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Model predictive control of condensate recycle process in a cogeneration power station: Controller design and numerical application

Wangyun Won*, Kwang Soon Lee*,†, In Seop Kim*, Bongkook Lee, Seungjoo Lee**, and Seokyoung Lee*****

*Department of Chemical and Biomolecular Engineering, Sogang University, Shinsoodong-1, Mapogu, Seoul 121-742, Korea
**LS Industrial System Co., Ltd., Anyang, Gyeonggido 431-749, Korea
***East-West Power Co., Ltd., Goyang, Gyeonggido 410-771, Korea
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Abstract−A model predictive control (MPC) system has been developed for application to the condensate recycle process of a 300 MW cogeneration power station of the East-West Power Plant, Gyeonggido, Korea. Unlike other industrial processes where MPC has been predominantly applied, the operation mode of the cogeneration power station changes continuously with weather and seasonal conditions. Such characteristic makes it difficult to find the process model for controller design through identification. To overcome the difficulty, process models for MPC design were derived for each operation mode from the material balance applied to the pipeline network around the concerned process. The MPC algorithm has been developed so that the controller tuning is easy with one tuning knob for each output and the constrained optimization is solved by an interior-point method. For verification of the MPC system before process implementation, a process simulator was also developed. Performance of the MPC was investigated first with a process simulator against various disturbance scenarios.

Key words: Cogeneration Power Station Control, Level Control, MPC

INTRODUCTION

Through continuous evolution and verification over the past few decades, model predictive control (MPC) has obtained solid recognition as a standard multivariable industrial control technique. During this period, applications of MPC have been continuously diversified to various industries like food processing, automotives, and even aerospace systems, whereas refineries and petrochemical industries still remain the major customers of MPC. Such success is frequently attributed to not only the prediction-based high performance multivariable control of MPC, but also the capability of constraint handling and economic optimization [1,2].

Like the processes in petrochemical industries, many processes in a power plant are multivariable systems, hence can be good targets where the operation can be improved by advanced control. Accordingly, the interest in the advanced control techniques, especially MPC, has been continuously increasing in power plants, although progress has been slow perhaps due to the high safety concern and also conservatism [3-9]. In fact, for some specific processes in a power plant such as the super-heater, advanced control studies have long been practiced. Due to its crucial role in turbine operation and fast dynamics, the design of the super-heater controller has been a constant and challenging research subject and, as a result, commercial techniques have appeared, too [10,11]. Another example is the combustion process where reduction of NO_x and other pollutants emission is important. To meet the ever severer regulations on pollutant emission, advanced control techniques have been actively investigated for the process [12,13].

This research has been conducted to develop an industrial MPC system for application to the condensate recycle process of a cogeneration power station of the East-West Power Plant, Gyeonggido, Korea. The cogeneration power station produces hot water and electricity simultaneously. Since the seasonal change in hot water demand is large, five different operation modes are provided from maximum hot water to maximum electricity production. Among them, two extreme modes pose operation problems and become the targets for the MPC application. The developed MPC system is based on a stochastic state space model with special disturbance model. It is designed to have one tuning knob for each output by utilizing Kalman filter-based tuning. Before implementation in a real process, the performance of the developed MPC system was evaluated in a numerical process. For this, a rigorous process simulator was constructed from the material balance and detailed pressure drop relations applied to the pipeline network around the condensate process. The performance of MPC was compared with the existing PI control loops for various disturbance scenarios.

CONDENSATE RECYCLE PROCESS

Fig. 1(a) shows a simplified process flow diagram of the concerned cogeneration power plant. It has a high pressure steam turbine (HP-ST) and a low pressure steam turbine (LP-ST). The exhaust steam from HP-ST is directed to the high pressure district heater (HPDH), which is concatenated to the low pressure district heater (LPDH). Hot water production for the nearby huge apartment complex is done by heat exchange through steam condensation in LPDH and HPDH. The reason to split the heat exchanger into HPDH and LPDH is to recover the heat of low pressure waste steams from various sources at LPDH as much as possible.

The condensate recycle process refers to the part that contains three tanks, LPDH, CONDENSER, and DEA plus the associated

†To whom correspondence should be addressed.
E-mail: kslee@sogang.ac.kr

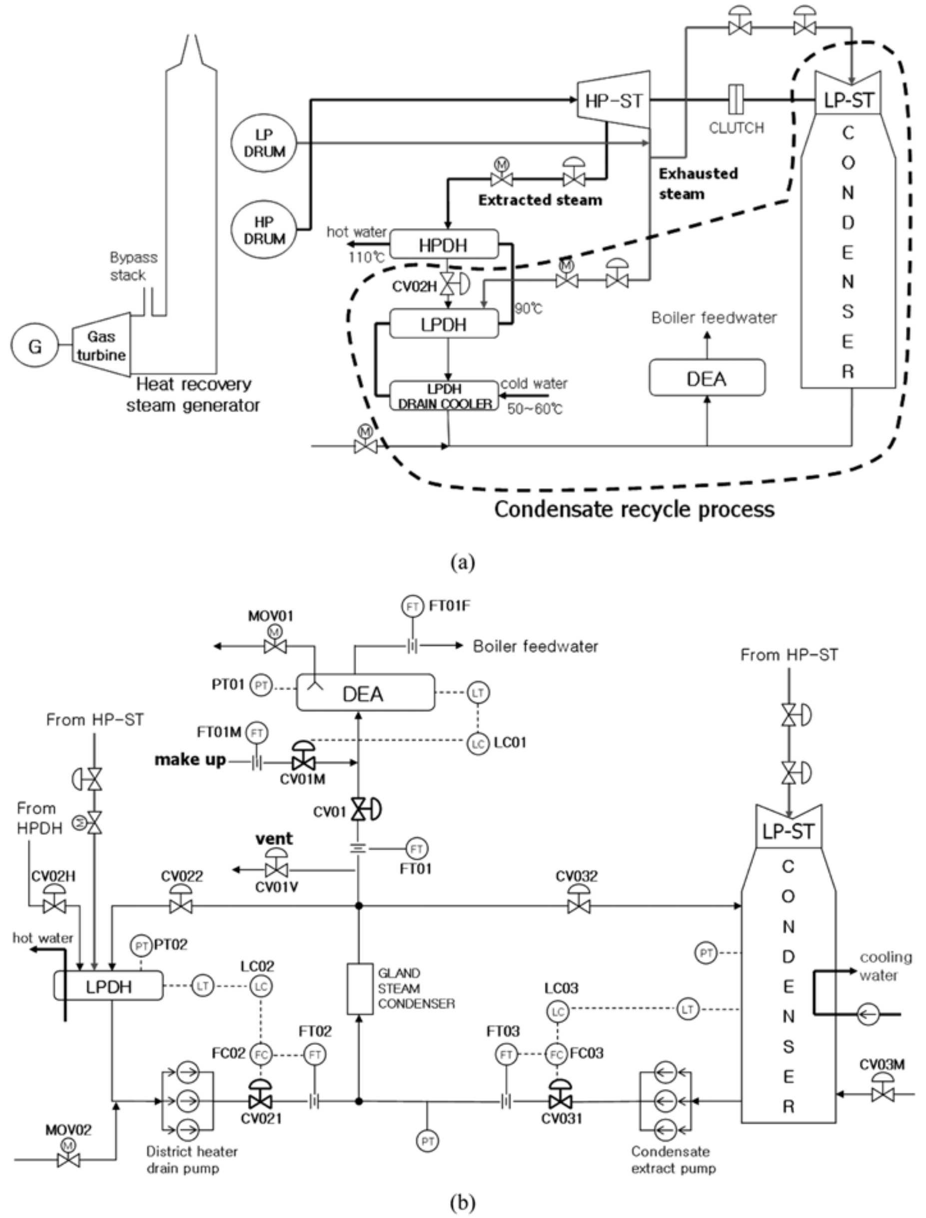


Fig. 1. Process flow diagrams of (a) cogeneration power plant and (b) condensate recycle process.

pipeline network. Among them, LPDH is the primary heat exchanger for hot water production. Since the waste steams that are directed to LPDH are not generated in an anticipatory manner, condensate level in LPDH is apt to be perturbed. CONDENSER is a huge drum where the discharge steam from LP-ST is condensed by heat exchange with cold water. Finally, DEA refers to the deaeration tank. The role of DEA is to collect the condensates from LPDH and CONDENSER and to supply the boiler feed water after removing dissolved oxygen in the water.

The plant is operated under five different modes according to the hot water and electricity demands that vary with season and weather conditions. Depending on the operation mode, all the steam may be directed to LPDH (MODE 1) through HP-ST, or it may be divided into LPDH and CONDENSER (MODE 5) through HP-ST and LP-ST, respectively. The other three are transition modes that are turned on temporarily during the mode change from 1 to 5 or vice versa. In Table 1, the process situations for MODE 1 and MODE 5

Table 1. Description of MODE 1 and MODE 5 operations

	MODE 1	MODE 5
	HP-ST on, LP-ST off	HP-ST on, LP-ST on
Max flow rate at FT01	900 ton/hr	900 ton/hr
Max flow rate at FT02	900 ton/hr	500 ton/hr
Max flow rate at FT03	0	400 ton/hr
CV01	Equal percentage type, CV=950	
CV021	Linear type, CV=2500	
CV031	Equal percentage type, CV=900	
CV01M	Equal percentage type, CV=92	

are described in more detail.

In Fig. 1(b), the control loops for MODE 5 are shown. Liquid levels of DEA, LPDH, and CONDENSER are regulated by independent PI controllers with or without cascaded flow control loops. Other valves like CV01V, CV022, CV032, CV03M, MOV01, and MOV02 that are not connected to the level control loops are manipulated by DCS logics that are not allowed to modify. In MODE 1, LC03 is turned off and CV01M and CV01 are directly manipulated by LC01 and LC02, respectively. For now, the condensate recycle process requires improvement in the control method for the following reasons.

First, the tank levels need to be more tightly regulated for economic reasons. Water in the power plant is recycled in a closed loop undergoing phase changes. This means that there is no need for water vent or purge in normal operation, although some make-up is inevitable to replenish loss. The vent valve CV01V is programmed to be opened in case that the levels of LPDH and CONDENSER increase beyond certain limits. Accordingly, if the level of DEA becomes low for some reason while the levels of LPDH and/or CONDENSER become high, both CV01V and CV01M will be opened for vent and make-up, respectively. This causes an economic loss but, in fact, is avoidable if tighter regulation of the levels is performed. As another case, suppose that the condensate input flow to DEA is larger than the output flow to the boiler. Note that LC01 can manipulate only the makeup water flow and has no handle to reduce the DEA level. If such a flow imbalance around DEA is sustained, the DEA level grows continuously and at last MOV01 will be opened to purge DEA water incurring an economic loss. Meanwhile, LPDH and CONDENSER levels are regulated by their respective controllers. If LPDH and CONDENSER could share the burden of DEA by increasing their levels through coordination, the purge loss would be avoided or at least delayed.

Secondly, due to its relatively small volume, the level of LPDH is easily shaken to a change in steam input and hot water flow, especially during MODE 1 operation. When the tank level becomes higher beyond a certain limit, the condensing area is intruded and condensing becomes difficult. This in turn increases the tank pressure and affects the upstream processes including HP-ST. In the reverse case when the tank level decreases below a certain limit, pump cavitations may occur.

In addition to the above, there are still more problems that cannot be overlooked. One of them is the inverse response in the DEA level to a change in the makeup water flow. It is caused by the difference in the specific volumes of the hot water in DEA and cold makeup water. The PI controller has no provision for the inverse response and shows limited performance.

NUMERICAL PROCESS

Unlike other industrial processes where MPC has been predominantly applied, the operation mode of the cogeneration power station changes continuously with weather and seasonal conditions. Also, in a certain mode of operation, the process variables swing over a wide range, especially due to the large change in hot water demand even within a day. In order to verify the performance of MPC under all those circumstances before installation, a dynamic simulator for the concerned level process was developed. The simulator is composed of detailed unsteady mass balance equations for the three tanks and steady state mass balance and detailed pressure drop equations for the pipeline network. For each control valve, first-order dynamics with 7 to 20 sec of time constant was assumed. All the disturbance streams to the process, mode change scenarios, and inverse response of DEA level were reflected to the simulator. Finally, key parameters were adjusted by using the operation data of a real process. Fig. 2 shows the input-output structure of the simulator. The variables indicated by the thick lines represent the manipulated and controlled variables with which the control loops are configured, whereas all the other variables represent disturbances. In this simulator, the DCS logics to manipulate the auxiliary valves like CV01V, CV022, CV032, CV03M, MOV01, and MOV02 were reflected as they stand.

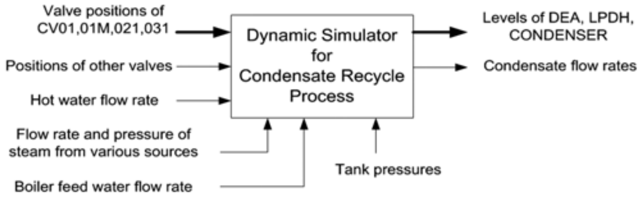


Fig. 2. Input-output structure of the dynamic simulator for the condensate recycle process.

MPC DESIGN

1. Basic Structure and Dynamic Optimization

The situation of a controlled process may change from time to time. Industrial controllers need to function incessantly overcoming such changes in the process. In this research, the MPC system is designed on the basis of a state space model to perform the following computations in order considering the above at every sampling:

▶ Step 1: Measure the controlled variables (CV's).

▶ Step 2: Check faulty CV's and check manipulated variables (MV's) in the manual-mode. Define the process (MV's and CV's) to control.

▶ Step 3: Compute the condition number of the controlled process using the singular value decomposition (SVD) of the steady state gain matrix. When the condition number is large, discard the lowest priority CV and reconfigure the controlled process until the condition number is smaller than the specified threshold value.

▶ Step 4: Compute future input moves that minimizes the sum of output prediction errors plus future input moves.

▶ Step 5: Implement the first input signal to the process and repeat the same calculation at the next sampling time.

In step 3, a large condition number means that the process has output directions along which the process is hardly driven. Under this condition, the MV change may become excessive and erratic. Step 3 solves such an ill-conditioning problem at the expense of giving up low priority CV's.

Step 4 represents the dynamic optimization, which is the core part of MPC. This step is composed of Kalman filtering for state estimation, output prediction based on a state space model, and minimization of a quadratic cost function. Mathematical description of the computation in step 4 can be written as

$$\min_{\Delta u(g)} \frac{1}{2}\left\{\sum_{k=1}^{p}\|r(t+k)-y(t+k|t)\|_Q^2+\sum_{i=0}^{m-1}\|\Delta u(t+i)\|_R^2+\|\gamma(t)\|_S^2\right\} \tag{1}$$

subject to
$y(t+k|t)=Mx(t|t)+L_0\Delta u(t)\cdots+L_{k-1}\Delta u(t+k-1)$ and
linear inequality constraints on $y(t+k|t)$, $u(t+k)$, and $\Delta u(t+k)$

In the above, $\Delta u(t)\triangleq u(t)-u(t-1)$ and $\|x\|_Q^2\triangleq x^TQx$; $y(t+k|t)$ and $x(t|t)$ refer to the optimal output prediction at t+k and the optimal state estimate at t based on the information up to t. $x(t|t)$ is computed by using the Kalman filter. The optimization may include linear inequality constraints imposed on input and output variables. $\gamma(t)$ is a slack variable that slackens the output constraints to avoid possible infeasibility when there is a large disturbance [14].

2. Additional Features

Besides the basic structures described above, the following features were considered.

2-1. Feedforward Compensation

There are a number of disturbance flows (about 20) in the concerned process. For only a few of them, flow measurements are available. For the rest, however, the valve positions are available. In order to accommodate the latter case in the feedforward compensation, too, the flow rates are estimated by using the valve position and pressure information. MPC was designed to compensate all the disturbance flows by providing feedforward control action.

2-2. Input Blocking

Regular MPC as in Eq. (1) has a large number of decision variables that renders a heavy computational burden on the optimizer. To improve this situation, input blocking was employed. The input blocking is a technique that reduces the dimension of the decision variables. In this research, the future MV movements are allowed to change only at limited times [15,16] such that

$$\Delta u(t)=b_1,\ \Delta u(t+k_2)=b_2,\ \ldots,\ \Delta u(t+k_n)=b_n,\ n=m,\ k_n<m \tag{2}$$
$\Delta u(t+i)=0$ for remaining i's in the control horizon

In this way, the decision variables for optimization are changed from $\Delta u(t+k)$'s to b_i's. This results in significant reduction in the computational burden and also enhancement in robustness.

2-3. Dynamic Optimization with Interior Point Method

Eq. (1) is a typical quadratic programming (QP), which guarantees the existence of a unique minimum. Nevertheless, the required computation can be heavy even with the input blocking. For further reduction of computation and improvement of numerical stability, the QP problem is converted to an approximate unconstrained optimization problem by using a barrier function and solved by an interior point method [17,18].

2-4. Output Disturbance Model

Feedback control handles the uncertainties from model error and unmeasured disturbance. Even then, if the information on the uncertainties can be reflected to the controller design at least partially, the control performance can be improved more. In this research, it is assumed that the unmeasured disturbance $\xi(t)$ is added to the process output and is modeled as a first-order filtered signal of integrated white noise as in Fig. 3. In this figure, A_w is a diagonal matrix whose elements are a_i's with $|a_i|<1$. It is known that such a model can reasonably represent the typical disturbance patterns occurring

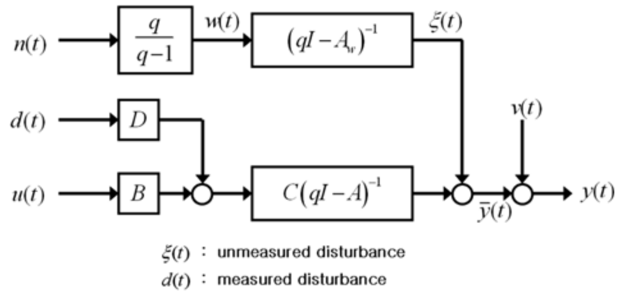


Fig. 3. Model structure with output disturbance for MPC design.

in industrial processes [19].

The process model augmented with the output disturbance model and rearranged with respect to $\Delta u(t)$ and $y(t)$ can be represented by the following state space Eq. [20]:

$$\begin{bmatrix}\Delta x(t+1)\\ \Delta\xi(t+1)\\ \bar{y}(t+1)\end{bmatrix}=\begin{bmatrix}A & 0 & 0\\ 0 & A_w & 0\\ CA & A_w & I\end{bmatrix}\begin{bmatrix}\Delta x(t)\\ \Delta\xi(t)\\ \bar{y}(t)\end{bmatrix}+\begin{bmatrix}B\\ 0\\ CB\end{bmatrix}\Delta u(t)$$
$$+\begin{bmatrix}D\\ 0\\ CD\end{bmatrix}\Delta d(t)+\begin{bmatrix}0\\ I\\ I\end{bmatrix}n(t)$$
$$y(t)=[0\ \ 0\ \ I]\begin{bmatrix}\Delta x(t)\\ \Delta\xi(t)\\ \bar{y}(t)\end{bmatrix}+v(t) \tag{3}$$

where n(t) and v(t) are independent zero mean white noises.

2-5. Easy Tuning Knob

In designing an industrial MIMO controller, it is crucial to devise an effective but simple tuning method. Borrowing the well-known fact that LQ control and the Kalman filter are dual in LQG control [21], we chose to tune the controller through the Kalman filter. A benefit of this approach is that the effectiveness of tuning is incessant even when an MV is stuck to a constraint. It is because the Kalman filter continuously runs irrespective of constraints, whereas the control part does not. As given in [20], the steady state Kalman gain for Eq. (1) is

$$\bar{K}=\begin{bmatrix}0\\ F_a\\ F_b\end{bmatrix},\quad \begin{aligned}&F_a=\mathrm{diag}\{f_{a1},\ldots,f_{an_y}\},\ \ F_b=\mathrm{diag}\{f_{b1},\ldots,f_{bn_y}\}\\ &f_{bi}\approx\frac{f_{ai}}{1+a_i-a_if_{ai}},\quad 0\le f_{ai}\le 1\end{aligned} \tag{4}$$

Hence, each output can be tuned with only one tuning parameter f_{ai} that changes between 0 and 1. When f_{ai} is close to 0, the Kalman filter trusts the model output more than the output measurement in the state estimation, and vice versa when f_{ai} is close to 1. As a consequence, $f_{ai}\to 0$ results in loose tuning and vice versa for $f_{ai}\to 1$.

Fig. 4 demonstrates the performance of the above tuning method when the following 2×2 system is controlled by MPC:

$$\begin{bmatrix}y_1\\ y_2\end{bmatrix}=\begin{bmatrix}\dfrac{0.1406s+0.0018}{s^2+0.254s+0.02} & \dfrac{0.2664s+0.0082}{s^2+0.254s+0.02}\\ \dfrac{0.0015s+0.0014}{s^2+0.254s+0.02} & \dfrac{-0.009s-0.0001}{s^2+0.254s+0.02}\end{bmatrix}\begin{bmatrix}u_1\\ u_2\end{bmatrix} \tag{5}$$

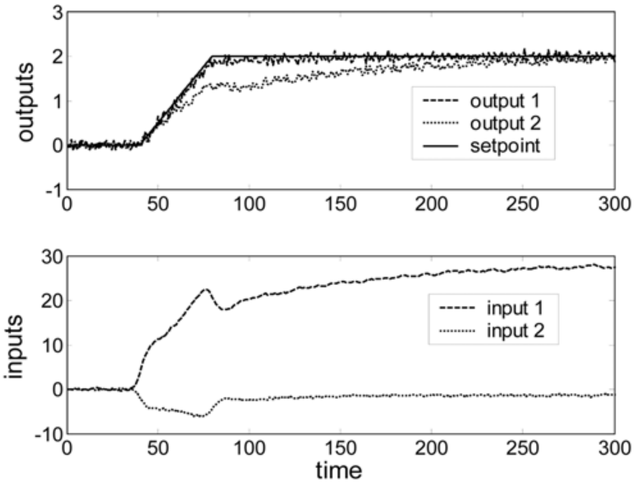


Fig. 4. Performance of Kalman filter-based MPC tuning applied to the system in Eq. (5) for the first output with f_{a1}=0.8 and the second output with f_{a2}=0.05.

It is assumed that each output is corrupted with random noise and there is no model error. The sampling time for control was chosen to be 1. When f_{ai} is close to 0, the input action becomes mild and the output shows sluggish response to the set point change, which corresponds to the closed-loop performance for a low Q/R tuning. In contrast, when f_{ai} is given close to 1, the tuning becomes tight, that corresponds to the high Q/R case.

PROCESS MODEL FOR MPC IMPLEMENTATION

1. Process Analysis and Choice of MV's for MPC

It was requested that MPC can handle both MODE 1 and MODE 5 operations using CV01, CV01M, CV021, and CV031. In both modes, the number of control valves is larger than the number of tank levels by one. Hence, a problem to choose appropriate MV's arises. In practice, the problem is reduced to select one between CV01 and CV021. For this, we investigated the valve position-to-flow rate relationships assuming that CV031 and CV01M are closed and the results are shown in Fig. 5. Fig. 5(a) shows the installed flow characteristic of CV021 with the valve position of CV01 as a parameter. Conversely, Fig. 5(b) shows the installed flow characteristic of CV01 with the valve position of CV021 as a parameter.

In MODE 1, the flow rate from LPDH to DEA is affected by two control valves of CV01 and CV021. Therefore, one of them should be fixed and the other one plus CV01M is used as MV's. From Figs. 5(a) and (b), CV01 is found to be more appropriate as an MV in that it has wider linearly controllable range than CV021.

In MODE 5, the sum of the outlet flow rates from LPDH and CONDENSER should be equal to the inlet flow rate to DEA. Based on this fact, CV01M, CV021, and CV031 are obvious choices for MV's with CV01 fixed at some position. The fixed position for CV01 was determined by referring to Fig. 5(a) considering the required maximum controllable flow rate and linearly controllable range.

Through this analysis, the MV's for MPC were chosen as

MODE 1: MV=CV01 and CV01M with CV021 fixed at 40%
MODE 5: MV=CV01M, set points of FC02 and FC03 with CV01 fixed at 80%

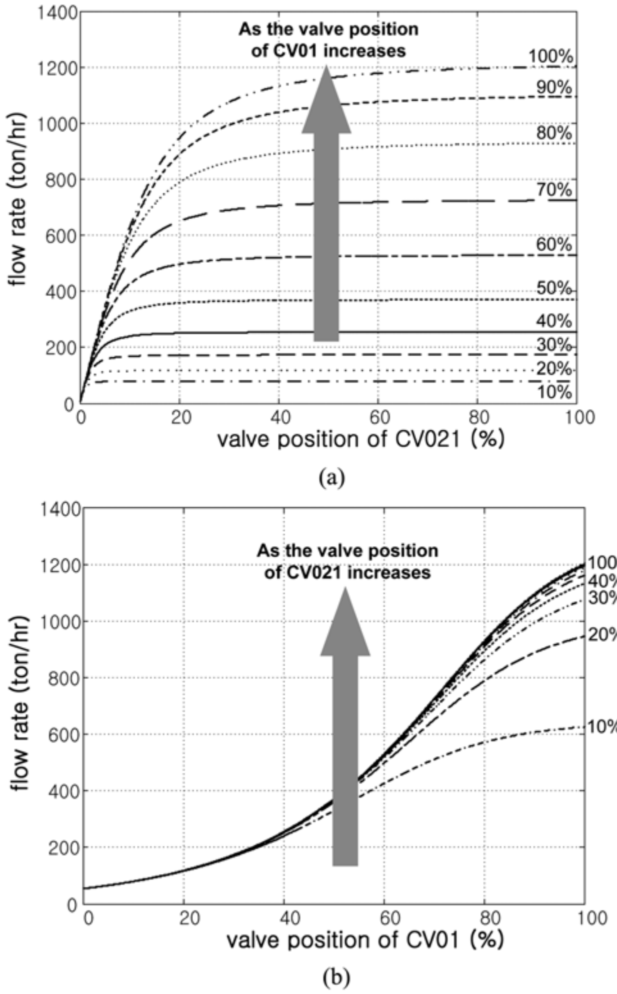


Fig. 5. Installed flow characteristics of control valves of (a) CV021 when CV01 is fixed and (b) CV01 when CV021 is fixed.

For some reason from the plant side, CV01M is directly manipulated not being closed by a flow rate controller.

2. Process Model for MPC

In accordance with the MV selection described above, the process models for MODE 1 and MODE 5 for MPC design were derived from the material balance and linearization as follows:

$$\text{MODE 1: } \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} a_{11}/s(\tau_{v1}s+1) & a_{12}(1-b_{12}s)/s(\tau_{12}s+1)(\tau_{v2}s+1) \\ -a_{21}/s(\tau_{v1}s+1) & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} + D_1 d_1 \quad (6)$$

y_1, y_2: levels of DEA and LPDH
u_1, u_2: vp's of CV01 and CV01M
d_1: vp's of CV01V, CV02H, CV022, etc.

$$\text{MODE 5: } \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$= \begin{bmatrix} c_{11}/s & a_{12}(1-b_{12}s)/s(\tau_{12}s+1)(\tau_{v2}s+1) & c_{13}/s \\ -c_{21}/s & 0 & 0 \\ 0 & 0 & -c_{32}/s \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} + D_5 d_5 \quad (7)$$

y_1, y_2, y_3: levels of DEA, LPDH, CONDENSER
u_1, u_2, u_3: set point of FC02, vp of CV01M, set point of FC03
d_5: vp's of CV01V, CV02H, CV022, CV03M, CV032, etc.

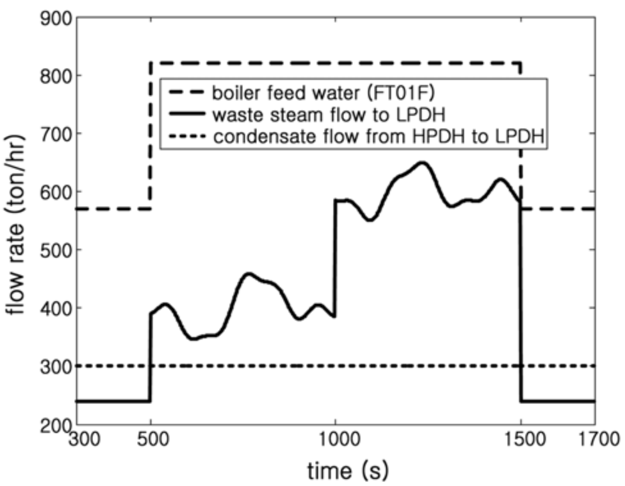
In the above, valve position is referred as vp; d_1 and d_5 represent the measured disturbances for feedforward compensation; τ_{v1} and τ_{v2} represent the time constants of CV01 and CV01M, respectively. It is assumed that the control valves have first-order dynamics and integrating characteristics and valve dynamics are the only source of process dynamics. Also, the inverse response of DEA level is reflected to the transfer function as a positive zero. In the MODE 1 model, a_{11} and a_{21} were given as functions of the pressures measured at PT01 and PT02 in order to reflect the effect of tank pressures on the flow rate. The parameters for inverse response and for LPDH tank were estimated by using operation data. Other parameters were derived referring to or through linearization of the process simulator. In the MODE 5 model, it is assumed that the flow control loops are tightly tuned and thus the valve dynamics can be negligible.

The above models were converted to the zero-order hold discrete-time state space models with sampling period of 5s.

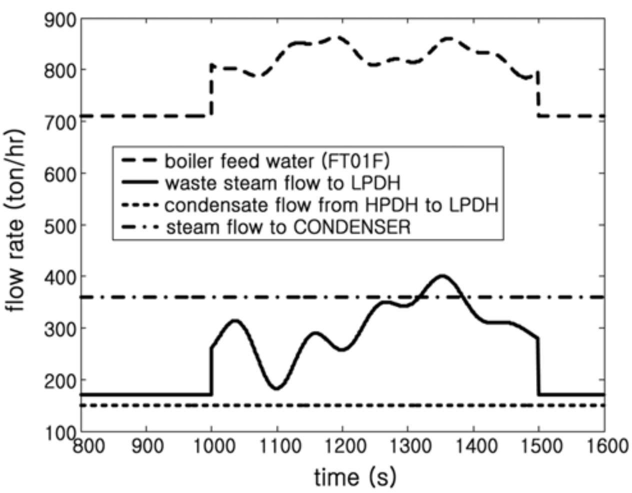
RESULTS AND DISCUSSION OF NUMERICAL EXPERIMENTS

1. Disturbance Rejection in Mode 1

In Figs. 7 and 8, closed loop responses of the MODE 1 process to perturbations in initial input level and waste steam flow to LPDH under PI control and MPC are compared. For PI control, CV01 is used as an MV for regulation of the LPDH level. The set points of the DEA level and the LPDH level are given at 2.35 m and 1.1 m, but initially they were perturbed to 2.25 m and 1.3 m, respectively. Normal waste steam flow rate to LPDH and condensate flow rate from HPDH to LPDH were given as 240 ton/hr and 300 ton/hr, respectively. From 500 sec to 1,500 sec, the waste steam and boiler feed water flow rates were assumed to vary as given in Fig. 6(a).

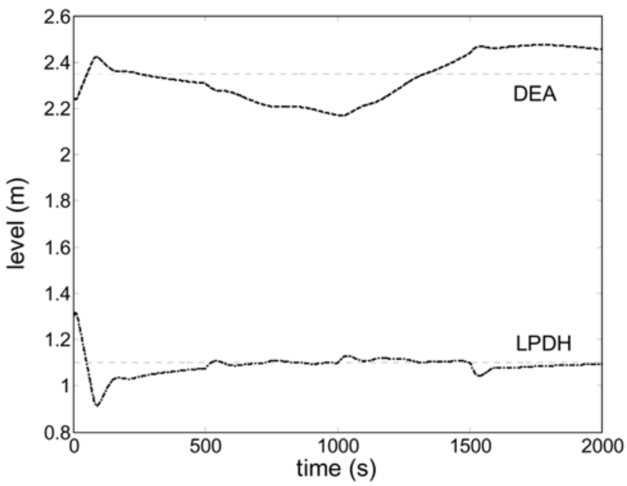


(a)

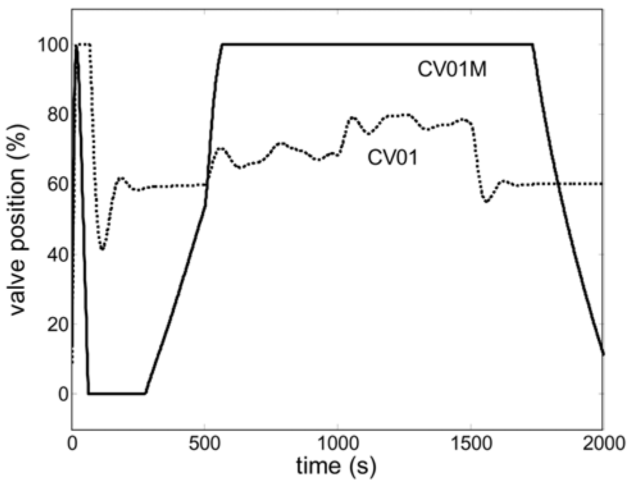


(b)

Fig. 6. Disturbance scenarios for (a) MODE1 and (b) MODE5 operations.



(a)



(b)

Fig. 7. Closed-loop response of MODE 1 process by PI control against the disturbance scenario in Fig. 6(a). (a) tank levels and (b) MV's.

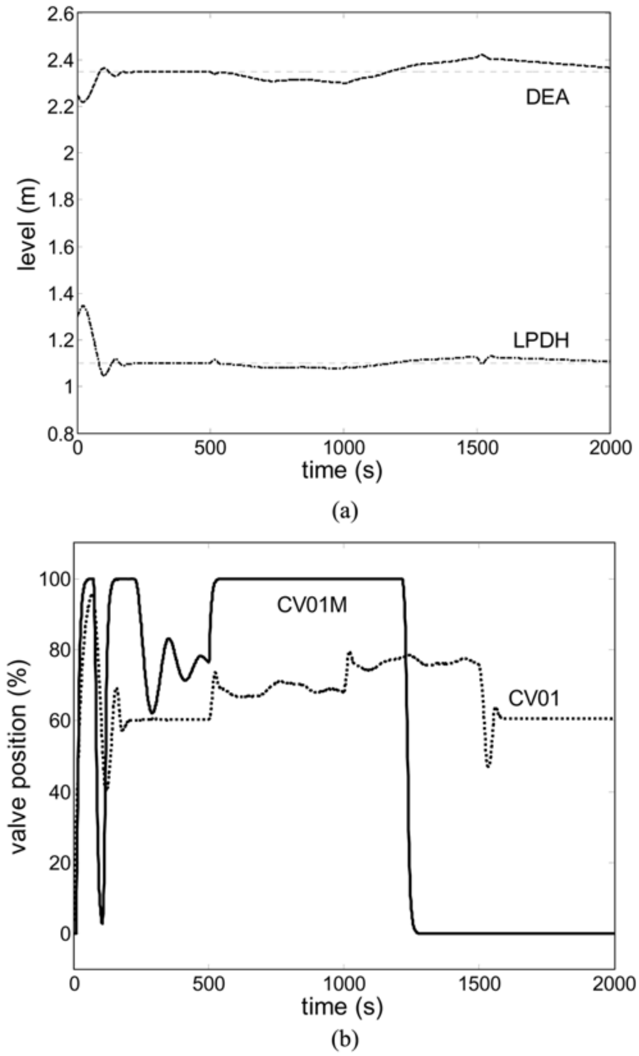


Fig. 8. Closed-loop response of MODE 1 process by MPC against the disturbance scenario in Fig. 6(a). (a) tank levels and (b) MV's.

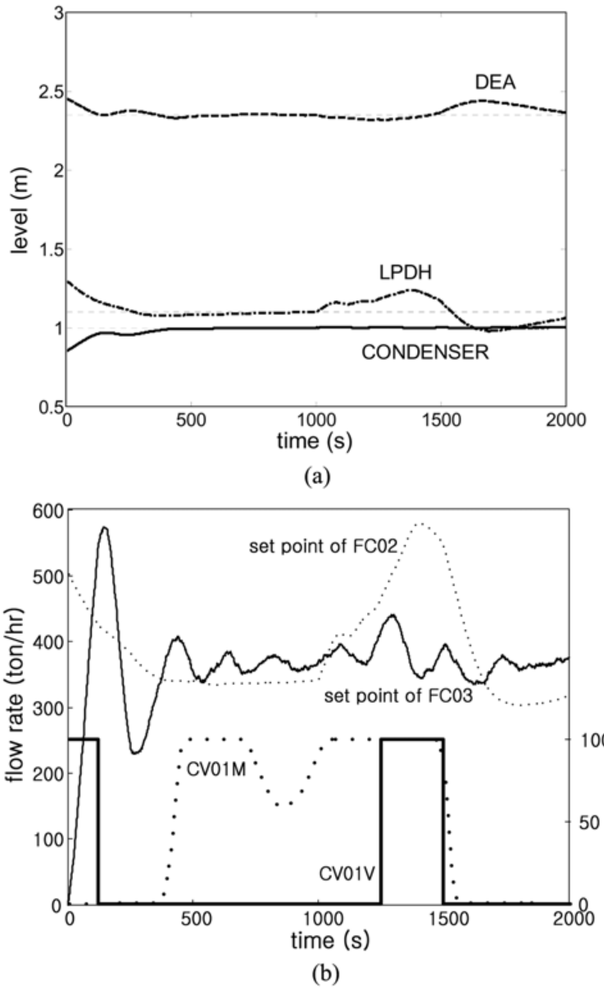


Fig. 9. Closed-loop response of MODE 5 process by PI control against the disturbance scenario in Fig. 6(b). (a) tank levels and (b) MV's and CV01V.

During the first half of this period, the outlet flow rate of DEA (boiler feed water) is given to be larger than the inlet flow rate (recycled condensate flow rate). During the next 500 sec, however, a reverse situation is assumed.

In Fig. 7(a), responses of the LPDH and DEA levels under decentralized PI control are depicted. The levels are rather shaky though not unacceptable. The LPDH level is subject to rather large change initially but can be regulated relatively well thereafter. However, the DEA level varies rather widely because of the limited makeup water flow rate (between 1,000 sec and 1,300 sec) and no MV to actively lower the level (after 1,300 sec). In Fig. 8, the performance of MPC against the same disturbance scenario is summarized. First, it can be observed that the closed loop response is remarkably improved. It is primarily due to the feedforward action as well as model-based control. In addition, the quadratic cost in Eq. (1) can appropriately distribute the control error to both levels through the weighting factors. Such coordination is not possible in decentralized PI control.

2. Disturbance Rejection in Mode 5

In Figs. 9 and 10, the transient responses of the MODE 5 process to a disturbance scenario shown in Fig. 6(b) under PI control and MPC are summarized. The control loops of MPC are composed of three tank levels and MV's that were proposed in subsection 5.1. The PI control loops are composed as in Fig. 1(b) with CV01 fixed at 80%. The set points of DEA, LPDH, and CONDENSER levels were givens at 2.35 m, 1.1 m, and 1 m, and the initial levels of these tanks were assumed to be 2.45 m, 1.3 m, and 0.85m, respectively. Normal steam flow rates to LPDH and CONDENSER were assumed to be 160 ton/hr and 360 ton/hr, respectively, and condensate flow rate from HPDH to LPDH was assumed to be 160 ton/hr.

As can be seen in Figs. 9 and 10, MPC outperforms PI control. Especially, upon the disturbance change, MPC stabilizes the tank levels rapidly by its effective feedforward compensation in addition to its optimizing multivariable control action. Hence, no vent flow that incurs unnecessary cost occurs. On the other hand, PI control shows a rather long transient before restoring the tank levels to their respective set points. The level of LPDH was shaken because PI control could not reject disturbances quickly. Consequently, vent flow is made by opening CV01V.

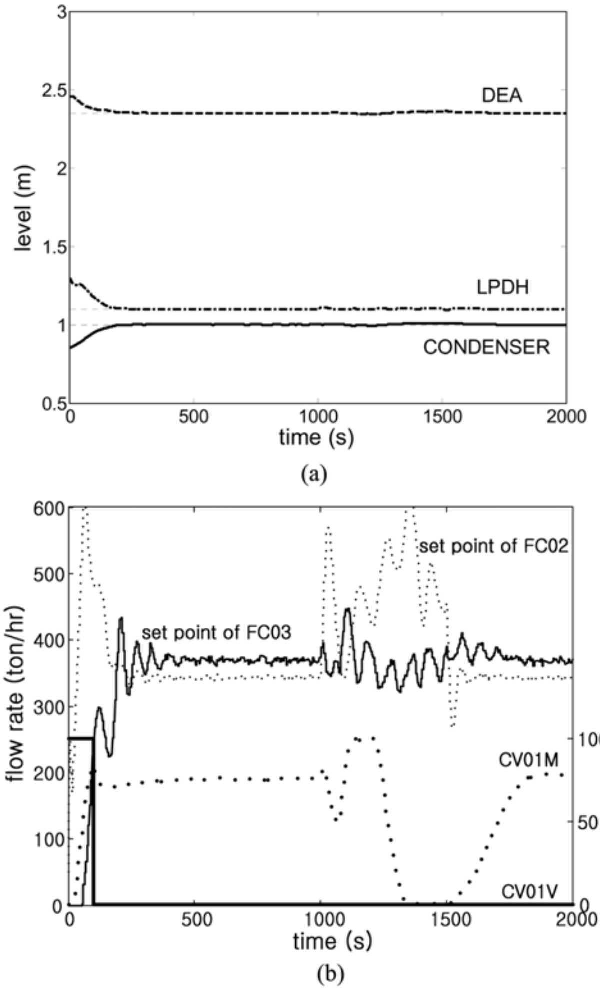


Fig. 10. Closed-loop response of MODE 5 process by MPC against the disturbance scenario in Fig. 6(b). (a) tank levels and (b) MV's and CV01V.

CONCLUSIONS

In this research, an industrial MPC system has been developed for implementation in the condensate recycle process of a cogeneration power station where hot water for a nearby huge apartment complex and electricity are generated simultaneously. The developed MPC system is based on a state space model and has a simple but powerful tuning knob derived from the Kalman filter-based tuning concept combined with a special output disturbance model, etc. The concerned cogeneration power plant is operated according to one of the five different modes depending on seasonal and weather conditions. The linear models of the concerned process for MPC design were derived by using fundamental laws instead of identification experiment. The developed MPC system was applied to a process simulator and, as a result, it was shown that the designed MPC system performs better than PI control against various disturbance changes.

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REFERENCES

1. M. Morari and J. H. Lee, *Computers and Chemical Engineering*, **23**, 667 (1999).
2. S. J. Qin and T. A. Badgwell, *Control Engineering Practice*, **11**, 733 (2003).
3. B. W. Hogg and N. M. El-Rabaie, *IEEE Transactions on Energy Conversion*, **5**, 485 (1990).
4. S. Lu and B. W. Hogg, *Control Engineering Practice*, **5**, 79 (1997).
5. W. K. Son, O. K. Kwon and M. E. Lee, *Fault tolerant model based predictive control with application to boiler systems*, In Proceedings of IFAC safeprocess'97, Hull, United Kingdom (1997).
6. K. Kawai, Y. Takizawa and S. Watanabe, *Control Engineering Practice*, **7**, 1405 (1999).
7. A. S. Lopez, G. A. Figueroa and A. V. Ramirez, *Electrical Power and Energy Systems*, **26**, 779 (2004).
8. Y. Majanne, *Control Engineering Practice*, **13**, 1499 (2005).
9. F. Jurado and J. Carpio, *Energy Conservation and Management*, **47**, 2961 (2006).
10. C. J. Moon and J. J. Choi, *KOPEC Trans.*, **2**, 68 (1991).
11. R. N. Silva, P. O. Shirley, J. M. Lemos and A. C. Goncalves, *Control Engineering Practice*, **8**, 1404 (2000).
12. A. D. Marco and G. Poncia, *Control Engineering Practice*, **7**, 483 (1999).
13. J. Y. Shin, Y. J. Jeon, D. J. Maeng, J. S. Kim and S. T. Ro, *Energy*, **27**, 1085 (2002).
14. E. Zafiriou and H. W. Chiou, *Output constraint softening for SISO model predictive control*, In Proceedings of ACC, San Francisco, California (1993).
15. J. H. Lee, Y. Chikkula, Z. Yu and J. C. Kantor, *Int. J. Control*, **61**, 859 (1995).
16. S. H. Kim, H. J. Moon and K. S. Lee, *ICASE Trans*, **4**, 413 (1998).
17. S. P. Boyd and L. Vandenberghe, *Convex optimization*, 1st ed., Cambridge, New York, NY (2004).
18. A. G. Wills and W. P. Heath, *Automatica*, **40**, 1415 (2004).
19. C. E. Garcia and A. M. Morshedi, *Chemical Engineering Communications*, **46**, 73 (1984).
20. J. H. Lee, *Model predictive control*, CRC Industrial Electronics Handbook, 515-521 (1996).
21. M. S. Grewal and A. P. Andrews, *Kalman filtering theory and practice*, Prentice-Hall, New York, NY (1993).