MODELLING OF THE CAR ENGINE CHARACTERISTICS USING ARTIFICIAL NEURAL NETWORKS

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Summary

The complexity of changes and processes occurring in a combustion engine leads to a situation when literature contains numerous mathematical models describing only selected aspects of the engine operation. Due to multidimensional and nonlinear types of the engine characteristics, as well as the degree of complexity and only partial depicting of particular interrelations, their usability is limited. Tests carried out by means of a digital simulation based on an analysis of static characteristics of the engine, are one of the methods used to solve that type of problem in the early phase of a power transmission system designing. This method enables, among others, determination of fuel consumption and engine torque depending on a selected operation point. Methods based on approximation and adaptation properties of artificial neural networks are used in innovative solutions. Authors of this paper prove that it is possible to use artificial neural networks to predict the engine characteristics with the use of Matlab software.

Keywords: neural networks, combustion engine characteristics, fuel consumption, driving cycle

MODELOWANIE CHARAKTERYSTYK SILNIKA SAMOCHODU Z WYKORZYSTANIEM SZTUCZNYCH SIECI NEURONOWYCH

Summary

Złożoność zmian i procesów zachodzących w silniku spalinowym prowadzi do sytuacji, w której literatura terenowa zawiera liczne modele matematyczne opisujące tylko wybrane aspekty pracy silnika. Ze względu na wielowymiarowość i nieliniowość charakterystyk silnika, a także stopień ich złożoności i jedynie częściowe obrazowanie poszczególnych zależności, użyteczność tych charakterystyk jest ograniczona. Testy przeprowadzone za pomocą cyfrowej symulacji opartej na analizie statycznej charakterystyk silnika są jedną z metod rozwiązywania tego typu problemów we wczesnej fazie projektowania układu napędowego. Metoda ta umożliwia między innymi określenie zużycia paliwa i wielkości momentu obrotowego silnika w zależności od wybranego punktu roboczego. Metody oparte na właściwościach przybliżających i adaptacyjnych sztucznych sieci neuronowych są stosowane w innowacyjnych rozwiązaniach. Autorzy niniejszej publikacji wykazują możliwość wykorzystania sztucznych sieci neuronowych do przewidywania charakterystyki silnika przy użyciu oprogramowania Matlab.

Słowa kluczowe: sieci neuronowe, charakterystyki silnika spalinowego, zużycie paliwa, cykle jezdne

1. INTRODUCTION

Correct preparation of engine characteristics considering its optimal efficiency, thus elementary fuel consumption and torque, requires carrying out relevant and time-consuming stand tests. Great complexity of an engine, where many mechanical and thermodynamic phenomena take place, hinders simple determination of occurring interrelations as the engine is in no way a stationary object. Testing of car power transmission systems by means of digital simulation or synthesis of its controlling algorithms requires a precise mathematical description of the driving unit [4]. General engine characteristics, which are depicted with the use of a numerical matrix including points of an equable network covering the engine operation field, are used in simulation tests. These are usually characteristics of torque and fuel consumption per time unit expressed as a function of crankshaft rotational speed and throttle inclination or partial vacuum in the intake manifold. There is a method that uses artificial neural networks for depicting the engine characteristics. The possibility of using artificial neural networks to predict selected operating indicators was examined in the study. Engine operating indicators obtained with the use of artificial neural networks were compared to indicators acquired by means of interpolation of traditional engine matrix characteristics, which uses "Lookup Table" matrix reading technique. Engine operating indicators obtained with the use of a digital simulation were compared to actual measurements acquired during stand tests of a spark ignition engine.

2. GENERAL ENGINE CHARACTERISTICS

The problem brought up in the study was examined using the characteristics of a spark ignition (SI) engine. Basic parameters of the tested engine were included in Table 1. Measurements were taken at a test stand [5, 6] by determining speed characteristics for 15 arbitrarily assumed values of throttle inclination.

Table 1. Engine technical parameters

Parameter	Volume
Cubic capacity (cm^3)	1598
DIN maximum power (kW)	59
Maximum power rotational speed (rotation/min)	5200
DIN maximum torque (N · m)	125
Maximum torque rotational speed (rotation/min)	3200

Every partial speed characteristic consists of 11 points where the engine operating indicators were measured and recorded for 10 seconds after a 30 second stabilization period. The engine speed characteristics were recorded every 500 RPM in the first stage. General characteristics, stored in a computer memory in the form of a matrix, were completed as a result of approximation of the engine speed characteristics, described in details in the literature.

a)

b)

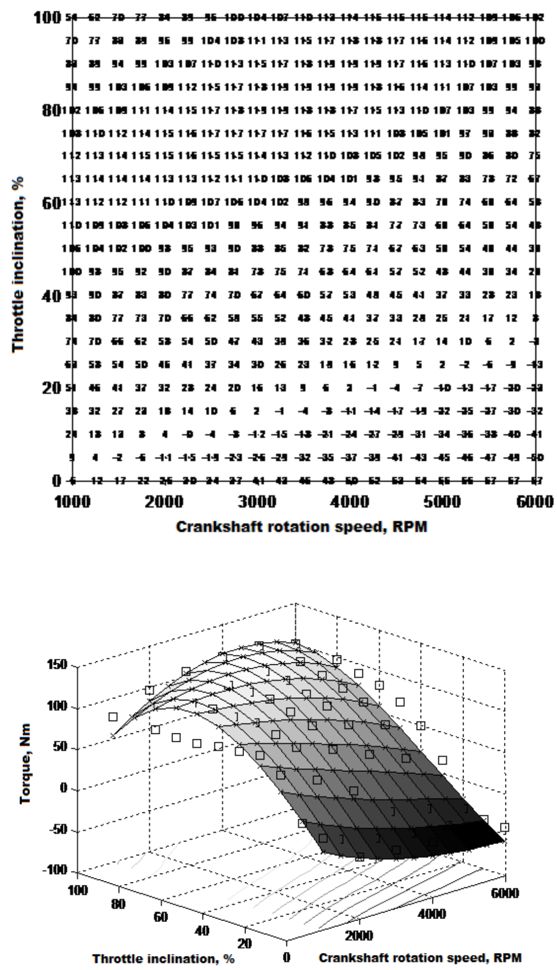


Fig. 1. Characteristics of engine torque as a function of rotation speed and a throttle inclination: a) presented as a numerical network of equidistant points covering the engine operation field, b) as a map

A result matrix of 101 × 101 elements dimensions, for rotation speed changes interval 1000 ÷ 6000 and a throttle inclination interval 0 ÷ 100 was assumed in the tested case. Appropriate determination of the precise claimed value of engine torque (Fig. 1) or fuel stream (Fig. 2) requires the use of numerical methods in order to interpolate values occurring among the matrix points. Every matrix point contains values corresponding to coordinates of the engine operation point:

- crankshaft rotation speed [rotation/min],
- throttle inclination [%],
- torque [Nm] or fuel stream [g/s].

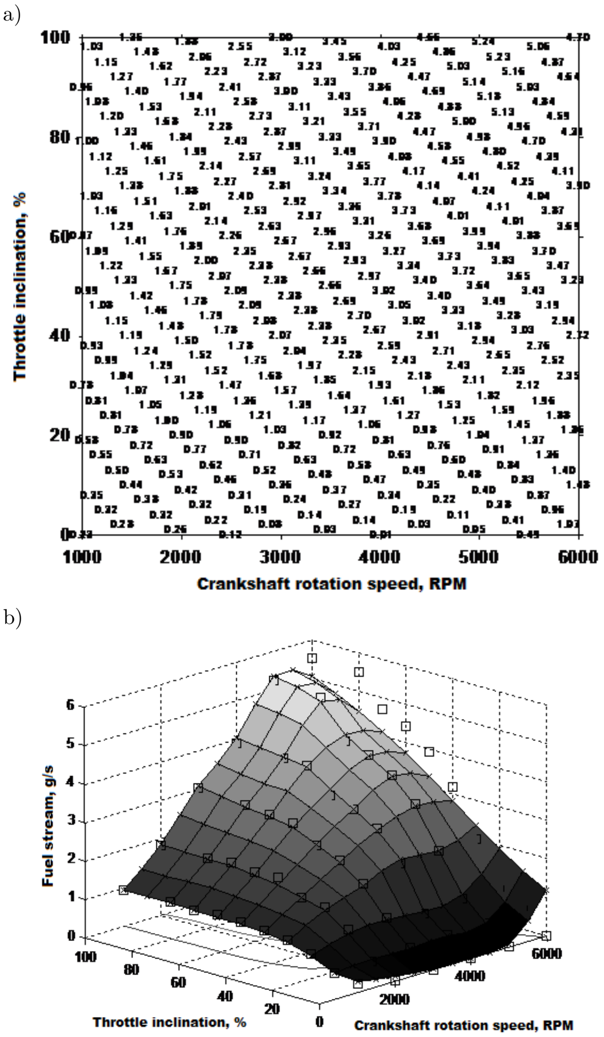


Fig. 2. Characteristics of fuel stream as a function of crankshaft rotation speed and throttle inclination: a) presented as a numerical network of equidistant points covering the engine operation field, b) as a map

The "Lookup Table" reading technique is commonly used in the first stage of the readout. It uses linear interpolation. The principle of this numerical operation is shown in figure 3. A network point is being determined for which the assumed value of throttle inclination and crankshaft rotation speed are the closest to the value of the constant matrix network point, for which the claimed engine parameters, such as torque, fuel stream, etc. are read. After such a point has been found, its position is being set as an element of the network [i, j]. Simultaneously other elements of the network [i + 1, j], [i, j + 1] and [i + 1, j + 1] are being determined. Apart from a complicated and time-consuming process of the characteristics preparation, such a way of recording of the engine characteristics matrix additionally requires the use of "Lookup Table" technique for reading selected operating indicators out of this matrix.

However, preparing the engine characteristics with the use of artificial neural networks is a new method used in simulation testing and consists in training artificial neural networks directly with measurements results. This assumption follows from the characteristic properties of the neural network, especially from the ability of representing strongly nonlinear, multidimensional correlations. Such complicated correlations occur in real driving conditions. By this means the 'feed-forward back propagation' type of artificial neural networks out of the Matlab calculation programs library was chosen to be used in this research (Fig. 4).

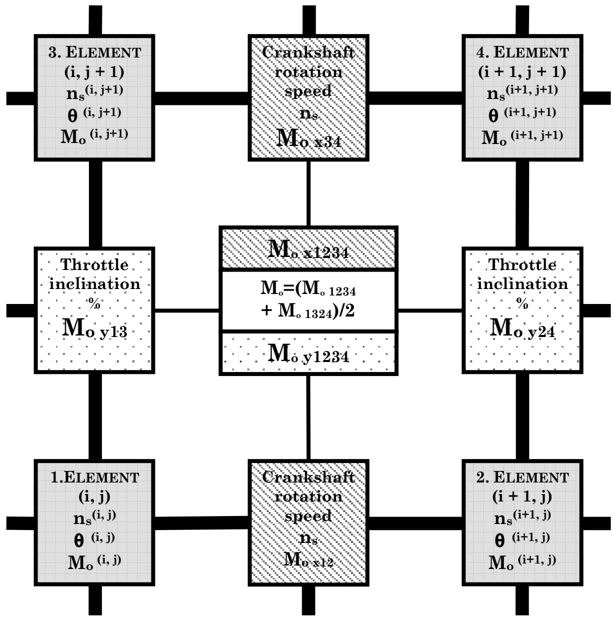


Fig. 3. The principle of torque interpolation for any chosen crankshaft rotation speed and throttle inclination: the grey fields mark the knots of the mesh, the dotted and lined fields mark the results of interpolations and the white field marks the final result

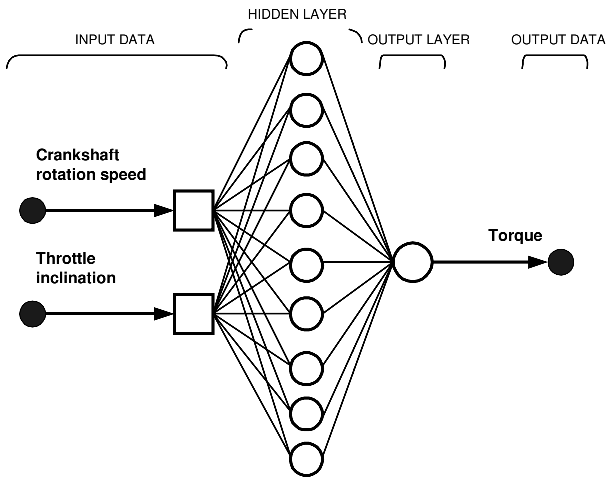
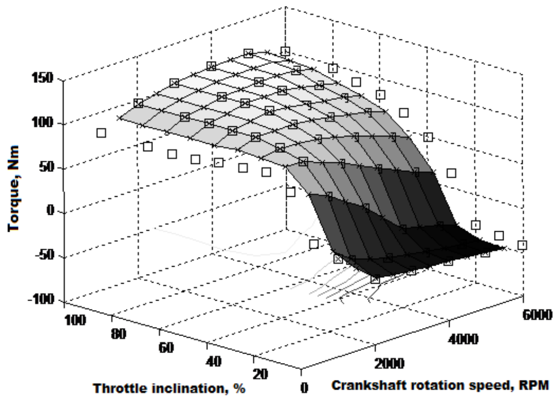


Fig. 4. The structure of used feed-forward back propagation neural network with the dimensions of 2x9x1neurons

The target network structure is shown in fig. 4. It includes two inputs, one output and one hidden layer consisting 9 neurons. For neuron training, the Levenberg-Marquardt algorithm was used with a considered aim of training. In this way, the number of neurons was sought to reach the assumed aim of the training accuracy with the minimum number of neurons, which was finally set to 9. Further increasing of the neurons number did not improve the accuracy of the network and the engine characteristics were shown in fig. 5. In this figure the points obtained directly from the measurements and the corresponding characteristics made using artificial neural networks are shown. For such a mapped characteristic, a relative error was calculated using formula (1).

The crankshaft rotation speed and the throttle inclination were chosen for the neural network input data; in the real system these are the main parameters describing the engines working conditions.

a)



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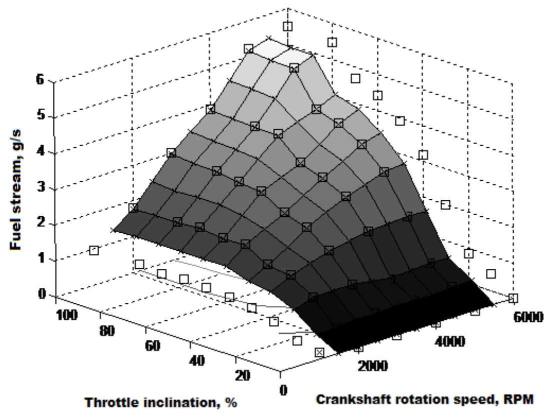
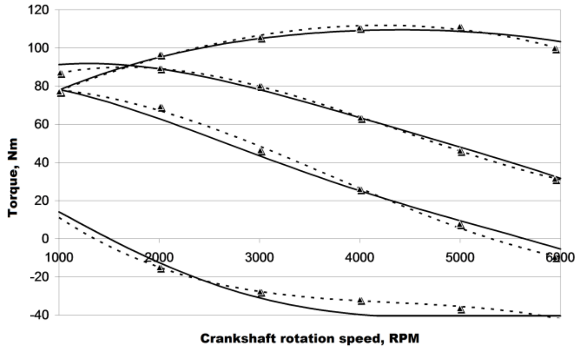


Fig. 5. Matrix characteristics of an engine generated with the use of artificial neural networks of: a) engine torque, b) fuel stream

The designed neural networks were trained on the basis of measurement data gathered during measuring of speed characteristics. Qualitative comparison of selected engine operating indicators during the work of an iteration program and of the artificial neural network was presented in fig. 6.

Measurement points were marked with triangles in fig. 6. Both the iteration process and the neural model operation take place near the measurement points. The quality of depicting the engine characteristics with the use of artificial neural networks is highly dependent on parameters used in the process of the network training. Networks containing a large number of neurons in the hidden layer and of low spread value, are characterized by fidelity of showing the measurement data. However, such networks easily oscillate during work of a neural engine model, whereas there is a need for reading of the engine operating indicators for non-total values of throttle inclination or the crankshaft rotation speed.

a)



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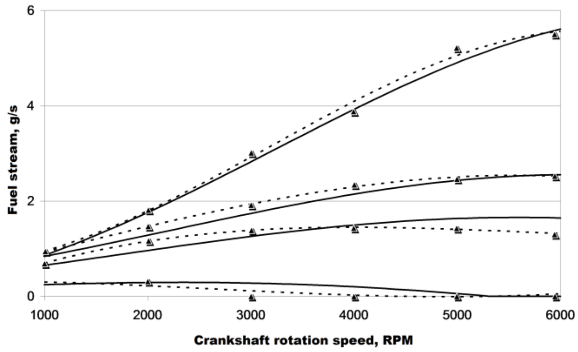


Fig. 6. Partial characteristics of the SI engine for: a) engine torque, b) fuel stream

The relative error was calculated using formula (1):

$$\Delta x = \frac{\sum_{i=1}^{n}(x_p - x_s)^2}{\sum_{i=1}^{n}(x_p)^2} \qquad (1),$$

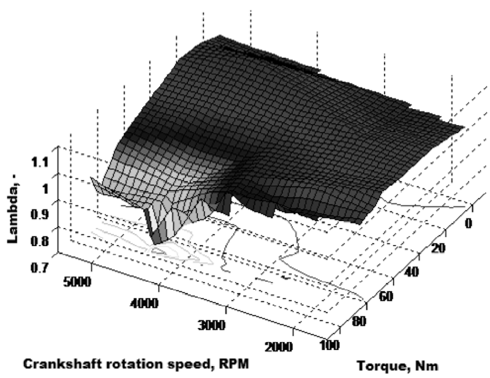
where:

x_p – result of the road test power measurement,

x_s – result of the simulation.

The calculated volume of the relative error according to the neural simulation of the engine torque and fuel steam was both lower than 1%. This can be the confirmation for the neural network usage in virtual engine characteristic preparing process.

a)



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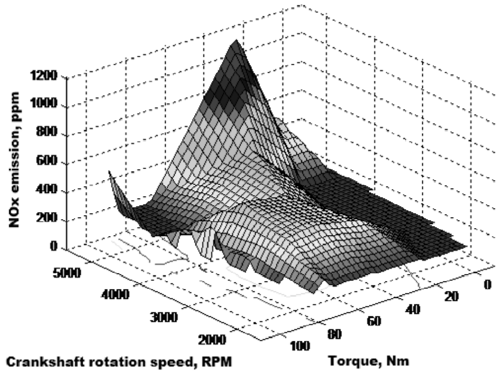

Fig. 8. Matrix characteristics of the SI engine generated with the use of artificial neural networks of: a) excess-air-ratio (lambda), b) NOx emissions

The artificial neural networks can also be used to prepare other engine characteristics, for instance: of excess-air-ratio or the toxic exhaust substances emissions. Examples of such characteristics obtained with a neural method are shown in fig. 8. In this case it is important for the graphs to match each other in some characteristic points or zones. According to the a) part of the fig. 8 at crankshaft rotation speeds between about 3500 RPM and 6000 RPM in high load conditions there is a zone of low lambda values, which shows the part of the characteristic where the air-fuel mixture was rich. In such conditions the mixture is burning in lower temperatures than at lean-burn, preventing the formation of NOx emissions. This fact is confirmed in the same zone of the b) part of the figure 8.

3. CONCLUSION

Presented diagrams and the error calculation results prove that it is a possible to use artificial neural networks to predict the engine operating indicators during a digital simulation. Moreover, they can also be used to depict the engine characteristics. The results obtained with this method have been remarkably consistent with the data derived from the measurements. The neural networks are an effective tool for such types of tasks and they successfully replace the "Lookup Table" technique of reading data out of the matrix.

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