Development of Optimal Control System for Air Separation Unit

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Abstract: In this paper, We described the method which developed the optimal control system for air separation unit to change production rates frequently and rapidly. Control models of the process were developed from actual plant data using subspace identification method which is developed by many researchers in resent years. The model consist of a series connection of linear dynamic block and static nonlinear block (Wiener model). The model is controlled by model based predictive controller. In MPC the input is calculated by on-line optimization of a performance index based on predictions by the model, subject to possible constraints. To calculate the optimal the performance index, conditions are expressed by LMI(Linear Matrix Inequalities).In order to access at the Bailey DCS system, we applied the OPC server and developed the Client program. The OPC sever is a device which can access Bailey DCS system.The Client program is developed based on the Matlab language for easy calculation,data simulation and data logging. Using this program, we can apply the optimal input to the DCS system at real time.

Keywords: Model predictive control, Wiener model, OPC sever, Client

1. Introduction

Oxygen is essential element in steel making process. The POSCO has been produced 20000 Nm^2/h of Oxygen with 99.6 percent of purity from eight air separation units. Figure 1 shows the block diagram of the air separation plants which fractionates air into Nitrogen, Oxygen, and Argon using different boiling points of each liquid.

The atmosphere air of 25°C is compressed to $5.6kg/cm^2$ with 150°C by the air compressor. The compressed air is cooled down to 30°C by a heat exchanger. The cooled air flows to the lower distillation column with $5.3kg/cm^2$ and is separated into pure gas nitrogen (99.999%) and liquid air flows into the upper distillation column at $0.8kg/cm^2$. The boiling points of liquid Oxygen and Nitrogen are −183°C,−195.8°C respectively. Therefore, Nitrogen with lower boiling points is produced at the upper part of the column and the lower part contains liquid and gas Oxygen. The temperature of the gas Nitrogen and Oxygen which are produced at the upper distillation column, are cooled down to 25°C through heat exchanger.

The production volume and the purity of Oxygen are controlled by adjusting control valves. Table 1 shows the list of control valves.

However, the controlling the volume and purity at same time, is very difficult job due to several reasons. First, it is not easy to develop precise mathematical model for the whole system. Besides that, two control goals, volume and purity, are highly coupled through mass and heat balance in columns.

At the POSCO, the overall demands of Oxygen are frequently changed time to time, so that it makes more difficult to operate in stable condition which is critical for purity control. In order to solve these control problem, we will develop an optimal controller which enables to accommodate rapid change of Oxygen demand and high degree of purity.

This process model will be developed from actual plant data. Normally, plant testing would be conducted in manually operation where principles of experimental design could be employed. Because the identification experiment is carried out in a closed-loop, an identification algorithm should be used that can cope with closed-loop data. The basic steps of indirect closed-loop identification algorithms are presented in H.H.J.Bloemen[1]. For modelling of nonlinear process, a Wiener model structure will be used. The model consists of a series connection of a linear dynamic block and a static nonlinear block. The model is used within a model-based predictive control (MPC) framework. The linear dynamic can either be preceded by static output nonlinearity. In MPC, the control input is calculated by on-line optimization of performance index based on model predictions, subject to possible constraints.

To calculate the optimal the performance index, conditions are expressed by LMI (Linear matrix inequality). And in order to apply at the Bailey DCS system, We develop the OPC server and client program. The program will be developed based on the Matlab language. Using this program, we will apply the optimized input to the DCS system.

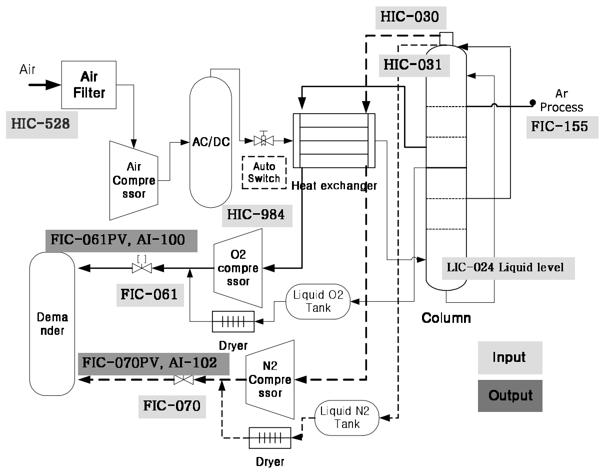

Fig. 1. Air Separation Unit

2. Control strategy for air separation unit

In this section, the development of Wiener model using subspace model identification and the method of output feedback model predictive controller design is described.

2.1. The development of Wiener model using subspace model identification

2.1.1 System description

Firstly, In order to develop optimal control system for air separation unit, we considered Wiener model which is derived from system identification using input and output data. The Wiener model consist of a linear dynamic block is preceded and static followed by nonlinear block. Although Wiener models only represent a small subclass of all nonlinear models, they have appeared useful in modeling several nonlinear processes encountered in the process industry such as distillation columns, a heat exchanger and pH neutralization processes.

In order to describe the process, the model is described as wiener model by an n^{th}-order deterministic system. Consider the wiener model represented by:

$$
\begin{aligned}
x(k+1) &= Ax(k) + Bu(k) \\
y(k) &= Cx(k) \qquad (1) \\
z(k) &= h(y(k)) \qquad (2)
\end{aligned}
$$

In which A, B, C are linear part of model, $x(k) \in \mathbf{R^n}$ is the state, $u(k) \in \mathbf{R^m}$is the control input, $y(k) \in \mathbf{R^p}$ is the output of the linear block respectively, h is the nonlinear mapping from $y(k)$ to $z(k)$ and is the output of the nonlinear block. The numbers of linear block output $y(k)$and nonlinear output $z(k)$ equal to p.

The nonlinearity of the Wiener model is transformed into a polytopic uncertainty description. Assume, without loss of generality that $h_1 \dots h_p$ are polynomials. The nonlinearity can be written as:

$$
\begin{aligned}
z(k) = h(y(k)) = H(y)y(k) = H(k)Cx(k) \qquad (3) \\
where \quad H(y) \in \Omega = Co\{H_1, \dots, H_{2^p}\} \qquad (4) \\
H(k) = \frac{\partial h(y)}{\partial y}, y = h^{-1}(x(c))
\end{aligned}
$$

in which $H(y)$ is a diagonal matrix because of the special structure of the nonlinearity. When the operating region for $y(k)$ is limited the entries of $H(y)$are bounded by minimum and maximum values. All the possible combinations of the maximum and minimum values of the element of $H(y)$ are used to generate 2^p vertices $\{H_1, \dots, H_{2^p}\}$of the polytopic description Ω which contains the nonlinear matrix $H(y)$.
(Co refers to the convex hull).

2.1.2 The modelling of air separation unit

To log data for obtaining the mathematical model such as (1), (2), we connected Bailey DCS system to lap-top computer which is installed OPC sever program. After that, a closed loop identification experiment was performed in which products of O_2 and N_2 was changed from $24000(Nm^2/h)$ to $20000(Nm^2/h)$ manually. The sampling time was 1 min, 600 samples of data was collected in this experiment.(Bloemen et al.2001 [1])

Using experiment data,we can obtain linear models at each operating points by using subspace model identification algorithm and then polynomial functions are obtained by the nonlinear function algorithm. We implemented a program to calculate model parameters with above algorithm using matlab language.

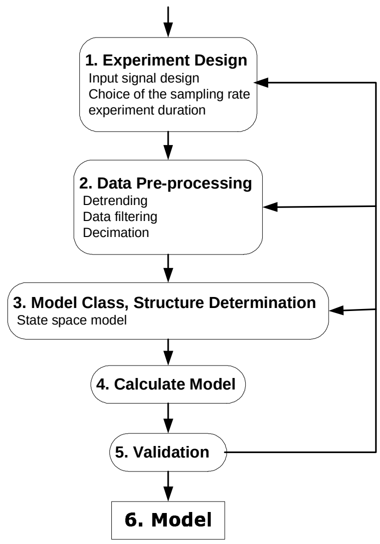

Fig. 2. Modelling diagram

Table 1. Control valves

HIC-528	Air flow control valve
HIC-984	Cold air flow control valve
HIC-030	Pure N_2 recycle flow control valve
HIC-031	Rough N_2 recycle flow control valve
FIC-061	O_2 product control valve
FIC-070	N_2 product control valve
FIC-155	Rough Ar flow control valve
FIC-156	Rough Ar product control valve
LIC-024	Liquid O_2 level control valve

Table 2. Output sensor

FIC-061PV	O_2 product sensor
FIC-070PV	N_2 product
AI-100	O_2 purity sensor
AI-102	N_2 purity sensor

2.2. Output feedback model predictive controller design

2.2.1 Problem statement

Model predictive control (MPC) scheme is very useful technique to handle time varying systems,input constraints and tracking problems.Kothare et al.(1996 [4]) presented a state

feedback MPC algorithm for time varying uncertain system with input constraint using Linear matrix inequality (LMI).With this model predictive control strategy, we will design an output feedback model predictive tracking controller which stabilized the system (1) and made outputs follow given command signals.
The controller structure is as follows:

$$\begin{aligned} x_c(k+1) &= A_c x_c(k) + B_c z_c(k) \\ u(k) &= C_c x_c(k) \end{aligned} \tag{5}$$

where A_c, B_c, C_c are design variables, And we consider the following performance index:

$$\begin{aligned} J(k, k+N) = &\sum_{i=0}^{k+N-1} [x(i)^T Q x(i) + u(i)^T R u(i)] \\ &+ x(k+N)^T P(k+N) x(k+N) \end{aligned} \tag{6}$$

where Q and R is positive definite diagonal weighting matrix. For our purposes, the above performance index is minimized at the time k. And we consider on integral action form because it provides a zero-offset for constant command signals. Define control increment

$$\begin{aligned} \delta u(k) &= u(k+1) - u(k) \\ \delta y(k) &= y(k+1) - y(k) \end{aligned} \tag{7}$$

We replace $u(k)$ with $\delta u(k)$ and we transform the model (1) and performance index (3) into the following structure.

$$\begin{aligned} x^e(k+1) &= A^e(k) x^e(k) + B^e(k) z^e(k) \\ z(k) &= C^e x^e(k) \end{aligned} \tag{8}$$

where

$$A^e(k) = \begin{pmatrix} I & H(k)CA \\ 0 & A \end{pmatrix}, \quad B^e(k) = \begin{pmatrix} H(k)CB \\ B \end{pmatrix}$$
$$C^e(k) = \begin{pmatrix} I & 0 \end{pmatrix}, \quad x^e(k) = \begin{pmatrix} z(k) \\ \delta x(k) \end{pmatrix} \tag{9}$$

To easily solve the tracking problem, we can define as following controller structure:

$$\begin{aligned} x_c(k+1) &= A_c x_c(k) + B_c(z_c(k) - z_r(k)) \\ \delta u(k) &= C_c x_c(k) \end{aligned} \tag{10}$$

The basic concept of this Wiener MPC algorithm is presented in (Norquay et al.1998 [2])and consists of inverting the output nonlinearity, thus removing it from the control problem.

2.2.2 Controller design
In order to design dynamic output feedback model predictive tracking control law, we considered as following structure:

$$\begin{aligned} \bar{x}(k+1) &= \bar{A}(k)\bar{x}(k) + \bar{B}(k)\bar{z}(k) \\ \delta u(k) &= K\bar{x(k)} \\ z(k) &= \bar{C}(k)\bar{x}(k) \end{aligned} \tag{11}$$

where

$$\bar{A}(k) = \begin{pmatrix} A^e(k) & 0 \\ B_c C^e(k) & A_c \end{pmatrix}, \quad \bar{B}(k) = \begin{pmatrix} B^e(k) \\ 0 \end{pmatrix}$$
$$\bar{C}(k) = \begin{pmatrix} C^e(k) & 0 \end{pmatrix}, \quad \bar{x}(k) = \begin{pmatrix} x^e(k) \\ x_c(k) \end{pmatrix}$$
$$K = \begin{pmatrix} 0 & C_c \end{pmatrix} \tag{12}$$

And we can consider the performance index as following structure:

$$\begin{aligned} \hat{J}(k, k+N) = &\sum_{i=0}^{k+N-1} [\bar{x}(i)^T \bar{Q} \bar{x}(i) + \delta u(i)^T R \delta u(i)] \\ &+ \bar{x}(k+N)^T \bar{P}(k+N) \bar{x}(k+N) \\ &where \quad \bar{Q}(i) = \begin{pmatrix} C^{eT} Q C^e & 0 \\ 0 & 0 \end{pmatrix} \\ &\bar{Q} \geq 0,\ R > 0,\ \delta u(i) = K\bar{x}(i) \end{aligned} \tag{13}$$

To design controller which minimizes the upper bound of the performance index, We toke as following formula from the paper of Kothare[4]:

$$\hat{J}(k, k+N) - \bar{x}(k)^T \bar{P}(k) \bar{x}(k) < 0 \tag{14}$$

Consequently, As following inequality is obtained:

$$(\bar{A}(k) + \bar{B}(k)K)^T \bar{P}(\bar{A}(k) + \bar{B}(k)K) - \bar{P} + \bar{Q} + K^T R K < 0 \tag{15}$$

LMI condition derived from Inequality(14) by Schur's complement.

$$\begin{pmatrix} T^T\bar{P}T & T^T(\bar{A}(k) + \bar{B}(k)K)\bar{P}T & 0 & 0 \\ * & T^T\bar{P}T & T^T\bar{P}K^T R^{1/2} & T^T\bar{P}Q^{1/2} \\ * & * & \gamma I & 0 \\ * & * & * & \gamma I \end{pmatrix} > 0 \tag{16}$$

where

$$\begin{aligned} \bar{P} &= \gamma \bar{P}^{-1}, \bar{P} = \begin{pmatrix} X & X \\ * & \bar{X} \end{pmatrix}, \bar{P}^{-1} = \begin{pmatrix} Y & V \\ * & \bar{Y} \end{pmatrix} \\ T &= \begin{pmatrix} Y & I \\ V^T & 0 \end{pmatrix} \end{aligned} \tag{17}$$

To solve the LMI(15) condition, we can transform LMI(15) into LMI(17) by replacing $A_c, B_c, C_c, X, Y, U, V$ of proper matrix. (E.Granado[3])

$$\begin{pmatrix} Y & I & YA + FC & Z & 0 & 0 \\ * & X & A & AX + BL & 0 & 0 \\ * & * & Y & I & 0 & Q^{1/2} \\ * & * & * & X & L^T R^{1/2} & XQ^{1/2} \\ * & * & * & * & \gamma I & 0 \\ * & * & * & * & * & \gamma I \end{pmatrix} > 0 \tag{18}$$

where

$$F = VB_c, L = C_cU^T, Z = YAX + FCX + YBL + VA_cU^T \quad (19)$$

If we choose a proper $\bar{P}$ to satisfy the LMI condition(17),we performance index is satisfied as following formula.

$$V(\bar{x}(k/k)) = \bar{x}(k)^T\bar{P}\bar{x}(k), \quad \bar{P} > 0 \quad (20)$$

If the cost function(12) is well defined, we can state that $V(\infty/k) = 0$ because $V(\bar{x}(\infty/k)) = 0$. In view of this,we impose a bound on the cost function $J_\infty(k)$ by the following design requirement:

$$\hat{J}_\infty(k) \leq V(\bar{x}(k/k)) = \bar{x}(k)^T\bar{P}\bar{x}(k) < \gamma \quad (21)$$

We can transform Inequality (20) into LMI (21) using Schur's complement. Derived LMI(20)is as following structure.

$$\begin{pmatrix} T^T\bar{P}T & I & Yx(k/k) \\ * & X & x(k/k) \\ * & * & I \end{pmatrix} > 0 \quad (22)$$

In practical process, We can add as following conditions because input and output have constraints.

$$\begin{aligned} \| u(k+i|k) \|_2 &\leq u_{max} \quad i \geq 0 \\ \| y(k+i|k) \|_2 &\leq y_{max} \quad i \geq 0 \end{aligned} \quad (23)$$

We can transform Inequality (22) into LMI (23), LMI (24) using Cauchy-Schwartz inequality and Schur's complement.

$$\begin{pmatrix} Y & I & 0 \\ * & x & L^T \\ * & * & u_{max}^2 I \end{pmatrix} > 0 \quad (24)$$

$$\begin{pmatrix} Y & I & (CA^T) \\ * & x & (CAX + CBL)^T \\ * & * & y_{max}^2 I \end{pmatrix} > 0 \quad (25)$$

Therefore, We can obtain $\bar{P}$ such that the following optimization problem is solvable:

min γ
Subject to

$$\begin{pmatrix} T^T\bar{P}T & I & Yx(k/k) \\ * & X & x(k/k) \\ * & * & I \end{pmatrix} > 0$$

$$\begin{pmatrix} Y & I & YA+FC & Z & 0 & 0 \\ * & X & A & AX+BL & 0 & 0 \\ * & * & Y & I & 0 & Q^{1/2} \\ * & * & * & X & L^TR^{1/2} & XQ^{1/2} \\ * & * & * & * & \gamma I & 0 \\ * & * & * & * & * & \gamma I \end{pmatrix} > 0$$

$$\begin{pmatrix} Y & I & 0 \\ * & x & L^T \\ * & * & u_{max}^2 I \end{pmatrix} > 0$$

$$\begin{pmatrix} Y & I & (CA^T) \\ * & x & (CAX + CBL)^T \\ * & * & y_{max}^2 I \end{pmatrix} > 0$$

(25)

If we can solve above optimization problem (25), the value of variable X, Y, L, F, Z will be obtain.Therefore, We consist of as following method:

$$\begin{aligned} V &= (I - YX)(U^T)^{-1} \\ A_c &= V^{-1}Z(U^T)^{-1} \\ B_c &= V^{-1}F \\ C_c &= L(U^T)^{-1} \end{aligned} \quad (26)$$

2.3. Implementation of the model predictive controller

At the air separation factory of the Pohang iron and steel company, Bailey DCS system has been used to control each valves. In order to apply our proposed control algorithm to the DCS system, we have to access the DCS network using OPC server and Client program. Because our proposed algorithm is casted by LMI at every sampling time, the program is developed based on the Matlab language. Using this program, we can apply the optimized input to the DCS system. This client program is as following structure.

This client program have a lot of functions such as real time simulation, saving data in file and data displaying and so on.Client program can't only access to OPC server but also automatically can write the control input casted by Matlab to the DCS system.

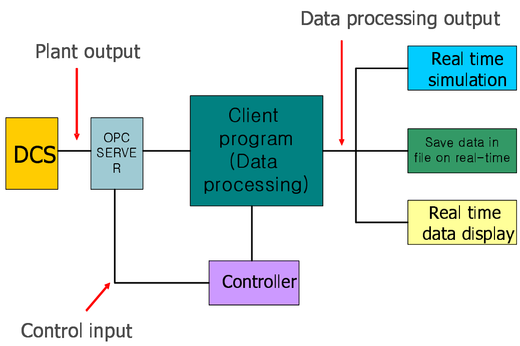

Fig. 3. The structure of client program

3. Simulation result

We maintained the purity of Oxygen more than 99.6 percent and production of Oxygen was changed from 20000 Nm^2/h to 25000 Nm^2/h at the basis of 99.8 percent for purity in our lab experiment such as fig.4, fig.5, fig.6. In order to maintain the impurity of 1PPM, We can change from 18000Nm^2/h to 23000Nm^2/h at the basis of 0.5PPM for impurity of Nitrogen.

As result, We can maintain the purity of Oxygen more than 99.6percent and the impurity of Nitrogen less than 1PPM. Ramping time decrease from 40 min to 20 min (fig.4) when we increase the production and from 20 min to 15min (fig.5) when we decrease the production. Moreover, control input maintain from -50 percent to 50 percent such as fig.6.

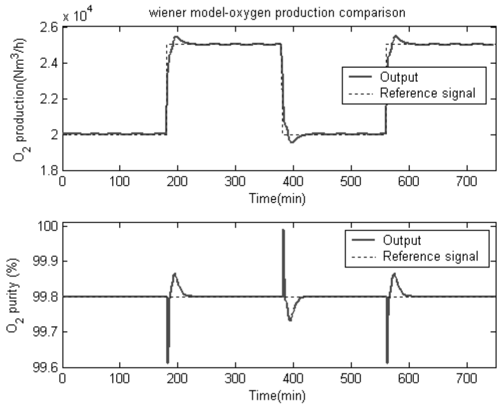

Fig. 4. The production and purity of Oxygen

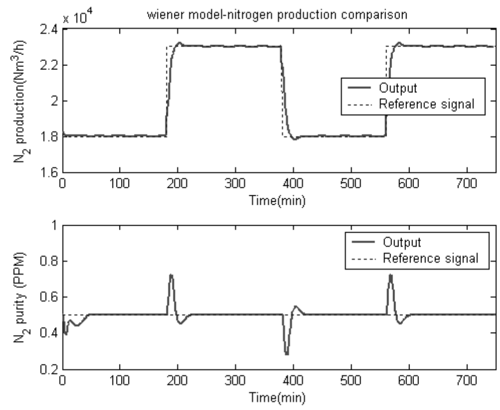

Fig. 5. The production and purity of Nitrogen

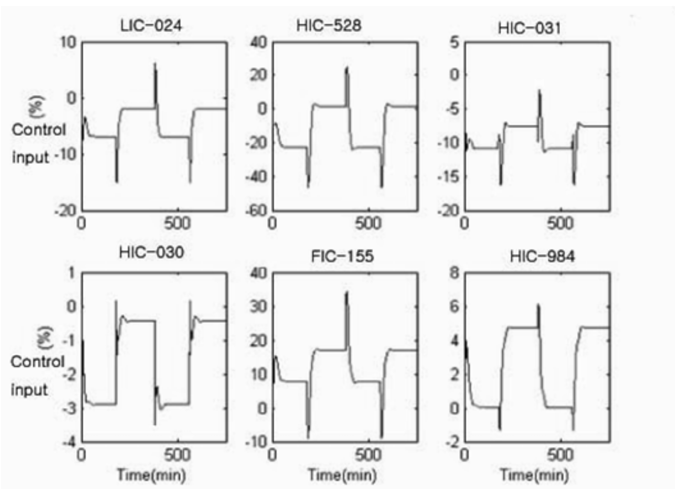

Fig. 6. Control input

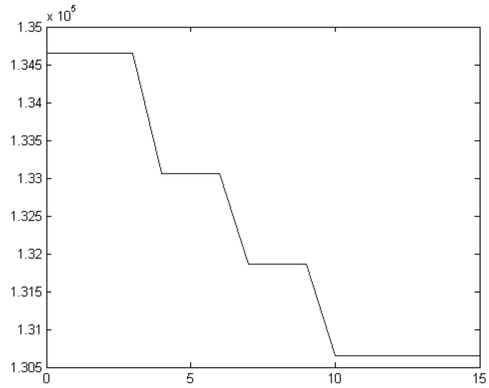

Fig. 7. Air flow control valve(HIC-528)

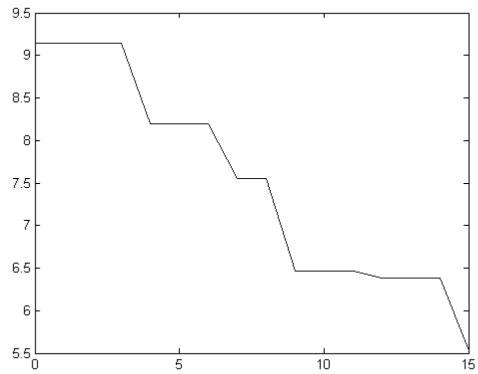

Fig. 8. Rough N_2 recycle flow control valve(HIC-031)

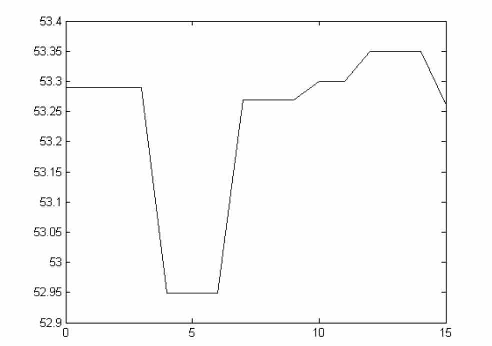

Fig. 9. Pure N_2 recycle flow control valve(HIC-030)

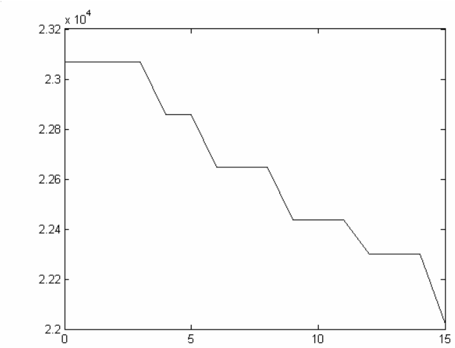

Fig. 10. N_2 product control valve(HIC-070)

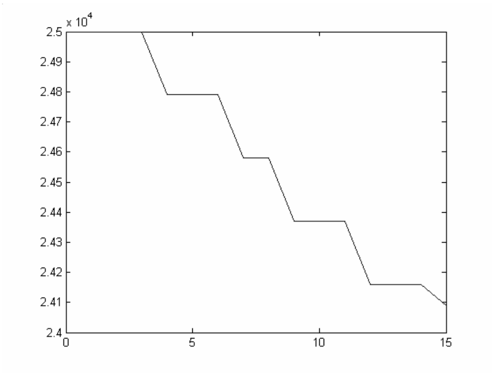

Fig. 11. O_2 product control valve (HIC-061)

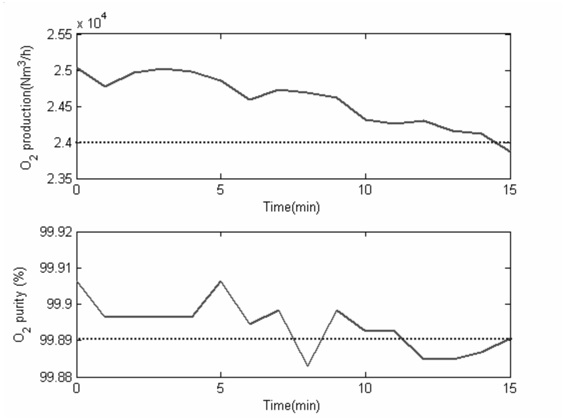

Fig. 12. Practical production and purity of Oxygen

In practical experiment, we logged data for two days and determine Wiener model parameter using the data. We chosen five number of control inputs for risk of practical experiment such as fig.7, fig.8, fig.9, fig.10, fig.11 and we only experimented for production and purity of Oxygen except production and purity of Oxygen. In fig.7, fig.8, fig.9, fig.10, fig.11, we can observe the result of control input.In this figure, as we decrease the production of Oxygen, control input also decrease. This means that we have to more open control valves. In fig.12, we can observe practical variation of production and purity of Oxygen.

4. Conclusion

We made on experiment with NO.6 plant using OPC server and client. We logged 1 data per 1 second and model is obtained by the data using system identification. We used system identification method as subspace model identification and model is considered by Wiener model. As a result, Precision of oxygen production showed more than 98 percent and purity showed more than 80 percent.Using Wiener model, we obtained output feedback MPC controller and we applied it to the plant in practice. Consequently, Air separation unit is controlled by five number of control input so we could decrease ramping time. In order to more decrease ramping time, We obtained the result that are haven to install faster moving valves than current valves.

We also developed Client program to apply control input to be casted by matlab. The client program is easy to manager plant because it is composed of GUI. In practical experiment, We used 1 data per 1 second for 1 week using this client program and we monitored all experiment process using function of display. Prospectively, we should add to the function to warn the accident in this client.

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