THE PERFORMANCE OF ARTIFICIAL NEURAL NETWORK IN PREDICTING OPTIMAL OPERATING CONDITIONS OF A CNG-FUELED HCCI ENGINE

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DOI: 10.29322/IJSRP.12.03.2022.p12344
http://dx.doi.org/10.29322/IJSRP.12.03.2022.p12344

Abstract- It is widely accepted that the Homogeneous Charge Combustion Ignition (HCCI) can enhance engines' efficiency. However, finding optimal operating conditions to yield optimal engines' ignition timing is still an on-going issue and difficult to achieve. This is because combustion in HCCI engines is automatically occurred from chemical kinetics of the fuel-air mixtures and therefore altering one parameter (out of many parameters) could change the engines' ignition timing, leading to highly nonlinear behavior of the HCCI engines. Therefore, the technics used to optimize HCCI engines must be able to handle highly nonlinear problems, such as Genetic Algorithm (GA) or Artificial Neural Network (ANN).

This study tested the performance of Artificial Neural Network (ANN) in optimizing the engine conditions to yield maximum efficiency and minimum NO_x emissions. Instead of using experimental data, the data used to train ANN were simulated from the Single Zone HCCI engine model [9]. It is found that with the proper designed and trained network, ANN can effectively predict the HCCI engine behaviors and hence can be used to find the optimal working condition of a CNG fueled HCCI engine with 75%H_2 + 25%O_2 reformer. The optimal operating condition is preliminarily found to be the point where equivalence ratio = 0.35, IVC temperature = 405, %EGR = 28 and %RG = 0.

Index Terms- Artificial Neural Network, Combustion, HCCI Combustion

I. Introduction

Although the tendency of mobility vehicles in the coming decades is moving towards electric vehicles (EV), the use of fossil fuels in combustion systems still exists in various applications [1]. Therefore, the development in enhancing efficiency of combustion engines is still important.

One of the proven technics to enhance the efficiency and reduce the emissions of combustion systems is to use Homogeneous Charge Compression Ignition (HCCI) technic, which is a hybrid between Spark Ignition (SI) and Compression Ignition (CI) [2,3]. In HCCI, homogeneous mixtures between air and fuel are ignited by high pressure and temperature at the end of compression stroke, causing instant combustions in several local spots. This leads to a more complete combustion and reduction in unburned fuels, resulting in better engines' efficiency.

Despite possessing precious advantages of better efficiency with less emissions, HCCI inherits major drawbacks in ignition control and higher NO_x emissions [4]. (Higher NO_x emissions results from high combustion temperature). The latter problem could however substantially reduce with normal lean operations of HCCI engines [5, 6]. Controlling ignition timing of HCCI engines to yield the optimal outcomes remains an important issue to address and has been researched both experimentally and computationally [7]. Since combustion in HCCI engines is automatically initiated, altering operating conditions, (e.g., air-fuel mixtures, initial temperature, %EGR, %RG), shifts ignition timing and their performances (efficiency and emissions).

Optimization technics can be used to find the optimal operating conditions. Nevertheless, not all technics are applicable since the HCCI combustion involves several factors and the relationship between inputs and outputs is highly non-linear. As being able to handle complex optimization problems, Artificial Neural Network (ANN) and Genetic Algorithm (GA) have been adopted by many researchers to optimize the combustion related problems [8].

This paper investigates the performance of Artificial Neural Networks (ANNs) to optimize operating condition(s) of a CNG fueled HCCI engine with reformer gas (75%H_2 + 25%O_2). (See Table 1). The data used to train ANNs were theoretically calculated from a verified Single Zone HCCI engine Model (SZM) [9].

Table 1. Engine specifications and initial conditions

Engine parameters (unit)	Values	Testing (Initial) Conditions	Values
Compression ratio	19.8	Intake pressure (MPa)	0.101
Bore (cm)	12.1	IVC temperature (K)	405 – 425
Stroke (cm)	11.4	Cylinder wall temperature (K)	400
Connecting rod (cm)	24.0	Minimum reaction temperature (K)	900
Intake valve closed (CA)	190	Equivalence ratio	0.35 – 0.55
Exhaust valve opened (CA)	540	%EGR	0 - 30
Engine speed (rpm)	1000	%RG	0 - 30

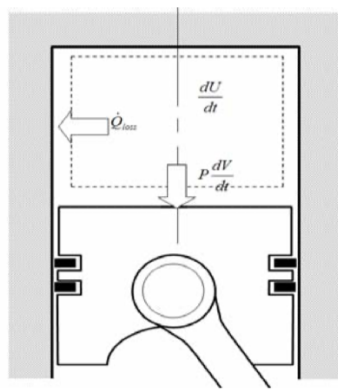

Figure 1 – Schematic of a Single Zone Model. Adapted from "A Stand-Alone Multi-Zone Model for Combustion in HCCI Engines," by P. Kongsereeparp, 2005, ASME 2005 Internal Combustion Engine Division Fall Technical Conference [10]

II. SINGLE ZONE HCCI COMBUSTION MODEL

In SZM, the cylinder charge is assumed to be lumped (see Figure 1) and mixture properties (pressure temperature and volume) inside a cylinder are assumed to be uniform at each time (iteration). During intake valve close (IVC) to exhaust valve open (EVO), the combustion chamber is a closed system and no blow-by is considered. The rates of change in mixtures properties are governed by Thermodynamics of the ideal gas law, while the change in concentration of radicals is found from chemical kinetic modelling. The heat transfer between the mixtures and the wall ($\dot{Q_{loss}}$) is calculated from Woschni's correlation. The governing equations are [9]:

$$\frac{dm_{cyl}}{dt} = 0 \tag{1}$$

$$\frac{dV_{cyl}}{dt} = V_c\left[\frac{1}{2}(r_c - 1)\left(\sin\theta\frac{d\theta}{dt} - \frac{1}{2}\left(R^2 - \sin^2\theta\right)^{-\frac{1}{2}}\left(-\sin 2\theta\right)\frac{d\theta}{dt}\right)\right] \tag{2}$$

$$\frac{dP}{dt} = \frac{1}{R_U}\frac{dR_U}{dt} - \frac{1}{V}\frac{dV_{cyl}}{dt} + \frac{1}{T}\frac{dT}{dt} \tag{3}$$

$$\overline{C_p}\frac{dT}{dt} = -\sum_{i=1}^{N} u_i\frac{dY_i}{dt} - \frac{\bar{R}T}{V_{cyl}}\frac{dV_{cyl}}{dt} - T\frac{d\bar{R}}{dt} - Q_{loss} \tag{4}$$

$$\frac{dY_i}{dt} = \frac{\dot{\omega}_i W_i}{\rho} \tag{5}$$

III. ARTIFICIAL NEURAL NETWORK

To apply Artificial Neural Network (ANN), %EGR, %RG, equivalence ratio and initial temperature were selected as controllable parameters, while the objective function was set to be,

$$f = \frac{y_{NO_x} - a_{NO_x}}{b_{NO_x} - a_{NO_x}} + \frac{y_{CO} - a_{CO}}{b_{CO} - a_{CO}} + \frac{b_\eta - \eta}{b_\eta - a_\eta} \quad (6)$$

This function is used as the objective function since it addresses the three major outcomes of a HCCI combustion engine: engine efficiency, CO emissions and NO_x emissions.

The following four steps were done to set up the ANN.

1. Preparing the data used to train the ANN – SZM was used to generate the outcomes of several initial conditions. In this study, 81 cases (with $\phi = 0.35 - 0.55, \%EGR = 0 - 30\%, \%RG = 0 - 30\%$ and initial temperature $= 405 - 425\ K$) were stimulated and used as the data to train and verify the ANN.
2. Arranging the architecture of the ANN – Four layers were applied in this study (one input layer, two hidden layers and one output layer). The tan-sigmoid transfer function is an activation function of hidden neurons while an activation function of output neurons is the linear transfer function. Backpropagation was used to train the specified static neural networks by using the Levenberg-Marquardt algorithm [11].
3. Training the ANN – The architected Network was trained by the data generated from Step 1. The total sum of squares was used to measure the Network performance.
4. Applying the well-trained network to find the optimal operating conditions.

IV. RESULTS AND DISCUSSIONS

The first objective of this study is to analyze the performance of ANN in predicting the outcomes from various operating conditions. Regression analysis between the targets (obtained from SZM) and Network outputs was plotted. If the Network can accurately predict the outcomes of various conditions, the slope of the regression plot will be close to one and the correlation coefficient (R-value) will also be close to one.

Figure 2 shows that the first trained ANN can barely capture the behavior of a HCCI engine and cannot be further used to perform engine optimization.

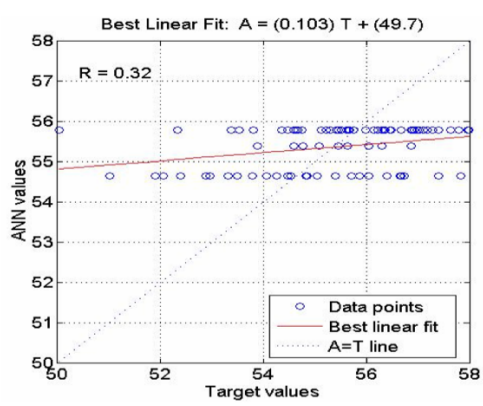

Figure 2 – Performance of the originally trained ANN in predicting engine efficiency

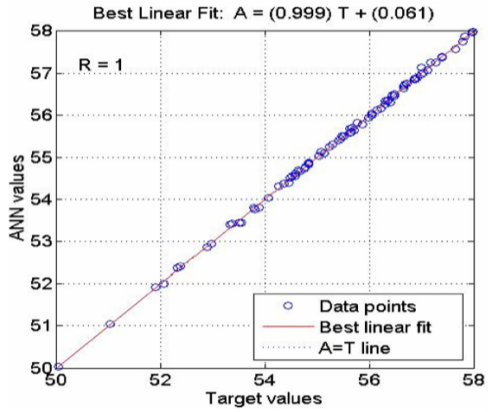

Figure 3 – Performance of the improved ANN in predicting engine efficiency

To improve the performance of ANN, the automated regularization was adopted "to determine the optimal regularization parameters in an automated fashion" [11]. This was done by combining Bayesian framework of David MacKay [12] to Levenberge-Marquardt training. With this approach, the performance of the Network is substantially improved (see Figures 3 and 4). Figures 5 and 6 compare the errors obtained from the original Network to those obtained from the improved Network. (Note that the error graphs are plotted in log-scale due to the wide range of %error, from 0.01% to 10,000%).

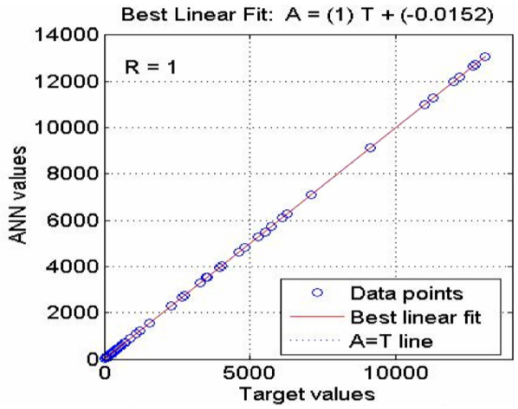

Figure 4 – Performance of the improved ANN in predicting NOx emissions

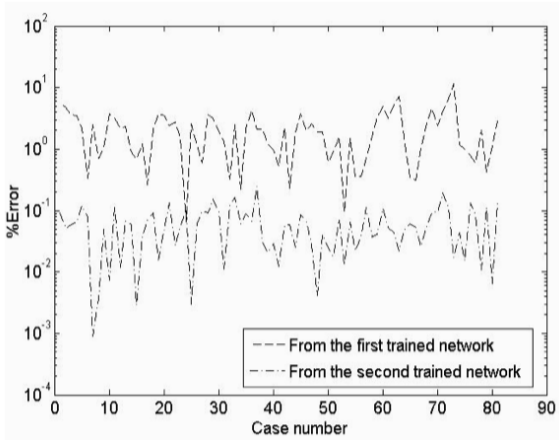

Figure 5 – The errors from the original ANN versus those from the improved ANN in predicting engine efficiency

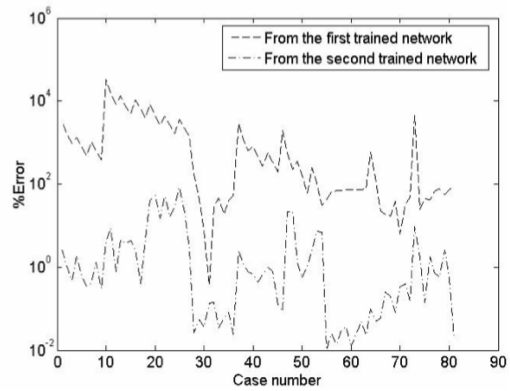

Figure 6 – The errors from the original ANN versus those from the improved ANN in predicting NO_x emissions

The improved Network was then used to find the optimal operating conditions (better efficiency with lesser NO_x emissions). Figures 7 and 8 are the engine efficiency and NO_x emissions results obtained from the improved Network, when %RG and %EGR changed. As expected, higher %EGR leads to better efficiency and less NO_x emissions since it increases initial temperature. Additionally, EGR helps leaning the amount of fuel in the mixtures, resulting in less fuel consumptions and lower peak temperature (producing less NO_x emissions).

To find the optimal operating conditions of a CNG fueled HCCI engine, several thousand initial conditions were used to train the modified ANN. The trained ANN was then simulated to find the minimum objective function value (Equation 6). The optimal operating condition was found to be the point where equivalence ratio = 0.35, IVC temperature = 405 K, %EGR = 28 and %RG = 0. Since this study was conducted based on SZM, the proposed condition is only a primary suggestion. Nevertheless, this study shows a very promising performance of ANN in predicting a CNG-fueled HCCI engine.

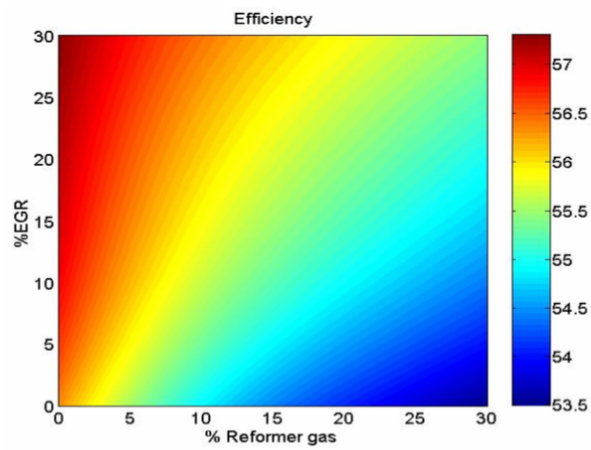

Figure 7 – Engine efficiency obtained from the improved ANN

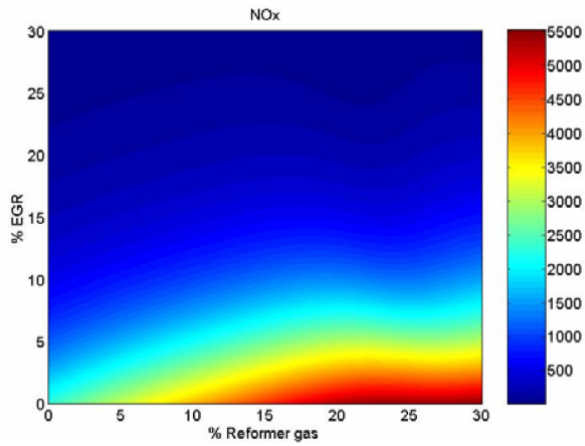

Figure 8 – NO_x emissions obtained from the improved ANN

V. CONCLUSION

The static ANN to optimize a HCCI engine was first investigated by using linear regression and error analysis. The results show that such a network cannot capture the behavior of a HCCI engine and must be improved. The automated regularization was then applied to improve the ANN. The results from the modified ANN show that the use of ANNs as a tool to optimize HCCI engines is very promising. Finally, the optimal operating conditions for the studied engine was primarily found to be the point where an equivalence ratio = 0.35, IVC temperature = 405 K, %EGR = 28% and %RG = 0%.

NOMENCLATURES

η	engine efficiency
θ	crank angle
P	pressure inside a combustion chamber
R_{ave}	average gas constant
$\bar{R}$	universal gas constant
T	temperature inside a combustion chamber
V_c	clearance volume
V_{cyl}	in-cylinder volume
Y_i	mole fraction of the species *i*
a_{CO}	lower limit of CO emissions
a_{NO_x}	lower limit of NO_x emissions
a_η	lower limit of engine efficiency
b_{CO}	upper limit of CO emissions
b_{NO_x}	upper limit of NO_x emissions
b_η	upper limit of engine efficiency
f	objective function value
m_{cyl}	mass of the air-fuel mixtures in the cylinder
r_c	compression ratio
t	time
y_{NO_x}	mole fraction of NO_x emissions

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