Article citation info:
BRZOZOWSKI K, NOWAKOWSKI J. Model for calculating compression ignition engine performance. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2014; 16 (3): 407–414.

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MODEL FOR CALCULATING COMPRESSION IGNITION ENGINE PERFORMANCE

MODEL DO WYZNACZANIA PARAMETRÓW PRACY SILNIKA O ZAPŁONIE SAMOCZYNNYM

Optimising the performance of an internal combustion engine requires both empirical and theoretical work. The latter involves reasoning based on results yielded by mathematical models. This paper presents a computationally efficient model of the working cycle for a compression ignition engine. The model enables analysis of the working cycle of an engine with an electronically controlled common-rail type power supply and a controlled exhaust gas recirculation system. The model's parameters are chosen in a two-stage identification process based on the results of the experiments. The first stage of identifying the parameters requires formulating and solving an appropriate dynamic optimisation problem for multiple discrete points describing the engine's operation. To this end a genetic algorithm is used with an additional condition controlling the quality of the solution. Artificial neural networks are used for the second stage of identification. The paper shows an example of using the model to assess the influence of the kinetic combustion phase, which results from the way in which the injection process proceeds on the course of the working cycle. The accuracy of calculations with respect to basic parameters characterising the working cycle is also discussed.

Keywords: *compression ignition engine, identification, engine performance parameters.*

Doskonalenie parametrów pracy silnika spalinowego poprzez odpowiednie sterowanie cyklem roboczym wymaga stosowania zarówno prac o charakterze doświadczalnym jak i obliczeniowym. W tym drugim przypadku podstawą wnioskowania są wyniki uzyskiwane z modeli matematycznych. Artykuł przedstawia efektywny obliczeniowo model cyklu roboczego silnika o zapłonie samoczynnym. Model umożliwia analizę cyklu roboczego silnika z elektronicznie sterowanym układem zasilania typu common-rail oraz układem sterowanej recyrkulacji spalin. Parametry modelu dobrano w dwuetapowym procesie identyfikacji bazującym na wynikach badań stanowiskowych. Pierwszy etap identyfikacji parametrów wymagał sformułowania i rozwiązania odpowiedniego zadania optymalizacji dynamicznej dla wielu dyskretnych punktów pracy silnika. W tym celu zastosowano algorytm genetyczny z dodatkowym warunkiem kontroli jakości rozwiązania. W drugim etapie identyfikacji do uogólnienia wyników wykorzystano sztuczne sieci neuronowe. W pracy przedstawiono przykład zastosowania modelu w ocenie udziału fazy spalania kinetycznego wynikającej z realizacji przebiegu procesu wtrysku na przebieg cyklu roboczego oraz przedstawiono dokładność obliczeń w odniesieniu do podstawowych parametrów charakteryzujących cykl roboczy.

Słowa kluczowe: *silnik o zapłonie samoczynnym, identyfikacja, parametry pracy silnika.*

1. Introduction

Empirical models of real phenomena are commonly used in practical applications. Their usefulness depends on knowing a number of parameters, the so-called model parameters. Using models of this type results from the requirement that the time complexity of numeric computations performed must be acceptable. The following papers from recent years present models of this type [3, 12, 14–16], most of which involve the assumption that the subject of study are the mean values of pressure and temperature in the entire combustion chamber. Such an assumption leads to formulating zero-dimensional models characterised by adequate numeric efficiency due to the duration of computations being the key parameter in determining the potential usefulness of a model in control tasks. The main problem in zero-dimensional empirical models is choosing the function describing the dynamics of the combustion process of an injected dose of fuel. This function can be expressed by way of elaborating the results of direct measurements of pressure in the cylinder, as in [3, 12]. A more common approach, however, is to choose one of the traditionally used functions describing the combustion process, whose parameters are determined in such way that the results of the experiments are matched relatively as closely as possible. Thor et al. [18] is one of several papers to use this function. Also, the paper [15] employs a composition of two empirical functions.

The parameters of zero-dimensional models are functions of a given excitation, and choosing appropriate values for them is the key problem concerning the accuracy of calculation. The problem of determining parameters for empirical models of an engine's working cycle is discussed in [11]. The task may be formulated as a dynamic optimisation problem, as in the current paper which proposes and applies an evolutionary algorithm to choose the values of the model parameters for the working cycle of a compression ignition engine. Evolutionary algorithms are a group of the so-called artificial intelligence methods applicable to problems defying efficient algorithmisation, and they complement classical approaches to computation. They are notable for their applications to problems concerning working cycles and control of internal combustion engines, as exemplified by [1, 6, 7, 10, 13, 19]. Genetic algorithms, which form a popular subset of evolutionary algorithms, are used in those optimisation problems which lend themselves easily to specialised methods and whose search space is too large for classical algorithms. The current paper also uses a genetic algorithm to choose the values of model parameters. It is based on the results of actual measurements taken on a test bench.

2. Model of the working cycle and the scope of experimental measurements

For a zero-dimensional model of an engine's working cycle the phenomena occurring in the engine's cylinder are described by ordinary non-linear differential equations obtained from the principle of mass conservation and energy balance [4]. By putting "d" and "w" into the lower index for the values characterising the inlet and exhaust system, respectively, the considered mathematical model of the working cycle of a compression ignition engine may be presented in the following form [10]:

$$\frac{dm}{d\varphi} = \frac{dm_d}{d\varphi} - \frac{dm_w}{d\varphi} + \frac{dm_B}{d\varphi}, \tag{1}$$

$$\begin{aligned} &B_0 W_0 \frac{dx_B}{d\varphi} + \frac{30}{\pi n} h_c A_c (T_{sc} - T) + c_{pd} T_d \frac{dm_d}{d\varphi} = \\ &c_v T \frac{dm}{d\varphi} + c_v m \frac{dT}{d\varphi} + p \frac{dV}{d\varphi} + c_{pw} T_w \frac{dm_w}{d\varphi} \end{aligned}, \tag{2}$$

$$\frac{dm_d}{d\varphi} = f\left(n, \mu_d p_d, p, T_d\right), \tag{3}$$

$$\frac{dm_w}{d\varphi} = f\left(n, \mu_w p_w, p, T\right), \tag{4}$$

$$\begin{aligned} \frac{dx_B}{d\varphi} = \beta &\left\{ -e_2 \left[1 - \left(\frac{\varphi - \varphi_z}{\Delta\varphi_s} \right)^{e_1 \tau} \right]^{e_2 - 1} \cdot (-e_1 \tau) \left(\frac{\varphi - \varphi_z}{\Delta\varphi_s} \right)^{e_1 \tau - 1} \right\} + \\ + (1 - \beta) &\left\{ -\exp\left[-e_3 \lambda \left(\frac{\varphi - \varphi_z}{\Delta\varphi_s} \right)^{e_4} \right] \cdot (-e_3 \lambda) e_4 \left(\frac{\varphi - \varphi_z}{\Delta\varphi_s} \right)^{e_4 - 1} \right\} \end{aligned} .\tag{5}$$

The above equations are complemented by algebraic relations resulting from the assumptions that the working medium is a semi-perfect gas and that the heat transfer coefficient is a function of state parameters and the engine's structural parameters [5]:

$$h_c = e_5 V^{e_6} p^{e_7} T^{e_8} \left(c_m + 1.4\right)^{0.8}, \tag{6}$$

where c_m is the mean piston speed.

A further discussion assumes that the vector of the model's independent input parameters is the following vector of the engine's control parameters:

$$\boldsymbol{X} = \left[n, B_0, \varphi_w, X_{EGR} \right]^T, \tag{7}$$

where X_{EGR} is the degree of exhaust gas recirculation and φ_w is the injection advance angle.

The input values, which are dependent on the control parameters vector $\boldsymbol{X}$, are the pressure and the temperature of the medium in the inlet system and the excess air coefficient. These values form the auxiliary parameters vector as follows:

$$\boldsymbol{G} = \left[p_d, T_d, p_w, T_w, \lambda \right]^T, \tag{8}$$

where λ is the relative air/fuel ratio.

Since the formulated model uses a few empirical relations and coefficients, a proper choice of their values depending on a given engine's design constitutes an important step. These coefficients are thus called the model parameters and they form the model parameters vector of the form:

$$\boldsymbol{E} = \left[\mu_d, \mu_w, \Delta\phi_s, \phi_z, \beta, e_1 \dots e_8 \right]^T. \tag{9}$$

A practical application of the formulated model of the engine's working cycle requires knowing the functions describing the dependency of the model parameters on the values of the control parameters for all technically feasible states of engine operation. Determining those functions is an identification problem and proceeds in two stages.

The first stage consists in identifying the values of individual components of the model parameters vector for discrete states of engine operation. Suitable experiments on a test bench are therefore required. Planning the agenda for experimental measurements should involve choosing states of engine operation as discrete points so that performing registration of the engine's operation parameters and those of the inlet and exhaust system encompasses a possibly wide range of actual operation states. Following the choice of loads in the ESC test [2], partial values of the maximal moment of force for each chosen value of angular velocity were chosen as the values of moment constituting the engine's load. Based on previous work [10, 17], discrete points describing the engine's operation were determined for four fixed values of angular velocity. For each of the angular velocities, experiments were performed with variable load, whereby five different values of the braking moment were used in each case. The load was changed in an increasing manner and different degrees of exhaust gas recirculation, starting with none, were tested for a given point at which measurements were taken. The degree of exhaust gas recirculation was subsequently increased by 5% until reaching its maximum defined for a given point. The definition of these maxima set them as high as possible while the engine could sustain the assumed moment of inertia. The exhaust gas recirculation system was inactive for maximal loads. The dose supplied during a single experiment to the operating engine consisted of two parts: a constant pilot dose and a variable main dose. For each point measurements were taken with a standard injection advance angle (preset by the built-in microcontroller controlling the engine's operation) and with angles advanced and delayed by 2°CA and 4°CA from the standard value, respectively. In the entire range of intermediate loads engine operation was regulated so that the assumed constant angular speed and constant moment of inertia were maintained. Such regulation enabled analysis of parameters of engine operation at constant mean effective pressure. Increases (or decreases) of moment of inertia were compensated by changing the doses of fuel. Fig. 1 schematically presents the proposed way of choosing the discrete points describing the engine's operation for which to carry out the experimental measurements.

The varying pressure in the cylinder was registered along with other characteristic parameters of the working cycle for each point describing the engine's operation. Experimental measurements allowed to collect data describing the parameters of the inlet and exhaust system's operation and parameters of the working cycle for $n_i = 400$ different sets of control parameters, whereby a presently produced four-cylinder compression ignition engine suitable for propelling an automobile was used as the subject of study. Characteristic technical data of the engine used in measurements and subsequent identification of model parameters are presented in Table 1.

Subsequently, the second stage of the identification problem of model parameters involves the task of generalising the results of discrete identification in order to obtain a relationship of the form:

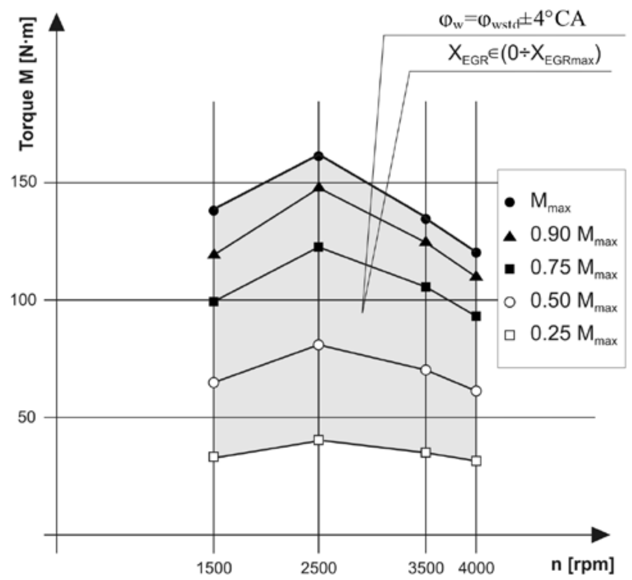


Fig. 1. Scheme of the scope of experimental measurements used in the first stage of model parameters identification

Table 1. The engine's technical data

Engine	Compression ignition engine supercharged by a turbo compressor with direct injection equipped with an electronically controlled Common Rail system
Layout of cylinders	4 in line
Number of valves per cylinder	4
Bore	69.6 mm
Stroke	82 mm
Total displacement	1248 cm^3
Compression ratio	16.8
Maximum power	55.2 kW / 4000 rpm
Maximum torque	190 N·m / 1500 rpm

$$\boldsymbol{E} = f_E(\boldsymbol{X}) \,, \tag{10}$$

and

$$\boldsymbol{G} = f_G(\boldsymbol{X}) \,. \tag{11}$$

The proposed method is discussed in the next chapter.

3. Determining the model parameters

The first stage of identifying the model parameters is performed for $i = 1,..,n_i$ discrete states of the engine's operation and consists in determining the values of the components of vector $\boldsymbol{E}$. The task may be considered as a minimisation problem for the following functional:

$$\Omega(\boldsymbol{X},\boldsymbol{E},\boldsymbol{G}) = c_1 \int_0^{4\pi} \left[p_E(\varphi) - p_F(\varphi) \right]^2 d\varphi + c_2 \left(\max p_E(\varphi) - \max p_F(\varphi) \right)^2 \to \min \,, \tag{12}$$

where: $p_{\mathbf{F}}(\varphi)$ – pressure calculated according to the model of the working cycle

$p_{\mathbf{E}}(\varphi)$ – smoothed pressure from bench testing:

$$p_{\mathbf{E}} = \frac{a_0}{2} + \sum_{j=1}^{m_j} a_j \cos\frac{j\varphi}{2} + b_j \sin\frac{j\varphi}{2} \,,$$

$$m_j = 60 \,,$$

$$a_j = \frac{1}{2\pi} \int_0^{4\pi} p(\varphi) \cos\frac{j\varphi}{2} d\varphi, \quad j = 0,1,..,n \,,$$

$$b_j = \frac{1}{2\pi} \int_0^{4\pi} p(\varphi) \sin\frac{j\varphi}{2} d\varphi, \quad j = 1,..,n \,,$$

c_1, c_2 – constant weight coefficients.

Solving a problem thus formulated requires knowledge of the actual pressure varying in the cylinder for each set of control parameters $\mathbf{X}^{(i)}$ and auxiliary parameters $\mathbf{G}^{(i)}$, where $i = 1,..,n_i$ denotes the discrete states of an engine's operation. Calculating $p_{\mathbf{F}}(\varphi)$, on the other hand, necessarily involves integration of the model's equations (1÷5) for every possible choice of the model parameters. The task is solved by using a genetic algorithm, thereby ensuring a concurrent search for the solution set by assuming the following fitness function:

$$\Phi(\boldsymbol{X},\boldsymbol{E},\boldsymbol{G}) = \frac{1}{\Omega(\boldsymbol{X},\boldsymbol{E},\boldsymbol{G})} \to \max \,. \tag{13}$$

A genetic algorithm with real encoding is used, thus making each individual's chromosome into:

$$\mathbf{Z} = [z_1, ..., z_{13}]^T \,, \tag{14}$$

where $z_1 = \mu_d, z_2 = \mu_w, z_3 = \Delta\varphi_s, z_4 = \varphi_z, z_5 = \beta, z_{5+i} = e_i \; for \; i = 1..8$.

For each of the genes z_i, the range of admissible values are defined, respectively, as $z_{i,\min}$ and $z_{i,\max}$, which are presented in Table 2.

The initial values are generated with a random strategy and the selection operation is done with the direct tournament selection method for pairs of chromosomes. The arithmetical crossover and the non-uniform mutation [8] were used as genetic operators. The set of chromosomes used in the next step of the algorithm is determined by ranking the fittest individuals. Since the number of individuals used ($n_p = 24$) is relatively small, the possibility of not obtaining a fully satisfying solution to an individual identification problem of the form (12) within the limited number of the algorithm's iterations ($k_{\max} = 15$) is assumed. This assumption leads to the introduction of the following additional criterion whose failure requires repeating the identification procedure:

*Table 2. Range of admissible values for particular genes of chromosome **z***

z_i	z_1	z_2	z_3	z_4	z_5	$z_6 \div z_8$	z_9	z_{10}	z_{11}	z_{12}	z_{13}
$z_{i,\min}$	0.1	0.1	15°	343°	0	0	0.5	10^{-3}	-0.1	0	-1
$z_{i,\max}$	0.4	0.95	36°	375°	0.3	5	5	5	0	1	0

$$\frac{\left|p_{i(r)E}-p_{i(r)F}\right|}{p_{i(r)E}} \le 5\% . \tag{15}$$

This means that the relative difference between the mean indicated pressure registered experimentally $p_{i(r)E}$ and the computed value of the mean indicated pressure $p_{i(r)F}$ for the fittest chromosome in the expansion phase of the cycle must be below 5%.

It turns out that using the criterion for restarting the identification procedure enables to obtain satisfying solutions to the whole set of analysed states of the engine's operation. The average number of necessary repetitions of the identification procedure for $n_i = 400$ identification problems solved consecutively is 4.5.

In the second stage of identifying a suitable approximation problem for the results obtained for discrete identification is formulated and solved in order to determine the appropriate functions $f_E(\mathbf{X})$ and $f_G(\mathbf{X})$. In the case of parameters needed to compute the heat transfer coefficient $e_5 \div e_8$, as their values are very close in discrete identification, a simplification is made by taking their mean. Other model parameters may be approximated using artificial neural networks. A series of numeric experiments allowed to conclude that the problem of determining $f_E(\mathbf{X})$ and $f_G(\mathbf{X})$ requires using two separate feed-forward multilayer neural networks (Fig. 2):

network I:

$$\boldsymbol{X}=\left[n, B_0, \varphi_w, X_{EGR}\right]^T \rightarrow Out_1=\left[p_d, T_d, p_w, T_w, \lambda, \mu_d, \mu_w, \Delta\varphi_s, \varphi_z\right]^T, \tag{16}$$

network II:

$$\boldsymbol{X}=\left[n, B_0, \varphi_w, X_{EGR}\right]^T \rightarrow Out_2=\left[\beta, e_1, e_2, e_3, e_4\right]^T . \tag{17}$$

As a result of the learning process, the architectures of the networks are set to be 15:9 (n_1:n_2) for network I and 31:5 for the network II reflecting the parameters of the Watson function. Both networks use a unipolar neuron activation function.

4. Computing the cycle's characteristic parameters

The formulated model enables assessment of the characteristic parameters of the working cycle for arbitrary states of the engine, i.e. for an arbitrary technically feasible vector of the control parameters. It therefore lends itself to an analysis of the ability to shape the working cycle in a real engine with an electronically controlled common-rail type power supply system and a controlled exhaust gas recirculation system. One application of such a model is assessing the influence of contribution of the kinetic combustion phase, resulting from the way in which the injection process proceeds, on the engine's working cycle. The analysis encompasses the computed varying pressures and temperatures of the medium in the cylinder and the changes of the characteristic parameters of the working cycle, such as mean indicated pressure p_i, thermal efficiency η_c and maximal temperature of the medium $T_{\max}$.

The course of heat emission, and hence also the contribution of the kinetic and diffusion combustion phase, may be adjusted by dividing the dose injected into the cylinder into individual partial doses depending on the load and the engine's angular velocity. Of particular importance are the choice of the pilot dose's value, the time interval between the pilot dose and the main dose, and the injection advance angle of the main dose. Figure 3 illustrates the influence of reducing the contribution of the kinetic combustion phase on the parameters of the working cycle at a selected point describing the engine's operation for set values of the control parameters.

Analogously, the model enables an assessment of the influence of the degree of recirculation on the working cycle. The value of the maximal degree of exhaust gas recirculation depends on the engine's boost pressure and design of the recirculation systems. It also follows from a compromise between the ability to reduce emission of nitrogen oxides, emission of solid particles (thus also smoke opacity of the exhaust gases) and decline in the engine's capabilities. An illustration of the influence of the degree of recirculation on the parameters of the working cycle at a selected point describing the engine's operation for set values of control parameters is shown in Fig. 4.

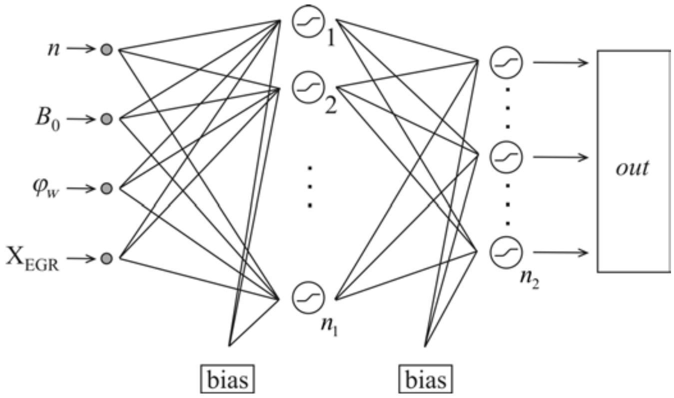


Fig. 2. Schematic layout of the artificial neural networks used in the work

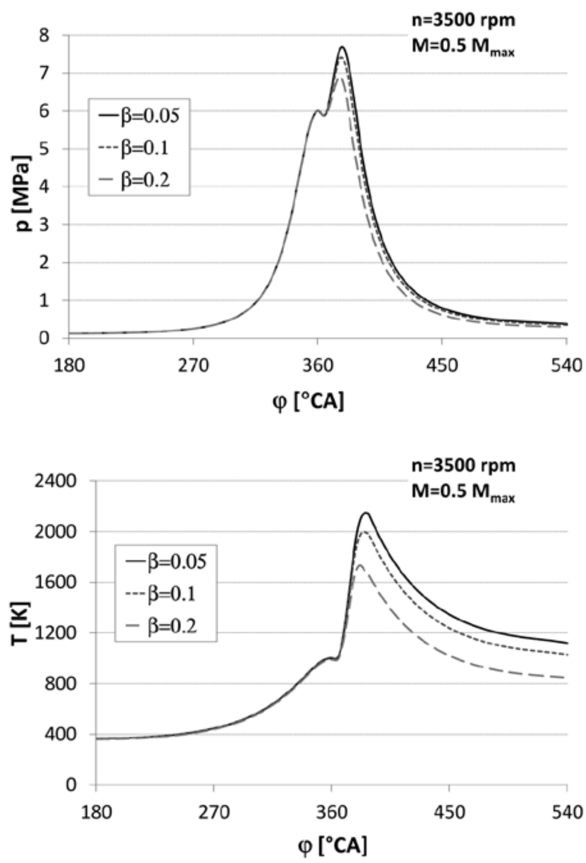


Fig. 3. Influence of the kinetic combustion phase's contribution on the working cycle for 3500 rpm

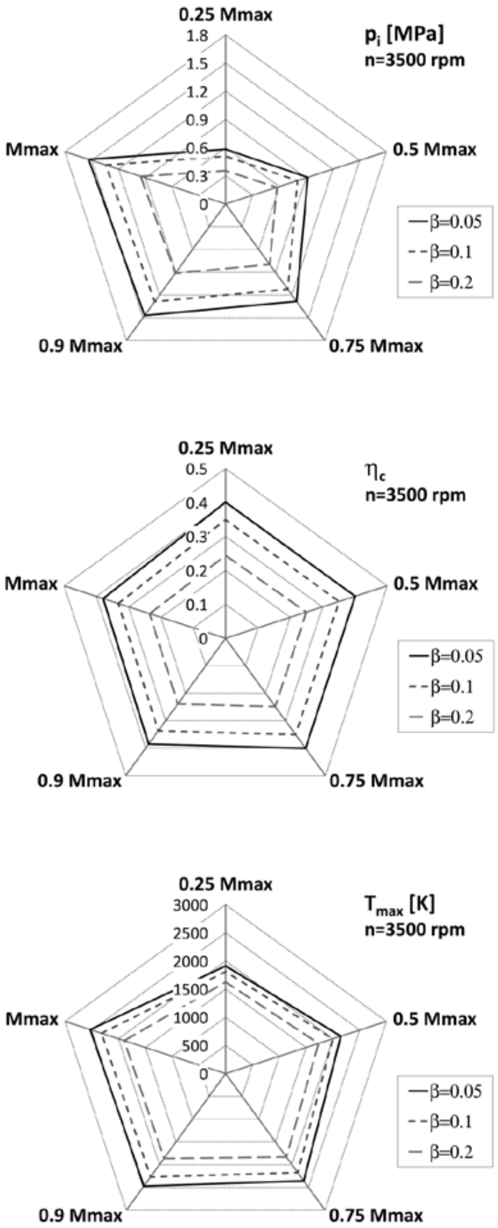


Fig. 3. (continued) Influence of the kinetic combustion phase's contribution on the working cycle for 3500 rpm

5. Conclusions

The model presented in the paper enables to perform a number of computations related to assessing the working cycle of an engine. Error of the calculation can be determined by comparing the computed and experimentally registered varying pressures in the cylinder for selected points describing the engine's operation. Sample comparisons of varying pressures in the cylinder at selected points describing the engine's operation (constituting elements of the set used to verify the quality of approx imation of model parameters by applying artificial neural networks) are shown in Fig. 5.

Accuracy of the model can be determined by comparing the computed and experimentally registered values of parameters such as: mean indicated pressure p_i, mean indicated pressure in the expansion phase of the cycle $p_{i(r)}$, maximal pressure in the cycle $p_{\max}$, and mass of the medium in the cylinder m. In Fig. 6 the values of the listed characteristic parameters of the working cycle obtained from the ex-

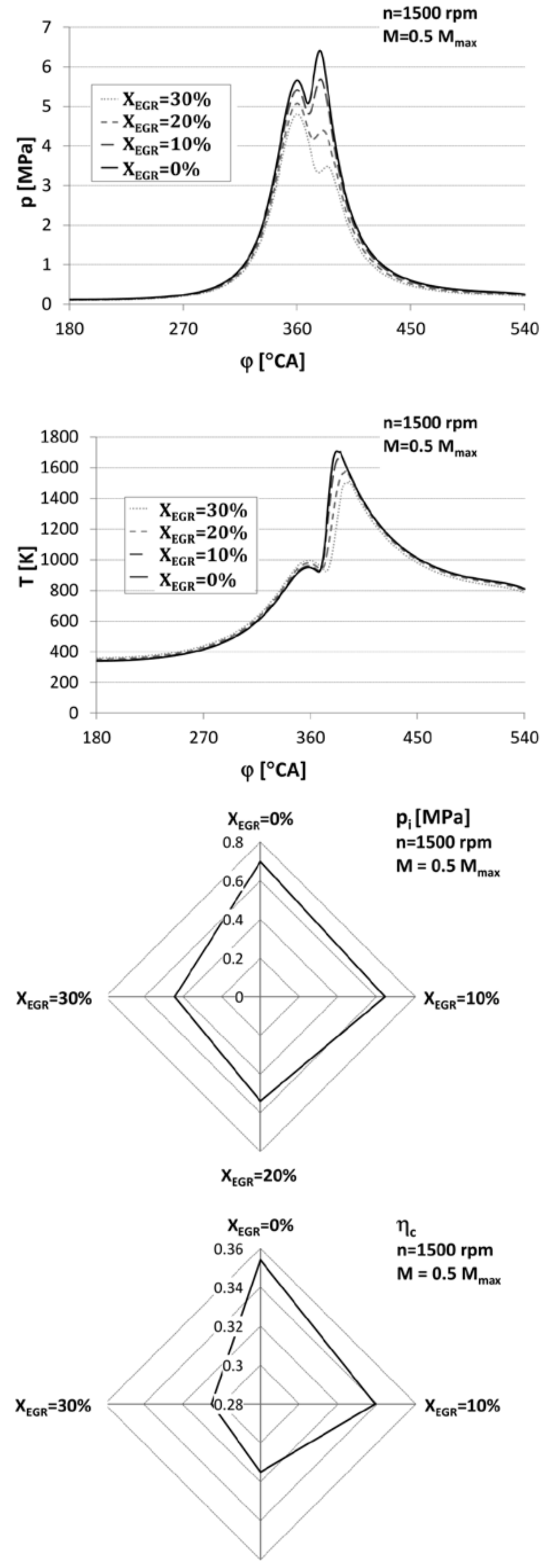


Fig. 4. Influence of the degree of recirculation on the working cycle for 1500 rpm and 50% of maximum load

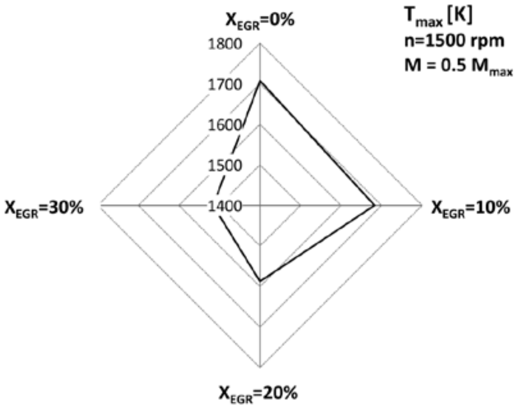


Fig. 4. (continued) Influence of the degree of recirculation on the working cycle for 1500 rpm and 50% of maximum load

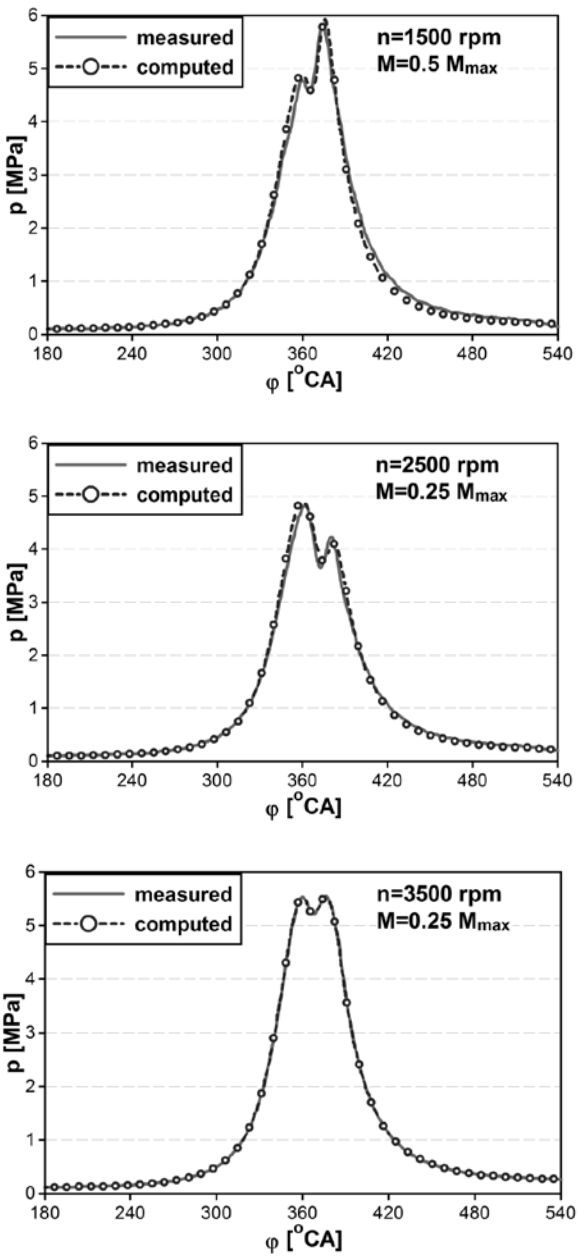


Fig. 5. Comparison of experimentally registered and computed varying pressures for selected states of engine operation

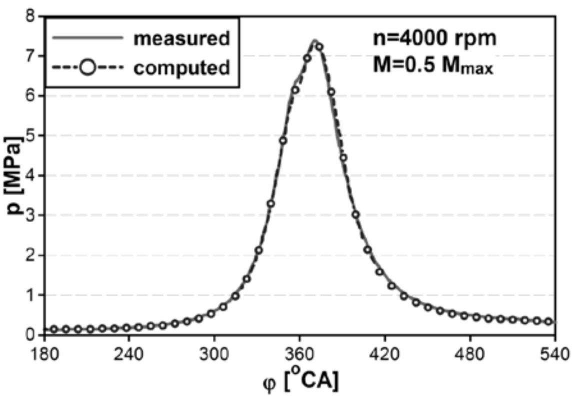


Fig. 5. (continued) Comparison of experimentally registered and computed varying pressures for selected states of engine operation

perimental measurements are compared to those computed according to the model. Values of mean relative error defined as the difference between the measured and computed value related to the measured value are collected for individual quantities in Table 3.

Based on the obtained values of mean relative error and on an interpretation of the comparisons of values of individual characteristic parameters of the working cycle, the conclusion follows that actual varying pressures are accurately represented by the functions computed by this model. This means that the model allows to forecast varying pressure and to determine quantities which characterise the working cycle for a given point describing the engine's operation with acceptable error. Maximal relative errors are in all cases below 15% for every characteristic parameter of the working cycle analysed, whereas the mean errors presented in Table 3 for the three of four characteristic parameters considered do not exceed 3%.

Table 3. Mean relative error of computation of individual characteristic parameters of the working cycle

Parameter	p_i	$p_{i(r)}$	$p_{\max}$	m
Value of mean relative error [%]	5.02	2.74	2.7	2.18
Coefficient of determination R^2	0.989	0.992	0.988	0.971

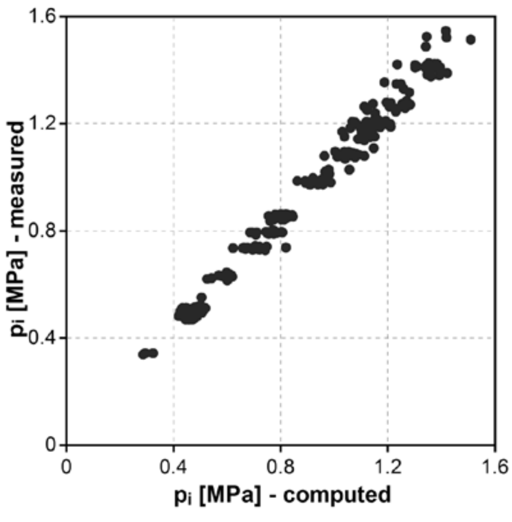
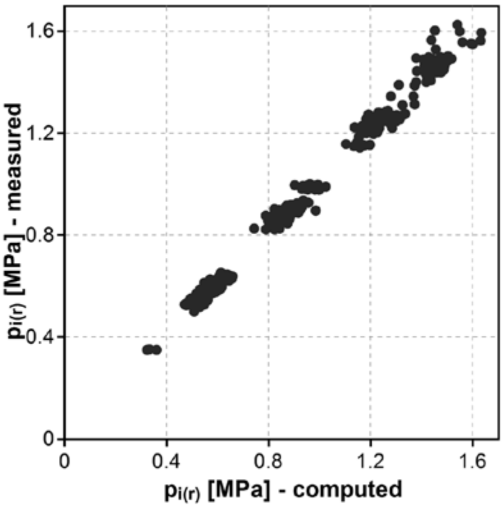
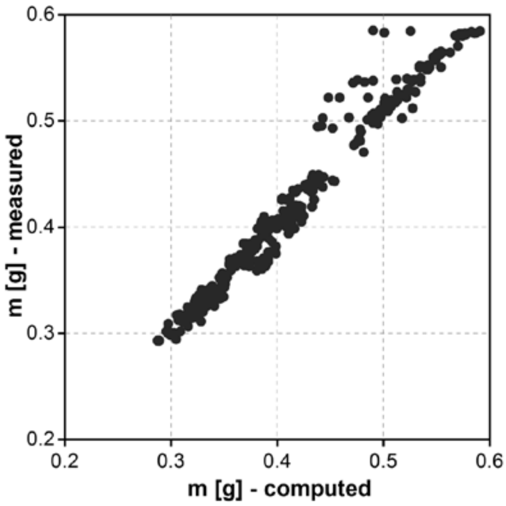


Fig. 6. Comparison of values of mean indicated pressure p_i, mean indicated pressure in the expansion phase of the cycle $p_{i(r)}$, maximal pressure in the cycle $p_{\max}$, mass of the medium in the cylinder m





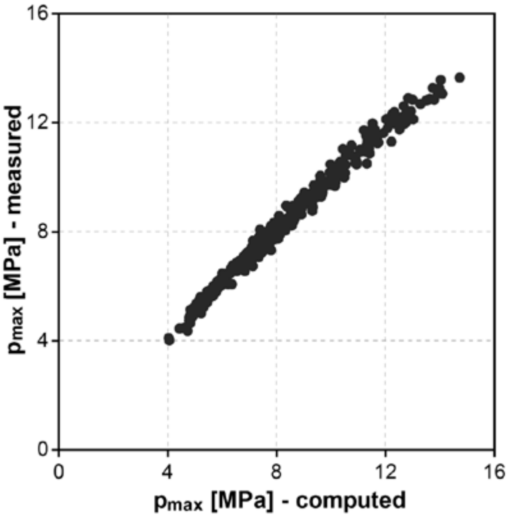


Fig. 6. (continued) Comparison of values of mean indicated pressure p_i, mean indicated pressure in the expansion phase of the cycle $p_{i(r)}$, maximal pressure in the cycle $p_{\max}$, mass of the medium in the cylinder m

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Nomenclature

A_c	heat transfer surface area [m^2],
B_0	injected fuel mass [kg],
c_p	specific heat of the medium at constant pressure [kJ/ (kg·K)],
c_v	specific heat of the medium at constant volume [kJ/ (kg·K)],
c_m	mean piston speed [m/s],
c_1 , c_2	constant weight coefficients,
e_i	model coefficients,
h_c	heat transfer coefficient [W/(m^2·K)],
m	mass of the medium [kg],
m_B	mass of fuel [kg],
n	crankshaft rotational speed [rpm],
p	pressure [Pa],
p_i	mean indicated pressure [Pa],
$p_{i(r)}$	mean indicated pressure in the expansion phase of the cycle [Pa],
T	temperature [K],
T_{sc}	wall temperature [K],
V	volume [m^3],
W_0	fuel caloric value [kJ/kg],
x_B	fuel mass burning rate,
X_{EGR}	degree of exhaust gas recirculation,
z_i	genes of chromosome,

Greek letters

β	proportionality factor,
η_c	thermal efficiency,
λ	relative air/fuel ratio,
μ	valve discharge coefficient,
τ	ignition delay time [s],
φ	crank angle [°CA],
φ_w	injection advance angle [°CA],
φ_z	start of combustion [°CA],
$\Delta\varphi_s$	total combustion duration [°CA],

Subscripts

d	inlet system,
w	exhaust system.

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