Abstract—This paper presents an iterative learning control (ILC)-based method to on-line calibrate the high-pressure common-rail (HPCR) injection system parameters for achieving precise injection quantity control for Diesel engines. Given the strongly increasing demands on engine fuel economy and emissions, precise injection quantity control is of importance for realizing desired combustion, particularly advanced combustion modes, on a cycle-by-cycle basis. Current Diesel engine injection quantity control methods heavily rely on pre-calibrated static tables or injector models, which cannot handle the effects of the rail pressure sensor reading inaccuracy and injector aging on injection quantity. In this paper, by using an exhaust manifold oxygen fraction model, an ILC-based HPCR injection system parameter on-line adaptation algorithm was developed to actively adjust the injection duration command for injection quantity correction. Simulation results based on a high-fidelity GT-Power engine model show the effectiveness of the designed injection quantity correction algorithm.

I. INTRODUCTION

DIESEL engine high-pressure common-rail (HPCR) injection systems have promising advantages in emission reductions and fuel economy improvement primarily because their high injection pressures can provide flexible injection timing and offer multiple injections (pilot-, main-, and post-injection) for each engine cycle. The precise fuel injection quantity control is significant not only for engine torque response and drivability concerns, but also particularly for control of advanced combustion modes, such as low temperature combustion (LTC) and homogenous charge compression ignition (HCCI), which are sensitive to injection and in-cylinder conditions (ICCs) variations [8][7][10].

Several injector models have been proposed in [17][11] for injection quantity control. In typical engine control practice, injection quantity is controlled by adjusting the injection signal pulse width based on the measured rail pressure and a pre-calibrated injector table or model [6]. However, precisely controlling the fuel injection quantity is quite challenging for HPCR systems due to the rail pressure reading inaccuracy and injector model uncertainties including the variations of fuel flow discharge coefficient, the area of total out flow section, and the density of fuel [19]. The discharge coefficient of fuel flow depends on flow velocity, fuel density and viscosity, and can also be influenced by occurrence of cavitation. The injector area of total out flow section changes with factors such as injector aging, soot accumulation, and environmental temperature. The fuel density may be altered by temperature, pressure, and fuel type (e.g. fossil Diesel and bioDiesel fuels) as well. For instance, for a typical Diesel fuel, the fuel density varies from 850kg/m³ (800 bar, 40°C) to 890 kg/m³ (1500 bar, 20°C) [19]. Such variations however are not directly measurable by engine on-board sensors. As the engine fueling control is mostly exercised in a feedforward fashion, periodic on-line calibration of the injection system parameters is beneficial to ensure the accurate fuel injection quantity control.

For accommodating the injector parameter uncertainties and inaccuracy of HPCR pressure reading, iterative learning control (ILC) could be an effective way. By combining the information of previous control signal and the feedback error, an updated control law can be generated to reduce the effect of system variations/uncertainties without exactly knowing the system dynamics [14]. In this paper, an ILC-based HPCR injection system on-line parameter calibration algorithm is presented. The algorithm can address the injection system parameter variations and help to achieve precise injection quantity control without additional hardware. In addition, such an algorithm can also be used for injection system on-board diagnostic purposes. To generate the error, based on which the effect of the pressure reading inaccuracy and parameter uncertainties can be reduced, an oxygen mass fraction model is introduced.

The arrangement of the rest of this paper is as follows. In section II, the oxygen mass fraction models are presented. Section III describes a fuel injection on-line parameter calibration algorithm based on the enhanced ILC (EILC) method. In section IV, the validation of the on-line calibration method is shown by applying it to a high-fidelity GT-Power engine model through simulations. Conclusive remarks are presented in the end.

TABLE I

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
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<tbody>
<tr>
<td>$a_{K_{tot}}$</td>
<td>Piston surface area effective parameter</td>
</tr>
<tr>
<td>$a_{K_{x2x3}}$</td>
<td>Piston surface area effective parameter</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Engine crank angle</td>
</tr>
<tr>
<td>$\eta_s$</td>
<td>Engine volumetric efficiency</td>
</tr>
<tr>
<td>$\Delta_\lambda$</td>
<td>Stoichiometric oxygen fuel mass ratio for complete combustion</td>
</tr>
<tr>
<td>$\rho_{fuel}$</td>
<td>Fuel density</td>
</tr>
<tr>
<td>$\Delta P$</td>
<td>Pressure difference between common rail and in-cylinder pressures</td>
</tr>
<tr>
<td>$\Delta \theta(t)$</td>
<td>Uncertainty parameter to be calculated</td>
</tr>
</tbody>
</table>
II. OXYGEN MASS FRACTION MODELS

In the EILC algorithm, a base error, which reflects the difference between actual value and desired value, is needed to render the effects of model uncertainty to be zero. The signal reflects the actual fuel injection quantity can be chosen to render the effects of model uncertainty to be zero. The value relating to the desired fuel injection quantity, we use an cycle-by-cycle basis [4].

A. Discrete Model

In this section, we develop a dynamic model that can describe the evolutions of both the in-cylinder gas oxygen fraction at the crankshaft angle of intake valve closing (IVC) and the predicted exhaust manifold oxygen fraction on a cycle-by-cycle basis [4].

The dynamic models were developed based on the mass conservation and are described by the following difference equations as:

\[
\begin{align*}
    m_e(k+1)F_e(k+1) &= \left( m_e(k) + m_f(k) \right) F_{eo}(k) + m_{te}(k)F_i(k) + m_{ce}(k)F_e(k) - m_{ce}(k)F_{eo}(k), \\
    \end{align*}
\]

where \( k \) is the index of engine cycle, \( m_e(k) \) and \( m_e(k) \) are the mass of charge in the cylinder and in the exhaust manifold at the \( k \)th IVC, respectively. \( m_{ic}(k) \), \( m_{ce}(k) \), and \( m_{ce}(k) \) are mass of charge from intake manifold to cylinder, from exhaust manifold to cylinder, from cylinder to exhaust during the period right before the \( k \)th IVC. \( F_i(k), F_e(k), F_i(k) \) and \( F_e(k) \) are the oxygen fractions of the gases in intake manifold, in exhaust manifold, in cylinder and out of cylinder after combustion at or right before the \( k \)th IVC, respectively. \( m_f(k) \) is the mass of injected fuel before the \( k \)th IVC. Figure 1 illustrates the in-cylinder mass evolving process.

![Gas exchanging process from the kth IVC to the (k+1)th IVC.](image)

We assume the mass of engine inlet gas equals to that of outlet gas for both the cylinder and the exhaust manifold in each cycle [9][12], i.e.,

\[
\begin{align*}
    m_{ce}(k) &= m_{ic}(k) + m_{ce}(k) + m_f(k) \\
    \end{align*}
\]

So,

\[
\begin{align*}
    m_e(k+1) &= m_e(k) + m_f(k) + m_{ic}(k) + m_{ce}(k) - m_{ce}(k) \\
    \end{align*}
\]

and

\[
\begin{align*}
    m_e(k+1) &= m_e(k) \\
    \end{align*}
\]

The oxygen fraction of the gas after combustion can be derived by:

\[
\begin{align*}
    \left( m_e(k) + m_f(k) \right) F_{eo}(k) &= m_{ce}(k) F_e(k) - m_f(k) \lambda_s \\
    \end{align*}
\]

i.e.

\[
\begin{align*}
    F_{eo}(k) = \frac{m_{ce}(k) F_e(k) - m_f(k) \lambda_s}{m_{ce}(k) + m_f(k)} \\
    \end{align*}
\]

where \( \lambda_s \) is the stoichiometric oxygen fuel mass ratio for complete combustion.

Thus, we get the resultant dynamic models as follows:

\[
\begin{align*}
    F_e(k+1) &= C_1 F_e(k) + C_2 F_e(k) + C_3 F_i(k) + C_4 m_f(k) \\
    \end{align*}
\]

where,

\[
\begin{align*}
    C_1 &= 1 - \frac{m_{ce}}{m_e + m_f} \\
    C_2 &= \frac{m_{ce}}{m_e} \\
    \end{align*}
\]
\[ C_3 = \frac{m_{ic}}{m_c}, \]  
\[ C_4 = \frac{\lambda_s m_{ce}}{m_c(m_c+m_f)} - \frac{\lambda_s}{m_c+m_f}, \]  
\[ C_5 = \frac{m_e}{m_e}, \]  
\[ C_6 = 1 - \frac{m_{ce}}{m_e}, \]  
\[ C_7 = \frac{m_{ce}}{m_e} \lambda_s, \]  
\[ C_5 = \frac{m_{ce}}{m_c} \lambda_s, \]

Here, we denote \( m_{ce} \), \( m_{ic} \), \( m_c \), \( m_e \), \( m_f \) as \( m_{ce}(k) \), \( m_{ic}(k) \), \( m_c(k) \), \( m_e(k) \) (or \( m_{ce}(k+1) \)), \( m_e(k) \) (or \( m_e(k+1) \)), \( m_f(k) \) respectively for simplicity.

### B. Mean-Value Model

According to the aforementioned models, we can derive the continuous mean-value models (MVM) as follows:

\[ \dot{F}_c = \rho_1 F_c + \rho_2 F_e + \rho_3 F_i + \rho_4 m_f, \]
\[ \dot{F}_e = \rho_5 F_c + \rho_6 F_e + \rho_7 m_f, \]

with the parameters being defined as:

\[ \rho_1 = -\frac{\dot{W}_{ce}}{m_c+m_f} + \frac{120 \dot{W}_{ce}}{Nm_c} \frac{W_{ec}}{m_c+m_f}, \]
\[ \rho_2 = \frac{1 - \frac{120 \dot{W}_{ce}}{Nm_c}}{m_{ce}}, \]
\[ \rho_3 = \frac{\lambda_s W_{ce}}{m_{ce}}, \]
\[ \rho_4 = \frac{\lambda_s W_{ce}}{m_c(m_c+m_f)} - \frac{N \lambda_s}{120(m_c+m_f)} - \frac{120 W_{ec}}{Nm_c} \frac{W_{ce}}{m_e}, \]
\[ \rho_5 = \frac{W_{ce}}{m_e} \frac{m_c}{m_e+m_f}, \]
\[ \rho_6 = -\frac{W_{ce}}{m_e} \frac{m_c}{m_c+m_f}, \]
\[ \rho_7 = -\frac{W_{ce}}{m_e} \frac{m_c}{m_c+m_f}. \]

where \( W_{ic} \), \( W_{ce} \) and \( W_{ec} \) are the mass flow rates from intake manifold to cylinder, from cylinder to exhaust manifold, from exhaust manifold to cylinder (during valve overlapping period). \( N \) is the engine speed.

From the aforementioned model, the oxygen fraction can be described as a linear parameter-varying system with

\[ \rho = (\rho_1 \rho_2 \rho_3 \rho_4 \rho_5 \rho_6 \rho_7)^T. \]

The system states are:

\[ x = [F_c F_e]^T. \]

System inputs are:

\[ u = [F_i m_f]^T. \]

System output is:

\[ y = F_e. \]

We consider the density of in-cylinder charge at IVC the same as the one in intake manifold [15][18]. By the ideal gas law, \( m_c \), \( m_e \) can be approximated as below:

\[ m_c = \frac{p_{iV} V_{IC}}{RT_i}, \]
\[ m_e = \frac{p_{eV} V_e}{RT_e}, \]

By using the speed-density equation, \( W_{ic} \) can be calculated as

\[ W_{ic} = \frac{N p_i V_{IC}}{120 R T_i}. \]

Here, \( p_i \), \( p_e \) and \( T_i \), \( T_e \) are pressures and temperatures of intake manifold and exhaust manifold, respectively. \( \eta_v \) is the engine volumetric efficiency. \( R \) is the gas constant.

The mass flowed from exhaust manifold to cylinder during intake and exhaust valve overlapping period can be derived by using the model developed in [18]:

\[ m_{ec} = (\Delta m_{restV} + \Delta m_{restB}), \]

where \( \Delta m_{restV} \) and \( \Delta m_{restB} \) are flowed mass caused by the volume change and pressure difference, respectively. The two terms can be written as:

\[ \Delta m_{restV} = d \cdot K_1, \]
\[ \Delta m_{restB} = SGN(p_e - p_i)A_K \sqrt{2 \Delta ABS(p_e - p_i)} \cdot \frac{m}{dp} K_2, \]

where

\[ K_1 = \int_{p_i}^{p_e} \frac{a_{K_{exh}}^2}{dp} \frac{\alpha_{K_{int}}}{a_{K_{int}}^2 + a_{K_{exh}}^2} d\varphi, \]
\[ K_2 = \int_{p_i}^{p_e} \frac{a_{K_{exh}}^2}{dp} \frac{\alpha_{K_{int}}}{a_{K_{int}}^2 + a_{K_{exh}}^2} d\varphi, \]

\[ W_{ec} = \frac{N m_{ec}}{120}, \]
\[ W_{ic} = W_{ic} + W_{ec}. \]

Here, \( d \) is the in-cylinder charge density during valve overlapping, and can be approximated by the intake manifold charge density calculated through ideal gas law. The term \( \Delta ABS(p_e - p_i) \) denotes the absolute value of pressure difference between intake manifold and exhaust manifold. \( A_K \) is the piston surface area. \( \alpha_{K_{int}} \) and \( \alpha_{K_{exh}} \) are piston surface area effective parameters. \( \varphi \) is the crank angle.

Figure 2 illustrates the comparison of the foregoing MVM model with a high-fidelity one-dimensional, computational,
GT-Power engine model. As can be observed, the MVM can predict both the steady-state and the transit processes well even the oxygen fractions in intake and exhaust manifolds and the engine speed vary.

The intake and exhaust manifold signals (including pressures, temperatures, and oxygen fractions) can be obtained by sensors and/or air-path observers [8][9] for calculating the predicted exhaust manifold oxygen fraction based on the desired (commanded) fuel injection quantity. As the effectiveness of the method proposed in this paper relies on the accuracy of the model, the parameters in which need to be carefully calibrated.

III. EILC-BASED HPCR ON-LINE PARAMETER CALIBRATION

A. EILC Algorithm Review

Here, ILC and Enhanced ILC algorithms are briefly reviewed.

In [2][3], the ILC algorithm can be written as:
\[ u_i(n) = u^f_i(n) + u^l_i(n), \]  \hspace{1cm} (40)
where \( u^f_i(n) \) is the feedforward control in the form of:
\[ u^f_i(n) = \sum_{j=-1}^{m} G_j u_j(n) + \sum_{j=-1}^{m} L_j e_j(n+1), \]  \hspace{1cm} (41)
and \( u^l_i(n) \) is the feedback controller in the form of:
\[ e_i(n) = p(z_i(n)) + q(z_i(n))e_i(n), \]  \hspace{1cm} (42)
\[ u^l_i(n) = r(z_i(n)) + s(z_i(n))e_i(n). \]  \hspace{1cm} (43)

Here, \( e_i(n+1) \) denotes the tracking error between the desired and system outputs at time \( n+1 \) in iteration \( j \). \( G_j \) and \( L_j \) denote the forgetting factor and learning gain operator. In the basic ILC, \( G_1 \) is chosen as 1. \( e_i(n) \) is the current tracking error and \( p, q, r \) and \( s \) are the functions for bounded conditions.

In ILC, the control law includes the control signal and the error signal in the last iteration. However, the convergence of ILC above requires the identical initial condition, which may not be satisfied in the highly nonlinear engine systems [2]. Thus, in this paper, we use the enhanced ILC [3] to release the identical initial condition requirement. The control law is given as:
\[ u_i(n) = u_{i-1}(n) + L e_{i-1}(n+1) + K[e_i(n) - e_{i-1}(n)]. \]  \hspace{1cm} (44)
Here \( K \) is the compensation gain and \( K[e_i(n) - e_{i-1}(n)] \) term compensates the state difference between two iterations at time \( n \). Thus there is no requirement for the same initial conditions for all iterations as in normal ILC [2].

B. HPCR Fuel Injection Parameter On-Line Calibration via EILC

The predicted exhaust manifold oxygen fraction can be generated by the oxygen fraction model presented in section II based on the desired fuel injection amount and the signals measured on the engine. Thus, the difference between the predicted exhaust manifold oxygen fraction and the one measured from the engine can be chosen as the base error in injector model parameter on-line calibration algorithm design.

The HPCR injection mass quantity can be modeled by [17]:
\[ m_f = \rho_{fuel} \cdot \text{sgn}(\Delta P) \cdot c_{d, cyl} \cdot A_{cyl} \cdot ET \cdot \frac{21[\Delta P]}{\sqrt{\rho_{fuel}}}, \]  \hspace{1cm} (45)
where \( A_{cyl} \) is the area of the total outflow section, \( c_{d, cyl} \) is the fuel flow discharge coefficient, \( ET \) is the injection duration and \( \Delta P \) is the pressure difference between common rail and in-cylinder pressures. \( \rho_{fuel} \) is the fuel density.

The model (45) can be used to generate the injection duration with the information of the desired fuel quantity and the pressure difference between HPCR and cylinder pressures. However, the pressure difference reading may not be accurate due to sensor bias, and the injector parameters may change with injector aging and environmental conditions. These uncertainties/ variations will affect the actual fuel injection quantity. To ensure the injection quantity control accuracy, we introduce, in the injector model, an uncertainty parameter \( \theta(t) \) to be calibrated on-line. Thus, the injection model (45) can be modified as:
\[ m_f = \theta(t) \cdot \rho_{fuel} \cdot \text{sgn}(\Delta P) \cdot c_{d, cyl} \cdot A_{cyl} \cdot ET \cdot \frac{21[\Delta P]}{\sqrt{\rho_{fuel}}}, \]  \hspace{1cm} (46)
where, the nominal value of \( \theta(t) \) is 1.

In the EILC algorithm (44), the \( e \) was chosen by the difference of the oxygen fraction \( \Delta F_e \), and the \( \Delta \theta = \theta(t) - 1 \) as the \( u \) in (44). Each of the iterations contains 10 engine cycles. Thus, the EILC algorithm in (44) can be written as:
\[ \Delta \theta_i(n) = \Delta \theta_{i-1}(n) + L \Delta F_{e,i-1}(n+1) + K(\Delta F_{e,i}(n) - \Delta F_{e,i-1}(n)). \]  \hspace{1cm} (47)

As can be seen from the simulation scheme in Figure 3, the input signal is the desired fuel injection quantity. The nominal values of the injector model parameters can be obtained by injector calibration and measurement from the rail pressure sensor. By applying the EILC, a compensating value \( \Delta \theta \) can be generated, and it can be used in the injector model to generate the adjusted injection duration signals for delivering accurate injection quantity to the cylinders.
IV. SIMULATION STUDIES

A. Simulation Setup

In this section, a high-fidelity GT-Power engine model is utilized to evaluate the injection quantity correction algorithm. In the GT-Power combustion model, the fuel injection quantity was assumed to be precise. To evaluate the algorithm, a “real” engine, including injection system, were constructed, with the typical parameters as follows: HPCR pressure is 1350bar; the fuel flow discharge coefficient $c_{d,cyl} = 0.75$; the fuel density $\rho_{fuel} = 850\text{kg/m}^2$; the area of injection section $A_{cyl} = 2 \times 10^{-8} \text{m}^2$. Whereas, the parameters of injector model with the uncertainty and variations were assumed as: HPCR pressure sensor reading $p = 1500\text{bar}$; the fuel flow charge coefficient $c_{d,cyl} = 0.71$; the fuel density $\rho_{fuel} = 870\text{kg/m}^2$; the area of injection section $A_{cyl} = 1.9 \times 10^{-8} \text{m}^2$.

Thus, without the active fuel injection system parameter on-line calibration, the actual fuel injection quantity delivered into GT-Power combustion model will be different from the desired one due to the unknown uncertainties. To evaluate the developed injection system parameter on-line calibration algorithm, co-simulations within Matlab/SIMULINK and GT-Power were conducted. The parameters in the controller are chosen as: $L = -1.2$, $K = -1.2$.

B. Simulation Results

In the simulation, the uncertainty parameter $\theta(t)$ on-line calibration was initiated at the 6th second. As can be seen from Figure 4, the error between the predicted and measured exhaust manifold oxygen fractions was rendered to zero after the algorithm was applied. The predicted exhaust manifold oxygen fraction, $Fe_{model}$ in Figure 4, was modeled based on the desired injection quantity and measured intake and exhaust manifold signals according to the MVM in section II. The difference between this predicted exhaust manifold oxygen fraction and the measured one is related to the injection quantity error. Therefore, such an oxygen fraction difference can provide an error signal in EILC algorithm.

As can be seen from Figure 5, the uncertainty parameter of the injection model, $\theta(t)$, was calibrated to 0.943 after the EILC conducted for a period of about 4s (that is 40 cycles or 4 iterations, with the engine speed being 1200 rpm).

In Figure 6, it is shown that the desire fuel injection amount is 20 mg, whereas the actual injection amount before
EILC algorithm correction was 21.3 mg, and 20 mg after parameter on-line calibration took place. The actual fuel injection quantity was adjusted to the desired value by updating the uncertainty parameter in the inverse injector model (46) and thus the injection duration for the injector.

![Graph](image)

**Figure. 6. Desired and actual fuel injection quantities during the injection model parameter on-line calibration.**

V. CONCLUSIONS AND FUTURE WORK

In this paper, a HPCR injection system on-line parameter calibration method based on the EILC algorithm was developed for precise fuel injection quality control of Diesel engines. Such an algorithm can significantly reduce the effects of the HPCR pressure sensor uncertainty and variations associated with injector aging and fuel properties on the fuel injection quantity control accuracy. Simulations using a high-fidelity GT-Power engine model with added pressure reading inaccuracy and model parameter uncertainty were utilized to demonstrate the effectiveness of the developed algorithm. It was observed that, by the on-line calibration, the actual HPCR fuel injection quantity can be precisely controlled around the desired value.

The future work will primarily include the experimental investigation of the algorithm as well as combination of the precise fuel injection algorithm with air-path system control for advanced combustion mode engine control.

REFERENCES


