



Article

Data Driven In-Cylinder Pressure Diagram Based Optimization Procedure

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Abstract: An engine optimization model is developed to fit the calculated in-cylinder pressure diagram to the experimental data by finding the optimal values of the start angle of injection and the amount of injected fuel for different engine loads. Firstly, the engine model is built in Ricardo Wave software and some parts are calibrated using data collected from the manufacturer. Then, an optimization process is performed based on the fitness function that includes the objective of the study and the penalty functions to express constraints. This optimization environment simulates the performance of a marine generator system for three different loads by minimizing the mean absolute percentage error (MAPE) between the in-cylinder pressure simulated data and the measured data along 40 degrees of the combustion process and by verifying the firing pressure and the engine brake power. The percentage of error between the calculated and the real thermodynamic data does not exceed 3.4% and the MAPE between the calculated and the real in-cylinder pressure diagram along the combustion process does not exceed 5.7% for the different loads. The proposed method can be further used to find the optimal value of different input parameters during the calibration process of different engine numerical models.

Keywords: marine genset; injection parameters; optimization model; data fitting technique; minimizing MAPE; in-cylinder pressure diagram

1. Introduction

Different studies are focusing on the simulation of the in-cylinder pressure diagram as an important source of information of the different processes inside the engine—especially the combustion—in the different types of internal combustion engines (ICEs) [1]. This pressure diagram is mainly used to study the shape of the burning mass fraction, the heat release rate and the thermodynamic properties inside the cylinders [2]. These studies lead to a significant improvement in different engine's parts such as the turbocharger system to compress more air with high pressure inside the cylinders [3] and the fuel injection system to optimize the fuel injection rate [4], injection pressure [5], injection timing [6] and injection strategies [7] in order to ensure the safety and injection durability of the engine [8] and to verify the limitations of emissions regulations [9].

Due to the high cost of the procurement of a marine diesel engine and of preparing the testbed facility, different simulation models are developed to simulate the dynamic performance of different types of engines. The most common alternative simulation models to tests can be the zero or one-dimensional model as shown in Figure 1. These models require a large amount of input data in order to increase the accuracy of the results. As the model becomes complex, more time is consumed to perform the simulation while more details can be exported from the computed results [10–12]. These simulation models allow the computation of the engine performance based on its type, the fuel

used and the required details in thermodynamics, combustion, heat transfer, fluid and chemical parts. Figure 2 presents a general overview of the model's structure to simulate the performance of different ICEs.

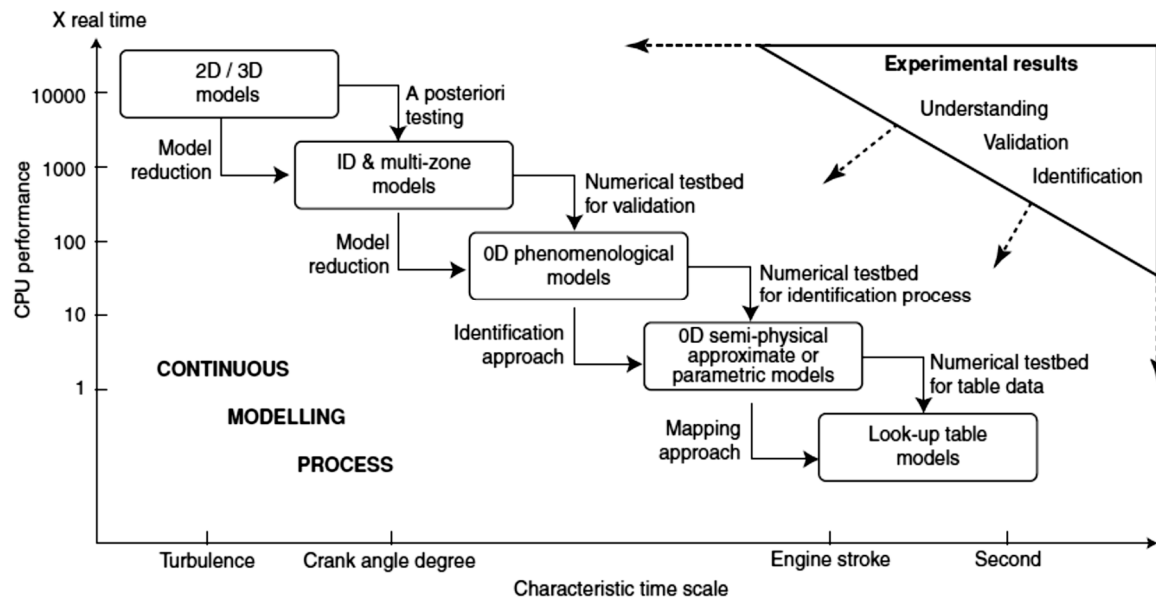


Figure 1. Continuous modelling process reproduced from [13], with permission from EDP Sciences, 2020.

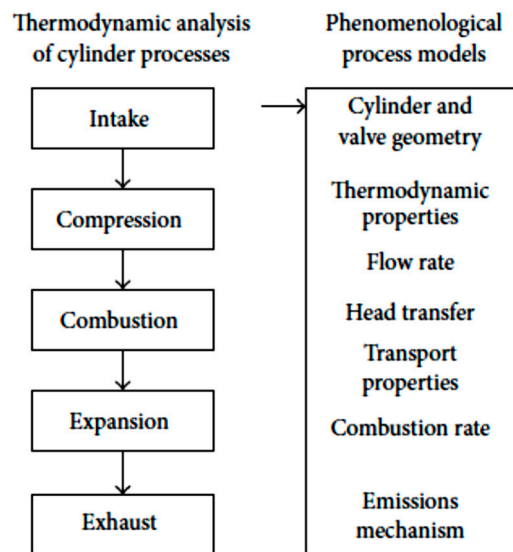


Figure 2. Structure of thermodynamic based simulation of ICE operating cycle reproduced from [14], with permission from Hindawi Publishing Corporation, 2020.

In most of these models, the combustion process and the injection system require careful attention in order to achieve the required power, to ensure the reliability and the safety of the engine and to reduce the brake specific fuel consumption (BSFC) of the engine. Huge work can be performed to find the best values of the different parameters using normal computations to validate the numerical model with real data [15–19].

Hence, different optimization and machine learning (ML) methods are taking place and are coupled with the numerical engine models to easily find the optimal values of different parameters and to fulfill the objective and the purpose of the studies [20,21]. However, before performing any simulations, the engine models must be calibrated using real data at different operating points such as

the compression ratio of the turbocharger, pressure before and after the intercooler, firing pressure, exhaust temperature before and after the turbine, amount of mass flow rate and BSFC to ensure the accuracy of the computed results [22,23].

Different studies have been performed based on optimization techniques. From the design point of view, Yan et al. [24] used a genetic algorithm (GA) to find the ratio between wall thickness and radius of the cylinder, thickness, length and the number of fins and the heat transfer coefficient to optimize the heat transfer through the fin arrays. Ahmadi [25] used an optimization model coupling GT-Power [26] and GA to maximize the volumetric efficiency by optimizing the geometry of the intake and exhaust system and the valve timing. Branney et al. [27] studied the effect of pressure loss by optimizing the shape of the airbox in the ICE using computational fluid dynamics (CFD). Liu et al. [28] considered a multi-objective genetic algorithm (MOGA) to optimize the combustion chamber shape and the diesel injection parameters of a dual fuel engine to minimize the fuel consumption and the pollution emissions.

From the calibration point of view, Munnannur et al. [29] investigated the effects of the start angle of injection (SOI), duration of injection and exhaust gas recirculation (EGR) using GA to minimize the fuel consumption and exhaust emissions of a heavy-duty diesel engine. A noticeable reduction was achieved in comparison with the baseline of the engine. Millo et al. [30] established a GA-based optimization model to reduce the exhaust emissions and BSFC for calibration purposes and a 20% reduction in nitrogen oxides (NO_x), accompanied by a 1% reduction in BSFC, was achieved. D'Errico et al. [31] used GA to optimize the performance of a spark-ignition engine with a single cylinder used in a motorbike by finding the optimal solutions of the throttle angle and valve timings. Zhao and Xu [32] found the optimal values of the injection system and valve timings using GA to minimize the fuel consumption of an Atkinson cycle along the engine load diagram. Zhu et al. [8] used the same concept of optimization presented by Zhao and Xu [32] in improving the performance of diesel engine working at a plateau after validating the combustion process presented by the curve of heat release rate (HRR) using artificial neural network (ANN) method [33], where the fuel injection parameters were calibrated with a relative error no more than 5%.

Tadros et al. [34] extended the research using a nonlinearly constrained optimizer and considered the exhaust emissions into the constraints to optimize the performance of a large marine diesel engine for different speeds and loads. Hiroyasu et al. [35] used MOGA to find the optimal values of the injection system and EGR of the diesel engine in order to improve the fuel economy and to reduce exhaust emissions. Dempsey and Reitz [36] coupled CFD software and MOGA to optimize the injection system and swirl ratio for the purpose of emissions reduction. Sakthivel et al. [37] combined fuzzy logic and GA to maximize the performance of the compression ignition (CI) engine fueled with fish oil as biodiesel and to minimize the different types of emissions. Then, the ANN was considered to estimate the thermal efficiency, volumetric efficiency and BSFC of a biogas engine for different levels of methane and different loads; good results with low error rates were achieved [38]. Goudarzi et al. [39] used the same method to study the heat transfer between the valve and the seat to avoid engine damage with an acceptable percentage of error.

The mentioned researches present different, useful solutions to optimize one parameter or more with a single value for given constraints, however, they cannot be used as a method to optimize a dataset for data fitting technique until a complementary algorithm is added to the fitness function of the optimization model to perform the fitting process and to evaluate the accuracy of fit.

The polynomial models and the least square method (LSM) [40] are the main known techniques used in data fitting to compare how close are two datasets one from another. The last one can be integrated into an optimization procedure to find the best fit between the numerical equations and experimental data by easily finding the optimal values of different input parameters based on routine processes [41]. This method was used by Vilhelmsson [42] to find the effective area of the cylinder valves without the need for determining the discharge coefficient. In addition, Ingesson [43] applied it to find the parameters of the ignition delay model during the combustion process of a gasoline engine.

2. Main Contribution and Brief Description of the Current Study

As there is not any explicit numerical equation to perform the fitting procedure as in LSM, the novelty of this work is to develop an innovative engine optimization model to be used as a data fitting technique for the calibration purposes of different engine models based on the collected data of the in-cylinder pressure diagram. The engine considered in this study is a marine genset, which is a combination of a diesel engine and an electric generator (alternator) to convert the heat capacity into mechanical energy and then generating electrical energy.

The engine optimization model that is developed in this article is inspired by the engine model developed by Tadros et al. [34]. Instead of minimizing the BSFC of the diesel engine, the main objective of this optimization model is to minimize the mean absolute percentage error (MAPE)—one of the methods that evaluate the goodness-of-fit—between the in-cylinder pressure diagram of a marine Genset exported from Ricardo Wave Software [22] and the corresponding data from the experimental part along the combustion process, by finding the optimal values of injection system parameters due to their lack of availability. As a data fitting technique, it was not considered in any of the studies as mentioned in the literature review, unlike the LSM or ANN which are widely used.

This present model couples 1D engine simulation software (Ricardo Wave) and a nonlinear optimization method (fmincon) [44], based on an interior point algorithm [45], to simulate the performance of a marine Genset and to fit the experimental data of an in-cylinder pressure diagram along the combustion process by finding the optimal values of SOI and the amount of injected fuel. Additionally, the optimization model verifies the firing pressure and the brake power at each load.

Firstly, the experimental data and the performance test results at different engine loads are collected from [46,47]. These data are measured in a marine medium-speed engine installed in a laboratory of the Federal University of Rio de Janeiro. The test stand in the Brazilian laboratory is connected to different types of sensors with different brands to measure the pressure and the temperature along the engine parts. For instance, the pressure inside the cylinder is measured using the KISTLER sensor while the intake air pressure is measured using the DANFOSS sensor. Similarly, the intake air temperature is detected using the MICROMATICA sensor and the exhaust temperature is detected using the AMETEK sensor. Finally, a SYSTEM TEKNIK A/S is installed to find out the amount of generated power from the Genset. This test stand is connected to a computer in the control room that use the INDI system to display the measured data especially the in-cylinder pressure diagram on the computer screen and then store and file them immediately.

Secondly, the engine model is established in Ricardo Wave software. The different parts of the engine model such as turbocharger, intercooler, intake and exhaust manifolds, and injection system are considered and the thermo-fluid, mechanical and chemical processes are simulated along the whole cycle of the selected engine. Then, some parameters are calibrated using data provided by the manufacturer. Finally, the fitness function of the optimization model is established by defining the objective function, the boundary conditions and the constraints which are expressed by different static penalty functions. Different simulations are carried out to simulate the performance of the marine Genset at different loads. The brake power, BSFC, volumetric efficiency, thermal efficiency and exhaust temperature are the main computed results. Due to the lack of data, the exhaust emissions are not considered in this study.

The rest of the paper is organized as follows: Section 3 presents the specifications of the selected marine Genset and gives an overview of the developed optimization model regarding the software used in the simulation of the engine performance and the nonlinearly optimization method; the results are discussed in Section 4 and finally some conclusions are presented in Section 5.

3. Engine Optimization Model

3.1. Engine specifications

In this study, the turbocharged intercooled diesel generator MAN 5L16/24 is chosen for investigation. It is a four-stroke engine with a five cylinder in-line with a rated speed of 1200 RPM and produces up to 475 kW [48]. The main data of the engine is presented in Table 1.

Table 1. Main specifications of MAN 5L16/24.

Parameter	Value
Bore (mm)	160
Stroke (mm)	240
Displacement (liter)	24.12
No. of cylinders	5
Compression ratio	15.2
Brake mean effective pressure (bar)	19.68
Piston speed (m/s)	10.5
BSFC (g/kW.h)	195
IVO (degree ATDC)	330
IVC (degree ATDC)	−136
EVO (degree ATDC)	140
EVC (degree ATDC)	383
Number of valves per cylinder	4

3.2. Overview of the Simulation Software

The developed nonlinear optimization model couples 1D engine simulation software (Ricardo Wave) with the nonlinearly constrained optimizer (fmincon) through the Matlab/Simulink environment as shown in Figure 3.

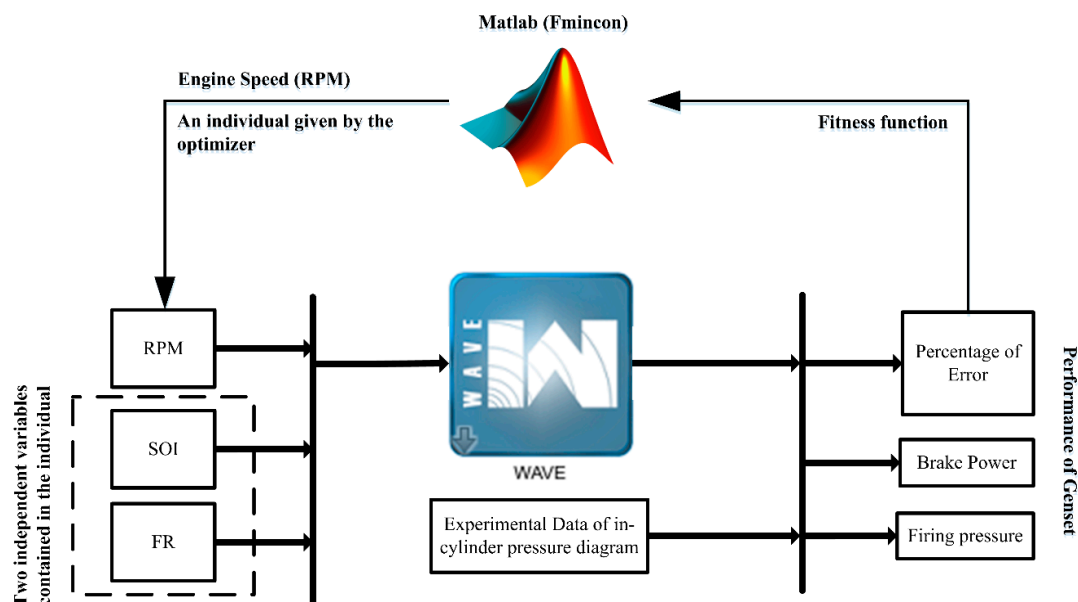


Figure 3. Engine optimization model.

This simulation environment finds the optimal values of SOI and the amount of injected fuel for different loads by reducing the MAPE between the calculated in-cylinder pressure diagram and the corresponding experimental data collected along 40 degrees of the combustion process, starting from −10 degrees after top dead center (ATDC) to 30 degrees ATDC. This model verifies the amount of

brake power and the value of the firing pressure inside the cylinders. The objective and the constraints of this study are combined in a developed fitness function that is described in detail in Section 3.2.2 and the nonlinear optimizer evaluates the fitness function based on the interior point algorithm.

3.2.1. Establishment of the Engine Model

In order to establish a 1D engine model, the different parts of the engine, such as the turbocharger, intercooler, intake and exhaust systems, injection systems and the five cylinders of the engine, must be considered as shown in the schematic diagram of the engine model in Figure 4. This schematic diagram is then converted to different mathematical modules in Ricardo Wave to simulate the engine performance in the 1D environment, as shown in Figure 5.

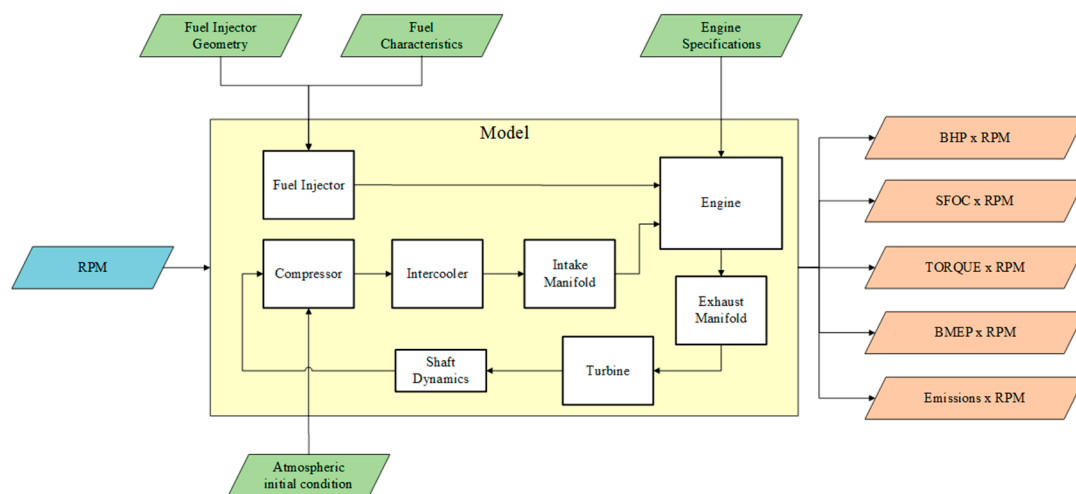


Figure 4. Schematic diagram of the engine model reproduced from [6], with permission from CRC Press, 2020.

The performance of the marine Genset is simulated using a 1D gas dynamic model based on the “filling and emptying” method [49] and the quasi-steady flow method [50]. The engine model is built with five cylinders in-line by considering the firing order of the cylinders. The main dimensions of each cylinder such as bore, stroke, connecting rod length, compression ratio, as well as the initial conditions of temperatures through the piston, cylinder and valves are defined based on the collected real data and the range suggestions by the software. The friction coefficients are computed using the Chen-Flynn friction model [51]. The operating speed and the reference initial conditions for each operating point are set and the fluid used is assumed ideal gas.

Each cylinder is equipped with two intake and two exhaust valves, all of them with a constant diameter equal to 33% of the cylinder bore. The profiles of both valves are assumed from real values collected from the project guide and are suitable for diesel engines with high forward and reverse flow coefficient. The valve timings are constant for all engine loads as presented in Table 1. The turbocharger is defined by three components: compressor, turbine and turboshaft. Due to the lack of their data, the map of the turbocharger compressor is scaled from existing maps in the software that has the similar outline defined by surge and choke limits as presented in [52] in order to fit the engine requirements from the intake air and high pressure. Additionally, the map of the turbine is rescaled from existing one based on the turbine efficiency, pressure ratio, speed and mass flow rate. The intercooler is defined by two junctions and multiple pipes in between with small diameter to allow the exchange of heat to reduce the temperature out from the compressor. It is calibrated based on the inlet and the outlet temperature. The intake and the exhaust manifolds, runners and ports are modelled using different junctions and pipes. Each part in the intake and the exhaust systems, intercooler and cylinder is assumed as a unique thermodynamic control volume computed using the filling and emptying method

as functions of time or crank angle. The thermodynamic properties of the fluid are computed at each step along the engine cycle using the first law of thermodynamics [53]. Due to the unavailability of injection system data, the fuel injection pressure, the injection rate in trapezoidal form and the injection duration are assumed and remain constant for the different loads according to the suggestions presented in [54].

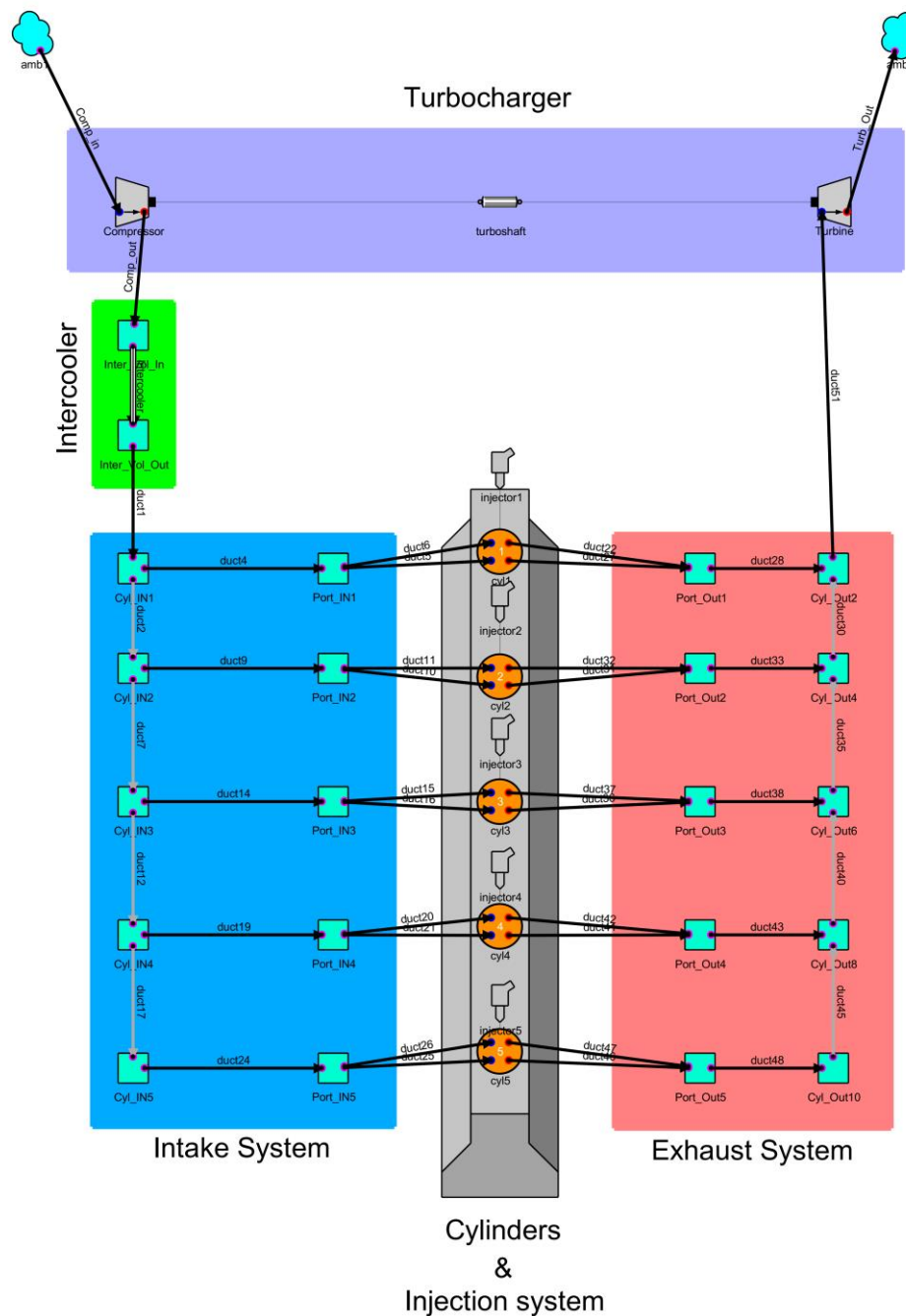


Figure 5. Engine model established in Ricardo Wave.

The combustion process is simulated based on the amount of fuel mass burned and controlled by the double Wiebe function suggested by Watson et al. [55] This Wiebe function is one of the classic functions [56] that is used as an alternative to the single Wiebe function to compute the premixed, diffusion and tail curves throughout the combustion process of diesel engines. It is specific for the simulation of combustion in diesel engines and it does not require any previous calibration for its parameters as in the single and multi-Wiebe functions. The burn duration is computed and scaled based on a selected reference speed, which is the rated speed (1200 RPM). Additionally, the ignition delay is calculated as in [55] and it is based on the quality of the fuel and the thermodynamic properties inside the engine. The heat transfer inside the cylinder is computed using the formula presented by Woschni [57], while the heat transfer in the ducts is computed using the Colburn analogy [58] and the heat transfer coefficients are defined based on previous studies [8,59]. The brake power, BSFC, thermal efficiency, volumetric efficiency, thermodynamic properties inside the engine and performance of the turbocharger are the main computed results.

3.2.2. Nonlinear Optimization Model

The nonlinear optimizer (fmincon) used in this study is a function integrated into Matlab. It is a single objective optimization method and it finds the optimal solution of variable x based on interior point algorithm and in the form of barrier method, to minimize the objective function ($f(x)$) and to verify the equality constraints ($c(x)$) as in Equations (1) and (2).

$$\text{minimize } f(x) \quad (1)$$

$$\text{subjected to: } \begin{aligned} c(x) &= 0 \\ x &\geq 0 \end{aligned} \quad (2)$$

For this study, the main objective is to reduce the MAPE between the simulated and experimental data of the in-cylinder pressure diagram and to achieve the values of firing pressure (P_{max}) and brake power (P_B). Two optimization variables—SOI in degree ATDC and fuel rate (FR) in kg/h—are considered to define the vector x .

Like other optimizers, the boundary conditions of each variable must be defined in order to easily achieve the optimal solution in the domain space. The initial estimate of each variable in the optimization method is defined by the minimum values of the boundary conditions. In this work, the boundaries are defined by the following expressions:

$$-15 \leq SOI \leq 0 \quad (3)$$

$$0.9 \times FR \leq FR \leq 1.25 \times FR \quad (4)$$

For this nonlinear problem, it is needed to convert the optimization with constraints to another one without constraints. Therefore, the fitness function, including the objective of this study and the constraints, will be the objective function of the optimization model. There are different ways to implement a fitness function for a constrained optimization problem [60]. It can be based on the death penalty, static penalties, dynamic penalties, annealing penalties, adaptive penalties, etc. These methods are prepared for the genetic algorithm method; however, it can be applied for the nonlinear optimization method used in this study. In previous research, the simple penalty function method shows effectiveness for many optimization projects [61].

In order to construct the fitness function, the two equality constraints are normalized as presented in Equations (5) and (6), so their absolute values will be less than one.

$$h_1(x) = \frac{P_B}{P_{B, obj}} - 1 \quad (5)$$

$$h_2(x) = \frac{P_{\max}}{P_{\max, obj}} - 1 \quad (6)$$

Then, the fitness function for the optimization model is written as in the following expression and the penalty parameter (R) is determined by 1000 after making many trials:

$$\text{Fitness Function} = \text{MAPE}(x) + R[|h_1(x)| + |h_2(x)|] \quad (7)$$

4. Results and Discussions

The engine optimization model is developed coupling Ricardo Wave and a nonlinear optimizer to compute the performance of the engine and to fit the calculated in-cylinder pressure diagram with the experimental data for a given load range varying from 25% to 75% at a constant speed (1200 RPM). Firstly, the engine model of the marine diesel engine MAN 5L16/24 is built by the authors and implemented in Ricardo Wave. The atmospheric initial conditions, turbocharger, intercooler, intake and exhaust systems, injection system and engine cylinders are taken into account during the establishment of the engine model. The fuel type used is the marine diesel oil (MDO) with 42.8 MJ/kg lower heating value (LHV). Due to the lack of information about the combustion process in the Genset, the Watson model, as one of the methods suggested by the software and recommended for diesel engines, is used to compute the burning mass fraction. The combustion model is defined by the cetane number, reference speed and the ignition delay model. Using these parameters, the coefficients of the combustion model do not require any calibration unlike the single and multiple Wiebe functions, which require calibration of the adjustable parameters. The ignition delay depends on the SOI and the in-cylinder thermodynamic properties, which are changing for every load. The success of this model in simulating the combustion process appears in the calculated pressure diagram inside the cylinders, where a good accuracy is achieved with the experimental results.

Firstly, the model is calibrated for the reference point (75% load) using some data from the manufacturer in order to select the appropriate maps for the compressor and turbine of the turbocharger due to the lack of their data. They are rescaling from existing maps to adjust the corrected mass flow rate and the corrected speed with the given pressure ratio exported from the in-cylinder pressure diagram to fit the current model. This step is important in calibrating the outlet pressure from the compressor by fitting the computed pressure diagram with the experimental one along the compression process. It also helps to define the amount of air and thus the volumetric efficiency. This process is repeated for the other two cases (25% and 50% load) for better calibration of the maps of the turbocharger and for improving the accuracy of the computed results along the different cases.

The speed of the turbocharger shaft is defined as an input for each load in order to compute the outlet pressure, temperature and flow rate from the compressor. Then, the coefficients and the initial conditions of the pressure, temperature and wall temperature of the intercooler are calibrated. The initial estimation of thermodynamic properties and different coefficients of each junction and pipe, in both the intake and exhaust systems, as well as the estimation of the geometry of the valves, are defined. The initial conditions of the atmospheric pressure and temperature are adapted for each load, according to the experimental data available for better accuracy.

After finishing the establishment and the calibration processes of the engine model, a nonlinearly constrained optimizer based on interior point algorithm is built and coupled with the engine model as shown previously in Figure 3, in order to find the optimal value of SOI and the amount of fuel injected for each load. This environment is considered as a data fitting technique that allows the calculated in-cylinder pressure diagram to fit the experimental curve by minimizing the MAPE between the two curves along 40 degrees of the combustion process starting from −10 degrees ATDC until 30 degrees ATDC. Additionally, it verifies the firing pressure and the brake power for each load as presented in Table 2, Table 3, Table 4. Based on this simulation, the BSFC and the value of the air fuel ratio (AFR) are computed and optimized for the different operating points. An earlier SOI and a higher AFR are considered in the low loads in order to increase the firing pressure and thus more power due to the

reduction in the amount of fuel injected. The SOI is retarded with the higher loads to control the pressure inside the cylinder and accompanied by more fuel injected to produce more power.

Table 2. Comparison between reference data and calculated results from Ricardo Wave at 25% engine load.

Items	Units	Reference Data	Ricardo Wave	Error%
Intake temperature	°C	41.00	40.98	0.04
Inlet manifold pressure	bar	1.35	1.34	0.74
Exhaust temperature	°C	405.00	417.54	3.09
Firing pressure	bar	72.91	72.50	0.56
Engine power	kW	118.75	121.75	2.46

Table 3. Comparison between reference data and calculated results from Ricardo Wave at 50% engine load.

Items	Units	Reference Data	Ricardo Wave	Error%
Intake temperature	°C	40.00	39.97	0.07
Inlet manifold pressure	bar	1.88	1.88	0.00
Exhaust temperature	°C	483.00	488.00	1.03
Firing pressure	bar	105.50	104.12	1.32
Engine power	kW	238.00	236.00	0.84

Table 4. Comparison between reference data and calculated results from Ricardo Wave at 75% engine load.

Items	Units	Reference Data	Ricardo Wave	Error%
Intake temperature	°C	45.00	45.00	0.00
Inlet manifold pressure	bar	2.64	2.66	0.75
Exhaust temperature	°C	497.00	513.86	3.39
Firing pressure	bar	139.6	139.18	0.30
Engine power	kW	357.00	356.17	0.23

The behavior of the combustion process for the three loads considered in this study is simulated using Watson model. The HRR and the normalized fuel mass burned are computed and presented in Figure 6. They are affected by the amount of AFR, SOI and the thermodynamic properties inside the cylinder. The non-premixed phase occurs due to the lean mixture where the AFR is greater than the stoichiometric air fuel mixture. Longer combustion duration than the real data is noticed, as the burn duration is computed based on user-entered reference speed which is recommended by the software to be the engine speed at the engine rated power (1200 RPM).

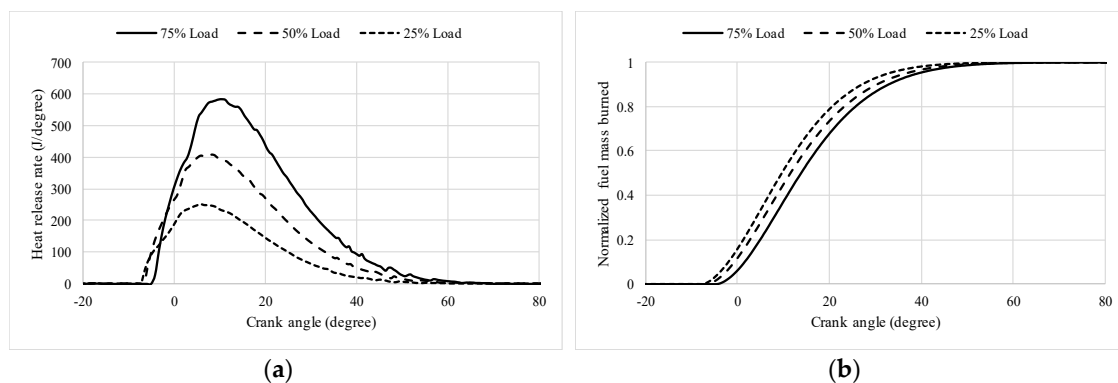


Figure 6. (a) Heat release rate and (b) normalized fuel mass burned for different engine loads.

A comparison between the collected data from the available references mentioned above and the calculated results from Ricardo Wave is presented in Table 2, Table 3, Table 4 where good accuracy with a maximum 3.4% error, which is acceptable, is achieved for inlet manifold pressure, exhaust temperature, firing pressure and engine power.

In Figure 7, the simulated in-cylinder pressure diagrams from the 1D engine model are compared with the experimental ones and a good fitting is achieved between the two curves along the different engine processes. The MAPE is used to evaluate the goodness-of-fit between the curves along the 40 degrees of the combustion process with 5.69%, 3.00% and 2.16% for 25%, 50% and 75% of the loads, respectively. The values of MAPE decreased with the increase of load when the difference between the calculated ignition delay period and the experimental tests decrease, and vice versa, due to some uncertainties in the value of the sub-models' parameters. The firing pressure is controlled depending on the ignition delay model used and the percentage of error in comparison with real data is less than 1.5%, as shown in Table 2, Table 3, Table 4.

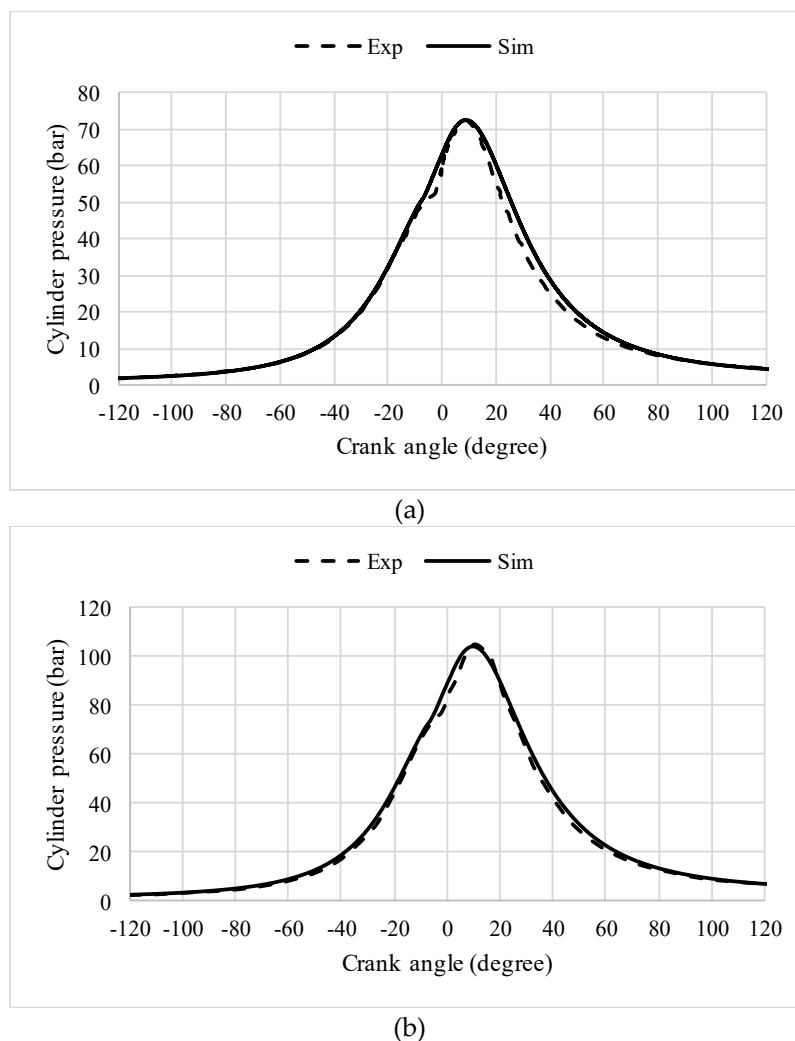


Figure 7. Cont.

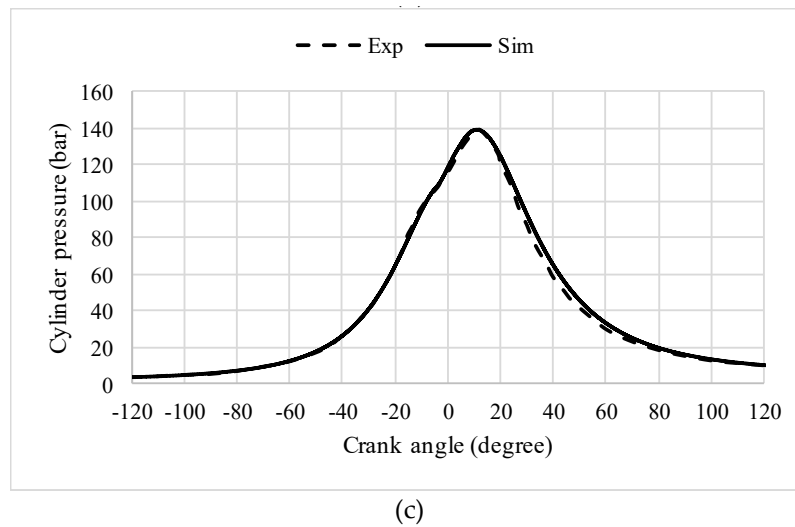


Figure 7. Pressure diagram at (a) 25% load; (b) 50% load; (c) 75% load at 1200 RPM.

An overview of the engine performance including brake mean effective pressure (BMEP), BSFC, thermal and volumetric efficiencies, AFR, firing pressure and pressure ratio of the compressor is presented in Figure 8. For more precise results, the simulation is performed according to the ambient temperature defined for each case as presented in Figure 8a.

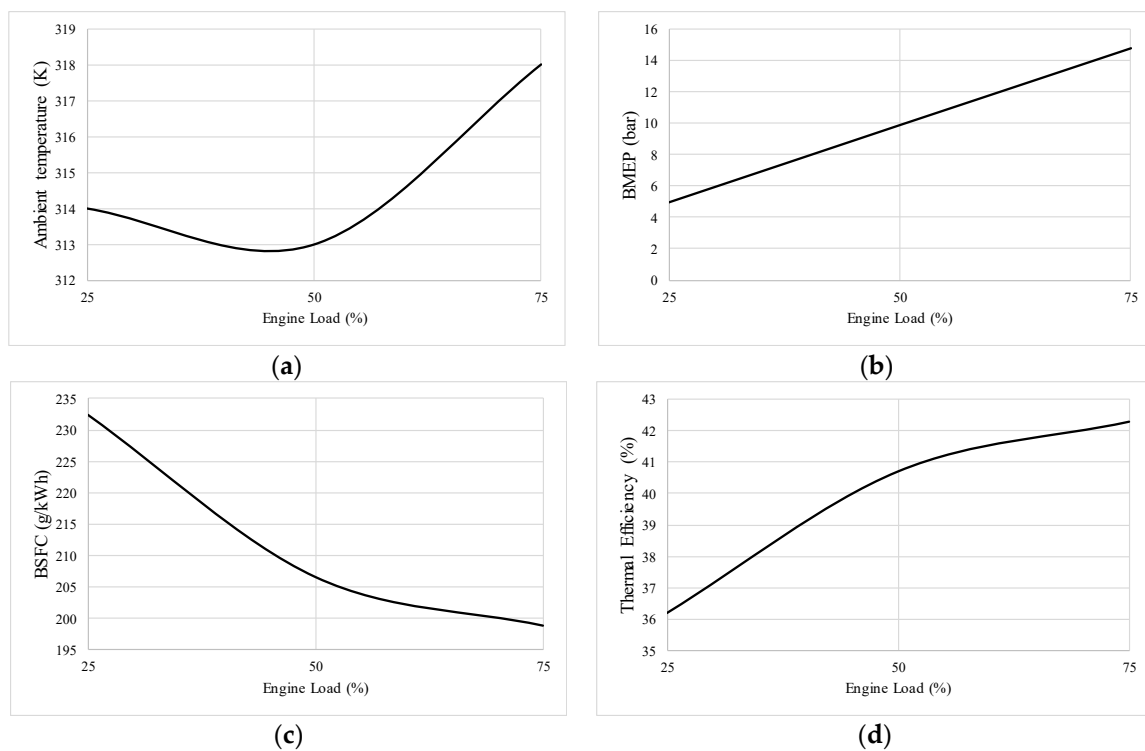


Figure 8. Cont.

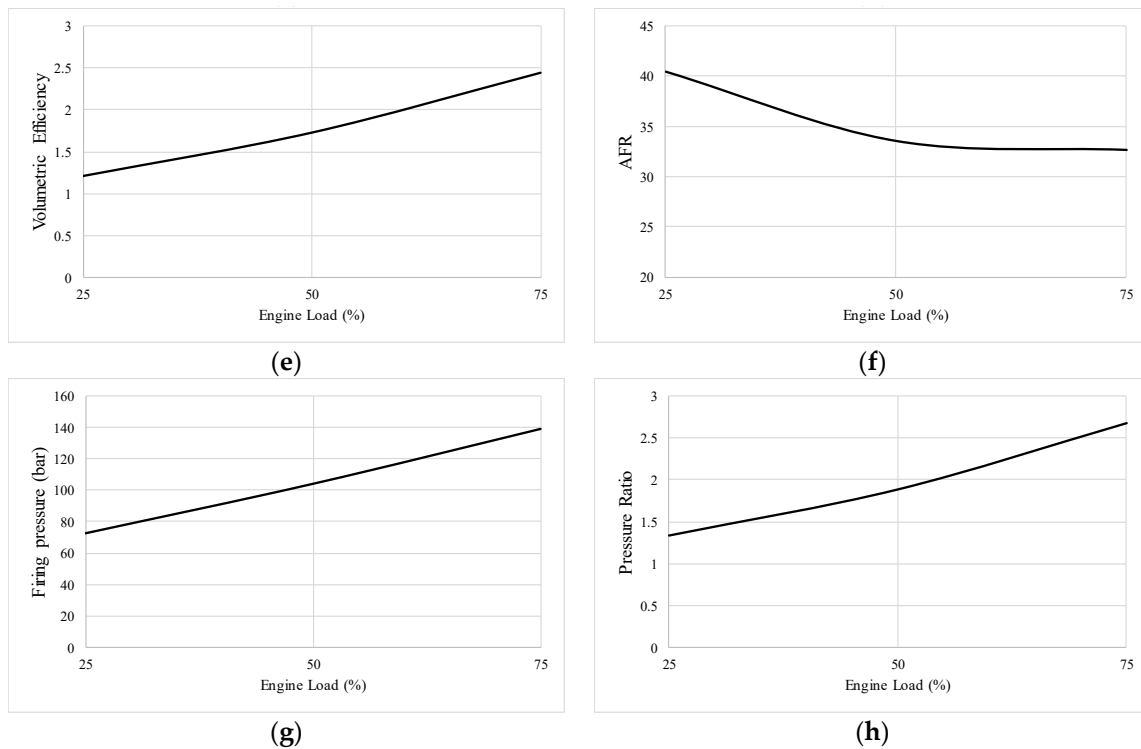


Figure 8. Variation of (a) ambient temperature; (b) BMEP; (c) BSFC; (d) thermal efficiency; (e) volumetric efficiency; (f) AFR; (g) firing pressure; (h) compressor pressure ratio for different engine loads.

As in other engines, when the engine load increases, it is required to increase the compression ratio of the compressor in order to compress more air, which leads to a significant increase in volumetric efficiency. By injecting more fuel, the firing pressure increases and thus produce more power while the BSFC decreases at the high loads. It is noticed that based on the cumulative results, the thermal efficiency increases at the high loads by 20% than the low loads.

5. Conclusions

In this study, a data fitting technique is adopted, based on an optimization procedure for calibration purposes. An engine optimization model, coupling 1D engine simulation software and a nonlinear optimizer, is developed to simulate the performance of marine Genset and to fit the simulated in-cylinder pressure diagram with the experimental one. It has been concluded that:

- (1) A good agreement is achieved between the simulated and experimental data for different engine loads.
- (2) The model finds the optimal values of SOI and the amount of injected fuel by minimizing the MAPE between the two curves (simulated and experimental).
- (3) The model succeeds in verifying the firing pressure and the engine brake power for the different loads.
- (4) The double Wiebe function based on the Watson model shows effectiveness in simulating the combustion process of the marine Genset considered in this study as shown from the computed in-cylinder pressure diagram. The main advantage of this model that it does not require any calibration of its coefficient, which can be used in the simulation of other diesel engines without the need for the real in-cylinder pressure diagram.
- (5) This model can be further used during the calibration procedures of other types of engine models by considering more variables during the simulation.

Author Contributions: The concept of the problem is developed by M.T., M.V. and C.G.S. The analysis is performed by M.T. and writing of the original draft manuscript is done by M.T., M.V. and C.G.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AFR	Air fuel ratio
ANN	Artificial neural network
ATDC	After top dead center
BMEP	Brake mean effective pressure
BSFC	Brake specific fuel consumption
CFD	Computational fluid dynamics
CI	Compression ignition
EGR	Exhaust gas recirculation
FR	Fuel rate
GA	Genetic algorithm
HRR	Heat release rate
ICE	Internal combustion engine
LHV	Lower heating value
LSM	Least square method
MAPE	Mean absolute percentage error
MDO	Marine diesel oil
ML	Machine learning
MOGA	Multi-objective genetic algorithm
NO _x	Nitrogen oxides
P _B	Brake power
P _{max}	Firing pressure
R	Penalty parameter
SOI	Start angle of injection

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