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Iterative Learning on Dual-fuel Control of Homogeneous Charge Compression Ignition ⋆

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Abstract: An Iterative Learning Controller (ILC) is used to control a dual-fuel Homogeneous Charge Compression (HCCI) engine. The engine is a CFR engine with in-cylinder pressure measurement ports and is operated at 100°C intake heating, 800 RPM and a compression ratio of 11:1. To control combustion timing and load, the amount of iso-octane and n-heptane injected into the manifold are used as inputs. The metrics used for combustion timing and load are CA50, crank angle when 50% of the fuel is burned, and gross IMEP, respectively. Using these inputs and outputs a system identification is performed and an ARMAX model is obtained. This model is then used to generate a norm optimal control. The norm optimal control is compared to a model-less control strategy that involves populating the off-diagonal of the learning matrix using a Jacobian estimate inverse. Both systems are used to follow a reference trajectory involving a step input in IMEP then CA50. The model-less control outperforms the norm optimal in both convergence speed and final iteration error. Application of non-causal filters within the iteration is also tested using a zero-phase filter and a Gaussian filter. The zero-phase has faster convergence than either the Gaussian or filter-less and has better final iteration error. This gives the best ILC control as model-less with zero-phase filter. This control is then compared with two PI controllers. It is found that the ILC outperforms the PI controllers after 3 iterations.

Keywords: Iterative learning controller, Dual-fuel, HCCI.

1. INTRODUCTION

Homogeneous Charge Compression Ignition (HCCI) is an advanced combustion strategy used in internal combustion engines. It allows for increased fuel efficiency, reduced emissions (Iida et al., 2003), and varying fuel selection (Kalghatgi and Head, 2004). The downside is the lack of direct control of ignition timing, therefore requiring control strategies. These include intake temperature control (Chia-Jui Chiang et al., 2012), valve control (Yeom et al., 2007), and fuel control (Bidarvatan and Shahbakhti, 2013). Dual-fuel control uses two fuels with different combustion reactivity. By changing the proportion of fuel injected the combustion timing can be altered. A control strategy must be implemented like MPC (Ebrahimi and Koch, 2015), or PI (Strandh et al., 2004). This paper investigates the use of an Iterative Learning Controller (ILC). ILC's are useful for repetitive processes like robotics (Parzer et al., 2015), and machining (Fiorentino et al., 2015). Several surveys have been done to highlight the current ILC knowledge and its strength and weaknesses (Bristow et al., 2006) (Moore et al., 2006) and (Wang et al., 2009). A norm-optimal control has been developed by Barton and Alleyne (2011). Several papers have investigated its convergence and robustness using worst-case norm optimal (Son et al., 2015), Linear Matrix Inequality (LMI) (Gauthier and Boulet, 2005) and (Galkowski et al., 2003), and interval values (Ahn et al., 2007).

ILC is useful for systems that are repetitive. These include electromagnetic valve control (Tsai et al., 2012), and Diesel combustion control (Hinkelbein et al., 2010). Dooren (2015) used an ILC to control multiple aspects of an spark ignition engine. An ILC can find the ideal input sequence for a process that is repetitive. ILC control has been shown to work well for systems with minimal system information (Ahn et al., 2007) and is easy to design. Any engine application that requires repetitive operation will be ideally suited for ILC implementation. This may include idle speed control for disturbance rejection, load changes for generator applications or even en route performance optimization for mass transit systems similar to the work done in Kapania and Gerdes (2015) which used an ILC for path optimization for an autonomous vehicle. A detailed description on how ILC works is given in Ahn et al. (2007). The application of an ILC to HCCI is the subject of this paper. Here the CFR engine is operated over repetitive load and combustion timing steps.

2. EXPERIMENTAL SETUP

The engine used is a modified Cooperative Fuels Research (CFR) which is often used for Octane testing. The advantage of this engine is the compression ratio can easily be altered. The standard CFR engine is modified as follows: head replacement, addition of two port injectors, and an intake air heater. The head has ports for both an in-cylinder pressure tranducer, Kistler 6043A piezoelectric pressure, and a jacket temperature thermocouple. The

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Table 1. Engine Specifications

Engine Parameter	Value/Type
combustion chamber	pancake with flat-top piston
engine type	water cooled
number of cylinders	1
displacement	612 cm^3
bore	82.6 mm
stroke	114.3 mm
compression ratio	variable from 4 to 18

Table 2. Engine Description

Label	Description
1	Air Flow meter
2	Intake Plenum
3	Intake Heater
4	Throttle
5	Intake Manifold
6	Fuel Injectors
7	EGR valve
8	Combustion Chamber
9	Lambda Sensor

engine specifications are given in table 1. A schematic of the setup is given in Fig. 1 with P denoting a pressure measurement port and T denoting thermocouple location. The components are listed in table 2 and the operating parameters for all tests are given in table 3.

Intake pressure, in-cylinder pressure and torque are collected on a 0.1° basis using a crank shaft encoder with a NI card PCIe-6431. All other data is collected at 10 Hz using two NI PCI-MIO-16E and a NI USB-6225. Labwindows/CVI is the platform used for data collection and control implementation. The CVI program communicates the injector opening time to an Arduino Due. A Tec GT ECU then relays the injector timing to the Arduino which then controls the injectors.

The system outputs are crank angle after top dead center when 50% of the mass fraction is burned (CA50) and the gross indicated mean effective pressure (IMEP). These are calculated from the pressure trace as:

$$dQ = \frac{\gamma}{\gamma - 1} PdV + \frac{1}{\gamma - 1} VdP \tag{1}$$

$$IMEP = \frac{1}{V_d} \int_{IVC}^{EVO} PdV \tag{2}$$

with Q being the chemical energy released from the fuel, γ is ratio of specific heats of the gas, P is the in-cylinder pressure, V is the in-cylinder volume and V_d is the displacement volume. Eqn. 1 assumes that none of the energy released from combustion is lost. Heat transfer to the walls and crevice losses are ignored to reduce the calculation time. CA50 is found by integrating dQ from IVC to EVO and finding θ when $Q(\theta) = Q_{max}/2$.

The system inputs are amount of iso-octane, E_{iso}, and n-heptane, E_{hept}, injected into the manifold. The injected energy is controlled by the opening time of the injectors. A calibration is found (Slepicka, 2016) to relate the injected energy to opening time.

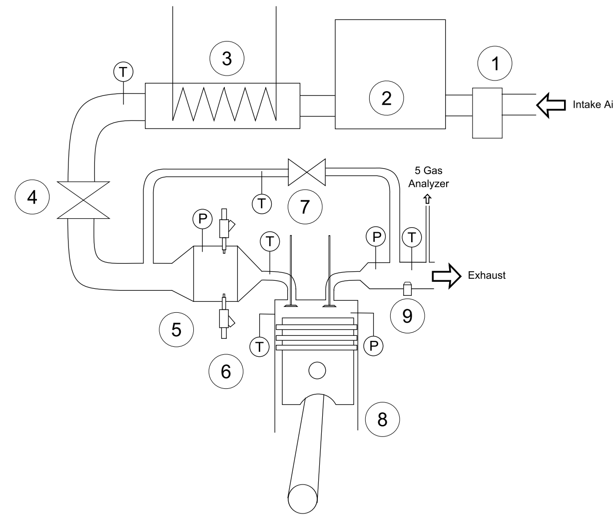

Fig. 1. Engine Schematic

Table 3. Operating Parameters

Parameter	Value
Intake Temperature	100°C
Intake Pressure	Atmospheric (92 to 94 kPa)
Speed	800 RPM
Compression Ratio	11:1

3. ILC SETUP

Given a system plant P:

$$P \equiv \begin{cases} x_j(k+1) = A(k)x_j(k) + B(k)u_j(k) \\ \delta y_j(k) = C(k)x_j(k) + D(k)u_j(k) \end{cases} \tag{3}$$

$$y_j(k) = \delta y_j(k) + y_o(k) + d_j(k) \tag{4}$$

With $x \in \mathbb{R}^n$ being the system states, $u \in \mathbb{R}^m$ contains the inputs, and $y \in \mathbb{R}^p$ contains the outputs where j is the iteration index, k is the time step in the iteration or "pass". P can be written as a block matrix:

$$P = \begin{bmatrix} H_{0,0} & & 0 \\ \vdots & \ddots & \\ H_{N-1,0} & \cdots & H_{N-1,N-1} \end{bmatrix} \tag{5}$$

With N being the number of time steps per iteration and $d_j \in \mathbb{R}^p$ is the disturbance. For Linear Time Invariant (LTI) system:

$$H_{i,l} : \begin{cases} D, & i = l \\ CA^{l-i-1}B, & l > i \end{cases} \tag{6}$$

Now assuming $D = 0 \in \mathbb{R}^{p \times m}$ as there is no feed through in the system we are investigating, P becomes:

$$P = \begin{bmatrix} 0 & & \cdots & & 0 \\ H(1) & 0 & & & \vdots \\ H(2) & H(1) & 0 & & \\ \vdots & & & \ddots & \\ H(N-1) & & \cdots & H(1) & 0 \end{bmatrix} \tag{7}$$