Numerical Estimation of Wiebe Function Parameters Using Artificial Neural Networks in SI Engine

Antonio J. Torregrosa, Alberto Broatch, Pablo Olmeda, and Sebastian Aceros

CMT-Motores Térmicos. Universitat Politècnica de València. Camino de Vera s/n. 46022 València (Spain)

Abstract

In modeling an Internal Combustion Engine, the combustion sub-model plays a critical role in the overall simulation of the engine as it provides the Mass Fraction Burned (MFB). Analytically, the Heat Release Rate (HRR) can be obtained using the Wiebe function, which is nothing more than a mathematical formulation of the MFB. The aforementioned function depends on the following four parameters: efficiency parameter, shape factor, crankshaft angle, and duration of the combustion. In this way, the Wiebe function can be adjusted to experimentally measured values of the mass fraction burned at various operating points using a least-squares regression, and thus obtaining specific values for the unknown parameters. Nevertheless, the main drawback of this approach is the requirement of testing the engine at a given engine load/speed condition. Furthermore, the main objective of this study is to propose a predictive model of the Wiebe parameters for any operating point of the tested SI engine. For this purpose, an Artificial Neural Network (ANN) is developed from the experimental data. A criterion was defined to choose the best-trained network. Finally, the Wiebe parameters are estimated with the neural networks for different operating conditions. Moreover, the mass fractions burned generated from the Wiebe functions are compared with the respective experimental values from several operating points measured in the engine test bench. Small differences were found between the estimated and experimental mass fractions burned. Therefore, the effectiveness of the developed ANN model as a prediction tool for the engine MFB is verified.

Introduction

Every year the ICE community has to face more and more restriction policies related to the control of pollutant emissions and the global problem of greenhouse gases [1]. For this reason, engine manufacturers are obliged to develop new technologies to meet these requirements, while maintaining adequate performance at acceptable costs.

It is well known that spark ignition (SI) engines are currently the most common powerplant in passenger cars. This fact is mainly due to the highly efficient three-way catalyst used to control the engine NO_x emissions, which is also very cheap when compared to the aftertreatment systems required by Compression Ignition (CI) engines in order to maintain the stringent pollutant emissions standards [2]. Nonetheless, CI engines are able to provide higher levels of efficiency due to the higher range of compression ratios (15:1-22:1) when compared to equivalent SI engines (9:1-12:1) [3]. For this reason, researches to improve the performance of SI engines in terms of thermal efficiency while maintaining low levels of emissions are of great interest for the transportation industry. In order to affront these challenges, computational models play a crucial role.

The use of engine simulations has become an important part of the design, calibration, and optimization process of SI engines. The combustion sub-model is a key piece in the global simulation of an engine since it provides the heat release rate (HRR) or mass fraction burned (MFB), that it is the accumulate of HRR, which represents how the combustion process is for a given engine geometry and specific operating conditions [4]. Currently, there are many combustion models integrated in commercial softwares that are able to accurately reproduce the physicochemical phenomena of turbulent premixed flames [5]. These models are well suited to describe the combustion process of SI engines taking into account detailed chemistry and turbulence-combustion interactions. However, this type of simulations (3D-CFD) are computationally expensive and require a significant amount of time [6]. Therefore, the development of simple 1D and 0D models to estimate the burning rates of conventional SI engines arises as an interesting solution to overcome these limitations. The experimental MFB is determined by applying the first law of thermodynamics in the cylinder of the engine using the measured in-cylinder pressure as input [7]. It is common for the MFB to be parameterized, in SI engines, from Wiebe functions [8]. This function is composed of a series of parameters related to the combustion

process, which are the duration of the combustion, the start of combustion, the degree of completeness of the process and a shape parameter. These parameters are usually identified using a least squares method (LSM). However, experimental data is required in order to obtain them. Moreover, defining empirical relationships between the Wiebe parameters and any given operating condition of the engine is a difficult task, as the former depend on multiple variables and do not have linear behaviors. To face this problem, Artificial Neural Networks (ANN) can be an effective solution and seem to be a suitable procedure for this specific task.

Nowadays ANNs applications have become popular in various area of human needs [9–14]. The ANN is found to be a very innovative and useful model applied to problem-solving and machine learning. A good advantage of applying ANN is that it can make models easier to use and more accurate from complex natural systems with large inputs, such as internal combustion engines. Using artificial neural networks in the field of internal combustion engines is not a novelty. These have been used mainly as predictive models of performance and emissions both in SI engines and in compression ignition engines [15–19]. Studies similar to the present work have also been carried out, using neural networks to predict the parameters of a dual Wiebe function in Diesel engines using different biofuel blends [20]. However, a methodology has not been developed to build an ANN capable of faithfully estimating the Wiebe parameters in an SI engine.

Furthermore, the objective of this research is to develop a novel methodology applying a modern ANN model for predicting the parameters of the Wiebe function, using the engine speed and torque as input variables. A robust criterion is also proposed in order to select the most accurate ANN. Finally, the ANN model is validated against experimental data. This model is of great importance due to its ability to accurately predict the MFB of the engine in a wide range of operating conditions with an associated low computational cost. Additionally, the model can be used in simulations with driving cycles without major problems, due to the simplicity of its inputs.

Materials and Procedure

In the present study, the engine used is a 1.0 L (999 cc) direct-injected, turbocharged, 3 cylinders in line, 4-stroke internal combustion gasoline engine. It produces 85.2 kW at 5250 rpm and 182.3 N·m at 2250 rpm. The engine features are summarized in Table 1. The main components installed in the test bench for correctly measuring pressure, temperature, and flows in both the gas and the hydraulic circuits are presented in Table 2. The engine was directly coupled to an electric dyno. A test system collects the main mean variables (acquired at a constant sample frequency of 10 Hz) necessary for controlling the engine operating point and also for the combustion diagnosis. The in-cylinder pressure is measured in one of the cylinders using a piezoelectric transducer (AVL GH13P pressure sensor) and sampled with constant angular frequency (0.2 degrees of CAD). Additionally, to measure engine emissions, exhaust monitoring equipment (Horiba MEXA 7100 and AVL Smoke meter) were installed on the engine.

Table 1. Engine features.

Displaced volume	999 cc
Stroke	72.2 mm
Bore	81.3 mm
Connecting Rod	132.51 mm
Compression ratio	11:1
Number of Valves	4 per cylinder
Torque (max.)	182.3 N·m @ 2250 rpm
Power (max.)	85.2 kW @ 5250 rpm

The experimental campaign conducted for this study considered various steady-state operating conditions within the engine performance map. Seventy-one points of constant operation are performed (Fig. 1): sixty-one points from the low load (3 BMEP) to high load (around 22 BMEP), and speeds from 1000 rpm to 5250 rpm with a step of 500 rpm, thus covering a wide engine map range; the remaining ten points range from 1000 rpm to 5250 rpm at full load. Also, ten points going from 1000 rpm to 5250 rpm in motoring conditions were measured. They have used to obtain the main uncertainties of the engine: compression ratio, heat transfer coefficients, thermodynamic delay, and deformations coefficient.

Table 2. Instrumentation of the test bench.

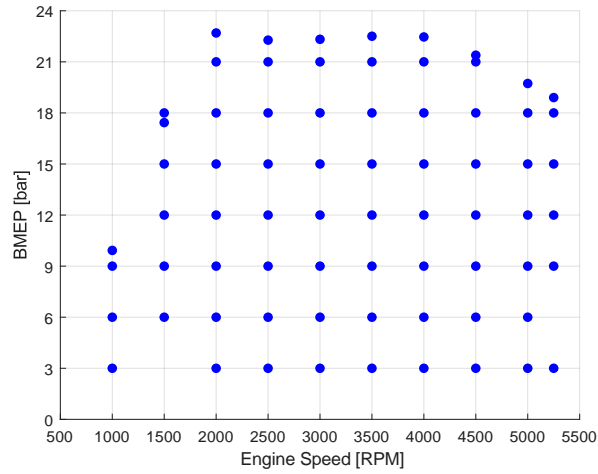| Variable	Instrument	range
Engine speed	Dynamometer	0-7500 rpm
Torque	Dynamometer	0-400 Nm
Air mass flow	Flowmeter	0-1700 kg/h
In-cylinder pressure	AVL GH13P	0-200 bar
Fluid temperature	k-type thermocouple	70-1520 K
Coolant flow	OPTIFLUX 4000	4.5-90 L/min
Oil pressure	Piezoresistive transducer	0-10 bar
Emissions	Horiba MEXA 7100	
Emissions	AVL Smoke meter	

Figure 1. Steady-state operating points measured

Thermodynamic model

In order to get the mass fraction burned, it is necessary to use a thermodynamic model. To do this, a home-developed combustion diagnostic tool called CALMEC [7] was used. The main input of the model is the filtered pressure signal. The first law of thermodynamics is applied between IVC and EVO. It uses the ideal gas equation of state to calculate the mean gas temperature in the chamber. Along with the two basic equations, several sub-models are used to calculate instantaneous mass, volume, and heat transfer. The main result is HRR and therefore also its accumulated (MFB). In Fig. 2 a general scheme of the process is shown. A detailed description of this tool can be found in [7], being the main hypotheses the following:

- Chamber pressure and temperature are supposed to be spatially uniform.
- Three species (air, fuel vapour, and stoichiometric combustion products) are considered [21].
- Perfect gas behavior is assumed for the gas mixture.
- The internal energy is calculated considering the mean gas temperature.
- The specific heat of the gas depends on both temperature and composition [22].
- The chamber volume deformation is calculated employing a simple deformation model [7]:

$$\Delta V = k_{def}\left(\Delta V_p + \Delta V_i\right) \qquad (1)$$

where k_{def} is a deformation constant to be adjusted, and ΔV_p and ΔV_i are the volume variations due to pressure and inertia efforts, respectively.

- Heat transfer to the chamber walls is calculated with a modified Woschni model [23], where the convective heat transfer coefficient is calculated using Eq. (2):

$$h = CD^{-0.2}p^{0.8}T^{-0.55}v_t^{0.8} \tag{2}$$

where C is a constant value, D the cylinder diameter, p is the instantaneous pressure, T is the instantaneous gas temperature and v_t is a tumble-generated gas velocity defined as follow:

$$v_t = C_{t1}c_m + C_{t2}\bar{v}_m f_w + C_2 \frac{V_d T_{IVC}}{V_{IVC}p_{IVC}}(p - p_0) \tag{3}$$

being C_{t1}, C_{t2} and C_2 constant values, c_m the mean piston speed, V_d the displaced volume, T_{IVC}, V_{IVC}, p_{IVC} the temperature, volume and pressure at IVC respectively, p_0 is the motoring pressure assuming polytropic evolution, $\bar{v}_m$ is the gas mean velocity during the intake process and f_w is a tumble gas velocity dissipation function (see [23] for the details of the calculation). C_{t1} and C_{t2} are constants whose values are fitted (along with k_{def}) from motoring tests on a specific engine. Finally, the calculation of the heat flux to the wall requires the estimation of the wall temperatures. A wall temperature prediction model based on a thermal resistor network, which is integrated in the combustion diagnosis tool CALMEC, is used to calculate the mean temperature of the liner, piston and cylinder head as explained in detail in [24,25].
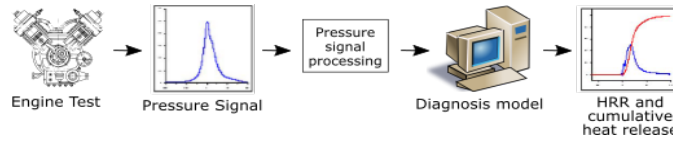

Figure 2. CALMEC general scheme

Wiebe Combustion Modeling

A combustion sub-model is helpful when performing a general engine simulation. One of the most used models for this purpose is the Wiebe function [4]. The Wiebe function is extensively used in ICE applications to describe the MFB in a combustion chamber during the combustion process. This function has an S-shaped characteristic curve, which raises from zero indicating the start of combustion and tends exponentially to one indicating the end of combustion. The Wiebe function is expressed as (Eq. 4):

$$MFB = 1 - exp\left[-a\left(\frac{\theta - \theta_0}{\Delta\theta}\right)^{m+1}\right] \tag{4}$$

Where a is an efficiency parameter; θ is the crank angle; θ_0 represents the start of combustion; $\Delta\theta$ is the combustion duration and m is a shape factor.

The objective of this research is to determine these parameters in order to know the heat release rate at any engine operating condition. The efficiency parameter a is stated to be 6.9078 [26,27] for a combustion duration of 0-99.9% . Another parameter that is known is the start of combustion, since it is established that it coincides with the spark timing which is obtain experimentally, and it is considered to be a good approximation [28]. Therefore, only two parameters remain to be determined, which are the duration of combustion $\Delta\theta$ and the form factor m, which are established by adjusting the function with the least squares method to coincide with the MFB obtained experimentally from the thermodynamic model.

Artificial Neural Network Model

ANN architecture

Artificial neural networks are a logic programming technique which try to emulate the functioning of the human brain, specifically, the nervous system. This computational model bases its structure on a set of nodes known as neurons that are interconnected. The network works like a "black box"; hence it does not require detailed information from the system. They have the ability to handle large and complex data arrays with many interrelated parameters and learn from these to create a transfer function.
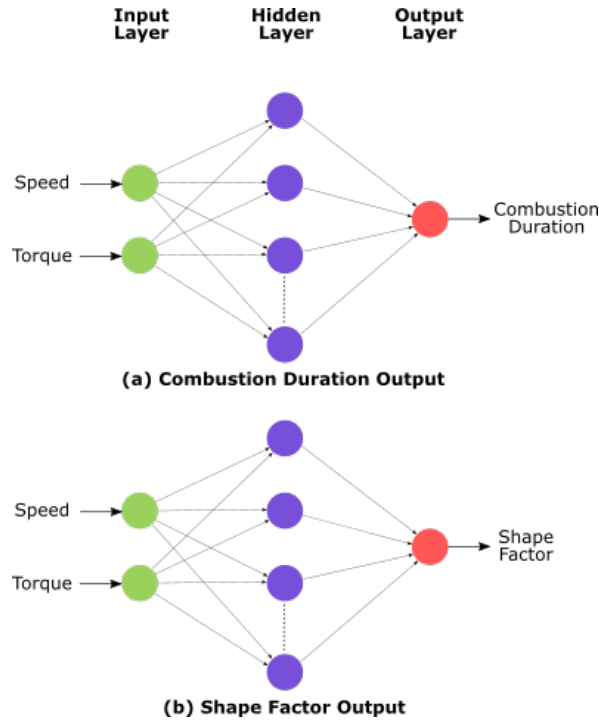
Figure 3. Configuration of artificial neural networks for predicting Wiebe parameters.

As shown in Fig. 3, the input layers of the two proposed ANNs are composed of two input neurons: one for engine speed and one for torque. In both, only a hidden layer is made up of 10 neurons. Finally, the output layer for each network is formed by a neuron, being for one case the duration of combustion $\Delta\theta$ and for the other, the form factor m, these being the two Wiebe parameters to be estimated. The back-propagation learning algorithm has been used in feed forward. The input layer neurons take information from the outside environment and transfer them to the neurons of the hidden layer without performing any calculation. The hidden layer neurons then handle the incoming information and extract useful features to recreate the mapping from the input. The nearby layers are interconnected by weights. Finally, the output layer neurons give network prediction.

ANN training and selection

The ANN model has two distinct steps: training and testing. In training, the network is taught to estimate output values relative to input data. The testing step is to quantify how well the ANN can predict foreign values from the lesson it learned in the past. When the tested error achieves a previously established tolerance value, the training process is completed [11,12]. Exhaustive information about ANN and its working principles can be found in [10]. In this study, a computer program has been developed and performed under Matlab. In the construction of the ANN architecture, 71 data sets from the experimental matrix, are used in the training and testing process. According to research works in the literature, it is found that different proportions for training and testing data could be used [17,18]. In this study, training and testing data ratios are taken as approximately 70%:30% respectively. Therefore, 50 training and 21 testing datasets are randomly selected from all the experimental data. The learning algorithm used in the study is Levenberg–Marquardt. Due to the size of the considered neural network and its predictive nature, the chosen algorithm is considered the fastest and the most accurate by numerous sources such as [18,20,29].

In order to achieve optimal training of neural networks, a process was developed in the same program, which consists of generating a large number of randomly trained networks and then evaluating the performance of their prediction according to statistical criteria such as the absolute mean error (MAE) and the determination coefficient (R^2), and thus be able to select the most convenient one. MAE and R^2 are represented in the following equations:

$$MAE = \frac{1}{n}\sum_i \left|\frac{t_i - o_i}{t_i}\right| \qquad\qquad (5)$$

$$R^2 = 1 - \left[\frac{\sum_i (t_i - o_i)^2}{\sum_i (t_i)^2}\right]$$ (6)

Where t_i is the target value, in this case, the experimental or value estimated by LSM, o_i is the output of the ANN and n is the number of samples, that is, 71.

In this study, 100 neural networks were generated for each output. After generating them, the mean absolute error (MAE) is calculated. This is an important criterion since the ANN with the smallest error should estimate more accurately. However, due to previous experiences using artificial neural networks, it was also decided to evaluate the performance of the ANN prediction according to a criterion of "sensitivity", defining this as how prone the ANN is to erroneously predict with slightly disturbed input data. The mathematical expression for this criterion is given by Eq (7).

$$MAEp = \frac{1}{n}\sum_i \left|\frac{o_i - o_{p,i}}{o_i}\right|$$ (7)

where $o_{p,i}$ is the ANN output with slightly disturbed input values. These input values were disturbed by subtracting 1% from their value.

Results

Comparison of Experimental and Adjusted Mass Fraction Burned

As described above, the first step of this work was to obtain the mass fraction burned from the experimental tests with the combustion diagnostic tool. Once this was achieved, the least squares method was carried out, adjusting to the Wiebe function in each of the tests, and thus obtaining the Wiebe parameters.

In figure 4, a comparison between the MFB obtained by the thermodynamic model and the fitted with LSM is represented. Only four representative tests are shown, trying to cover different points of the engine operation map. Nevertheless, the methodology was made for all 71 operating points. As can be seen, except for some differences at the beginning (0% -25% $\Delta\theta$) and end of the combustion (70% -100% $\Delta\theta$), the adjustment is quite reliable throughout the combustion process. The differences may be due to various sources in the thermodynamic model, the main suspect being cycle-cycle variation in-cylinder pressure, which is usually high in spark-ignition engines. If in the measurement there are pressure curves that are very atypical, these considerably influence the estimated mean pressure, and therefore the MFB, which depends to a great extent on this variable. Observing the four curves in Fig. 4, it can also be concluded that establishing the spark timing as the start of combustion do not represent great inconveniences, since in all curves the start of combustion is well approximated.

However, despite these slight deviations, a faithful reproduction of the behavior of the MFB curve is made for different operating conditions. Due to these results, it is verified that the Wiebe parameters obtained by LSM are acceptable to reproduce the heat release at the measured operating points.

Evaluation and Selection of Artificial Neural Networks

Once all the Wiebe parameters were obtained for the measured operating conditions by the LSM, an artificial neural network model was developed in order to have a tool capable of estimating these parameters for any operating point. For this purpose, and following the aforementioned methodology, 100 ANN were generated for each output (combustion duration and shape factor).

Fig. 5, shows a map of points for each output, where each point represents a generated ANN, the abscissa axis is the MAE, and the ordinate axis represents the sensitivity. The vertical and horizontal red lines represent the average of the MAE and MAEp respectively. In this step, an analysis of the impact that sensitivity has on the prediction performance of the networks is carried out. For this, two points were selected on each map: the one with the lowest MAE and another point that represents a compromise between error and sensitivity. To fulfill this criterion, the point chosen corresponds to an error and sensitivity that are both considerably below the average for the considered sample, which can easily be appreciated and selected from the aforementioned figure. Both points are marked in a red circle in Fig. 5.
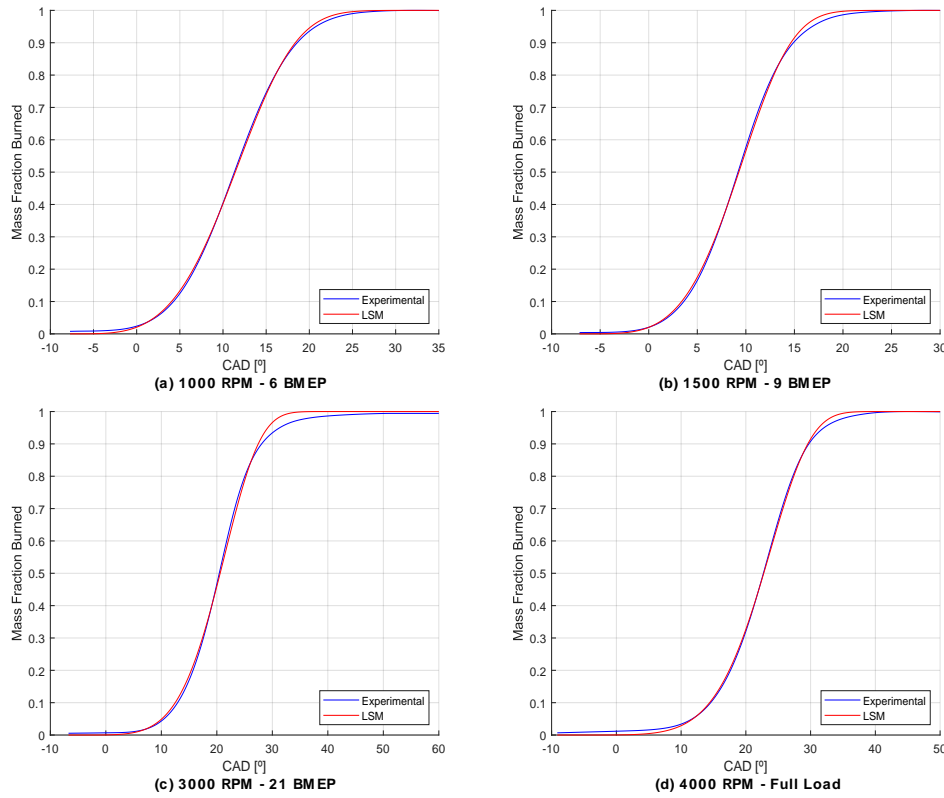
Figure 4. Comparisons of MFB obtained by LSM and experimental obtained by CALMEC.

The comparison between the ANN prediction and the data obtained by the least-squares method, for each of the selected ANNs, is observed in Fig. 6. In both cases, it can be seen that the ANN with the lowest MAE has a greater number of points on the reference line, indicating that it performs a better prediction of the parameters. In Fig. 7, a comparison is shown between the values estimated by the ANN and the same, but with the input data slightly disturbed. Visually it is difficult to distinguish differences, however, as expected, the determination coefficient of the predictions with the less sensitive ANNs is higher, which is why they are more robust networks. On the other hand, the differences between determination coefficient for combustion duration and shape factor are very small (0.18% and 0.02% respectively), so it can be concluded that selecting the network with the lowest MAE is the most convenient for this type of application.
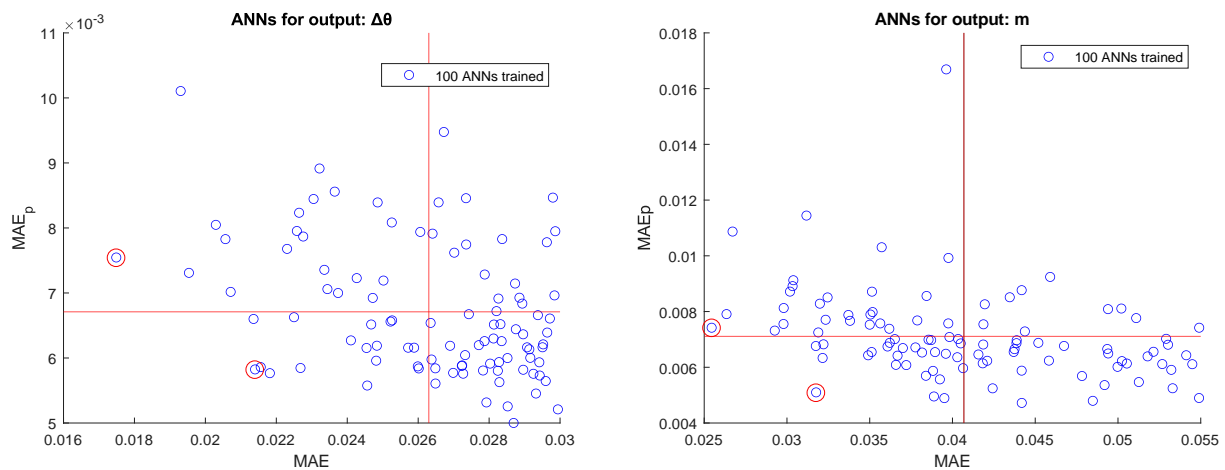

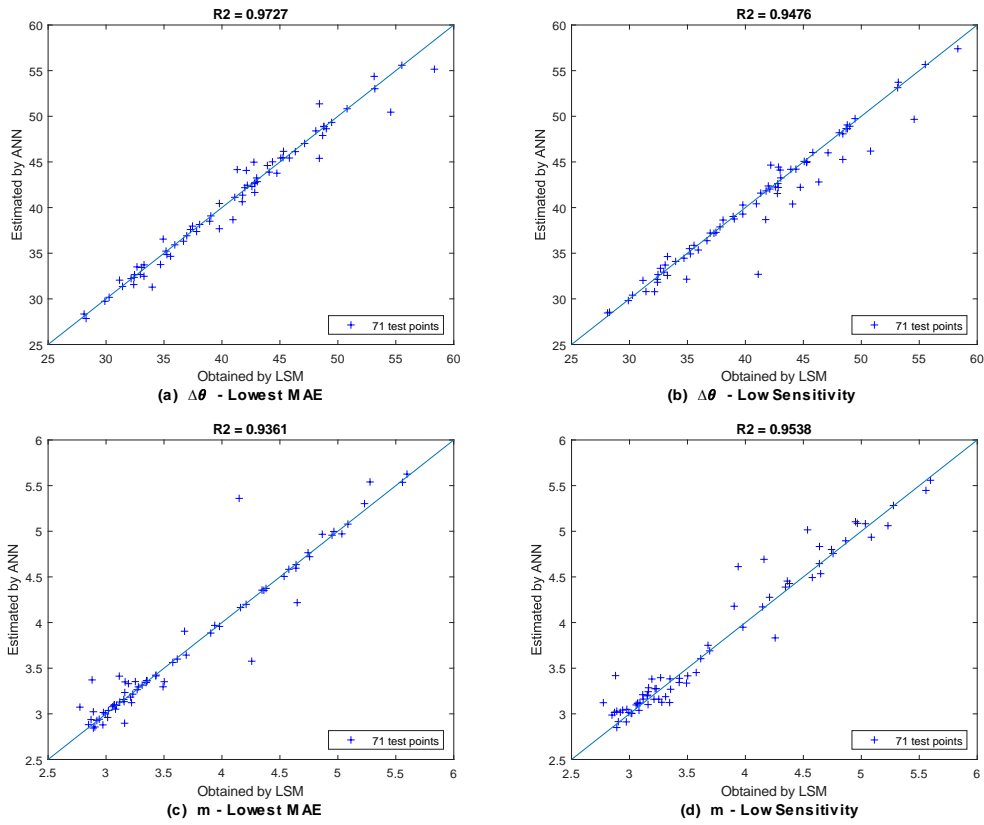Figure 5. ANN maps evaluating MAE and MAEp.

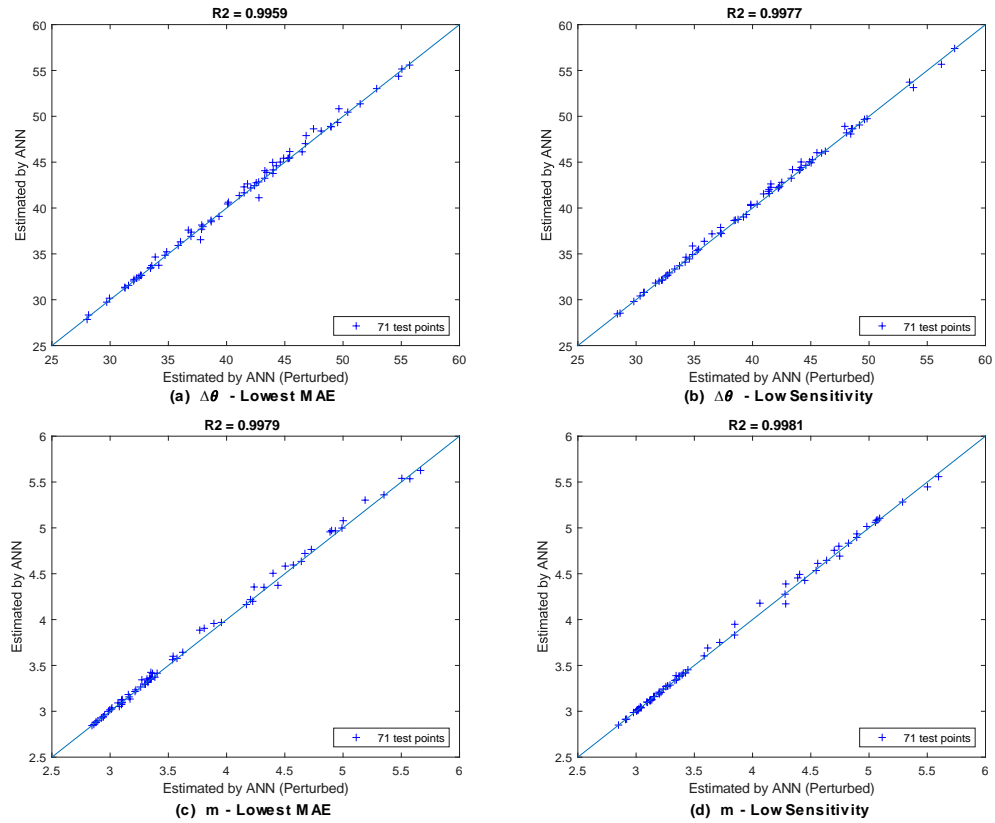Figure 6. Comparisons of ANN predicted values and LSM obtained values.

Figure 7. Comparisons of ANN predicted values and ANN predicted values with perturbed input data.

Comparison of Experimental and Estimated Mass Fraction Burned

Finally, with the neural networks trained and selected, a comparison was carried out between the mass fraction burned curves generated from the Wiebe function with the parameters estimated by the ANN and the experimental MFB, considering their cycle-to-cycle variation. This comparison is represented in Fig 8. As before, four representative operating points were selected to analyze results with different conditions. Like the comparison made of the MFB generated with the parameters obtained by LSM, the predicted curves generally approximated well to the experimental one. Mainly, differences are found in the initial and final stages of the combustion process. Rather than being due to inaccuracies in the neural network model, this is due to the errors carried in the thermodynamic model.

Additionally, the Fig. 8 includes the MFB of each cycle, thus representing the cyclic dispersion. It is appreciated that the cycle-to-cycle dispersion of the engine is very high, for this reason, the estimate made by the ANN can also be validated, since, despite the differences already mentioned between the results obtained by the ANN and the MFB media obtained by the thermodynamic model, the estimate is always located between the limits established by the cyclic dispersion. These results are satisfactory since it is concluded that the network is capable of predicting Wiebe parameters, with which the heat release of the engine studied can be faithfully reproduced at any point of operation.

Furthermore, the model has a great feature, and that is that its inputs (engine speed and torque) are very basic variables, and no sub-model or experiment is necessary to obtain them. This makes the model very versatile since it can be implemented to get the heat release rate of the engine in a transient state. Just by knowing the driving cycle, the model can estimate the Wiebe parameters at any time during this.
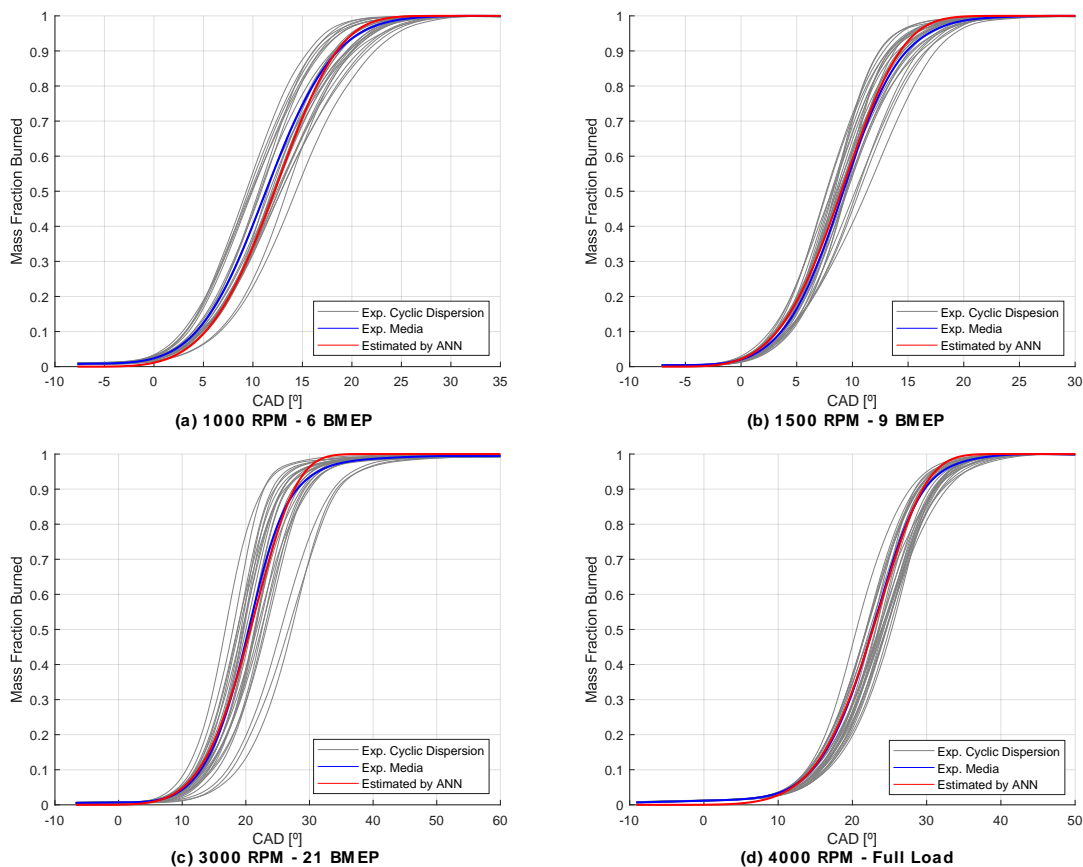

Figure 8. Comparisons of ANN predicted MFB and experimental with cyclic dispersion included.

Summary/Conclusions

A neural network model capable of predicting the parameters of a Wiebe function was developed to estimate the MFB at any operation point of a spark ignition engine, and it was compared with experimental MFBs obtained with a combustion diagnostic tool. It was verified that a single Wiebe function and only adjusting by the method of least squares of the parameters $\Delta\theta$ and m, is sufficient to obtain a good estimate of the heat release rate of the tested engine. Setting the spark timing as the start of combustion was a good approximation.

For the training and selection of artificial neural networks, an innovative methodology was developed to achieve the most accurate and robust network possible. For each output, 100 random ANNs were generated. Subsequently, two of the ANNs were selected to analyze the importance of the MAE and sensitivity as indicators for selecting the best network. It was determined that the sensitivity was less critical than the mean absolute error for the studied cases. Therefore, the network with the lowest MAE was selected.

The neural network model was validated by comparing the predicted MFB with the experimental one, obtaining a great similarity. Some differences in the curve, especially at the beginning and end of the combustion process, are due to errors attributed to the thermodynamic model, specifically to the variation between cycles in the cylinder pressure. Nonetheless, the robustness of the model has been verified, making it a very versatile tool for both predicting Wiebe parameters in any engine operating condition (speed/torque) and implementing it on real driving cycle simulations to assess the performance of the engine in a full vehicle model. In addition, due to its benefits, the methodology could be useful to support engine design from the early stage of development.

Finally, this study was limited to a single architecture. For future work, it could be interesting to use the methodology proposed in other engine architectures, with the intention of verifying that the procedure works in different settings. In this way, for future improvements, the ANN could be tested by considering a greater number of input variables. It is possible that by doing this type of study, an input variable that has a great impact on some Wiebe parameter is found, and in this way to be able to perform a parametric analysis.

References

1. Krzyzanowski, M., Kuna-Dibbert, B., and Schneider, J., "Health effects of transport-related air pollution," ISBN 9289013737, 2005.

2. Heck, R.M. and Farrauto, R.J., "Automobile exhaust catalysts," *Appl. Catal. A Gen.* 221(1–2):443–457, 2001, doi:10.1016/S0926-860X(01)00818-3.

3. Attard, W.P., Konidaris, S., Hamori, F., Toulson, E., and Watson, H.C., "Compression ratio effects on performance, efficiency, emissions and combustion in a carbureted and PFI small engine," *SAE Tech. Pap.* (724):776–790, 2007, doi:10.4271/2007-01-3623.

4. Payri González, F. and Desantes Fernández, J.M., "Motores de combustión interna alternativos," Editorial Universitat Politècnica de València, ISBN 9788483637050, 2011.

5. Bellis, V. De, Bozza, F., and Tufano, D., "A Comparison between Two Phenomenological Combustion Models Applied to Different SI Engines," *SAE Tech. Pap.* 2017-October, 2017, doi:10.4271/2017-01-2184.

6. Giglio, V. and Gaeta, A. di, "Novel regression models for wiebe parameters aimed at 0D combustion simulation in spark ignition engines," *Energy* 210:118442, 2020, doi:10.1016/j.energy.2020.118442.

7. Payri, F., Molina, S., Martín, J., and Armas, O., "Influence of measurement errors and estimated parameters on combustion diagnosis," *Appl. Therm. Eng.* 26(2–3):226–236, 2006, doi:10.1016/j.applthermaleng.2005.05.006.

8. Heywood, J.B., Higgins, J.M., Watts, P.A., and Tabaczynski, R.J., Development and Use of a Cycle Simulation to Predict SI Engine Efficiency and NOx Emissions, 1979, doi:https://doi.org/10.4271/790291.

9. Abiodun, O.I., Jantan, A., Omolara, A.E., Dada, K.V., Mohamed, N.A.E., and Arshad, H., "State-of-the-art in artificial neural network applications: A survey," *Heliyon* 4(11):e00938, 2018, doi:10.1016/j.heliyon.2018.e00938.

10. Eyercioglu, O., Kanca, E., Pala, M., and Ozbay, E., "Prediction of martensite and austenite start temperatures of the Fe-based shape memory alloys by artificial neural networks," *J. Mater. Process. Technol.* 200(1–3):146–152, 2008, doi:10.1016/j.jmatprotec.2007.09.085.

11. Yang, I.H., Yeo, M.S., and Kim, K.W., "Application of artificial neural network to predict the optimal start time for heating system in building," *Energy Convers. Manag.* 44(17):2791–2809, 2003, doi:10.1016/S0196-8904(03)00044-X.

12. Kalogirou, S.A., "Artificial neural networks in renewable energy systems applications: A review," *Renew. Sustain. Energy Rev.* 5(4):373–401, 2000, doi:10.1016/S1364-0321(01)00006-5.

13. Yadav, A.K. and Chandel, S.S., "Solar radiation prediction using Artificial Neural Network techniques: A review," *Renew. Sustain. Energy Rev.* 33:772–781, 2014, doi:10.1016/j.rser.2013.08.055.

14. Abhishek, K., Kumar, A., Ranjan, R., and Kumar, S., "A rainfall prediction model using artificial neural network," *Proc. - 2012 IEEE Control Syst. Grad. Res. Colloquium, ICSGRC 2012* (Icsgrc):82–87, 2012, doi:10.1109/ICSGRC.2012.6287140.

15. Kara Togun, N. and Baysec, S., "Prediction of torque and specific fuel consumption of a gasoline engine by using artificial neural networks," *Appl. Energy* 87(1):349–355, 2010, doi:10.1016/j.apenergy.2009.08.016.

16. Deh Kiani, M.K., Ghobadian, B., Tavakoli, T., Nikbakht, A.M., and Najafi, G., "Application of artificial neural networks for the prediction of performance and exhaust emissions in SI engine using ethanol- gasoline blends," *Energy* 35(1):65–69, 2010, doi:10.1016/j.energy.2009.08.034.

17. Roy, S., Banerjee, R., and Bose, P.K., "Performance and exhaust emissions prediction of a CRDI assisted single cylinder diesel engine coupled with EGR using artificial neural network," *Appl. Energy* 119:330–340, 2014, doi:10.1016/j.apenergy.2014.01.044.

18. Çay, Y., Korkmaz, I., Çiçek, A., and Kara, F., "Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network," *Energy* 50(1):177–186, 2013, doi:10.1016/j.energy.2012.10.052.

19. Oğuz, H., Saritas, I., and Baydan, H.E., "Prediction of diesel engine performance using biofuels with artificial neural network," *Expert Syst. Appl.* 37(9):6579–6586, 2010, doi:10.1016/j.eswa.2010.02.128.

20. Tarabet, L., Lounici, M.S., Loubar, K., and Tazerout, M., "Dual Wiebe Function Prediction of Eucalyptus Biodiesel/Diesel Fuel Blends Combustion in Diesel Engine Applying Artificial Neural Network," *SAE Tech. Pap.* 2014-Octob, 2014, doi:10.4271/2014-01-2555.

21. Payri, F., Olmeda, P., Martín, J., and García, A., "A complete 0D thermodynamic predictive model for direct injection diesel engines," *Appl. Energy* 88(12):4632–4641, 2011, doi:10.1016/j.apenergy.2011.06.005.

22. Lapuerta, M., Armas, O., and Hernández, J.J., "Diagnosis of DI Diesel combustion from in-cylinder pressure signal by estimation of mean thermodynamic properties of the gas," *Appl. Therm. Eng.* 19(5):513–529, 1999, doi:10.1016/S1359-4311(98)00075-1.

23. Olmeda, P., Martín, J., Novella, R., and Carreño, R., "An adapted heat transfer model for engines with tumble motion," *Appl. Energy* 158:190–202, 2015, doi:10.1016/j.apenergy.2015.08.051.

24. Broatch, A., Olmeda, P., García, A., Salvador-Iborra, J., and Warey, A., "Impact of swirl on in-cylinder heat transfer in a light-duty diesel engine," *Energy* 119:1010–1023, 2017, doi:10.1016/j.energy.2016.11.040.

25. Torregrosa, A., Olmeda, P., Degraeuwe, B., and Reyes, M., "A concise wall temperature model for di Diesel

engines," *Appl. Therm. Eng.* 26(11–12):1320–1327, 2006, doi:10.1016/j.applthermaleng.2005.10.021.

26. Cooney, C., Worm, J., Michalek, D., and Naber, J., "Wiebe function parameter determination for mass fraction burn calculation in an ethanol-gasoline fuelled SI engine," *J. KONES* 15(3):567–574, 2008.

27. Serrano, J.R., Climent, H., Guardiola, C., and Piqueras, P., "Methodology for characterisation and simulation of turbocharged diesel engines combustion during transient operation. Part 2: Phenomenological combustion simulation," *Appl. Therm. Eng.* 29(1):150–158, 2009, doi:10.1016/j.applthermaleng.2008.02.010.

28. Yeliana, Y., Cooney, C., Worm, J., Michalek, D.J., and Naber, J.D., "Estimation of double-Wiebe function parameters using least square method for burn durations of ethanol-gasoline blends in spark ignition engine over variable compression ratios and EGR levels," *Appl. Therm. Eng.* 31(14–15):2213–2220, 2011, doi:10.1016/j.applthermaleng.2011.01.040.

29. Yu, H. and Wilamowski, B.M., "Levenberg-marquardt training," *Industrial electronics handbook*, ISBN 10.1201/b10604: 12.1-12.16, 2011.