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Diesel Engine NO_x Reduction Using a PD-type Fuzzy Iterative Learning Control with a Fast Response NO_x Sensor

Armin Norouzi*, Masoud Aliramezani, Charles Robert Koch

Department of Mechanical Engineering, University of Alberta, Edmonton, Canada T6G 1H9

Abstract

A new control strategy is developed to reduce the diesel engine NO_x emission and to control the engine Brake Mean Effective Pressure (BMEP). A Multi-Input Multi-Output (MIMO) dynamic diesel engine NO_x emission and BMEP model which was developed based on the experimental data is implemented to estimate the open-loop NO_x emission and engine BMEP as a function of engine speed, injected fuel amount and the injection rail pressure. A fast response electromechanical NO_x sensor is used to measure the NO_x concentration inside the exhaust gas. Then, a PD-type Fuzzy Iterative Learning Control (PD-FILC) is designed. The fuzzy logic mechanism is used in this controller to update the proportional and the derivative terms of the PD-type ILC controller to achieve the fast and accurate response. The PD-FILC controller uses the injected fuel amount and the fuel rail pressure modification to track the desired engine BMEP and to reduce the NO_x concentration simultaneously.

Keywords— Diesel Engine Control, NO_x emission, electromechanical NO_x sensor, Iterative Learning Control, Fuzzy Logic Control

1 Introduction

The non-homogeneous air-fuel mixture and high combustion temperature of diesel engines increases their NO_x and particulate matter emissions [1, 2]. Different methods have been developed to address this problem and reduce diesel engine NO_x emission including Exhaust Gas Recirculation (EGR) [3], Low Temperature Combustion (LTC) [4] and urea-based Selective Catalytic Reduction (SCR) [5]. However, new engine control strategies and after treatment systems are still needed to meet stringent NO_x and particulate emission regulations [6]. Using fast response engine emission sensors for engine feedback control is a promising way to meet the strict emission regulations by minimizing the engine-out emissions [7] and carrying out on-board diagnostics [8].

Iterative Learning Control (ILC) is a promising control strategy for internal combustion engines due to their repetitive behavior and cyclic performance. ILC is widely used in literature for various repetitive systems such as industry robotics arms [9–11], injection molding machine [12], twin-roll strip casting [13], autonomous vehicles [14], high-speed trains [15], economic optimization for batch processes [16], electromechanical Valve Actuator in Camless Engines [17], antilock braking of electric and hybrid vehicles [18], helical contouring control for CNC machine [19], PM Synchronous Motors [20], and pitch of wind turbine [21].

Different methods are used to modify the performance of an ILC controller to achieve fast and accurate response. An adaptive control law is combined with the ILC method to control six degree-of-freedom manipulator robot [22]. In [11], PD-type Fuzzy ILC controller is designed to control MIMO manipulator robot and conclude that the PD-type Fuzzy ILC is faster and more accurate than simple ILC. Optimizing PID-type ILC is another method of using PID-type ILC which is used in controlling aluminum extruder [23]. Loop-shaping design of a linear quadratic (LQ) ILC is used for controlling a rapid thermal processing [24]. Using the local symmetrical double-integral type ILC (LSI^2 type ILC) for controlling omni-directional autonomous mobile robot is another method to improve the performance of ILC controller. The results of LSI^2-type ILC shows the accurate path-following for autonomous mobile vehicle [14]. Permanent magnet synchronous motors (PMSMs) are controlled by using current and future error term in ILC controller [20]. PD-type ILC controller is used to controlling robust anti-lock braking of electric and hybrid vehicles [18]. P-type ILC control for

*Corresponding author: norouziy@ualberta.ca

flexible valve actuation control of non-throttled engine load control is proposed in [17]. PD-type spatial iterative learning control (SILC) is used to control the pitch of wind turbine, and the convergence of the designed controller is derived based on tracking error in the form of Lebesgue-ρ norm [21].

First dynamic diesel engine model for NO_x emission and BMEP is developed based on experimental data. Then, a PD-FILC controller (PD-type Fuzzy Iterative Learning Control) is introduced as a promising method to reduce the engine NO_x emission. The ILC is coupled with the engine model to reduce NO_x emission at a desired BMEP.

2 Dynamic Diesel Engine Model for NO_x and BMEP

2.1 Control Oriented Model

A two-state control oriented engine model developed in [25] is used to estimate the Brake Mean Effective Pressure (BMEP) and the engine NO_x emission as a function of injected fuel, the injection rail pressure and engine speed. The control oriented model is as follows [25]:

The model inputs, states, parameters and outputs are classified as vectors. The vector $\mathbf{x}$ contains two model states:

$$\mathbf{x(k)} = \begin{bmatrix} NO_x(k) & BMEP(k) \end{bmatrix} \tag{1}$$

where, NO_x and BMEP are the engine NO_x emission [ppm] and brake mean effective pressure [bar]. respectively.

The vector $\mathbf{u}$ contains three model inputs:

$$\mathbf{u(k)} = \begin{bmatrix} m_f(k) & P_r(k) & n(k) \end{bmatrix} \tag{2}$$

where, m_f P_r and n are the injected fuel amount [mg/stroke], rail pressure [bar] and engine speed [rpm] respectively.

The vector ζ contains 14 model parameters with values defined in [25]:

$$\zeta = \begin{bmatrix} \tau_{NOx} & \tau_{BMEP} & a_o & a_1 & a_2 & a_3 & a_4 & a_5 & a_6 & a_7 & b_o & b_1 & b_2 \end{bmatrix} \tag{3}$$

The control oriented model states are [25]:

$$\begin{aligned} \mathbf{x_1}(k+1) = \left(1 - \frac{\zeta_1}{\zeta_2+\zeta_1}\right) x_1(k) + \frac{\zeta_1}{\zeta_2+\zeta_1} \Bigg(\zeta_4 + \zeta_5 u_1(k+1) + \zeta_6 \Big[u_1(k+1)\Big]^2 + \zeta_7 \Big[u_1(k+1)\Big]^3 \\ + \zeta_8 u_2(k+1) + \zeta_9 \Big[u_2(k+1)\Big]^2 + \zeta_{10} u_3(k+1) + \zeta_{11} \Big[u_3(k+1)\Big]^2 \Bigg) \end{aligned} \tag{4}$$

$$\mathbf{x_2}(k+1) = \left(1 - \frac{\zeta_1}{\zeta_3+\zeta_1}\right) x_2(k) + \frac{\zeta_1}{\zeta_3+\zeta_1} \zeta_{12} \left(\Big[u_3(k+1)\Big]^{\zeta_{13}} \Big[u_1(k+1)\Big]^{\zeta_{14}} \right) \tag{5}$$

The vector $\mathbf{y}$ contains the two model outputs:

$$\mathbf{y(k)} = \begin{bmatrix} x_1(k) & x_2(k) \end{bmatrix} \tag{6}$$

The model parameters are estimated based on the experimental data and are available in [25].

2.2 Model Validation Experimental Setup

To study the engine NO_x emission at different engine operating conditions, an electrochemical NO_x sensor was mounted in the exhaust pipe of a four cylinder medium duty Tier III diesel engine (Cummins QSB4.5 160 - Tier 3/Stage IIIA). The engine charactristics are available in [25]. To record the engine main variables and operating parameters, the Engine Control Unit (ECU) is connected to a hardware interface (INLINE 6) via CAN BUS J1939 connector. A production ECM NO_x sensor (P/N: 06-05) is used to measured and the engine-out NO_x emission. More information about the NO_x sensor is available in [26].

3 Controller Design for NO_x and BMEP

3.1 Iterative Learning Control

The general type of ILC control is defined as

$$u_j(k) = Q(u_{j-1}(k)) + L(e_{j-1}(k)) \tag{7}$$

where L and Q are L-Filter (learn filter) and Q-filter respectively, k is discrete time index from k = 0 to k = N which results in a cycle period of τ = NT, where T is the sample time. The index j represents the iteration cycle. Different types of ILC can be defined by using a different function for L-Filter and Q-Filter. The simplest ILC controller is P-type ILC controller which is defined by assuming Q-filter and L-filter to be constant matrices and Q-filter is assumed to be the identity matrix so that the P-type ILC controller is

$$u_j(k) = u_{j-1}(k) + Pe_{j-1}(k) \tag{8}$$

A derivative term can be added to L-Filter to achieve PD-type ILC controller. So, the PD-type ILC controller with Q = I is

$$u_j(k) = u_{j-1}(k) + Pe_{j-1}(k) + D(e_{j-1}(k) - e_{j-1}(k-1)) \tag{9}$$

where P are the proportional and D is derivative learning gain respectively [27].

3.2 PD-type Fuzzy Iterative Learning Control (PD-FILC)

PD-type Fuzzy Iterative Learning Control (PD-FILC) is used for NO_x reduction control and desired BMEP tracking. In order to examine the performance of the closed-loop system, the closed loop results are compared to the reference (open-loop) system results. In this case, the objective of the closed loop system is to reduce the NO_x concentration up to 20% of the reference NO_x value while keeping the BMEP at the desired value which is equal to the reference value. The block diagram of the proposed emission control is shown in Fig.1 (a). In this control strategy, fuel rail pressure and injected fuel amount are adjusted based on the NO_x reduction error and the desired BMEP. The BMEP and NO_x tracking errors are calculated as follows:

$$\begin{aligned} e_1 &= BMEP_d - BMEP \\ e_2 &= NO_{x,ref} NO_{x,rlm} - NO_x \end{aligned} \tag{10}$$

where $BMEP_d$, $BMEP$, $NO_{x,ref}$, and $NO_{x,rlm}$ and NO_x are the desired BMEP, actual BMEP (controlled system), NO_x reference system response, NO_x reduction lower limit and the NO_x concentration after implementing the controller. The corrected rail pressure and injected fuel amount are calculated based on the PD-type ILC controller as follows:

$$u_{i,j}(k) = u_{i,j-1}(k) + P_i e_{i,j-1}(k) + D_i(e_{i,j-1}(k) - e_{i,j-1}(k-1)), \quad i = 1, 2 \tag{11}$$

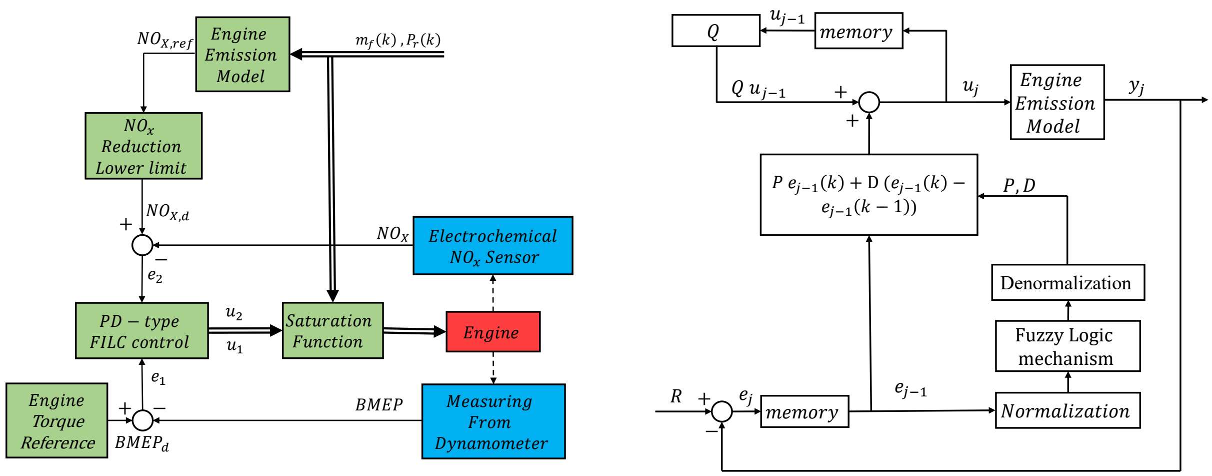
Where P_i and D_i are the proportional and derivative gains, $u_3(k)$ is the engine speed which is assumed to be constant ($u_3(k) = 1500rpm$) in this study. The corrected control input is limited by using a reference system which is function of injection rail pressure and injected fuel amount that was calibrated for the stock engine controller. This saturation limit was applied to avoid unexpected increases in the other emission types such as unburned hydrocarbons (HC) and particulate matter (PMs) and to minimize a possible decrease in the combustion efficiency.

A fuzzy logic rule used for updating controller gains (P_i and P_i) is based on the Euclidean norm of system errors (e_1 and e_2) over the cycle j. Euclidean norm for both e_1 and e_2 are defined of each iteration as:

$$||e_{i(j)}||_2 = \sqrt{e_{i(j)}^T e_{i(j)}} \quad i = 1, 2 \tag{12}$$

where $e_{1,j}$ and $e_{2,j}$ are the error of BMEP and NO_x control in the j^{th} iteration respectively. Therefore, the controller gains are updated using the fuzzy logic mechanism. The advantage of using fuzzy logic methodology is that a larger learning gain can be applied for the larger errors. This makes the controller reduce the errors faster than a simple ILC controller. To apply the control over a wide range of error, the normalized error, based on a maximum gain of P_i and

D_i is used. Because the maximum Euclidean norm of all cycles occurs in the first cycle ($j = 1$), the Euclidean norm of the first cycle is used for normalization. Then, the outputs of fuzzy mechanism need to be denormalized based on maximum value of controller coefficient ($p_{i,max}$ and $D_{i,max}$ where $i = 1, 2$). The PD-FILC controller structure is shown schematically in Fig. 1 (b).



(a) Block Diagram of Emission Control strategy

(b) Block Diagram of PD-type FILC controller

Fig. 1: Block Diagrams of PD-FILC Controller for diesel engine NO_x reduction

4 Results and Discussion

The simulation results of PD-FILC controller along with the emission model output are shown in Fig. 2. The step function is assumed as $BMEPref$, and the fraction of the reference system response of NO_x($NO_{x,ref} = NO_{x,ol}NO_{x,rlm}$) is considered as the reference of NO_xcontrol. For the controller, the amount of NO_x is reduced as a result of reducing the fuel rail pressure. Reducing the rail pressure decreases by 13% (mean value) the NO_x in a cycle. In some cycles, the controller cannot reduce the amount of NO_x as it has to tracking the BMEP. The controller attempts to track the desired BMEP by overshooting the injected fuel and rail pressure steps. As shown in Fig. 2, the controller has accurate performance in controlling the BMEP, and by modifying injected fuel and fuel rail pressure, the engine has less NO_x emission and an accurate output BMEP tracking. The engine NO_x reduction is maintained while the BMEP is also controlled. In addition, to study the convergence of the controller, the Euclidean norm error versus the iteration domain is also shown in Fig. 2 which reveals that the controller converges in the 50 iterations for the case tested.

5 Conclusion

A MIMO dynamic diesel engine NO_x emission and BMEP model which was developed based on the experimental data is implemented to design a closed loop engine controller. The PD-FILC controller is designed to reduce NO_x emission and to track the desired BMEP. In the proposed control strategy, fuel rail pressure and injected fuel amount are modified based on the reference values of the NO_x concentration and BMEP. Using a fraction of reference system response of NO_x concentration as the desired input of the NO_x controller, results in an average of 13 percent reduction in the NO_x emission along with more accurate BMEP tracking in comparison with the reference (open-loop) system. Based on the results, the engine output performance is modified, and the NO_x concentration is reduced simultaneously. As the proposed controller does not depend on the model, it can be easily used in the real-time implementation. In future work we plan on using PD-FILC on the real engine using a fast response electrochemical NO_x sensor.

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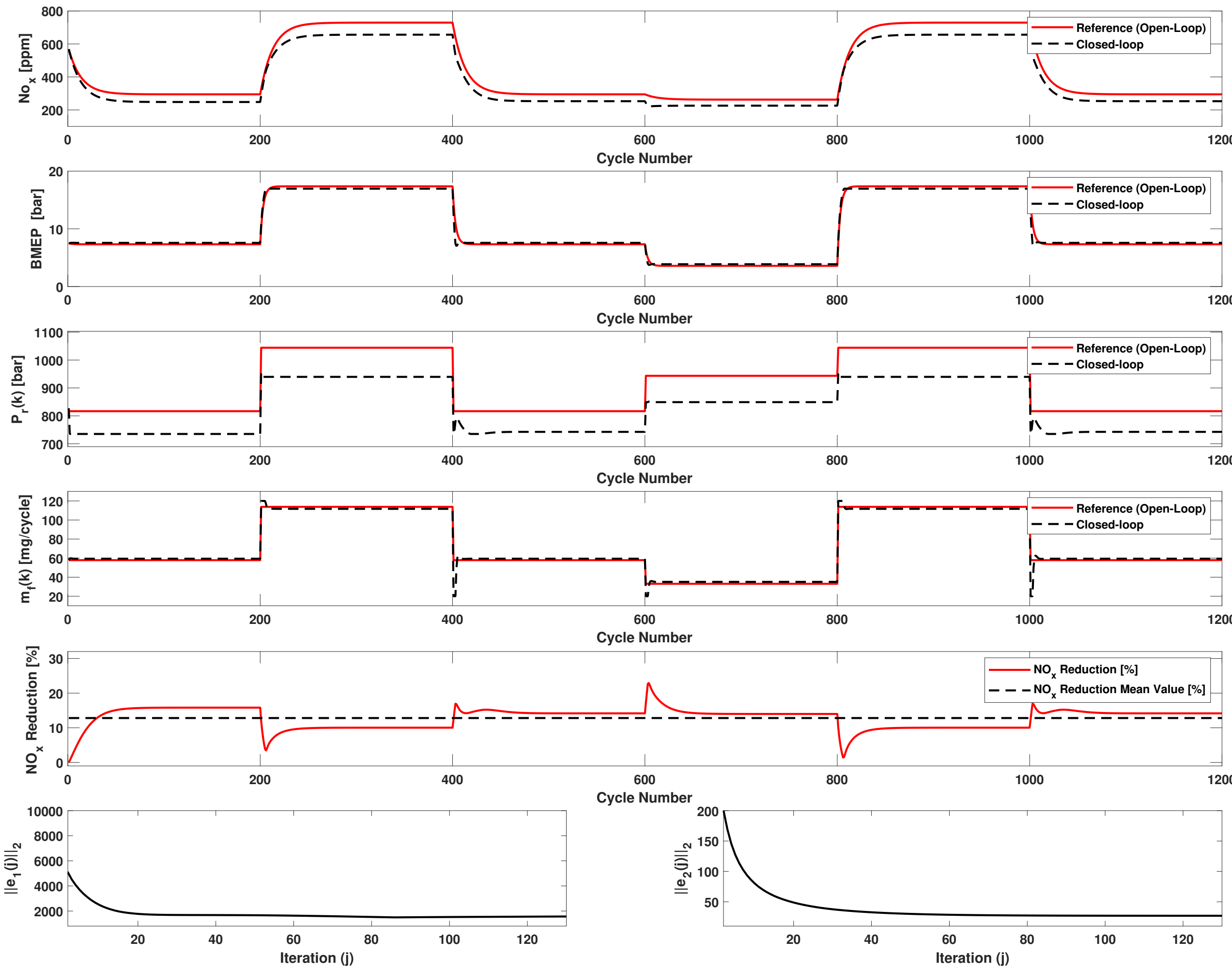

Fig. 2: Simulation to follow step function of $BMEP$ and results for NO_x reduction control at $n = 1500\ rpm$

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