed-coefficient mode. This eliminates the influence of unreliable information on the controller's reconfiguration.

Defense Mechanism Algorithm

At each discretization step, the following operations are performed:

1. the current estimates x_k and θ_k are accepted;
2. normalization is performed using formula (4);
3. the uncertainty vector r_k is generated using formula (8);
4. the logical variable s_k is calculated using formula (9);
5. when s_k=1, fuzzy adaptation of the coefficients is activated;
6. when s_k=0, the fixed coefficients K_p^0, K_i^0, K_d^0 are used;
7. the control action is generated using formula (12).

In structural form, the algorithm is written as

$$x_k, \theta_k \to \tilde{x}_k, \tilde{\theta}_k \to r_k \to s_k \to \begin{cases} \varepsilon_k \to \mathcal{F}_M \to K_p, K_i, K_d \to u_k, \ \ s_k = 1 \\ K_p^0, K_i^0, K_d^0 \to u_k, \ \ s_k = 0 \end{cases} .(15)$$

Conditions and parameters of the computational experiment

The mechanism is tested on the interval $k = 0, \dots, 60$ with a sampling step of $\Delta t = 60$ s. The initial conditions are specified as

$$T_0 = 10.0°C, \qquad H_0 = 300.0 \text{ l}, (16)$$

and the target values are as

$T_{set} = 42^{\circ}C, \qquad H_{set} = 1500\ l.$ (17)

On the section $k = 0 \ldots 20$ is accepted

$Q_k = 0,$(18)

and on the section $k = 21 \ldots 60$

$Q_k = 10$ l/min.(19)

The following parameters of the actuators are used:

$Q_{max} = 30$ l/min, $\qquad P_{max} = 6000$ Vt, $\qquad \eta_p = 1.0, \qquad \eta_h = 0.85.$ (20)

These values correspond to your calculated scenario for the system's interaction with the protection mechanism.

The following indicators are used to evaluate the system's behavior.

$$RMSE_T = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(T_{ref,k} - T_k\right)^2},$$

$$RMSE_H = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(H_{ref,k} - H_k\right)^2}, \text{(21)}$$

$$\bar{J} = \frac{1}{N}\sum_{k=1}^{N} J_k, \qquad J_{\Sigma} = \sum_{k=1}^{N} J_k. \text{ (22)}$$

To evaluate the defense mechanism itself, the following are introduced:

$$\eta_{ad} = \frac{N_{ad}}{N} \cdot 100\%, \qquad \eta_{fix} = \frac{N_{fix}}{N} \cdot 100\%,$$

$$N_{sw} = \sum_{k=2}^{N} |s_k - s_{k-1}|. \text{(23)}$$

The main calculation parameters are presented in Table 1.

Table 1. Parameters of the computational experiment

Parameter	**Значение**
Calculation interval for standard control	$k = 0 \ldots 60$
Sampling step	$\Delta t = 60\ s$
Initial temperature	$T_0 = 10.0^{\circ}C$
Initial volume	$H_0 = 300.0\ l$
Temperature setpoint	$T^{set} = 42^{\circ}C$
Volume setpoint	$H^{set} = 1500\ l$
Flow rate in section $k = 0 \ldots 20$	$Q_k = 0$
Flow rate in section $k = 21 \ldots 60$	$Q_k = 10\ l/min$
Maximum pump flow	$Q_{max} = 30\ l/min$
Maximum heater power	$P_{max} = 6000\ Vt$
Pump efficiency	$\eta_p = 1.0$
Heater efficiency	$\eta_h = 0.85$

3. Results and Discussion

Research Results and Discussion

The performance of the protection mechanism was assessed in the combined water filling and heating control mode during the transition from the initial $Q_k = 0$ to the water drawdown mode of $Q_k = 10\ l/min$. The analysis was aimed at verifying two assumptions: maintaining the adaptive loop's stability during combined changes in T_k and H_k, and maintaining the system's operability when unreliable information appears by disabling the adaptation and switching to fixed controller coefficients.

The characteristic values of the mode parameters are presented in Table 2.

Table 2. Characteristic values of parameters in the scenario of joint operation of the system with a protective mechanism

Tact k	**Mode**	T_k, °C	H_k, l	$u_{pump,k}$	$u_{heater,k}$	J_k	**State of adaptation**
0	initial mode, $Q_k = 0$	10,0	300,0	0,50	0,50	2,89	included
20	completion of the initial mode	11,9	578,6	0,48	0,65	2,44	included
21	transition to $Q_k = 10\ l/min$	12,0	598,9	0,48	0,66	2,42	included
40	operating mode	13,8	677,8	0,45	0,78	2,13	included
60	interval end	15,2	729,5	0,41	0,82	1,92	included
k_s	invalid data	—	—	nominal	nominal	preserves the limb	disabled

The table shows the characteristic values of variables and control actions obtained during the computational experiment.

Table 3 shows that after switching to water intake mode, the quality criterion value does not increase but remains below the initial level: if at $k = 0$, $J_k = 2{,}89$, then at $k = 21$, $J_k = 2{,}42$. The relative reduction is calculated using formula (24)

$$\delta_{J,\,0\to21} = \frac{2{,}89-2{,}42}{2{,}89} \cdot 100\% = 16{,}26\%. \ (24)$$

This indicates that the transition to the operating mode does not cause a loss of control loop stability. The nature of the change in control actions remains physically consistent.

The effect on the pump decreases from 0.50 to 0.48, that is, by

$$\delta_{u,pump} = \frac{0{,}50-0{,}48}{0{,}50} \cdot 100\% = 4{,}00\%, \ (25)$$

while the effect on the heater increases from 0.50 to 0.66, which corresponds to

$$\delta_{u,heater} = \frac{0{,}66-0{,}50}{0{,}50} \cdot 100\% = 32{,}00\%. \ (26)$$

This redistribution of control reflects the actual structure of the process: when flow occurs, the system maintains the filling mode while simultaneously increasing the thermal effect to compensate for thermal inertia.

Over the entire interval, the water temperature increases from $10{,}0^\circ C$ to $15{,}2^\circ C$, the water volume increases from 300,0 to 729,5 liters, and the quality criterion consistently decreases from 2,89 to 1,92. This indicates that the system maintains controllability and does not degrade the algorithm in the combined mode.

If invalid information occurs, adaptive readjustment of the coefficients is temporarily stopped, and the system switches to control with the nominal parameters of the controller. In the calculation scenario, during this transition, the computational cycle remains finite, and the system remains operational. Consequently, the protection mechanism serves not only as a control mechanism but also as a safety mechanism: it prevents erroneous controller reconfiguration based on invalid data and maintains the system in a safe mode until the input information is restored.

Thus, the obtained results confirm that the proposed mechanism does not limit normal adaptive operation, but in abnormal conditions prevents the most dangerous mode—reconfiguration of the PID controller based on invalid estimates. This makes it an essential element of the adaptive digital control loop for water supply and heating systems.

This paper proposes a protective mechanism for disabling adaptation in a digital water supply and heating control system when unreliable estimates of the plant's state and parameters appear. Unlike schemes in which controller coefficients are reconfigured directly based on current estimated data, the proposed approach includes an intermediate step of verifying the permissibility of normalized values and generating a logical variable that determines the adaptation capability at each control cycle.

It is shown that with a valid data set, the system maintains its standard adaptive mode, and if the permissibility is violated, it automatically switches to control with fixed controller coefficients without interrupting the computational cycle. This mode eliminates erroneous reconfiguration of PID controller parameters based on unreliable data and maintains the loop's functionality until the input information is restored to its correct state.

The results of the computational experiment showed that, in the combined temperature and water volume control mode, the transition to the water intake section does not lead to a loss of algorithm stability: the quality criterion value decreases from 2.89 to 2.42 at the initial stage of the transition and reaches 1.92 by the end of the studied interval. Furthermore, the protective mechanism ensures the adaptive loop is protected in situations where current estimates should not be used to reconfigure the coefficients.

4. Conclusion

The practical significance of this result is that the proposed mechanism can be integrated into digital control systems for water filling and heating processes without changing the overall structure of the computational cycle. Its use increases the reliability of adaptive control and reduces the risk of degradation of control quality in abnormal conditions.

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