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Control of a selective catalytic reduction system based on NARMA-L2 model

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Abstract. The plant of the selective catalytic reduction (SCR) system is characterized by significant nonlinearity, time delay and temperature sensitivity. In order to control the urea injection accurately, the (nonlinear auto regressive moving average) NARMA-L2 model based control is applied to the SCR system. In this paper, a data-based technique is taken and a model of the plant is identified on the basis of input-output data. Then the identified model is used to the design of a NARMA-L2 controller. Simulation of the NARMA-L2 model based control for the SCR system is presented to demonstrate the effectiveness and superiority. The comparison results show better performance over the traditional PID control.

1. Introduction

Diesel engines have attracted increasing attention in the past decades because of the well-known performance in fuel economy, power capability, durability and reliability. However, due to their special combustion process, diesel engines typically generate more NO_x emissions than gasoline engines [1-3]. One of the promising aftertreatment methods is combining the SCR system with other filters such as diesel oxidation catalyst (DOC) and diesel particulate filter (DPF) [3].

The performance of the SCR system can be influenced by many factors such as SCR catalyst size, SCR gas space velocity, temperature, NH_3/NO_x ratio and NO/NO_2 ratio. To simultaneously minimize the NO_x emissions and limit the ammonia slip, plenty of researches have been conducted [4-7]. The NARMA model is an exact representation of the input–output behavior of a finite-dimensional and nonlinear discrete time dynamic system in a neighborhood of the equilibrium state [9]. However, due to the dynamic nonlinearities, it is relatively difficult to implement it for real-time control systems. Fortunately, NARMA-L2 model is convenient to be practically implemented using multi-layer neural networks. The main concept of a NARMA-L2 controller is to transform a nonlinear dynamic system into a linear dynamic system. Therefore, the NARMA-L2 model can be a good choice for the control of a nonlinear and complex system.

In this paper, a NARMA-L2 model based control strategy is applied to a nonlinear selective catalytic reduction system. Because the plant is characterized by significant nonlinearity, time delay and temperature sensitivity, we utilize NARMA-L2 model to identify the plant model and then design the input controller. We compared the proposed method with the traditional PID control strategy. Simulation results show that the NARMA-L2 model based control gives better results.

2. Controlled process description

A schematic diagram of SCR system is given in Fig.1. As can be seen from the figure, temperature, NO_x and NH_3 sensors are placed upstream and downstream of the SCR catalyst. A DOC is typically installed upstream of a SCR catalyst to convert part of NO to NO_2. In the meantime, a DPF is generally installed between a DOC and a SCR for reducing PM emissions. The objective of this work is to achieve high NO_x conversion efficiency and keep the ammonia slip to a desired set point by accurately controlling the injection of Adblue.
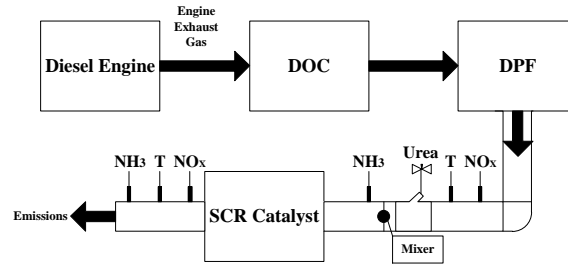

Figure 1. Schematic diagram of SCR system

3. NARMA-L2 control

Due to the high approximation accuracy and fast convergence speed, NARMA model can be used to capture the dynamics of nonlinear and complex systems. The main objective of the control method is to transform the nonlinear system into approximate linear system. There are two basic steps in NARMA: system identification and nonlinear controller design. Generally, one standard model of discrete-time nonlinear systems is represented as

$$y(k+d) = N[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)] \tag{1}$$

where $u(k)$ is the system input, $y(k)$ is the system output an d is the relative degree. The positive integers m and n are respectively the number of measured values of inputs and outputs. Three-layer neural networks can be trained to approximate the function N. In order to let the system outputs follow a reference trajectory $y(k+d) = y_r(k+d)$. The control input can be expressed as

$$u(k) = G[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)] \tag{2}$$

It is hard to achieve parameters of the neural network function G during plant real time control using static back propagation. One of the effective solutions is to use a NARMA-L2-based model

$$\begin{aligned} y(k+d) = &f[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)] + \\ &g[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)]u(k) \end{aligned} \tag{3}$$

where f and g are the neural networks to get prediction of $y(k+d)$.

Considering the realization, then the resulting theoretical controller is

$$u(k+1) = \frac{y_r(k+d) - f[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)]}{g[y(k), \cdots, y(k-n+1), u(k), \cdots, u(k-m+1)]} \tag{4}$$

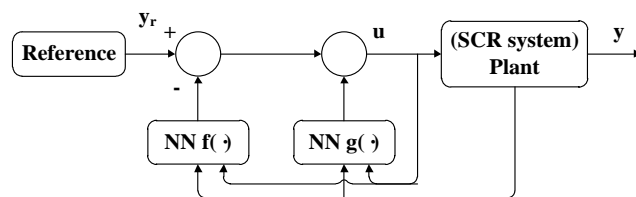which is realizable for $d \geq 2$. Block diagram of NARMA-L2 controller is shown in Fig. 2.

Figure 2. Block diagram of NARMA-L2 controller

4. Results and discussion

To illustrate the validity for the after-treatment process, NO_x conversion efficiency and ammonia slip are taken as the output and the injection of urea (concentration of the inlet ammonia) is taken as the input. To show the effectiveness of the NARMA-L2 controller, we compare it with the traditional PID control strategy. Based on a certain type of diesel engine, the SCR system is established. The detail parameters of the parts are listed in Table 1 and Table 2. The simulations are operated in the case of set-point tracking and the two control strategies are shown as follows.

Table 1. The detail parameters of the Engine

Parameter	Value and Unit
Engine Type	4-cylinder
Engine Capacity	3.0 L
Bore	100 mm
Stroke	110 mm
Connecting Rod Length	145 mm

Table 2. The detail parameters of the SCR

Parameter	Value and Unit
Cell Density	400 $inch^{-2}$
Length	250 mm
Discretization Length	25 mm
Active Surface Density	125 $mole/m^3$

4.1 The traditional PID controller

The simulation results obtained by the PID controller are shown in Fig. 3 and Fig. 4. As can be seen from the graphs, the controller reaches an optimal operating point in which about 96.2% of NO_x is reduced while allowing about 25 ppm NO_x slip past the catalyst. And the control response obtained using PID controller has a large overshoot and a long settling time.

4.2 The NARMA-L2 controller

There are two neural networks to be trained and the neural network model has 3 delayed plant inputs, 2 delayed plant outputs and 6 neurons in the hidden layer. As can be seen from the graphs, the controller reaches an optimal operating point in which about 96.4% of NO_x is reduced while allowing about 25 ppm NO_x slip past the catalyst. And the control response obtained using NARMA-L2 controller has a smaller overshoot and a relatively shorter settling time.
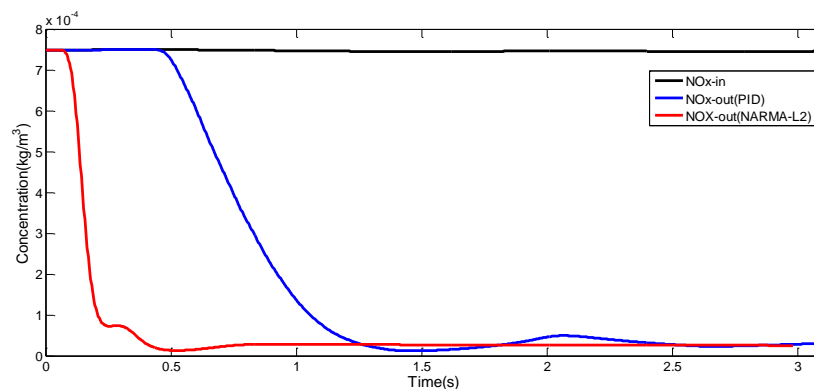

Figure 3. NO_x concentrations before and after the SCR system for the two controllers
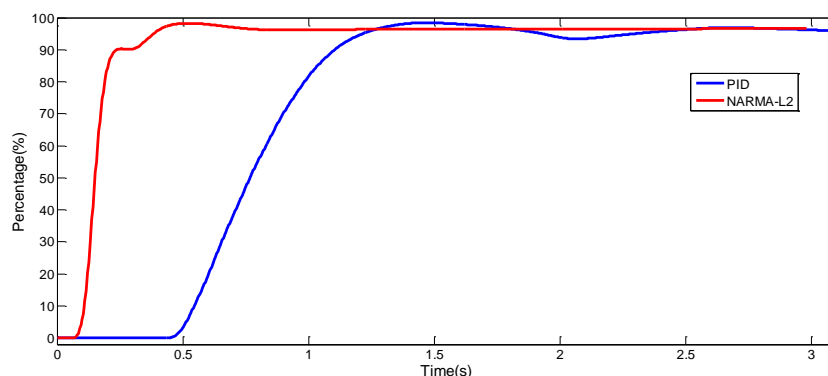
Figure 4. NO$_x$ conversion efficiency for the two controller

5. Conclusions

In this paper, a NARMA-L2 controller is applied to a nonlinear selective catalytic reduction system. The main concept of a NARMA-L2 controller is to transform a nonlinear dynamic system into a linear dynamic system. NARMA-L2 includes two neural networks to approximate the dynamics of the system.. The simulations showed the better tracking capability and response speed of the NARMA-L2 controller. The controlled SCR system achieved a higher NO$_x$ conversion efficiency within a shorter settling time.

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