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Modeling Waste Heat Recovery System of Industrial Ammonia Process Plant Using LPV Identification

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Abstract: This paper presents modeling of Waste Heat System of an industrial ammonia process plant. Linear Parameter Varying (LPV) identification is utilized to cover changes in process operating conditions, such as start-up, normal operation and shut-down. Recursive Least Square (RLS) based algorithm is employed in the LPV identification process. Experimental input-output signals required for identification process are taken from DCS historian data of the ammonia process plant during plant operations. The resulting LPV model is simulated and validated with respect to the measured data. Promising results are obtained in applying advanced LPV identification to cover variations of process operating conditions in an industrial process plant.

1. INTRODUCTION

System or process identification is the field of mathematical modeling of systems (processes) from test or experimental data [Ljung, 2002]. Process model obtained from identification process can be used for process simulation, analysis and design of control systems, design of safety systems. Most of the existing works on process simulation is based on LTI, which is satisfactory for a number of systems. However, system identification based on LTI model appears to be of limited value when the plant operating conditions significantly varies. One of the effective methods to handle varying operating conditions in the plant is to employ Linear Parameter Varying (LPV) model[Shamma and Athans 1991, Rugh and Shamma 2000]. LPV constitutes linear dynamic systems whose state space matrices depend on parameters which may vary in time. Such a system was recently studied within the context of gain-scheduling control analysis and design which provides stability and performance guarantee along the trajectory of the varying parameters[Apkarian 1998]. More recently, some results of LTI system identification was extended to LPV model in [Bamieh and Giarre 2002, Lee and Polla 2002, T'oth et al. 2006, Felici et al. 2007].

System identification of primary reforming process in an industrial ammonia process plant was recently studied for simulation purpose by the first author in [Bambang and Hendarwin 2006], based on LTI model. Simulation result shows that the model obtained was satisfactory for reforming process operation in normal operating condition. Simulation for start up operating condition has not been sucessfully conducted, however, as high overshoots of step responses appear in several process models which exceeds maximum operation limit, prohibiting the simulation to proceed in a realistic way. A careful observation of feed gas pre-heater, in particular, and in reforming process in general, reveals that some nonlinearity occurs in the system.

The term Linear Parameter Varying (LPV) system was originally coined by Shamma dan Athans within the context of gain-scheduling design. LPV model appears in many physical modeling and control problems, such as aerospace, vehicle system applications [Lee and Polla 1995], stall and surge control of jet engine [Bamieh et al. 1991]. As far the authors concern, application of LPV model identification in chemical processes has not been studied, despite the fact that process plant dynamics is known to be varied with respect to operating conditions.

This paper presents the LPV model identification for Waste Heat Recovery System (WHS) as a sub-system in reforming process in an industrial ammonia plant. The identification process is based on historical data recorded in a distributed control system (DCS). The LPV model is chosen in this paper based on the observation that ammonia plant is operated along several operating conditions (start up, normal, shutdown, and emergency operations) and that in each operating conditions there are significant parameter changes. LPV identification process adopted is based on Recursive Least Square (RLS), a technique originally developed by [Bamieh and Giarre 2002].

The rest of this paper is outlined as follows. In Section 2, WHS in an ammonia process plant is described. In Section 3, LPV identification algorithm is presented. In Section 4, results of LPV identification for WHS are presented. Finally, conclusion is drawn in Section 5.

2. WASTE HEAT RECOVERY SYSTEM IN AMMONIA PROCESS PLANT

This section gives an overview of WHS in an industrial ammonia process plant shown in Figure 1. The ammonia process plant from which modelling is performed is located at PT Pupuk Kaltim, Kalimantan Island. In this process plant ammonia is produced from the reaction of hydrogen (H_2) and nitrogen (N_2) in the ratio of 3:1. Hydrogen is produced by steam reforming of desulphurized natural process gas in the primary reformer section, whereas N_2 is obtained by introducing compressed air into secondary reformer, an autothermal reactor used to further reform the remaining natural process gas.

The resulting raw synthesis gas mainly contains H_2, N_2, carbon monoxide (CO), carbon dioxide (CO_2) and steam. CO is converted to CO_2 and the additional H_2 is produced by water gas shift reaction. In the CO_2 Removal section, CO_2 is removed from the gas and then sent to Urea Plant. The remaining CO and CO_2 are converted into methane (CH_4) by reacting them with H_2 in the Methanation section. The synthesis gas, mostly contains H_2 and N_2, is then fed into the Ammonia Synthesis Loop section and converted into ammonia before being sent to Urea Plant.

In the primary reformer section, the natural gas is steam reformed. Heat needed for the reaction is supplied in the forn of radiant heat from firing of natural fuel gas. Sensible flue gas heat flows along convection section is used to heat several media in the waste heat recovery [Nugraha, 2002].

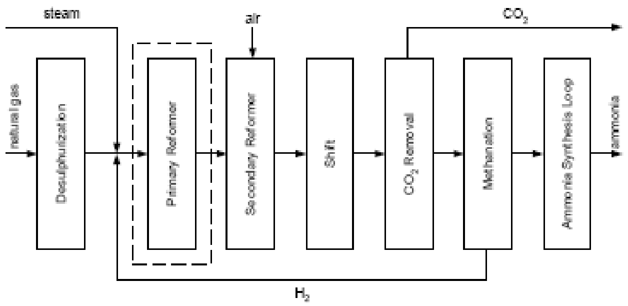


Fig. 1: Ammonia process

The primary reformer section consists of:

- 144 catalyst tubes in the two radiant section and side firing burner systems. Firing burner control system is shown in Figure 2.
- Waste Heat Recovery System (WHS) utilizes sensible flue gas heat produced from primary reformer radiant section in order to heat various coils by convective heat exchange. The system shown in Figure 3 involves
    1. Mixed feed pre-heater coil used to heat hydrocarbon and steam before fed into catalyst tubes.
    2. Process air heater coil used to heat compressed air before fed into secondary reformer section.
    3. Super heater steam coil used to heat steam to produce superheated steam.
    4. Feed gas pre-heater coil used to heat natural gas before being fed into desulphurization section.
    5. Boiler feed water pre-heater coil used to heat boiler feed water.

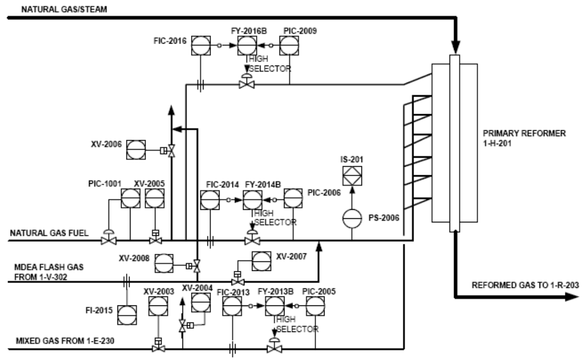


Fig. 2: Firing burner control system

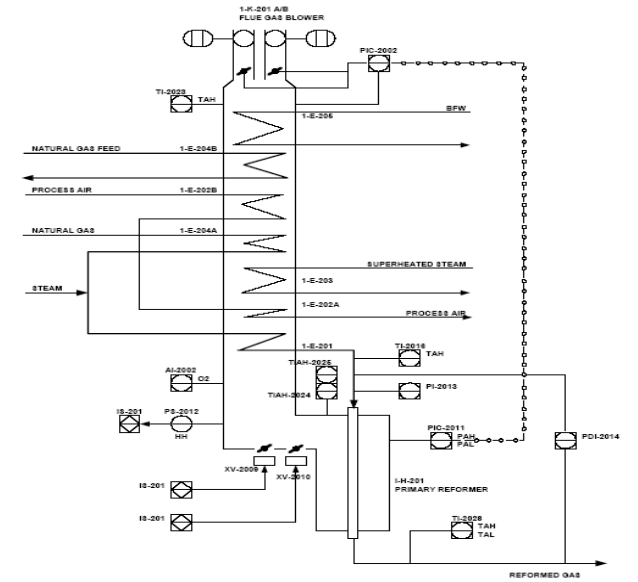


Fig. 3. Waste heat recovery system

3. LPV IDENTIFICATION

Linear Parameter Varying (LPV) system is a special class of nonlinear system [Nemani, 1995], where the system coefficients are rational function of a parameter. In LPV model, system matrices depends on one or more time-varying parameters and hence represents a family of LTV systems (one for each parameter trajectory) [Shamma and Athans, 1991].

A discrete time LPV systems represented in the state space form as:

$$\begin{aligned} x(t+1) &= A(p(t))x(t) + B(p(t))u(t) \\ y(t) &= C(p(t))x(t) + D(p(t))u(t) \end{aligned} \tag{1}$$

LPV systems model may also be characterized in the form of [Bamieh and Giarre 2002]:

$$A(\delta, p)y(k) = B(\delta, p)u(k) \quad (2)$$

where u is input, y is output, δ is delay operator, i.e. $(\delta y)_k := y(k-1)$, and

$$B(\delta, p) = b_0(p) + b_1(p)\delta + \ldots\ldots + b_{n_b}(p)\delta^{n_b} \quad (3)$$
$$A(\delta, p) = 1 + a_1(p)\delta + \ldots\ldots + a_{n_a}(p)\delta^{n_a} \quad (4)$$

$n = n_a + n_b + 1$ is the number of parametric functions to be identified. Assume that the varying parameter p is a function of discrete time ($p = p(k)$).

Parameter function { a_i }, { b_i } are assumed to be a linear combinations of a set of known fixed basis functions {f_1, ..., f_N}.

$$a_i(p) = a_i^1 f_1(p) + \ldots\ldots + a_i^N f_N(p) \quad (5)$$
$$b_i(p) = b_i^1 f_1(p) + \ldots\ldots + b_i^N f_N(p) \quad (6)$$

where the constants a_i^k , b_i^l are real numbers. Thus any particular model is completely characterized by the real numbers { a_i^k } and { b_i^l }. The goal of a parametric identification scheme in this paper is then to find these constants from process measurement data.

For this general framework, many choices are possible for the function $f_1(p)$. In particular if we consider a polynomial dependence, then the function $f_1(p)$ are simply powers of p

$$f_1(p) = p^{l-1} \qquad l = 1,\ldots,N \quad (7)$$

In this case the parameter functions are rewritten as

$$a_i(p) = a_i^1 + a_i^2 p + \ldots\ldots + a_i^N p^{N-1} \quad (8)$$
$$b_i(p) = b_i^1 + b_i^2 p + \ldots\ldots + b_i^N p^{N-1} \quad (9)$$

In recursive least mean square (RLS) identification algorithm, the objective is to minimize errors between measurement and estimation variables, which is known as loss function

$$J = J(\mathbf{\Theta}) = \frac{1}{T}\sum_{k=0}^{T} E\left\{\varepsilon(k,\mathbf{\Theta})^2\right\} \quad (10)$$

where $\mathbf{\Theta}$ is n x N matrix that contains coefficients to be identified:

$$\mathbf{\Theta} := \begin{bmatrix} a_1^1 & \ldots & a_1^N \\ a_2^1 & \ldots & a_2^N \\ & \vdots\vdots\vdots & \\ a_{na}^1 & \ldots & a_{na}^N \\ b_0^1 & \ldots & b_0^N \\ & \vdots\vdots\vdots & \\ b_{nb}^1 & \ldots & b_{nb}^N \end{bmatrix} \quad (11)$$

and $\varepsilon(k,\mathbf{\Theta})$, called prediction error, is defined as

$$\varepsilon(k,\mathbf{\Theta}) = y_k - \left\langle \mathbf{\Theta}, \mathbf{\Psi}_k \right\rangle \quad (12)$$

where y_k is measurement data (output of the system) and $\left\langle \mathbf{\Theta}, \mathbf{\Psi}_k \right\rangle$ is estimation output. An extended regressor Ψ, is build by past I/O data and parameter trajectories,

$$\mathbf{\Psi}_k := \phi_k \pi_k := \begin{bmatrix} -y_{k-1} \\ \vdots \\ -y_{k-n_a} \\ u_k \\ \vdots \\ u_{k-n_b} \end{bmatrix} \begin{bmatrix} f_1(p_k) & f_2(p_k) & \ldots & f_N(p_k) \end{bmatrix} \quad (13)$$

In this paper, $\hat{\mathbf{\Theta}}_k$ is parameter coefficients matrix which is estimated at time k. Following RLS algorithm and under appropriate assumptions [Bamieh and Giarre 2002], identification algorithm is given by:

$$\varepsilon_k = y_k - \left\langle \hat{\mathbf{\Theta}}_{k-1}, \mathbf{\Psi}_k \right\rangle = y_k - \mathrm{trace}(\hat{\mathbf{\Theta}}_{k-1}^* \mathbf{\Psi}_k) \quad (14)$$
$$\hat{\mathbf{\Theta}}_k = \hat{\mathbf{\Theta}}_{k-1} + \mathbf{K}_k \varepsilon_k \quad (15)$$
$$\mathbf{K}_k = \mathbf{P}_k \{\mathbf{\Psi}_k\} \quad (16)$$
$$\mathbf{P}_k = \mathbf{P}_{k-1} - \mathbf{P}_{k-1} \frac{\mathbf{\Psi}_k \otimes \mathbf{\Psi}_k}{1 + \left\langle \mathbf{\Psi}_k, \mathbf{P}_{k-1}\mathbf{\Psi}_k \right\rangle} \mathbf{P}_{k-1} \quad (17)$$

where P is covariance matrix expressed in recursive form in Equation (17). Convergence condition of the identification algorithm is attained if $\mathbf{\Theta}_0$ is the true value, thus

$$\lim_{k\to\infty} \hat{\mathbf{\Theta}}_k = \mathbf{\Theta}_0 \quad (18)$$

4. LPV IDENTICATION RESULTS OF WHS

In this section, some results of LPV identification for WHS process is presented. Various measured input-output signals required for identification process are taken from DCS historian data of the ammonia process plant during plant operations. In other words, particular experimentations with some excitation signals are not performed as it will disturb the plant operation process. Data needed for identification process is taken from DCS historian data from February 15, 2006 to March 3, 2006 with sampling time of 5 minutes. All operating conditions of the process (start up, normal, and shut down) are covered in the duration considered. Plots of a sample of historical input signals (TI2010PNT and FIC2001MEAS) are shown in Figure 4. In the subsequent discussions, Prefix T, P and F in various signals identification number represents temperature, pressure and flow, respectively. In the following, we present LPV identification results for Mixed Gas Preheater, Process Air Preheater, Steam Superheater, and Feed Gas Preheater A—the main subsystems of WHS. Preprocessing of measured data involves data merging, normalization (offset correction) and scaling. Data merging is required because, due to limited available storage in DCS, historian data for several operating conditions are not provided in time-sucessive manner, but instead in time-truncated way.

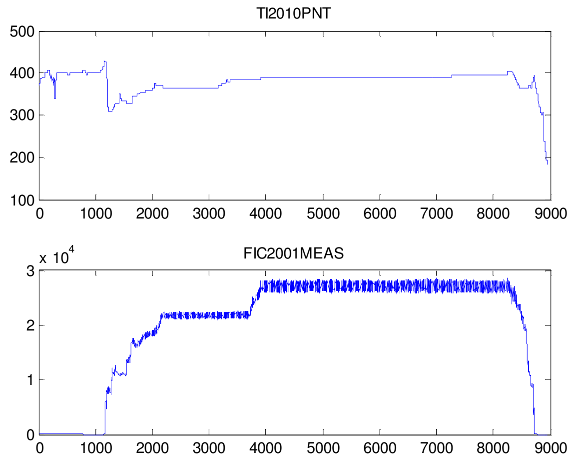


Fig. 4. Sample of measured data : temperature TI2010PNT (upper) and flow FIC2001MEAS (lower)

4.1 Mixed Feed Gas Preheater(1-E-201)

Mixed Feed Gas Preheater consists of 7 inputs, consisting of temperatures and flows and 1 output (temperature) as shown in Figure 5. Plot of simulated LPV model, along with the corresponding measured data used for identification process is shown in Figure 6.a. A best fit of 88.9171 and loss function of 0.0123 are obtained. Comparison of the simulated LPV model with measured data not used in identification process is shown in Figure 6.b, with best fit of 83.4495 and loss function of 0.0274. Note that estimated output predict the measured output very well.

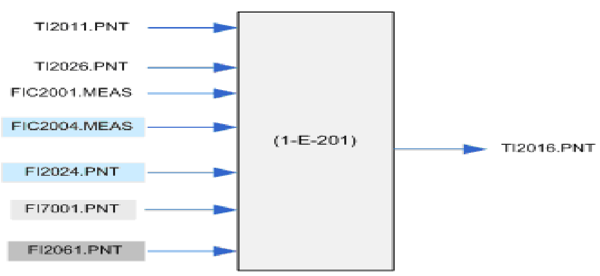
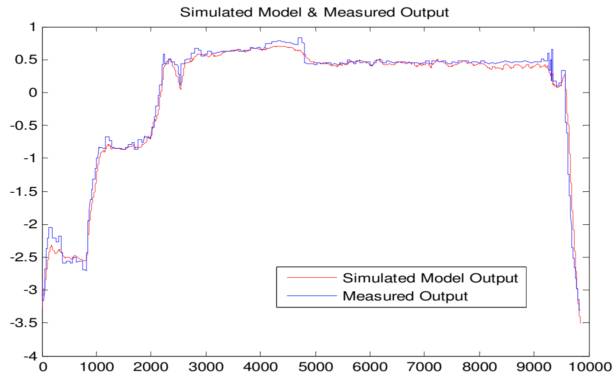
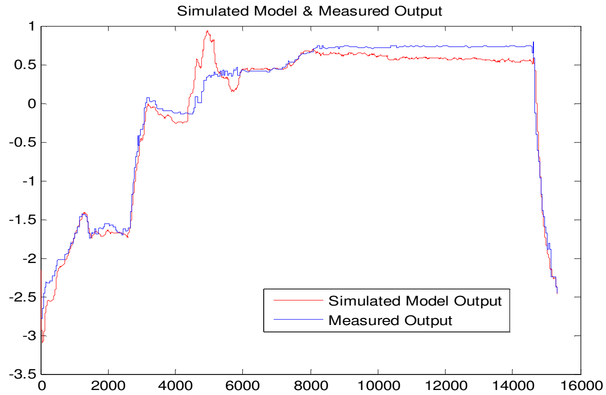


Fig. 5. Mixed Feed Gas Preheater input-output



(a)



(b)

Fig. 6. Actual/measured and predicted/simulated outputs of Mixed Feed Gas Preheater, (a) measured data were used in identification, (b) measured data were not used in identification

The LPV model obtained is of the form (in MATLAB symbol):

```
y1(k)=-A1p*y1(k-1)-A2p*y1(k-2)...
      +B11p*u1(k-1)+B21p*u2(k-1)+B31p*u3(k-1)
      +B41p*u4(k-1)+B51p*u5(k-1)...
      +B61p*u6(k-1)+B71p*u7(k-1)...
      +B12p*u1(k-2)+B22p*u2(k-2)+B32p*u3(k-2)
      +B42p*u4(k-2)+B52p*u5(k-2)...
      +B62p*u6(k-2)+B72p*u7(k-2);
```

where

```
A1p=Theta(1,:)*p;  A2p =Theta(2,:)*p; B11p = Theta(3,:)*p;
B21p =Theta(4,:)*p;B31p = Theta(5,:)*p;B41p=Theta(6,:)*p;
B51p=Theta(7,:)*p;B61p = Theta(8,:)*p;B71p= Theta(9,:)*p;
B12p=Theta(10,:)*p;B22p =Theta(11,:)*p;
B32p=Theta(12,:)*p; B42p=Theta(13,:)*p;
B52p=Theta(14,:)*p;B62p=Theta(15,:)*p;
B72p=Theta(16,:)*p;
```

and

```
p=[1; sin(0.0001*k); (sin(0.0001*k))^2];
```

Theta is 16x3 matrix representing identified parameters.

4.2 Process Air Preheater (1-E-202B)

Process Air Preheater consists of 4 inputs, consisting of temperatures, heat and flows and 1 output (temperature) as shown in Figure 7. Plot of simulated LPV model, along with the corresponding measured data used for identification process is shown in Figure 8.a. A best fit of 92.0809 and loss function of 0.063 are obtained. Comparison of the simulated LPV model with measured data not used in identification process is shown in Figure 8.b, with best fit of 85.2738 and loss function of 0.0271. Note that estimated output predict the measured output very well.

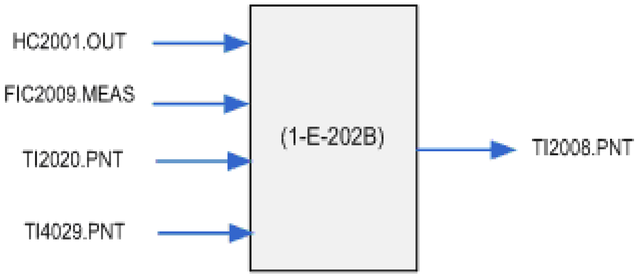
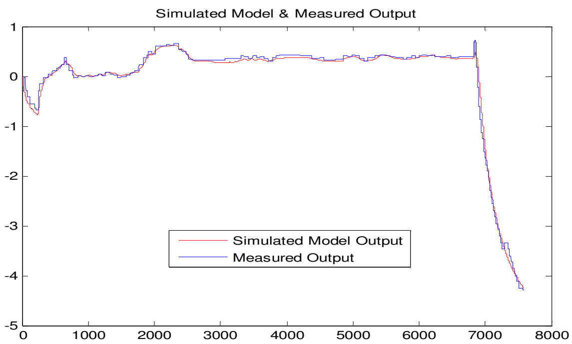
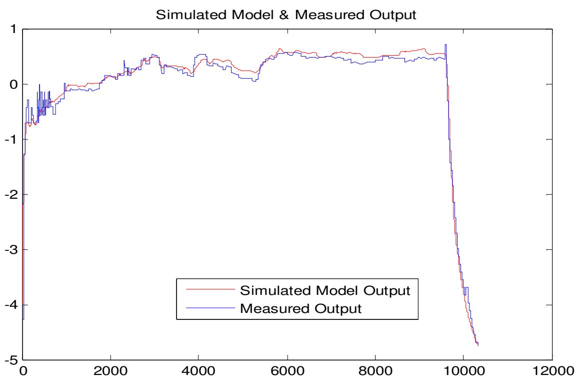


Fig.7 Process Air Preheater systems's input-output



(a)



(b)

Fig. 8. Actual/measured and predicted/simulated outputs of Process Air Preheater, (a) measured data were used in identification, (b) measured data were not used in identification

The LPV model obtained for Process Air Preheater is of the following form

y1(k)=-A1p*y1(k-1)-A2p*y1(k-2)...
+B11p*u1(k-1)+B21p*u2(k-1)+B31p*u3(k-1)
+B41p*u4(k-1)...
+B12p*u1(k-2)+B22p*u2(k-2)+B32p*u3(k-2)
+B42p*u4(k-2);

4.3 Steam Superheater (1-E-203)

Steam Superheater consists of 4 inputs, consisting of temperatures and flows and 1 output (temperature) as shown in Figure 9. Plot of simulated LPV model, along with the corresponding measured data used for identification process is shown in Figure 10.a. A best fit of 92.0212 and loss function of 0.0064 are obtained. Comparison of the simulated LPV model with measured data not used in identification process is shown in Figure 10.b, with best fit of 79.4781 and loss function of 0.0421. Note that estimated output predict the measured output very well.

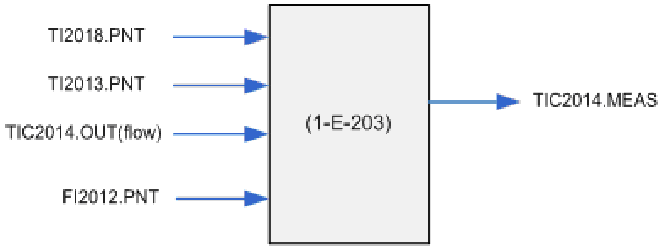
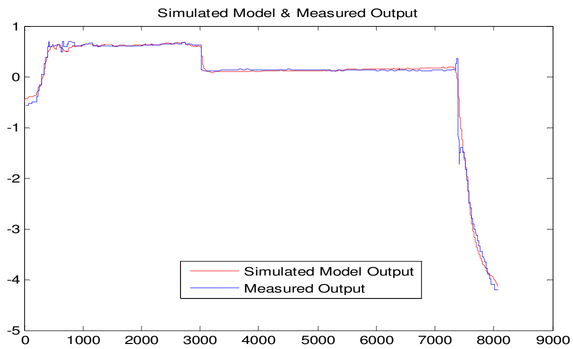
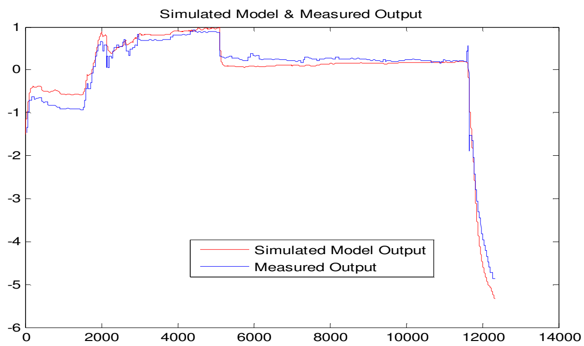


Fig. 9. Super Preheater system's input-output



(a)



(b)

Fig.10. Actual/measured and predicted/simulated outputs of Steam Superheater, (a) measured data were used in identification, (b) measured data were not used in identification

The LPV model obtained takes the following form

```
y1(k)=-A1p*y1(k-1)-A2p*y1(k-2)...
      +B11p*u1(k-1)+B21p*u2(k-1)+B31p*u3(k-1)
      +B41p*u4(k-1)...
      +B12p*u1(k-2)+B22p*u2(k-2)+B32p*u3(k-2)
      +B42p*u4(k-2);
```

4.4 Feed Gas Preheater A(1-E-204A)

Steam Superheater consists of 4 inputs, consisting of temperatures, pressures and flows and 1 output (pressure) as shown in Figure 11. Plot of simulated LPV model, along with the corresponding measured data used for identification process is shown in Figure 12.a. A best fit of 81.8123 and loss function of 0.0331 are obtained. Comparison of the simulated LPV model with measured data not used in identification process is shown in Figure 12.b, with best fit of 79.4781 and loss function of 0.0421. Note that estimated output predict the measured output very well.

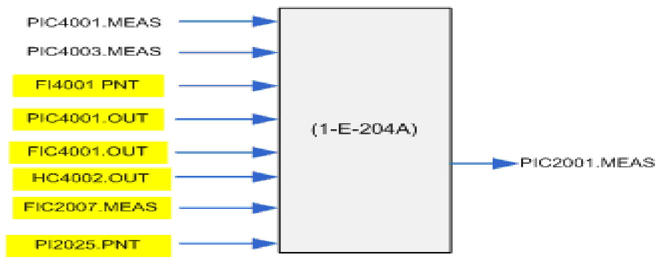
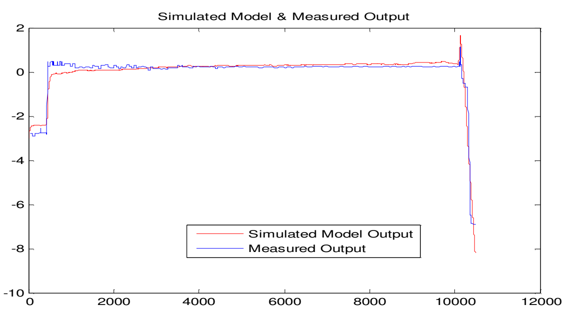
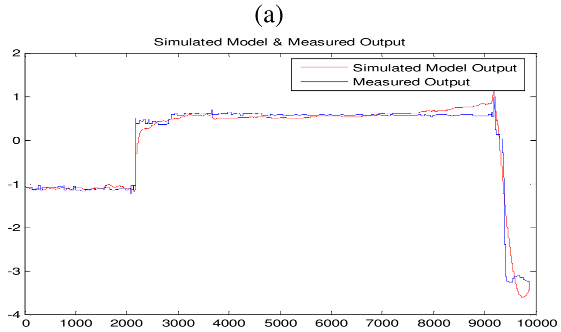


Fig.11 Feed Gas Preheater A systems's input-output



(a)



(b)

Fig.12. Actual/measured and predicted/simulated outputs of Feed Gas Preheater A, (a) measured data were used in dentification, (b) measured data were not used in identification

Several remarks on varying parameter are in order. The varying parameter used in the identification process described above is sinusoidal function of sufficiently small frequency to obtain satisfying results. Although not shown, we noticed in our experiments that the use of higher frequencies tends to produce smaller best fit. It seems to the authors that such a result is due to the fact that the ammonia process is sufficiently slow. Motivated by Felici et al. (2007) other forms of varying parameters were also used in the experiments, such as $p_k = 0.2\cos(2\pi k/p)+0.8$ and $p_k = 0.2\cos(2\pi k/p)+0.8\sin(2\pi k/p)$, and we found that by using these varying parameters satisfying results were obtained.

5. CONCLUSION

LPV identification results obtained were promising to cover several operating conditions of WHS, including start-up, normal-operation, and shut-down, which is difficult to handle using LTI identification. The basis function employed in this paper was sinusoidal. How to choose other basis functions to obtain better identification performance is worth studying. Finally, LPV identification for the overall dynamics of industrial ammonia plant is challenging problem and is of practical interest.

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