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Fuzzy Learning Control of Rail Pressure in Diesel-Dual-Fuel Premixed-Charge-Compression-Ignition Engine

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ABSTRACT

Common rail systems have added a new degree of freedom in controlling diesel engines. A diesel-dual-fuel, premixed-charge-compression-ignition (DF-PCCI) engine was modified from a diesel engine by injecting compressed natural gas (CNG) into the intake ports as the main fuel and injecting a smaller amount of diesel directly into the cylinders. The diesel injection timing was advanced to early in the compression stroke creating a mixture of diesel, CNG and air before being ignited almost simultaneously in the combustion chamber. The DF-PCCI engine had several modes of fueling; only diesel was used during idling, both diesel and CNG were used at low load with cylinder skipping, and both diesel and CNG were used with various energy replacement ratios during medium and high loads. As a result, a rail pressure set point was required to vary over a wide range and with a more abrupt change than that of a diesel engine mainly to obtain appropriate diesel atomization and to avoid excessive combustion. The rail pressure set point was also used as a factor in choosing the appropriate injection timing and duration during calibrations; therefore, it was necessary to track the set point of the rail pressure even more accurately. A novel rail pressure control system was presented based on fuzzy logic. One standard fuzzy system, having the tracking error and its integral as inputs, produced a necessary variation of the common-rail duty cycle to minimize the tracking error. The other fuzzy learning system, connected in parallel with the first fuzzy system, having engine speed and load as inputs, received this variation and used it to adjust centers of output membership functions to produce an appropriate mean value of the common-rail duty cycle to the engine. The fuzzy learning system's rule-base was initialized from scratch, that is, with output membership functions centered at zeros. The rule-base can also be pre-programmed with the best human experience obtained during steady-state engine calibrations. A DF-PCCI engine, modified from a Toyota 2KD-FTV diesel engine, was connected to an engine test-bed. A new European driving cycle test was performed. Substantial improvement of the common-rail pressure tracking was observed during subsequent urban cycles because the fuzzy learning system was able to learn from the earlier urban cycle. Transient tracking results were also improved.

Keywords: rail pressure control, fuzzy control, learning control, diesel engine, diesel-dual-fuel engine

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INTRODUCTION

A diesel-dual-fuel (DDF) engine uses compressed natural gas (CNG) as an alternative to diesel fuel. In retrofitting existing diesel engines, to obtain a low conversion cost, minor modifications on the engine are allowed and no electrical spark plugs are used to assist in combustion initiation. CNG is injected at intake ports as the main fuel and diesel is injected directly into cylinders to initiate combustion like liquid spark plugs.

A newly patented engine, called the diesel-dual-fuel, premixed-charge-compression-ignition (DF-PCCI) engine by the PTT public company in Thailand, operates between the homogeneous-charge-compression-ignition (HCCI) mode and the DDF mode by advancing diesel injection timing to early in the compression stroke to create a finer mixture of diesel, CNG and air. The mixture is auto-ignited producing more efficient combustion than that of the HCCI engine.

The DF-PCCI engine has three different injection modes. At low speeds and loads, only diesel is used for more stable combustion. At low-to-medium speeds and loads, both diesel and CNG are used with cylinder skipping, that is, only two out of four cylinders are ignited for stronger combustion per cylinder and hence more stable combustion with CNG. At medium and high speeds and loads, both diesel and CNG are used without cylinder skipping and with various energy replacement ratios, which are the ratios of energy of CNG to diesel, with more CNG used with higher speeds and loads.

As a result of having multiple injection modes, rail-pressure set points vary more significantly and abruptly during actual engine operations than those of the diesel engine. In the engine used in the current study, the common-rail pressure was also used as an input to several maps to determine appropriate diesel injection timing and duration. Therefore, good tracking of the common-rail pressure is vital to DF-PCCI engine operation.

Published works regarding common-rail pressure control are limited. Chatlatanagulchai *et al.* (2009) proposed a robust common-rail pressure control for a DF-PCCI one-cylinder engine using quantitative feedback control. Chatlatanagulchai *et al.* (2010) used a gain-scheduling, integrator-augmented, sliding-mode control to control the common-rail pressure for a DF-PCCI four-cylinder engine.

More recently, research has tended to use intelligent systems such as neural networks and fuzzy logic. Su *et al.* (2010) controlled the common-rail pressure of a diesel engine using a standard fuzzy system to output an appropriate set of proportional-integral-derivative (PID) gains to a PID controller. Inputs to the standard fuzzy system were the common-rail pressure tracking error and its derivative. Two fixed maps provided a feed-forward duty cycle which compensated for different injection quantity, engine speed, temperature, battery voltage and engine aging. An and Shao (2008) used a single neuron adaptive PID controller to control the common-rail pressure of a diesel engine. Tiexiong and Shilun (2009) combined a sliding mode control with adaptive fuzzy logic to control the common-rail pressure of a diesel engine.

Some pertinent works include Zhang and Sun (2009) who took into account pressure pulsations due to engine rotation as a function of the engine rotational angle in controlling the common-rail pressure using an internal model-based control. Gaeta *et al.* (2009) presented a control-oriented mathematical model of a common-rail system, which predicted satisfactorily the common-rail pressure under both stationary and transient conditions. Lino *et al.* (2007) presented a control-oriented, common-rail-system model, developed from physical laws. The model was simplified, yet still nonlinear, and the sliding-mode control was used for tracking. Balluchi *et al.* (2007) proposed a hybrid model of a common-rail system with discrete and continuous interactions

and showed that with PID control, the proposed model delivered better tracking performance than the traditional mean-value model.

In the current paper, the fuzzy control system consists of one standard fuzzy system as a feedback controller and one fuzzy learning system as a feed-forward controller. The standard fuzzy system has common-rail pressure tracking error and its integral as inputs, while it produces a common-rail pump's duty cycle as output. The rule-base was designed to drive the tracking error to zero.

The duty cycle output from the standard fuzzy system was also sent to the fuzzy learning system to adjust its output membership functions' centers. The fuzzy learning system has the engine speed and the indicated mean effective pressure (IMEP) as its inputs. The centers are adjusted to output appropriate mean values of the pump's duty cycle for each speed and load.

The objective of this study was to evaluate a newly proposed rail pressure control system using fuzzy learning control which should have as advantages over other techniques: 1) the fuzzy learning system remembers the appropriate common-rail pump's duty cycle for each speed and load. When an operating point is revisited, a previously memorized duty cycle is used instead of learning from scratch. This can improve the tracking performance during transient engine operations, when the operating point is changed abruptly; 2) the fuzzy learning system adapts according to the output of the standard fuzzy system. The adaptation is in the direction to minimize the tracking error. When the engine condition changes, for example, the battery voltage drops or due to engine aging, the fuzzy learning system will adapt to new appropriate values to deliver the appropriate duty cycle under different engine conditions; and 3) a plant mathematical model is not required in the algorithm. However, the plant model may be used in simulation or during the rule-base design of the standard fuzzy system.

MATERIALS AND METHODS

Diesel-dual-fuel, premixed-charge-compression-ignition specifications

The DF-PCCI engine was modified from a Toyota 2KD-FTV diesel engine, whose specifications are given in Table 1. The diesel engine had no intercooler, only a plenum. There was no variable geometry turbine (VGT) and no adjustable waste gate. The air path was controlled by actuating the throttle and the exhaust gas recirculation valve.

As modifications to the DF-PCCI engine, four CNG injectors were installed at each intake port. The four CNG injectors were controlled separately by the control algorithm in the engine control unit (ECU).

Figure 1 depicts a diagram of the common-rail system of the Toyota 2KD-FTV diesel engine. In controlling the common-rail

Table 1 Engine specifications.

Model	Toyota 2KD-FTV, diesel Engine
Number of cylinders	4 (Inline)
Number of valves	16 (DOHC)
Manifold	Cross-flow with turbocharger
Fuel system	Common-rail direct injection
Displacement	2,494 cc
Bore	92.0 mm
Stroke	93.8 mm
Connecting rod	158.5 mm
Compression ratio	18.51
Max power	75 kW at 3,600 rpm
Max torque	260 Nm at 1,600 - 2,400 rpm
Valve timings	
Intake valve open	718 deg CA
Intake valve closed	211 deg CA
Exhaust valve open	510 deg CA
Exhaust valve closed	0 deg CA
Firing order	1-3-4-2

pressure, the duty cycle percentage of the pulse-width modulation signal sent to the high pressure pump's metering unit is adjusted. The common-rail pressure values sensed by the common-rail pressure sensor are sent back to the ECU. The control algorithm is written in the ECU to compute the appropriate duty cycle percentage.

Figure 2 shows a diagram of the proposed control system, where p_d is the desired common-rail pressure expressed in megapascals which is obtained from a static map during engine calibrations and p is the measured common-rail pressure expressed in megapascals as measured by the common-rail pressure sensor and $e = p_d - p$ is the tracking error. The tracking error and its integral are used as inputs to the standard fuzzy controller.

The standard fuzzy controller is normalized, that is, its input and output universes of discourse are from -1 to 1. The scaling gain g_{11} is set to 0.01, the scaling gain g_{12} is set to 0.00001, the scaling gain h_1 is set to 0.02. All gains were obtained during experiments to ensure ranges of -1 to 1. There were five input membership functions and nine output membership functions. All membership functions had a symmetrical triangular shape with full overlap.

The rule-base is given in Table 2. The linguistic numeric values -2 to 2 were used to represent the five levels of input membership functions, from large negative to large positive values. The linguistic numeric values -4 to 4 were used to represent the nine levels of output membership functions, from large negative to large positive values.

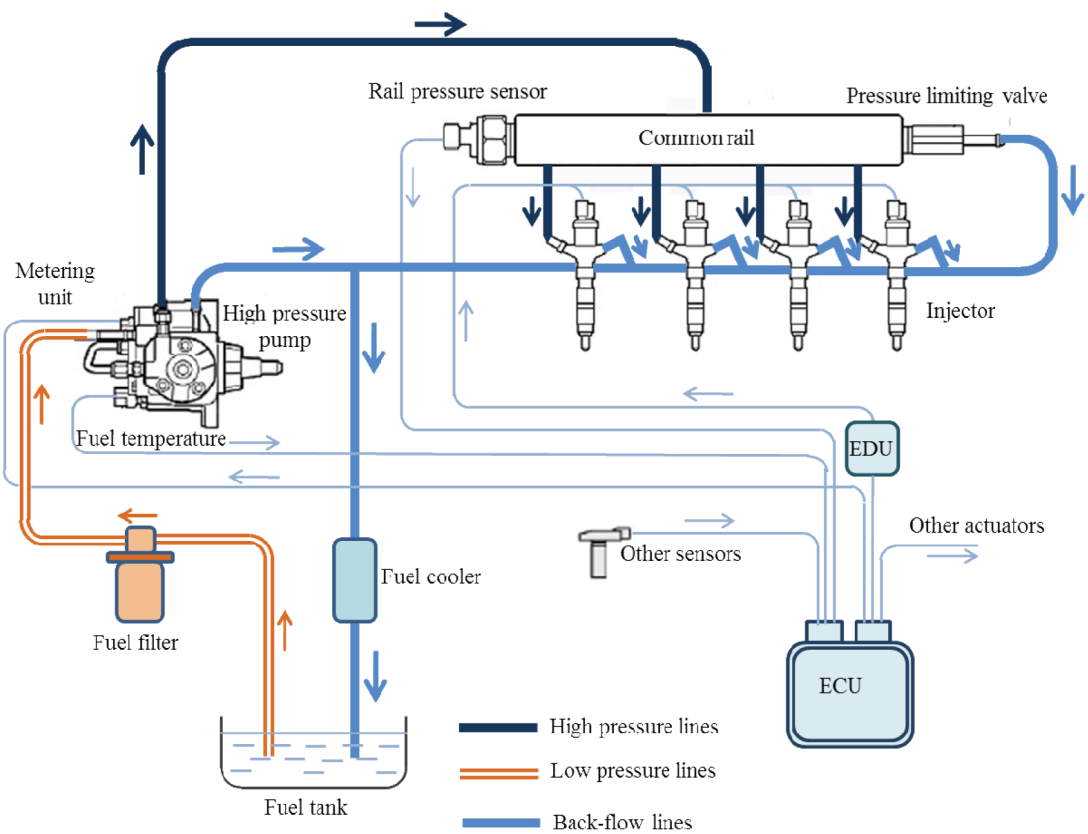


Figure 1 Common-rail system of the Toyota 2KD-FTV diesel engine (ECU = Electronic control unit, EDU = Electronic drive unit).

Minimum fuzzification and center of gravity (COG) defuzzification are used. The output of the standard fuzzy system is called $\overline{P}_{dc1}$. After multiplication with the gain h_1, it will become p_{dc1}, which is the feedback portion of the duty cycle. Note that the rule-base is designed to drive the tracking error to zero.

In Figure 2, the gains g_{21} and g_{22} are set as 0.0003 and 0.001, respectively. These input gains are used to normalize the inputs to the fuzzy learning controller to 0 to 1. There are 11 input membership functions for each input. The input membership functions of both inputs are shown in Figures 5a and 5b. The horizontal axes of the membership function represent their normalized universes of discourse. The universe of discourse is the domain of input or output. The unit of the axis is the unit of that input or output. The vertical axis is the degree of the membership function. There are 121 output membership functions. Each output membership function has a symmetrical triangular shape with 0.2 base width. The output universe of discourse is also 0 to 1. At the beginning, all output membership function centers are set at zero. The rule-base is given according to Equation 1:

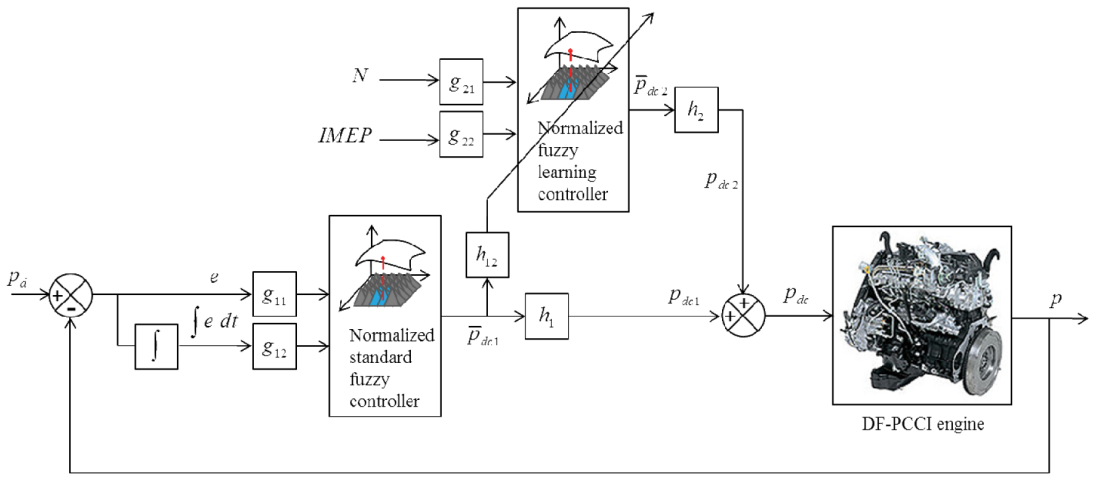


Figure 2 Proposed control system diagram for a diesel-dual-fuel, premixed-charge-compression-ignition (DF-PCCI) engine where g and h represent scaling gains; $\overline{P}_{dc1}$. is the output of the standard fuzzy system, N is the engine speed in revolutions per minute, $IMEP$ is the indicated mean effective pressure in kilopascals used as load and $e = p_d - p$ is the tracking error.

Table 2 Rule-base of the standard fuzzy system.

$\overline{P}_{dc1}$		$\int e\ dt \times g_{12}$				
		-2	-1	0	1	2
$e \times g_{11}$	-2	-4	-3	-2	-1	0
	-1	-3	-2	-1	0	1
	0	-2	-1	0	1	2
	1	-1	0	1	2	3
	2	0	1	2	3	4

$\overline{P}_{dc1}$ = Output of the standard fuzzy system; g_{11} and g_{12} are gains.

If input 1 is i^{th} and input 2 is j^{th}, then output is $[(i-1)\times 11+j]^{th}$. (1)

Minimum fuzzification and COG defuzzification are used. The output scaling gain h_2 is set to 100. The output membership function centers are updated according to Equation 2:

$$c_{h2,k^{th}}(n)=c_{h2,k^{th}}(n-1)+\bar{p}_{dc1}\times h_{12}, \quad (2)$$

where $c_{h2,k^{th}}(n)$ is the k^{th} output membership function center at a time step n, $c_{h2,k^{th}}(n-1)$ is the k^{th} output membership function center at time step $n-1$. Note that the centers are adjusted by the amount $\bar{p}_{dc1}\times h_{12}$, which is the output of the standard fuzzy controller. Only the centers of the rules that are active are updated.

The gain h_{12} is set to 0.1. It can be viewed as a gain connecting the two fuzzy systems. The gain h_{12} determines the learning rate of the fuzzy learning controller. The output of the fuzzy learning system is called $\bar{p}_{dc2}$. After multiplication by the gain h_2, it will become p_{dc2}, which is the feed-forward portion of the duty cycle.

The functions of the whole control system can be explained as follows. The standard fuzzy system outputs $\bar{p}_{dc1}$ in the direction to minimize the common-rail pressure tracking error. The scaled output $h_{12}\times\bar{p}_{dc1}$ updates the output membership function centers of the fuzzy learning system so that next time, the same operating point (speed and load) is re-visited, the fuzzy learning system will output an appropriate duty cycle to reduce the tracking error. The output of the fuzzy learning system can be viewed as the mean duty cycle, while the output of the standard fuzzy system can be viewed as the varying duty cycle. The mean duty cycle is updated by the varying duty cycle to be suitable for any particular operating point. The DF-PCCI engine was connected to an engine dynamometer. The dynamometer was programmed to run the NEDC test.

RESULTS

The dots in Figure 3 represent operating points visited by the NEDC run. Figure 3a represents the process at the beginning before the NEDC program commenced. Figures 3b–3e represent the first to fourth urban cycles, respectively. Figure 3(f) is during the suburban cycle. Figure 3 also shows the feed-forward control p_{dc2} from 0 to 100%. It can be seen that when an operating point is visited, the fuzzy learning system output is updated as a result of updating the output membership function centers.

Figure 4(a) shows the feed-forward control p_{dc2} during the suburban cycle. The engine speed and the IMEP are divided into 10 equally spaced intervals. Each vertical and horizontal line marks the center of the input membership function with the corresponding output membership function number. The nine white dotted squares in the middle mark the input ranges of the output membership function numbers 30, 63, 96, 27, 60, 93, 24, 57 and 90.

Figures 4b–4j plot the centers of the output membership function numbers 30, 63, 96, 27, 60, 93, 24, 57 and 90, respectively as functions of time. The centers of the output membership function numbers 30 and 27 do not change, since their corresponding operating point inputs are not visited by the NEDC run. The center of the output membership function number 96 only changes during the last suburban cycle. The centers of the output membership function numbers 63, 60, 93, 24, 57 and 90 always change because their corresponding operating point inputs are visited by all urban and suburban cycles.

Figures 5c–5f show the distribution of the output membership function centers at 20, 220, 850, and 1,145 s, which are at the start of the first urban, second urban and suburban cycles and at the end of the suburban cycle, respectively. It can be seen that after the first urban cycle (220 s), the centers have a greater distribution than after the fourth urban cycle (850 s) because during the first urban cycle, the operating points fluctuate more due to poorer common-rail pressure tracking.

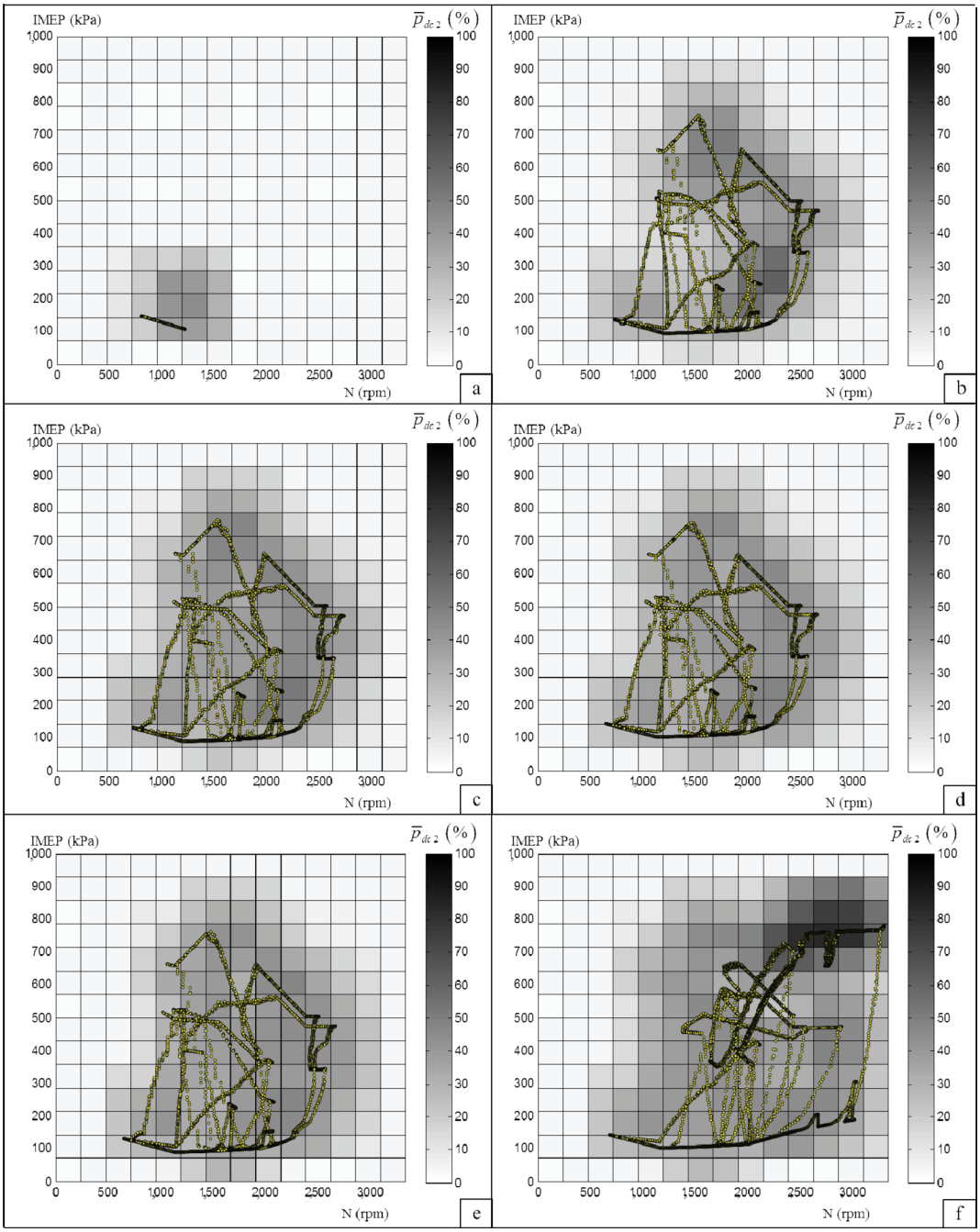


Figure 3 Output of the standard fuzzy system ($\overline{p}_{dc2}$, indicated by shading) as a function of engine speed (N, measured in revolutions per minute, rpm) and indicated mean effective pressure (IMEP): (a) process at the beginning before the new European driving cycle program commenced; (b)–(e) first to fourth urban cycles, respectively; (f) suburban cycle.

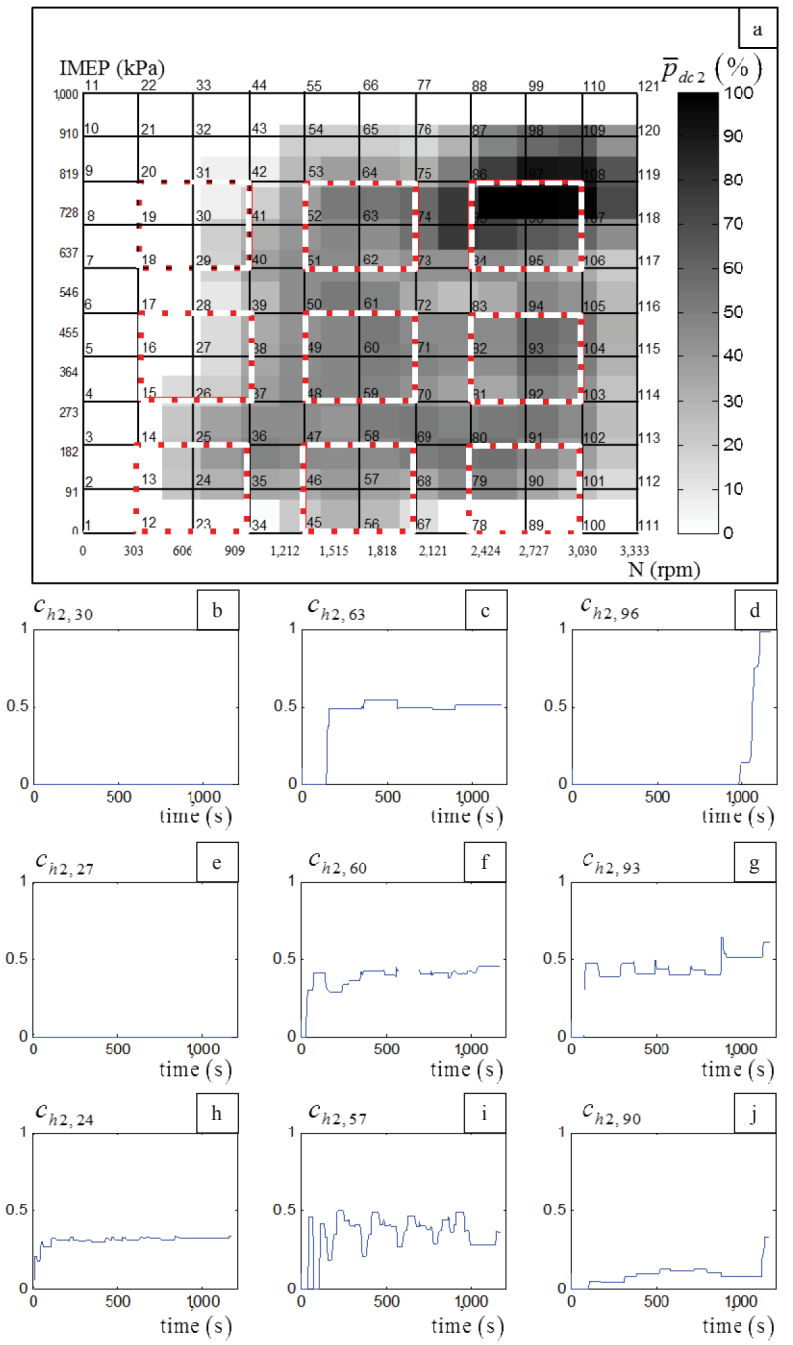


Figure 4 Normalized fuzzy logic control (NFLC) output membership functions: (a) Number; (b)–(j) Centers (c). (Output of the standard fuzzy system ($\overline{p}_{dc2}$, indicated by shading) as a function of engine speed (N, measured in revolutions per minute, rpm) and indicated mean effective pressure (IMEP).

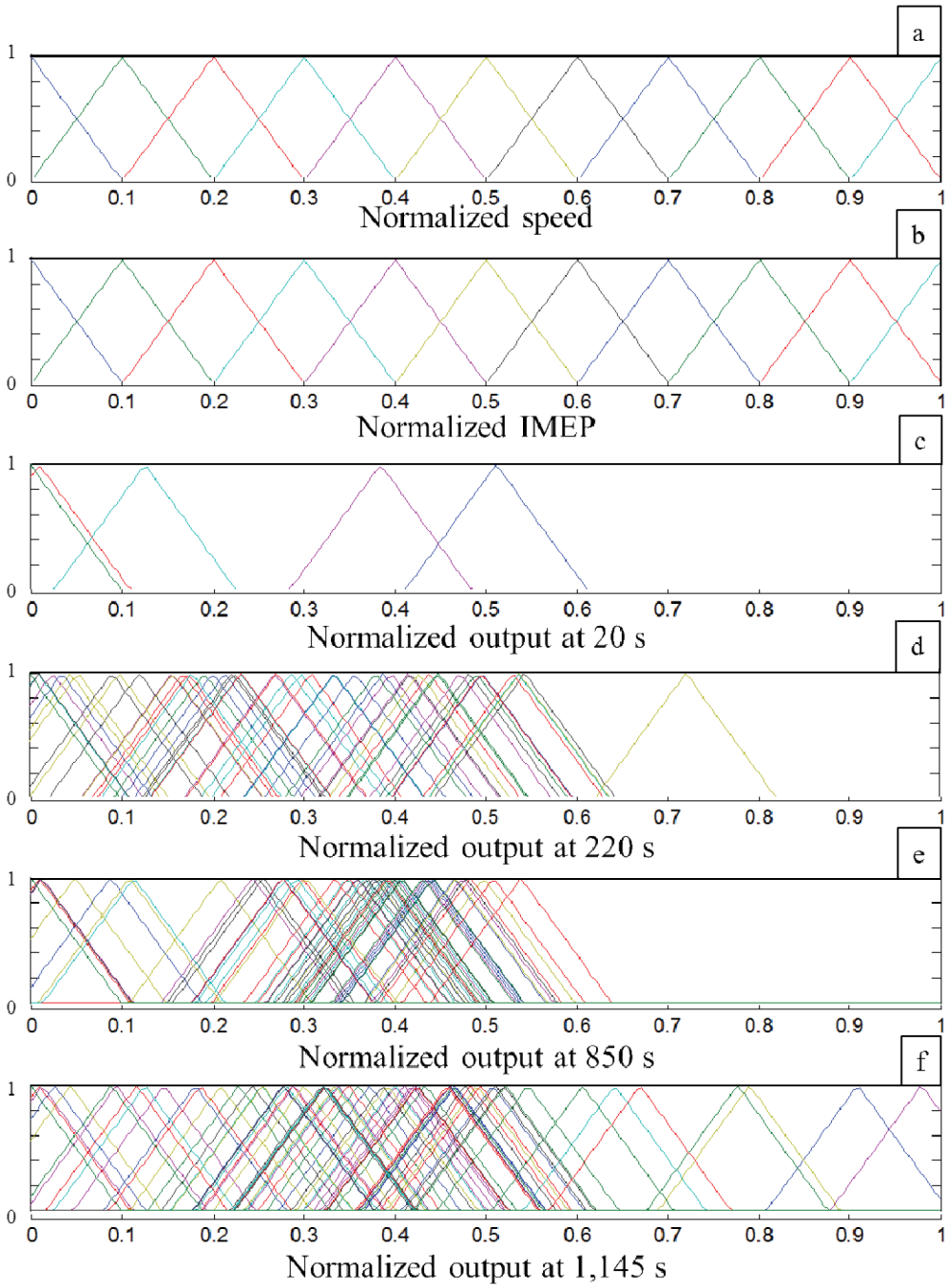


Figure 5 Normalized fuzzy logic control (NFLC) input membership functions: (a) Speed; (b) Indicated mean effective pressure. NFLC output membership functions at (c) 20 s; (d) 220 s; (e) 850 s; (f) 1,145 s.

Figures 5c–5f show the distribution of the output membership function centers at 20, 220, 850, and 1,145 s, which are at the start of the first urban, second urban, suburban cycles and at the end of the suburban cycle, respectively. It can be seen that after the first urban cycle (220 s), the centers have more distribution than after the fourth urban cycle (850 s) because during the first urban cycle, the operating points fluctuate more due to poorer common-rail pressure tracking.

Figure 6a shows the time plot of the tracking error $p_d - p$. Figure 6b shows the feed-forward duty cycle p_{dc2}. Figure 6c shows the feed-back duty cycle p_{dc1}. The actual pressure is closely tracked by the desired pressure except for some negative spikes.

From Figures 6a and 6b, the root mean square tracking errors of the first, second, third and fourth urban cycles and the suburban cycle are 5.95, 3.17, 2.41, 2.31 and 3.28, respectively. The tracking error reduces during subsequent urban cycles since the fuzzy learning system has learned from the previous urban cycles. The transient tracking error during the suburban cycle is not as good as the fourth urban cycle due to its new set-point. From Figures 6c and 6d, the control efforts of the first urban cycle fluctuate more than those of subsequent cycles due to the larger tracking error during the first urban cycle. The control effort fluctuation is reduced for the subsequent cycles because the learning fuzzy controller learns from the previous cycles and is able to deliver appropriate control effort.

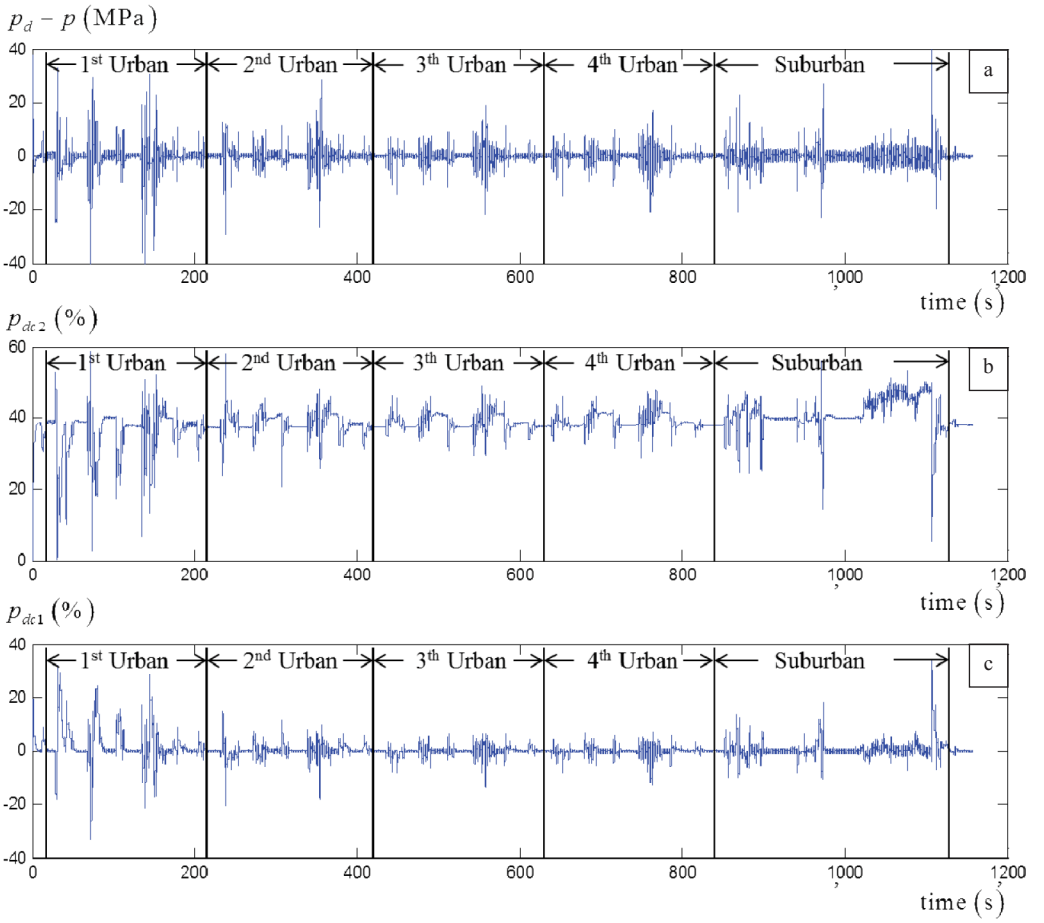


Figure 6 New European driving cycle (NEDC) results: (a) Tracking error ($p_d - p$); (b) Feed-forward duty cycle (p_{dc2}); (c) Feed-back duty cycle (p_{dc1}).

By comparing the last urban cycle with the first urban cycle, it can be seen that the transient tracking performance is improved significantly.

DISCUSSION

Many researchers have attempted to improve the rail pressure control performance as mentioned earlier. The work by Chatlatanagulchai and coauthors mentioned earlier involved a robust common-rail pressure control in DF-PCCI engine using quantitative feedback control and a common-rail pressure control using a sliding-mode control with gain scheduling and an augmented integrator. Others researchers have proposed a very good control method using an adaptive control with most using some technique to adjust controller gain.

This paper presents an intelligent control system—an algorithm that is able to learn and improve control performance—for common-rail pressure control of a DF-PCCI engine. The control system consists of a standard fuzzy system and a fuzzy learning system. The standard fuzzy system outputs the duty cycle to minimize the tracking error. At the same time, this duty cycle is learned by the fuzzy learning system by shifting the output membership function centers so that the next time the same operating point is revisited, a more appropriate duty cycle can readily be sent out. By following the NEDC, the common-rail pressure tracking performance is improved during subsequent urban cycles by learning from earlier cycles.

A fuzzy system has two advantages, which make it suitable for engine control applications. First, a human sets the rule-base on how to control the system. For a complicated application such as engine control, the ability for a human to set the rule-base enables cooperation between combustion engineers (who set the rule-base from their experience) and the control engineers (who design and implement the controller). Furthermore, the rule-base can be designed to handle difficult situations, where human intuition is required to accommodate multiple inputs and outputs. Second, the fuzzy system has learning capability. Learning is adaptive with memory. The adaptive attribute helps with the change of operating points, while the memory attribute helps with the abrupt or transient changes.

CONCLUSION

This paper presented an intelligent control system that was able to learn and improve the control performance using a suitably developed algorithm.

This study showed that the learning capability helped to improve the tracking performance once the control efforts of the previous operating points had been learned. Engineers can also pre-specify the rule-base of the standard fuzzy system or the output membership function centers of the fuzzy learning system to improve the controller performance even further. In the future, the learning capability of the fuzzy learning system should be explored with other engine applications; for example, the estimation of the in-cylinder air and the air-path control.

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