

Krzysztof BRZOZOWSKI  
Jacek NOWAKOWSKI

## TOXICITY OF EXHAUST GASES OF COMPRESSION IGNITION ENGINE UNDER CONDITIONS OF VARIABLE LOAD FOR DIFFERENT VALUES OF ENGINE CONTROL PARAMETERS

### TOKSYCZNOŚĆ SPALIN SILNIKA O ZAPŁONIE SAMOCZYNNYM W WARUNKACH ZMIENNEGO OBCIĄŻENIA DLA RÓŻNYCH WARTOŚCI PARAMETRÓW REGULACYJNYCH\*

*This work presents a procedure leading to empirical identification of the dependency of smoke level and emission of harmful compounds on selected engine control parameters in a compression ignition engine. In the course of experiments identification of emission of nitrogen oxides, carbohydrates, carbon oxide and smoke level of exhaust gases was carried out, depending on: rotational speed, fuel amount, exhaust gas recirculation factor and injection timing. Using artificial neural networks has been proposed to generalize the results of experiments. The computed values of coefficients used to evaluate approximation errors and prediction of smoke level and emission of harmful compounds confirm effectiveness of the proposed method of generalizing the identification procedure.*

**Keywords:** *compression ignition engine, engine control parameters, emission of harmful compounds.*

*W pracy przedstawiono postępowanie prowadzące do eksperymentalnej identyfikacji zależności zadymienia i emisji związków szkodliwych od wybranych parametrów regulacyjnych silnika o zapłonie samoczynnym. W ramach badań przeprowadzono identyfikację emisji tlenków azotu, węglowodorów, tlenku węgla oraz zadymienia spalin w zależności od: prędkości obrotowej, dawki paliwa, stopnia recyrkulacji spalin i kąta wyprzedzenia wtrysku. Do uogólnienia wyników badań eksperymentalnych zaproponowano wykorzystanie sztucznych sieci neuronowych. Obliczone wartości wskaźników wykorzystanych do oceny błędów aproksymacji oraz predykcji zadymienia i emisji związków szkodliwych spalin potwierdzają skuteczność zaproponowanej metody uogólnienia badań identyfikacyjnych.*

**Słowa kluczowe:** *silnik o zapłonie samoczynnym, parametry regulacyjne, emisja związków szkodliwych.*

#### 1. Introduction

Development of piston combustion engines is currently determined to a large extent by actions aimed at limiting environmental impacts of their usage. This direction of research makes fulfilment of future requirements on emission of harmful compounds in exhaust gases as well as fuel consumption a necessity. Introduction of electronically controlled high pressure injection systems enabled fulfilment of existing legal requirements and improvement of algorithms controlling these systems will enable further decrease of negative impact on the natural environment. It is therefore an important research problem to develop suitable (optimal) algorithms for controlling engine operation under variable conditions of usage taking into account basic engine control parameters, such as [12, 15, 19]:

- rotational speed,
- fuel amount, divided and injection pressure,
- injection timing,
- exhaust gas recirculation factor.

In the case of compressor supercharged engines the control algorithms may also take additional parameters on input, such as [12, 21]:

- pressure of load in the intake manifold,
- temperature of load in the intake manifold.

The standard procedure in order to define the engine control algorithm includes experimental studies upon which so called discrete control maps are determined. Having been input to the controller, for given ranges of rotational speed and load these maps define the values of other control parameters and correction coefficients for transient states [17]. Such approach though leaves a possibility to apply more precise control based on continuous dependencies, i.e. without averaging experimental results for ranges of rotational speed value and range of load value given a priori. Such task had already been accomplished by the authors in papers [6, 13] among others. In the context of implementing control accounting for emission of harmful compounds identification of engine exhaust gases toxicity under conditions of variable load for arbitrary technically admissible

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values of control parameters is a basic element in designing suitable algorithms.

Similar problems related to searching for continuous approximations of emission were treated among others in papers [7, 8, 9, 10, 11, 16, 20]. In [9] the authors used a neural network of a simple architecture for modeling emissions of particulate matter, presenting the results as an approximating surface for selected ranges of values of rotational speed and torque. Smoke level modeling using neural networks was also dealt with by the authors of [10], mapping the smoke levels in particular modes of the ECE-R49 test. Neural networks for prediction of emission of exhaust gases from diesel-powered engine, biodiesel and blends of both fuels was proposed in [7]. However, experimental studies were carried out only for one selected point corresponding to engine operation at full load at a speed of 1400 rpm, which were then used both in the learning process and verification of the neural network. The authors used the neural network to determine the emission for blends of diesel and biodiesel varying in percentage. Similar problem was considered in [8], doing research for maximum load at different rotational speeds. In turn, in the paper [16] emission from the engine using neural networks depending on the compression ratio, the percentage of biodiesel and injection timing was modeled. Presented results were limited only to the conditions corresponding to full load. In [20], the last one of the previously mentioned works, the neural network was applied to modeling torque, fuel consumption and emission of exhaust gases of compression ignition engine fueled doubly by diesel and CNG. Data for network training were obtained only under conditions of maximum load at a given rotational speed. The problem of modeling emission using artificial neural networks was also the subject of paper [11], again only under conditions of maximum load at a given rotational speed. A common feature indicated by the authors of cited works is the conclusion that neural networks reproduce with sufficient accuracy the emission of harmful compounds in exhaust gases thus providing an alternative to full, time-consuming experimental studies.

The paper presents an own method of identifying the dependency between emission and values of particular control parameters as well as a way of generalizing them using artificial neural networks. In this extent the present work comes as a supplement and expansion upon concepts described in [18].

## 2. Summary of identification experiments

Identification experiments searching for dependency between emission of nitrogen oxides, carbohydrates and carbon oxide and the values of control parameters were carried out for an compression ignition engine, dedicated and used for propelling automobiles, whose technical details are laid out in Table 1.

Tab. 1. Technical details of the engine

Engine	CI 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 <sup>3</sup>
Compression ratio	16.8
Maximum power	55.2 kW / 4000 rpm
Maximum torque	190 N·m / 1500 rpm

Research was conducted on a dynamic engine test stand consisting of the following devices:

- dynamometric brake of AVL Dynoexact APA 202 type,
- control system AVL PUMA OPEN 1.3,
- stand control panel AVL EMCON 400.

Emission of harmful components of the exhaust gases was registered using an AVL CEB 200 set of analyzers equipped with CLD, HFID and NDIR analyzer modules and to measure smoke level of exhaust gases a filtration opacimeter of AVL 415S was used.

Realization of set forth identification experiments required varying standard engine operation parameters. Within the present work identification of emission of nitrogen oxides, carbohydrates, carbon oxide and exhaust gases smoke level was performed depending on: rotational speed, fuel amount, exhaust gas recirculation factor and ignition timing, whereas varying the three latter parameters required alteration of engine controller software which was done using the INCA V6.2 software and a reprogramming device ECU - ETAS ES590. The range of identification experiments carried out is shown in fig. 1.

It should be underlined here that in the entire range of realized experiments shown in fig. 1 the fuel amount was supplied divided into a constant initial amount independent of the point of engine operation and a variable main amount. For the standard algorithm of controlling injection amounts in the tested engine contains different strategies of injection sequence depending on the point of engine operation. This renders unambiguous identification of emission of nitrogen oxides, carbohydrates, carbon

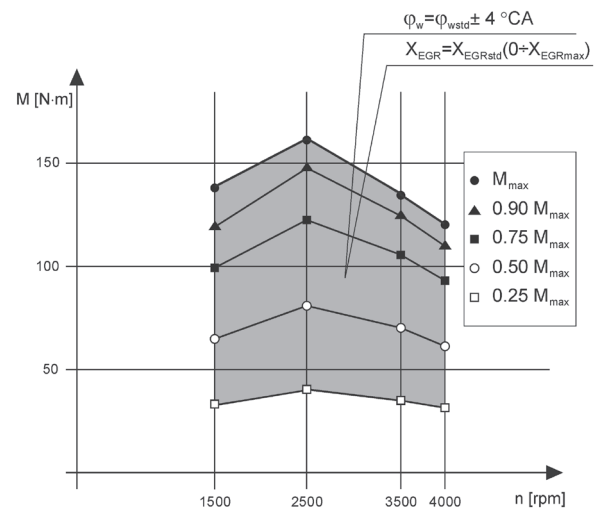


Fig. 1. Plot of the range of identification experiments

oxide and smoke level of the exhaust gases depending on the engine control parameters impossible.

The next stage of identification work encompassed generalization of results of engine tests for arbitrary technically admissible values of control parameters. Realization of this stage required formulating an appropriate approximation task of a multivariate function. Two approaches are possible here:

- approximation for a form of approximation function given a priori whose coefficients are determined by means of the least squares method,
- approximation by means of feedforward artificial neural networks with radial or sigmoidal neuron activation functions.

The first of the mentioned approximation methods was used among others in the paper [1] assuming a polynomial of the form:

$$F^*(\mathbf{x}) = \sum_{i_1=0}^{n_1} \dots \sum_{i_j=0}^{n_j} \dots \sum_{i_r=0}^{n_r} a_{i_1, \dots, i_j, \dots, i_r} x_1^{i_1} \dots x_j^{i_j} \dots x_r^{i_r} \quad (1)$$

where:  $a_{0, \dots, 0, \dots, 0, \dots, 0}$ ,  $a_{n_1, \dots, n_j, \dots, n_r}$  - polynomial coefficients,  $n_1, \dots, n_r$  - integer and non-negative maximum powers of corresponding elements of the vector  $\mathbf{x}$  of control parameters.

The polynomial (1) on applying larger exponents enables obtaining a very good fit to test results. Its disadvantage however lies in the strongly local character of the fit and consequently weak generalization properties outside of the closest neighbourhood of the approximation nodes. Therefore in the papers [12, 13] approximations of the results of toxicity tests were realized using power functions,

$$F^*(x) = \alpha_0 x_1^{\alpha_1} \dots x_j^{\alpha_j} \dots x_r^{\alpha_r} \quad (2)$$

where  $\alpha_0 \div \alpha_r$  are coefficients with real values.

These functions, although worse fitting at approximation nodes than polynomials, ensure acceptable generalization properties. Modifications of power functions of the form (2) were also used, e.g. in [2] introduction of a constant term was proposed in order to ensure non-negativity of the function on the entire domain of arguments:

$$F^*(\mathbf{x}) = \alpha_0 x_1^{\alpha_1} \dots x_j^{\alpha_j} \dots x_r^{\alpha_r} + \alpha_{r+1} \quad (3)$$

The second of the abovementioned methods using the means of artificial intelligence does not require giving a priori the form of the approximation function. This is the path chosen for the present work.

### 3. Approximation using feedforward artificial neural networks

For generalizing of the results of identification experiments feedforward artificial neural networks may be used with an architecture featuring so called hidden layer or layers. Authors have already in their earlier papers [3, 4, 5, 6] employed artificial neural networks in the approximation task of experimental results of emissions with an activation function on one or multiple neurons in the output layer. In emission approximation tasks it means that on the output of the network there appeared a single signal (when the network served to approximate the emission of one component of the exhaust gases) or multiple signals in leveraging a single neural network to approximate the emission of all components analyzed. Summary of approxi-

mation errors presented e.g. in [4], including their comparison to approximation errors when using power functions [2, 3], confirms their usefulness in approximation tasks of emission of harmful compounds in exhaust gases. Therefore in the present paper artificial neural networks with a sigmoidal neuron activation function in unipolar form has been used to generalize the results of identification:

$$f(\mathbf{w}^t \mathbf{z}) = \left[ 1 + e^{-\mathbf{w}^t \mathbf{z}} \right]^{-1} \quad (4)$$

where:  $\mathbf{w}$  - vector of weights on neuron's input connections,  $\mathbf{z}$  - vector of input signals to the neuron.

Assuming a single neuron in the output layer the value of the output signal for a last hidden layer of  $k$  elements is calculated as:

$$F^*(\mathbf{x}) = f\left(\sum_{i=1}^k w_i \cdot z_i\right) \quad (5)$$

Network learning, which consists in modifying the weights of individual connections between the neurons forming the network, was performed until the mean relative error for the entire training set has reached at least the expected value. For generalization of the results of identification experiments using four networks with general architecture as in fig. 2 was proposed.

The networks proposed in the current paper have four varia-

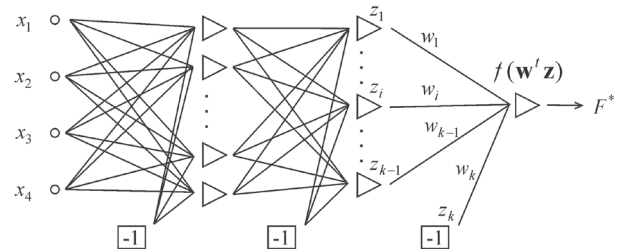


Fig. 2. General architecture of the neural networks used in the approximation task

ble signals on input corresponding to elements of the vector  $\mathbf{x}$  of control parameters and one constant input and on output just one signal corresponding to the emission of a given compound. The networks were trained till the mean relative approximation error for each component of the exhaust gases reached a value below 10% both in the training and verifying set for the ability to generalize the responses of each of the four networks.

For training the networks the momentum method was used with incremental updating of weights, i.e. in step  $n + 1$  of network learning the weights were modified according to the formula [14]:

$$\mathbf{w}^{(n+1)} = \mathbf{w}^{(n)} - \beta^{(n)} \nabla E(\mathbf{w}^{(n)}) + \delta(\mathbf{w}^{(n)} - \mathbf{w}^{(n-1)}) \quad (6)$$

where:  $\beta$  - learning coefficient,  $E$  - goal function in the form of mean square error of network's response relative to the values expected for a given training vector,  $\nabla E(\mathbf{w})$  - gradient vector of the goal function,  $\delta$  - moment coefficient from the interval [0,1].

In the learning process a random choice of weights was used after every iteration of network training and random determination of training patterns. If for a given network architecture after applying many iterations the assumed value of the mean relative error wasn't reached, the architecture was modified.

As the result of the described scheme of action for each compound the minimal network architecture was found enabling approximation of emission, in each case requiring two hidden layers, albeit with different numbers of neurons in particular layers. Summary of information about the resultant architectures of the neural networks and values of coefficients used for evaluation of approximation and prediction errors are presented in table 2.

Figure 3 shows a comparison of smoke levels and emissions of the compounds concerned obtained as the responses of

artificial neural networks ( $F^*$ ) for control parameters constituting input signals from the training and verifying sets related to the values observed experimentally ( $F$ ).

The values of resulting approximation and prediction errors presented in Table 2 confirm effectiveness of the proposed method of generalizing identification experiments in the domain of mapping toxicity and smoke level of exhaust gases. Mean relative errors of both the approximation of data from the training set and the prediction in the case of the verifying set do not exceed 10%.

Tab. 2. Architecture of neural networks and values of coefficients used for evaluation of approximation error in the training set and prediction of error in the set used for the verification process

	CO	HC	NO <sub>x</sub>	D
<i>Architecture</i>				
The number of neurons in the first hidden layer	7	5	4	9
The number of neurons in the second hidden layer	5	4	3	9
<i>Evaluation of approximation error (training set)</i>				
Average relative percentage error	8.48	8.98	8	9.85
Median of average relative percentage error	5.82	6.71	6.50	6.56
Coefficient of determination	0.979	0.976	0.986	0.991
<i>Evaluation of approximation error (verifying set)</i>				
Average relative percentage error	9.82	9.55	6.79	7.92
Median of average relative percentage error	7.24	7.33	6.86	6.00
Coefficient of determination	0.983	0.983	0.972	0.97

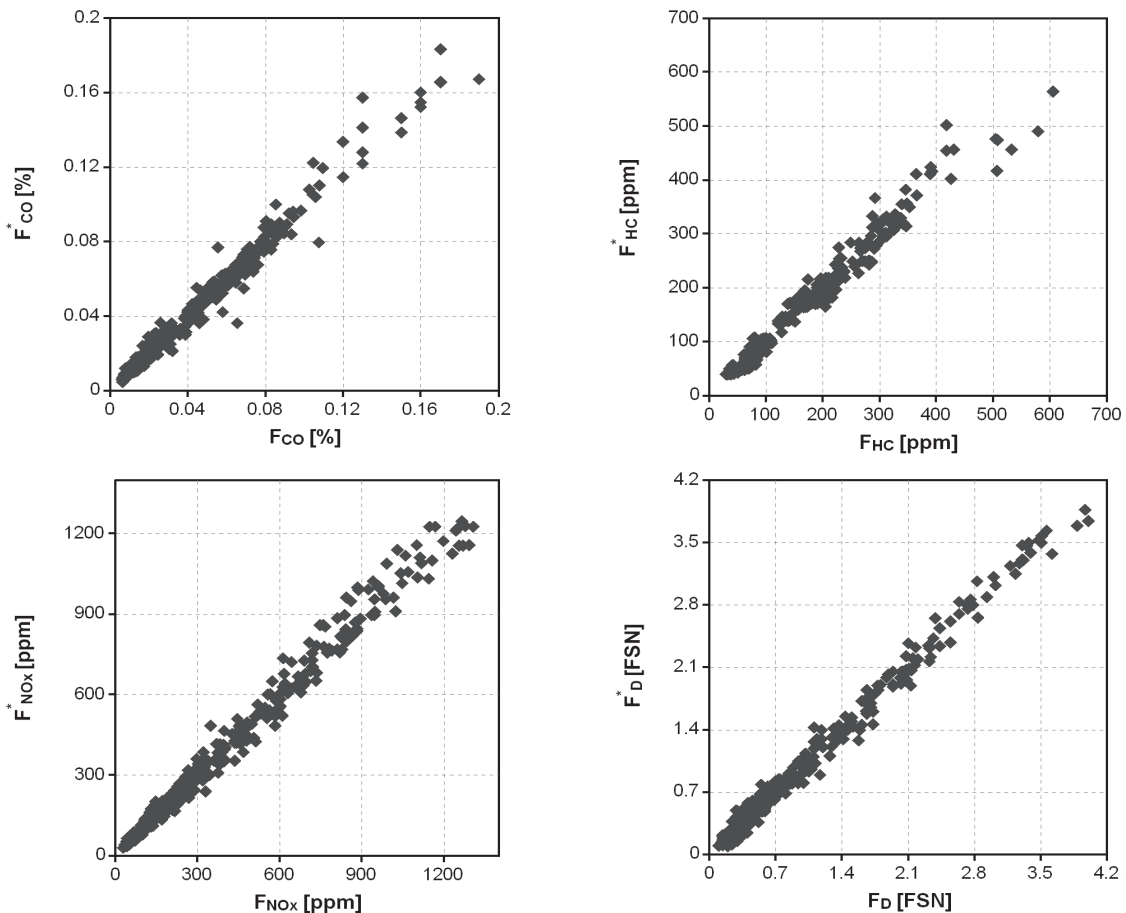


Fig. 3. A comparison of emissions of the compounds concerned and smoke levels obtained as the responses of artificial neural networks ( $F^*$ ) related to the values observed experimentally ( $F$ )



4. Conclusion

The identification procedure presented in the current work is one of the stages in designing algorithms for controlling the control parameters in order to limit smoke level and emission of harmful compounds in exhaust gases. The obtained surfaces

presenting the approximated values of the results of experimental research of smoke levels and emission of harmful compounds for two selected rotational speeds and two values of load are shown in fig. 4 and 5. Markers visible on the surfaces present the discrete values obtained in the course of identification experiments.

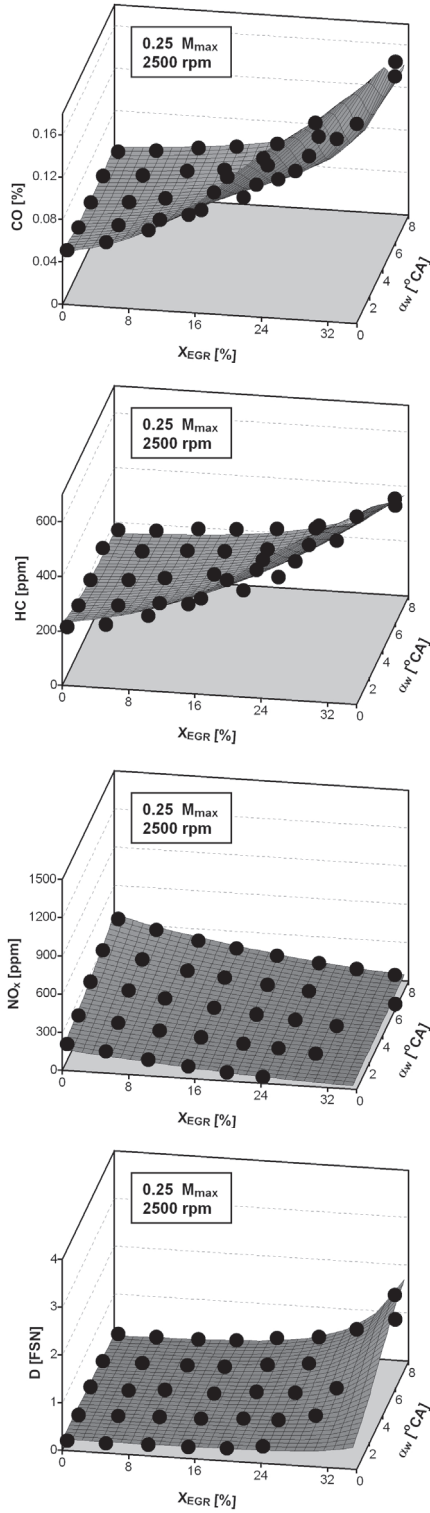


Fig. 4. Surfaces approximating smoke level and emission of harmful compounds in exhaust gases determined by using artificial neural networks for rotational speed 2500 rpm and load 0.25 M<sub>max</sub>

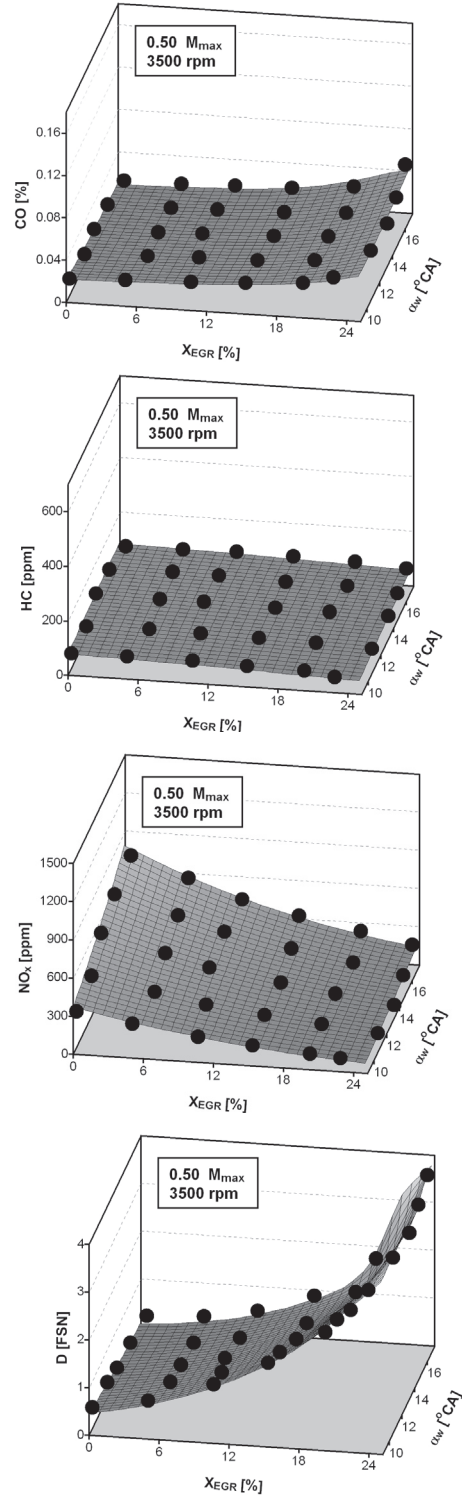


Fig. 5. Surfaces approximating smoke level and emission of harmful compounds in exhaust gases determined by using artificial neural networks for rotational speed 3500 rpm and load 0.5 M<sub>max</sub>

The target realization of the task of emission control simultaneously ensuring sustainment of traction parameters requires additionally formulating a model of the working cycle and solving an optimization task by means of appropriate choice of values of control parameters. Methodology of the action is schemed in fig. 6.

It is worth noting that in the presented scheme of action the approximation task would be formulated also in relation to the parameters of a theoretical-empirical model of a working cycle of a CI engine. Authors plan to employ artificial intelligence methods in this case to realize it as well.

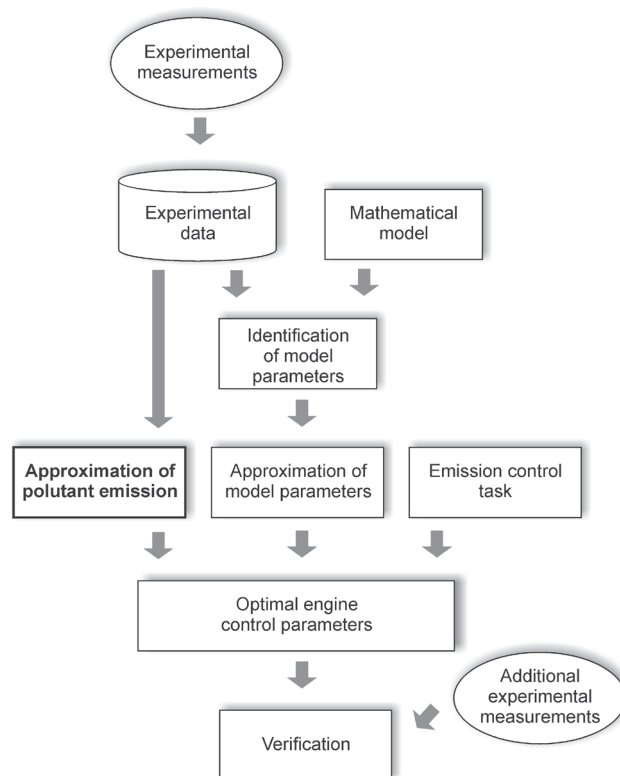


Fig. 6. Scheme of methodology of action aimed at formulating and solving the task of emission control

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**Dr hab. inż. Krzysztof BRZOWSKI, prof. ATH**

Department of Transport and Applied Computer Science  
University of Bielsko-Biała  
Ul. Willowa 2, 43-309 Bielsko-Biała, Poland  
e-mail: kbrzozowski@ath.eu

**Dr hab. inż. Jacek NOWAKOWSKI, prof. ATH**

Department of Combustion Engines and Vehicles  
University of Bielsko-Biała  
Ul. Willowa 2, 43-309 Bielsko-Biała, Poland  
E-mail: jnowakow@ath.bielsko.pl

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