Applied Energy 119 (2014) 330–340

Contents lists available at ScienceDirect

Applied Energy

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

Performance and exhaust emissions prediction of a CRDI assisted single cylinder diesel engine coupled with EGR using artificial neural network

Sumit Roy *, Rahul Banerjee, Probir Kumar Bose

Department of Mechanical Engineering, NIT Agartala, Tripura, India

HIGHLIGHTS

- CRDI/high pressure fuel injection reduces PM and BSFC with the penalty of increase in NOx emissions.
- EGR operation at lowest injection duration case of CRDI operation reduces NOx.
- Artificial neural network modeling of BSFC, BTE, CO_2, NOx and PM.
- ANN is capable in predicting performance and emission parameters of the experimental engine.
- MSE, RMSE, MAPE, MSRE, THEIL U2, R, R2, NSE, KGE metrics used as evaluation benchmarks.

ARTICLE INFO

Article history:
Received 6 August 2013
Received in revised form 8 January 2014
Accepted 11 January 2014
Available online 31 January 2014

Keywords:
Artificial neural network
CRDI
EGR
Engine performance
Exhaust emissions

ABSTRACT

The present study explores the potential of artificial neural network to predict the performance and exhaust emissions of an existing single cylinder four-stroke CRDI engine under varying EGR strategies. Based on the experimental data an ANN model is developed to predict BSFC, BTE, CO_2, NOx and PM with load, fuel injection pressure, EGR and fuel injected per cycle as input parameters for the network. The study was carried out with 70% of total experimental data selected for training the neural network, 15% for the network's cross-validation and remaining 15% data has been used for testing the performance of the trained network. The developed ANN model was capable of predicting the performance and emissions of the experimental engine with excellent agreement as observed from correlation coefficients within the range of 0.987–0.999, mean absolute percentage error in the range of 1.1–4.57% with noticeably low root mean square errors. In addition to common correlation coefficients, the present study incorporated special statistical error and performance metrics such as mean square relative error, forecasting uncertainty Theil U2, Nash–Sutcliffe Coefficient of Efficiency and Kling–Gupta Efficiency. Low values of MSRE and Theil U2 combined with commendable indices of NSE and KGE proved beyond doubt the robustness and applicability of the model so developed. Furthermore, the developed ANN model was capable of mapping the PM–NOx–BSFC trade-off potential of the CRDI operation under EGR for all cases of actual observations with significant accuracy.

1. Introduction

Research studies [1–5] have clearly established that the chronological evolution of emission mandates have continuously challenged diesel engine design to be contemporary in the present millennium. Such challenges have demanded paradigm shifts in diesel engine technology to meet the desired emission directives on one hand and consumer expectations of superior fuel economy on the other. Among various contingent technological advancements, Common Rail Diesel Injection (CRDI) systems have spearheaded the technological renaissance [6,7]. CRDI systems have been observed to significantly reduce the specific fuel consumption [8,9] and soot emission precursors [10–12] as compared to conventional diesel operation, however, with a propensity of increased NOx formation [7,13,14]. Therefore, a trade-off scenario arises wherein lower soot emissions and fuel consumption footprint of a CRDI system is penalized by higher NOx emissions [6,13,15]. Exhaust Gas Recirculation (EGR) has been proved to be a cost effective tool in NOx containment [16–19]. It has been employed widely due to its simplicity of operation and efficiency

Abbreviations: ANN, Artificial Neural Network; BDO, baseline diesel operation; BP, brake power; BSFC, Brake Specific Fuel Consumption; BTDC, before top dead centre; BTE, Brake Thermal Efficiency; CO_2, Carbon-di-oxide; CI, compression ignition; CRDI, Common Rail Diesel Injection; DI, direct injection; EGR, Exhaust Gas Recirculation; IC, Internal Combustion; KGE, King–Gupta Efficiency; MAPE, Mean Absolute Percentage Error; MSE, Mean Square Error; MSRE, Mean Squared Relative Error; NOx, oxides of nitrogen; NSE, Nash–Sutcliffe Coefficient of Efficiency; PM, particulate matter; ppm, parts per million; R, correlation coefficient; RMSE, Root Mean Square Error; Theil U2, Theil uncertainty.

* Corresponding author. Tel.: +91 9402108135; fax: +91 3812346360.
E-mail address: sumitroy@hotmail.de (S. Roy).

0306-2619/$ - see front matter © 2014 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.apenergy.2014.01.044

as compared to the operational and development challenges of NOx after-treatment systems.

The present day responsiveness to legislative and consumer requirements is necessitating an extraordinary increase of dependence on several new degrees of control simultaneously. Furthermore, the highly nonlinear dependence of the pollutants on engine operating variables, have made classical one-dimensional map-based control redundant for efficient engine control [20,21] in the present day. Advanced on board diagnostic capability and the ability to reconfigure control on the fly has become an essential criterion in implementing the complex control paradigms. The need of the day warrants a truly multidimensional, adaptive, learning control system [22] having credible performance and emissions prediction capabilities across the entire design range of engine operation.

In contrast to traditional nonlinear identification methods, Artificial Intelligence (AI) platforms have proved to substantially reduce the cost, time and complexity associated with engine development, performance mapping and control system development [23–26]. The inherent adaptive strengths of ANN based AI systems have established itself as a robust system identification and mapping tool [22,27–29] in the control paradigm of Internal Combustion (IC) engines. ANNs have the ability in simulating accurate engine behavior and as such have become an inexpensive basis of a virtual sensing system for onboard measurements of engine emissions continuously in real time [30–35]. Early researchers in the field of IC engines [36–42] were quick to recognize the ability of ANN platforms in capturing nonlinear trends in complex data to model the same to any desired accuracy and thus establish their inherent robustness as 'universal approximators' [43,44].

1.1. Motivation of the present study

An experimental investigation was carried out on an existing diesel engine to exploit the synergetic benefits of a CRDI system by containing the expected increase in NOx emission through EGR. Subsequent to the experimental investigation, data analysis revealed a marked sensitivity of the output variables with the chosen inputs under study. Juxtaposing the context of the discussion enumerated previously, it was evident that precise controls of the input variables were desired to reap the maximum benefits of the performance–emission trade-off merit posed by the CRDI–EGR system. Consequently a potential domain of study was established to investigate the benefits of an AI based ANN system to model the performance-emission characteristics.

Such a predictive model in real time would then serve as an indispensable tool in predictive controller domains which can be used to adjudge the trade-off characteristics in real time onboard systems. The applications of ANN are not new in the field of IC engines and have been successfully employed in engine management systems, fuel management systems and in predicting the common pollutants of CI/SI engines. In The present study, an endeavor was undertaken to bridge the gap by a first-of-a-kind study, incorporating both CRDI control parameters and EGR quantification for a direct correspondence to emission and performance outputs through predictive modeling. Further such an effort would also stand in good stead for the establishment of a virtual sensing platform for the difficult to measure pollutants in on-board diagnostic systems in real time.

2. Experimental investigation

2.1. Experimental setup and methodology

2.1.1. Experimental engine

The experiment was conducted on an existing single cylinder four-stroke CI engine assembled with Common Rail Direct Fuel Injection system as detailed in Table 1. The engine was coupled to an air-cooled eddy current dynamometer of PowerMag® make.

2.1.2. Common rail direct injection setup

The CRDI setup is an attachment to the experimental engine. It consists of a high-pressure fuel pump, rail, high-pressure fuel injector and the heart of the system being the Electronic Injection Controller (EIC). The description of the fuel injection system is given in Table 2.

2.1.3. Exhaust gas recirculation setup

The EGR circuit essentially consisted of an EGR control valve, exhaust control valve, bypass valve, EGR cooler (water-cooled; double pass), exhaust cooler (water-cooled), digital manometers, air box orifice meters along with condensate traps. The EGR was controlled with a digital control valve fitted to the EGR setup. The EGR fraction was calculated as in Eq. (1) [45]

$$\%EGR = \frac{\dot{m}_{a_{w/oEGR}} - \dot{m}_{a_{EGR}}}{\dot{m}_{a_{w/oEGR}}} \tag{1}$$

where $\dot{m}a$ = mass of air.

2.1.4. Emission analysis instrumentation

The exhaust gases were sampled by a *5 Gas analyzer* and an *AVL smoke meter (415S)* was used to measure the soot content, present in the exhaust. The specifications of the emission measuring apparatus are detailed in Tables A1 and A2 in Appendix-A.

NOx was calculated in terms of NO as per the specifications of the AVL Digas 444. NOx measured in ppm was recalculated in brake specific units as per the equation given below (Eq. (2)):

$$[E]_{SPECIFIC} = \frac{[\dot{m}]_{air+fuel} \times [E]_{PPM} \times [M]_E \times 1000}{BP \times [M]_{EXHAUST}} \tag{2}$$

where E is the pollutant under consideration, $[M]_E$ is the molar mass of the pollutant and $[M]_{EXHAUST}$ is the average molar mass of the exhaust gases. The constant 1000 is included in the numerator to convert the mass flow unit from (kg/h) to (g/h).

Table 1
Experimental engine specification.

Specification	Resources
Make	Vidhata
No of cylinder	One (1)
Bore	120 mm
Stroke	139.7 mm
Displacement	1580 cc
Cooling	Water
Compression Ratio	18:1
Valve timing	
Exhaust valve opening	35 deg before BDC
Exhaust valve closing	4 deg after TDC
Inlet valve opening	4 deg before TDC
Inlet valve closing	35 deg after BDC

Table 2
Specification of the fuel injector.

Specification	Resources
Type	Common rail injection system
Make	Bosch
Injection Pressure	10–120 MPa
Number of holes	5 (Symmetric)
Nozzle diameter	0.15 mm
Injection angle	120°