Fuel 159 (2015) 76–83

Contents lists available at ScienceDirect

Fuel

journal homepage: www.elsevier.com/locate/fuel

Cycle-based ammonia-coverage-ratio reference generator design for Diesel engine two-cell selective catalytic reduction systems via a fuzzy approach

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HIGHLIGHTS

- Optimal control via the DP algorithm.
- Dynamic ammonia coverage ratio references.
- Comparisons through different methods.

ARTICLE INFO

Article history:
Received 9 April 2015
Received in revised form 18 June 2015
Accepted 19 June 2015
Available online 28 June 2015

Keywords:
Selective catalytic reduction (SCR)
Reference generator
ANFIS
Emission control

ABSTRACT

In this paper, we investigate the cycle-based ammonia-coverage-ratio reference generator design for Diesel engine two-cell selective catalytic reduction (SCR) systems. Since the dynamic programming algorithm is time-consuming, the motivation of this research is to develop the ammonia-coverage-ratio reference generator which has the capacity to produce the optimal desired ammonia coverage ratios onboard. With the sizing optimization results obtained from the dynamic programming algorithm, we propose an ammonia-coverage-ratio reference generator by using the adaptive-network-based fuzzy inference system (ANFIS). In the generator, the inputs include the engine-out NO_x concentration, the ammonia concentration between the two cans, and the ammonia concentration in the tailpipe. The performance of the generator is comparable to the optimized results using the dynamic programming algorithm.

1. Introduction

It is well known that the dynamic programming algorithm can achieve the globally optimal result for optimization problems. However, in most of the application cases, the computational load of the dynamic programming algorithm is intensive. Therefore, the online implementation is a serious issue for the application of the dynamic programming algorithm. The heavy computational load motivates us to develop simple rule-based generators or predictors which are based on the optimal solution of the dynamic programming algorithm and have comparable results with the optimal solution. What is more, the computational load of the generators should be light and the online performance can be guaranteed.

With regard to the rule-based generators or predictors development, the fuzzy logic is a good choice since a reasonable fuzzy logic has good performance in dealing with the undetermined system dynamics [1–4]. Examples of the applications includes the hybrid electric vehicles [8,10,11] and the jet engines [9]. When designing the fuzzy logic controllers, one of the main challenges is the fuzzy rules. Generally, there are two kinds of approaches on extracting the fuzzy rules [12]. One is the experience-based, which is mostly dependent on the expert's experience and knowledge on the system. The other one is data-based [16], which employs the data to train the fuzzy rules. Among all the training methods, the adaptive-network-based fuzzy inference system (ANFIS) [13] has demonstrated good performance and has been applied to many practical applications. The input selection of the ANFIS was discussed in Ref. [14] and the illustrative examples included the automobile MPG (miles per gallon) prediction and the nonlinear system identification. In Ref. [15], a model which can forecast the

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http://dx.doi.org/10.1016/j.fuel.2015.06.065
0016-2361/

short-term electricity load was established via the radial basis function neural network and ANFIS. The failure detection of turning tool by using the ANFIS was discussed in Ref. [17]. The authors in Ref. [18] exploited the structural control using the MR damper as the actuator and the ANFIS method as the control strategy. The wind speed profile was estimated and predicted by using the estimator established with ANFIS in Ref. [19]. In Ref. [20], a damping controller of a static VAR compensator was designed by utilizing the ANFIS such that the compensator had adequate damping characteristics at the dominant modes of the synchronous generator under various operating conditions. In Ref. [21], the authors discussed the real-time implementation of ANFIS control and the studied plant was a renewable interfacing inverter in a 3P4W distribution network environment. Other applications can be seen in [22–25] and the references therein.

The Diesel engines have a lot of good features. However, the high NO_x and particulate matter (PM) emissions are the two main barriers for the application of Diesel engines. Since the emission regulations are becoming stringent, the aftertreatment system is necessary for Diesel engines to fulfill the regulations. As pointed out in Refs. [26–31], the urea-based SCR system is a promising technique to remove the NO_x emission. Moreover, compared with the one-cell SCR system, the two-cell system is easier to achieve better performance and tradeoff between the NO_x reduction and the ammonia slip. For the Diesel engine two-cell SCR system, the first cell ammonia coverage ratio always keeps at a high level such that most of the NO_x emissions can be reduced in the first cell. Whereas, the second cell ammonia coverage ratio is required to be small and the ammonia slipped from the first cell is mostly stored in the second cell. In the feedback control, the ammonia coverage ratio references are critical for the NO_x conversion and tailpipe ammonia slip. The authors in Ref. [32] used constant values 0.6 and 0.3 as the first cell and the second cell ammonia coverage ratio references, respectively. To achieve better control performance, the constant references for sure are not the best choices as the constant references are not adaptive to the engine-out information and the SCR conditions including the NO_x and NH_3 concentrations during the SCR operations. Therefore, the question is how to generate the ammonia coverage ratio references for the two SCR cans onboard?

Motivated by the above aspect, we focus on answering the question in this research. For the ammonia coverage ratio reference development, we employ the ANFIS to train the fuzzy logic controller with the optimized data from the sizing optimization results. A reference generator is developed. The generator uses the engine-out NO_x information, the ammonia concentrations between and after the cans in the forward simulation. It is necessary to mention that the generator is robust to the ammonia coverage ratio initial values, that is, the discrepancy between the actual initial values in the implementation and the initial values in the optimization with the dynamic programming optimization will not lead to significantly different references.

2. Ammonia coverage ratio generator development via fuzzy logic

With a modified dynamic programming approach, we obtain the optimized ammonia inputs for the US06 test cycle, as shown in Fig. 1. In the optimization, the objective is to minimize the tailpipe NO_x emissions with two constraints. One is the tailpipe ammonia slip and the other one is the maximal ammonia input. All the engine-out information such as the flow rate, engine-out NO_x emissions, and the temperatures are directly measured from a practical US06 test cycle for a medium-duty Diesel engine. We can see from Fig. 1 that the maximal ammonia input is 0.04 mol/m^3

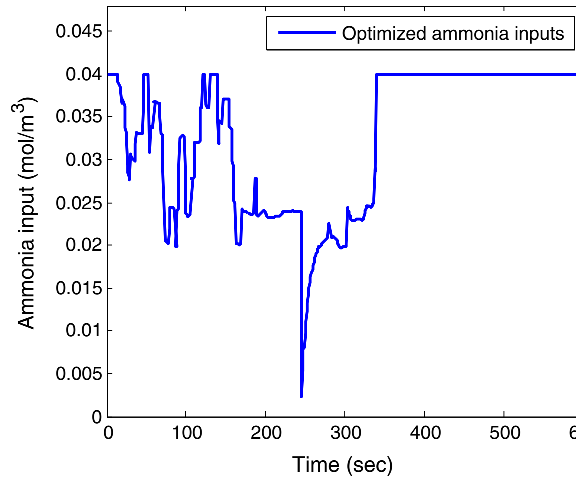

Fig. 1. Optimized ammonia inputs for the US06 test cycle with dynamic programming algorithm.

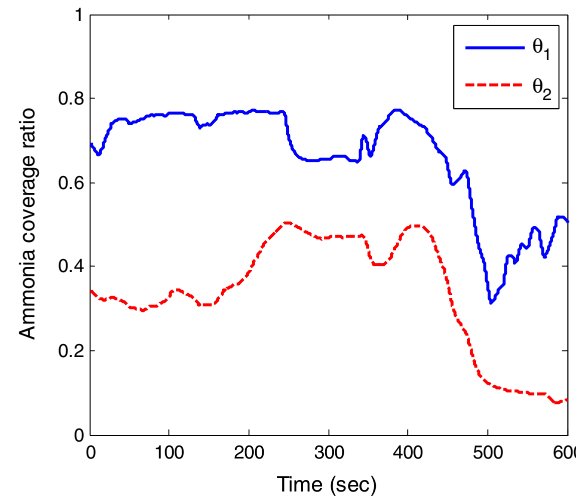

Fig. 2. Ammonia coverage ratios of two cells obtained with the optimized controller.

and the ammonia inputs are saturated at the end of 350 s. The corresponding ammonia coverage ratios for both cells are illustrated in Fig. 2 in which the [1]blue-solid line is the ammonia coverage ratio for the first cell and the red-dash curve is the ammonia coverage ratio for the second cell. We can see that the desired ammonia coverage ratio for the first cell is always larger than the one for the second cell.

It is well known that there are two challenges on designing the fuzzy logic controller: (1) How to determine the membership functions? (2) How to establish the fuzzy control rules? Generally, there are two main kinds of approaches. Since we already have the optimal solutions in the previous work, it is suitable to use the data-based training methods. In order to design the fuzzy logic generator with a good control performance, we employ the adaptive-network-based fuzzy inference system (ANFIS) [13].

The ANFIS is based on the Takagi–Sugeno (T–S) fuzzy model which was firstly reported in Ref. [5]. It shows in Ref. [6] that the first-order T–S fuzzy model can be used to approximate a complex function by using linear sub-functions and the approximation

[1] For interpretation of color in Fig. 2, the reader is referred to the web version of this article.