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THE USE OF ARTIFICIAL INTELLIGENCE METHODS IN THE ANALYSIS OF THE RESULTS OF VEHICLE BRAKING DECELERATION TESTS IN THE DIAGNOSTICS OF THE BRAKING SYSTEM OF A MOTOR VEHICLE

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Abstract – The article presents the concept of using an artificial neural network to approximate the parameters describing the vehicle braking process, from the point of view of the application of this method in the diagnostics of the braking system. The artificial neural network of non-linear autoregression was used to approximate the dependence of the braking deceleration and the pressure in the braking system. The effectiveness of the neural network was checked depending on the number of neurons in its hidden layer and on the applied learning algorithm. The operation of the neural network was verified based on the actual braking processes of the Skoda Octavia, carried out with different dynamics, with different car weights and different tire inflation pressures. After verifying the neural network, it was used to approximate the braking deceleration values for the pressure values exceeding those present in the input data set. This action allows the analysis of the possibility of the vehicle obtaining a braking deceleration, which qualifies its braking system as efficient. Two concepts of using a neural network to solve this problem were analyzed. Conclusions related to the validity of the development of the discussed methods were drawn.

Key words – artificial intelligence, braking system, deceleration, diagnostics, motor vehicle

JEL Classification – C63, C67

INTRODUCTION

Diagnostics of the hydraulic braking system of the motor vehicle as a whole is not covered by modern on-board diagnostic systems. Only the mechatronic part of this system is controlled. In many modern vehicles, the mechatronic part consists of ABS / ESP systems, which are the so-called pending systems, i.e. systems operating periodically during the operation of the braking system. ABS / ESP systems are tested for electrical efficiency in the on-board diagnostic systems. The increasingly common hybrid and electric vehicles feature mechatronically controlled braking systems. In these systems, the controller, operating in the feedback loop, is responsible for the implementation of the current braking processes. In the on-board diagnostic systems of these systems, there is no control of the condition of their hydraulic and mechanical parts. The electrical efficiency of sensors and actuators is checked. Slight deterioration of braking efficiency in relation to technical efficiency, which may be a significant factor in emergency braking situations, is not signaled. At the same time, the development of the accuracy of the mechatronic control of the braking system means that slight weakening of the braking operation increasingly affects the effectiveness of the control algorithms implementation.

The operational processes of car braking are often short-term and gentle processes, with a change in the braking pressure to a limited extent. Therefore, the precise method of approximating the course of the dependence of the quantity constituting the braking excitation on the quantity constituting the response to this excitation will allow to increase the accuracy of diagnostics and to assess how the braking system would behave in its current state in emergency situations. Due to this fact, an attempt at such an approximation with the use of an artificial neural network was made in the paper. On the basis of the quantities describing the braking process of a vehicle with a braking system with a specific technical condition, it is possible to train the neural network so that it recognizes the response of the braking system in this technical condition to new values of inputs that do not occur in a given braking process. The resulting extension of diagnostic information contributes to the uniqueness of the assessment of the technical condition. The algorithm of this assessment is the next step, after the approximation presented in the paper, in the formulation of the diagnostic brake system monitor, using the artificial intelligence.

1. Literature background

The conducted analysis of the current state of knowledge allows us to conclude that neural networks are successfully used in the diagnosis of various technical objects and machine parts. An example is a gas turbine [8]. In work [8], machine learning algorithms and multi-layer, connected neural networks were used to predict the output pressure level from the compressor and predict its failures. Direct measurement of the outlet pressure is an expensive measurement due to the location of the sensor. This fact proves the undoubted advantage of the application of the discussed methods, which allow for its prediction on the basis of the values of the turbine operating parameters, the measurement of which is less difficult.

The vibration process is a phenomenon whose changes during the operation of various objects are symptoms of failures and wear. It was analyzed in [9-11]. The work [9] covers the problems of recognizing the type and determining the degree of operational damage to the gear transmission. These are, among others tooth breakage or fracture of the tooth foot. An analysis of statistical features of vibration waveforms was carried out with the use of a self-organizing Kohonen neural network and a multilayer perceptron. The paper [10] also deals with the problem of gears diagnostics, however, the possibilities of detecting chipping fatigue wear (the so-called pitting) were analyzed. For this purpose, the proprietary concept of an algorithm for the analysis of the raw acoustic emission signal was proposed. This algorithm used a one-dimensional convolutional neural network with an unsupervised learning algorithm. This algorithm used a sparse auto-encoder. The advantage resulting from the discussed method is the fact of automatic extraction of the characteristics of acoustic emission signals, indicating the occurrence of breaking wear, without the need to convert the signal to the frequency and time domain.

The work [11] uses the analysis of vibration signals to evaluate the valve clearance in the internal combustion engine of a motor vehicle. A three-axis acceleration sensor was used, mounted on the engine head. Measurement tests included engine operation at various rotational speeds and various loads. The vibration signals were parameterized. Three diagnostic models were used - the neural classifier, using the binary tree model, the k-nearest neighbors method and the unidirectional neural-multilayer perceptron. It had 3 outputs corresponding to the classification of the valve clearance as too small, optimal and too large. The best efficiency was ensured by the binary tree model, which was a combination of 3 trees that were specialized in the assessment of each of the three discussed valve clearance states.

A common feature of the technical objects used in the works discussed above is the fact that diagnostic symptoms manifest themselves in the form of changes in physical quantities, which are quantities that can be registered with the use of sensors generating electrical signals. The analysis of the diagnostic applications of artificial intelligence methods allows for the formulation of the main advantages of their application. They are: - it is not necessary to define the physical laws linking the defect with the corresponding change in the operating parameters of the facility, - no need to formulate a diagnosis by a service technician or diagnostician. The significance of the first of the presented advantages is visible in situations where it is not possible to determine the physical law linking the fault with the parameters of the device. This applies, for example, to a situation where changes in the geometrical features of a given object occur, due to cracks, the nature of which is different in different copies of a given object. In turn, the second of the mentioned advantages allows for the development of a diagnostic monitor, operating in real time, during the operation of the technical facility. The issue of developing such a diagnostic monitor for the vehicle braking system is particularly important due to its application in autonomous vehicles.

The analysis of works related to the use of artificial neural networks to solve problems similar to those presented by the author confirms the legitimacy of the attempt to use them to approximate the values describing the braking process of the vehicle in order to increase the effectiveness of the brake system diagnostics. In the work [1], a multilayer neural network with feedback was used to solve the optimization task. It consisted in determining the values of the braking moments of the vehicle wheels, which allow to ensure its stability during the maneuver of changing lanes from the surface with greater adhesion to the less grippy surface. A tree-structured vehicle model was formulated, consisting of elements with a certain number of degrees of freedom. The flexibility of the tire and suspension is reduced to the point of contact between the wheel and the road. The forces at this point were determined using the Duugoff-Uffelman model. The solution of the formulated task, carried out by means of a genetic algorithm, turned out to be too time-consuming to be used in the current control. However, the results of this algorithm were used as a training set for the neural network. This allowed for a reduction in the computation time. The computational methodology was verified by analyzing the displacement of the center of mass of the vehicle during a lane change, with the use of the determined braking torque values. The effectiveness of the artificial neural network was assessed as sufficient with the use of adequately accurate training data. In [2], the concept discussed in the previous work was applied to ensure the stability of emergency maneuvers of a multi-unit vehicle. A multilayer and radial neural network was used. Various methods of teaching the neural network were tested, with the Levenberg-Marquardt method being the most effective of them. Another application of the artificial neural network, related to the operation of the vehicle braking system, is presented in [3]. The artificial neural network was integrated with the proportional-integral controller in order to improve the effectiveness of the anti-lock braking system ABS. The neural network was used to determine the parameters of the proportional-integral controller. When the neural network was learned with the use of data related to various types of pavement, it ensured the effectiveness of the ABS controller in a wide range of road conditions.

In the work [4], the vibrations of wheels on the balancing stand were analyzed. The neural network compares them with the reference values, which allows the technical condition of the wheel rims to be assessed. Thus, data classification is made. This action was carried out by the author in [5]. A neural network was formulated, which mapped the model data (vehicle acceleration in three axes, wheel slip) on the basis of data obtained in the current processes of braking and acceleration of the vehicle. Model data came from the discussed road tests, carried out in winter conditions, with the use of winter tires with the appropriate inflation pressure. On the other hand, the data on the basis of which the model data was attempted came from road tests analogous to the standard road tests, however, carried out with the wrong inflation pressure in winter tires and with the use of summer tires with different inflation pressures. Inadequacy of the tires used together with inadequate pumping pressure resulted in the fact that the measurement data differed from the reference data. The greater the differences, the greater the error of the discussed mapping carried out by the neural network. Thus, it was possible to use the neural mapping error as an active safety diagnostic indicator related to the use of a type of tire suitable for road conditions with the appropriate inflation pressure. Another direction of work related to the use of artificial neural networks in vehicle diagnostics is the construction of on-board diagnostics systems, allowing for their universal application in various types of motor vehicles. This problem was addressed in [6], comparing the composition of neural networks of different types. Application directions, of particular importance nowadays, are the use of neural networks in diagnostics of electric propulsion systems and in on-board diagnostics of autonomous vehicles.

2. THE MODEL FORMULATION

The novelty of this work consists in the use network (directly and with the use of a formulated calculation loop) of a specific type of neural network for a specific application related to the approximation of the dependencies of the quantities describing the vehicle braking process. As the dependence of the response to the imposition of the braking process on the quantity that forces this process, the dependence of the braking deceleration (response to the excitation) on the pressure in the braking system (the quantity which forces braking) was selected. The paper [7] confirms the possibility of its determination in vehicle operation conditions and its use for current diagnostics of the braking system of a motor vehicle. This relationship directly influences the technical condition of the hydraulic braking system in the Skoda Octavia research vehicle.

In the case of vehicles with a mechatronically controlled braking system, it is possible to apply the approximation methodology formulated in the work, using an artificial neural network. However, it is necessary to replace the used dependence of the braking deceleration on the pressure in the braking system with another dependence, linking the imposition of the braking process with the response to this excitation. The choice of this dependence should result from the design of the mechatronically controlled braking system, which differs depending on the vehicle model.

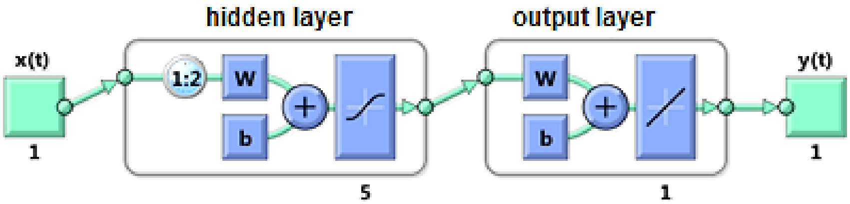
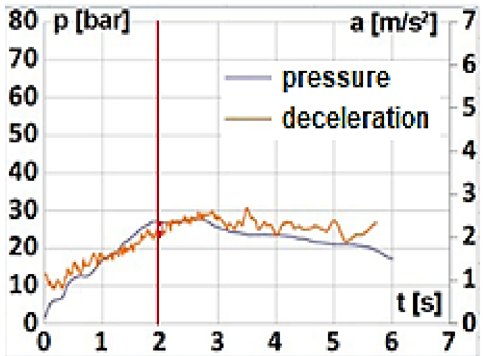


Fig. 1. Schematic representation of the used neural network

The above figure shows a diagram of the neural network used to approximate the course of the braking deceleration as a function of the pressure in the braking system. It is a two-layer network with a sigmoidal function of activating neurons in the hidden layer and a linear function of activating neurons in the output layer. The neural network maps the next pressure deceleration dependency point on the basis of the two previous points of this relationship. After it is mapped, the neural network maps the next data point using the data point resulting from the neural mapping in the previous step and the data point before it. This operation is performed for the entirety of the input data, so when, for example, we use a 100-point set as input, the neural network will return 98 points as approximation results, comparable with the reference input data. The input data was randomly divided into training, validation and test sets. After the learning process, the neural network was used to map the braking deceleration for new pressure values in the braking system, not present in the input data set. The analysis of the effectiveness of approximation of the deceleration-pressure relationship was carried out on the basis of the following research braking processes:

- process 1: Initial braking speed 50 km/h, additional test vehicle load 300 kg, tire inflation pressure 1.5 bar, intention to brake softly
- process 2: Initial braking speed 30 km/h, additional test vehicle load 300 kg, tire inflation pressure 1.5 bar, intention to brake softly
- process 3: Initial braking speed 30 km/h, no additional load on the test vehicle, wheel pumping pressure 2.0 bar, intention to intensive braking
- process 4: Initial braking speed 50 km/h, no additional load on the test vehicle, wheel pumping pressure 1.5 bar, intention of moderate-intensity braking, mileage with a defect introduced - brake fluid leakage in one of the brake circuits.

The test braking runs differed in conditions related to the condition of the vehicle. The lower pumping pressure of the wheels reduced the effects of the braking process forced by the driver. In turn, the increased load of the vehicle increased the drag force of its inertia. Increasing the initial braking speed increased the air resistance force acting on the braked vehicle. Thus, the conditions of reduced initial braking speed, low vehicle load and increased wheel pumping pressure were the conditions enhancing the effects of specific braking dynamics and thus causing a faster change in vehicle braking deceleration. Thus, they were conditions that increased the difficulty of approximating the deceleration-pressure relationship by a neural network using as the input data set the quantities derived from the braking processes with rapidly changing deceleration. In each of the runs, the pressure in the brake system was measured using a strain gauge system placed on the brake hoses and the linear speed of the car was measured using the Correvit optical head. The car speed signal was differentiated to obtain a braking deceleration.



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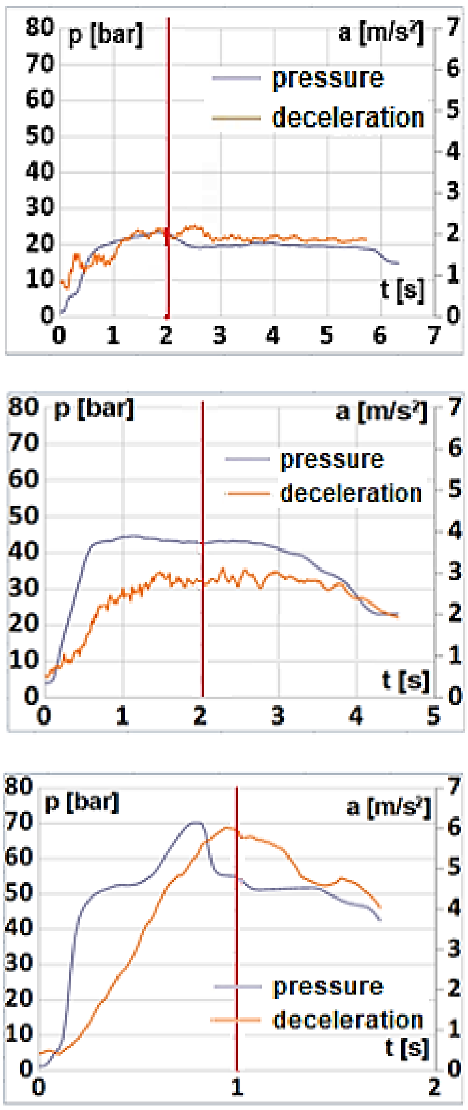


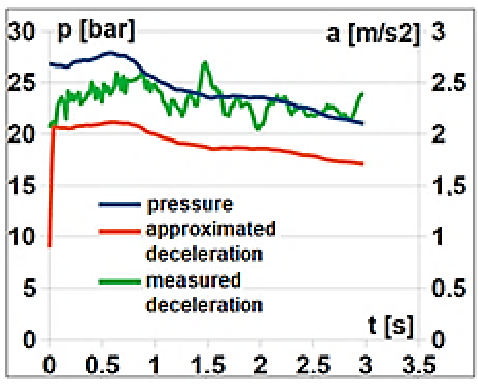
b)

c)

d)

Fig. 2. Time courses of the input data to the neural network and the data used for its verification in individual test braking runs: a) run 1, b) run 2, c) run 3, d) run 4

The above graphs show the time dependencies of the pressure in the brake system in the braking waveforms of the test vehicle used for the analysis. They were courses that differed in their conditions, including the dynamics of the temporal change of pressure in the braking system. The course shown in Figure 2 d is the braking course carried out with the defect - the braking pressure was limited to a value of a few bars in one of the circuits of the dual-circuit braking system of the test vehicle. The data shown in the above graphs were recorded with a time step of 0.02 seconds. The red lines on the graphs distinguish the input data for the neural network (on the left side of the red lines) and the data on the basis of which the mapping of the vehicle deceleration value was verified through the neural network (on the right side of the red lines). The data on the left-hand side of the red lines has been randomized into the training, validation, and test dataset in a 70/15/15 ratio. The neural network, on the basis of the discussed input data, maps the braking deceleration values for the pressure values on the right sides of the red lines. They are then compared with the Deceleration Pattern values (to the right of the red lines). Contrary to the nonlinear autoregression methods, we do not program the time change of the input quantities (pressures and corresponding deceleration values). However, due to the fact that the data reading frequency (50 Hz) is constant, it is included in the input data used, both the input and the pressure values for which the neural network maps the deceleration. The effect of a more intense change in time of data manifests itself in an increased dispersion of the measurement results, which results from the limited frequency of data readings by the measuring equipment. The greater dispersion of the measurement data, on the basis of which we enter the data for the neural network, deteriorates the unequivocal nature of the dependence of the braking deceleration on the pressure in the braking system, causing the increase in the difficulty of the neural network in mapping the braking deceleration value.



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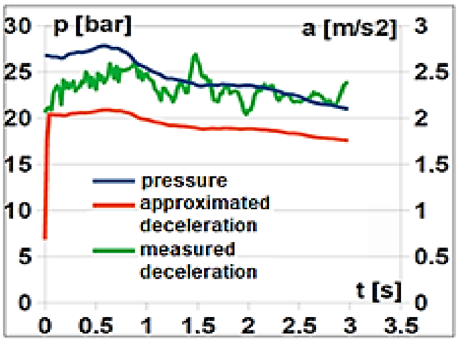

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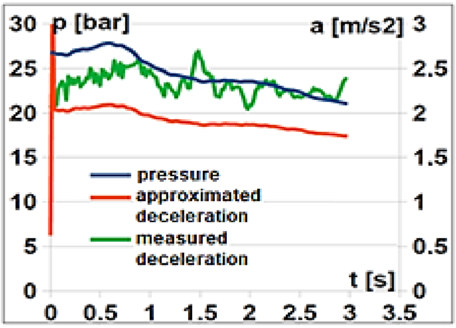

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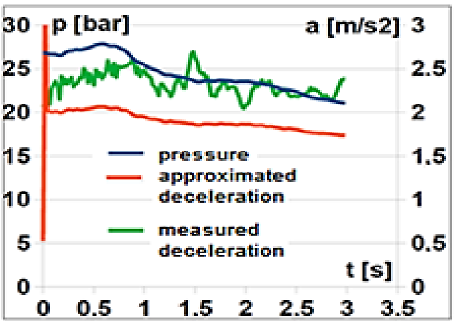

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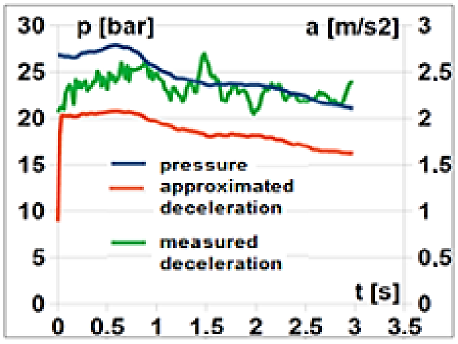

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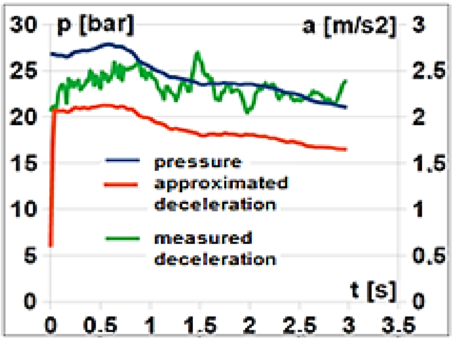


f)

Fig. 3. Results of the neural mapping of the deceleration for the test inhibition 1 run: a) Bayes regularization, 2 neurons in the hidden layer, b) Bayes regularization, 5 neurons in the hidden layer, c) Bayes regularization, 10 neurons in the hidden layer, d) Algorithm Levenberg- Marquardt, 2 neurons in the hidden layer, e) Levenberg-Marquardt algorithm, 5 neurons in the hidden layer, f) Levenberg-Marquardt algorithm, 10 neurons in the hidden layer

On the basis of the test braking process No. 1, which was characterized by the most established character of the increase in the deceleration value with the increase in the braking pressure (Fig. 2), the operation of the used neural network was verified with different numbers of neurons in the hidden layer and with the use of various network learning algorithms. The analyzed numbers of neurons in the hidden layer are 5 and 10. The Levenberg-Marquardt network learning algorithm and the Bayes Regularization algorithm were tested. The results of the neural mapping in each case along with the model deceleration values are shown in Figure 3. The input data in each case were the values of the brake system pressure and the car deceleration, located on the left side of the red line in diagram 2 a. On the other hand, the pressure values for which the neural network was to map the deceleration values (blue waveforms in Figure 3) are the pressure values presented on the right-hand side of the red line in diagram 2 a. The dependence of the braking deceleration on the pressure in the braking system, taking into account the deceleration values mapped by the operation of the neural network, in each of the cases shown in Figure 3 is characterized by a minimized dispersion in relation to the standard pressure-deceleration relationship. The values obtained by the neural mapping have a smaller dispersion than the test results that were used to verify the neural mapping process. The unambiguousness of the deceleration-pressure relationship is, from the point of view of brake diagnostics, an advantage of using an artificial neural network for its approximation. It favors the uniqueness of the diagnostic process. In order to compare the efficiency of the neural network in each of the cases presented in Figure 2, the values of the average error of the neural mapping were calculated, given by the formula:

$$\sigma = \frac{|a_{reference} - a_{obtained}|}{\max\left(a_{reference}, a_{obtained}\right)} \qquad (1)$$

where: σ- relative error of the neural mapping, - $a_{reference}$ - reference value of the braked deceleration of the car, - $a_{obtained}$ - value of braking deceleration of the car, resulting from the neural mapping.

The arithmetic mean values of the neural mapping error for each of the cases shown in Figure 2 were analyzed. The smallest value of the mean error of the neural mapping occurs for the course presented in Figure 3 b. It is approximately 0.17. All cases of applying the Bayesian Regularization algorithm are characterized by average neural mapping error values that are smaller compared to the waveforms using the Levenberq-Marquardt algorithm. For the waveforms presented in Figure 2 a and 2 c, they are respectively 0.17563 and 0.17628. The mean values of the neural mapping error in the case of the Levenberq-Marquardt algorithm are for the cases shown in Figure 2 c, 2 d and 2 e, respectively, 0.18252, 0.19169 and 0.19971. Thus, when this algorithm is used, increasing the number of neurons in the hidden layer causes a deterioration in the accuracy of the neural mapping. The use of 2 neurons in the hidden layer brought the most favorable results and as the number of neurons in the hidden layer increased, the neural network lost the ability to generalize, which resulted in a deterioration of the effectiveness of its operation. In the case of using the Bayesian Regularization algorithm, the differences in the mean value of the neural mapping error between individual cases are much smaller, which confirms the smaller impact of the number of neurons in the hidden layer on the effectiveness of the neural mapping of the braking deceleration value. In this case, the best efficiency was achieved for the average of the analyzed numbers of neurons in the hidden layer. Thus, it was a compromise between ensuring the network's generalizability (lower numbers of neurons in the hidden layer) and the sensitivity of the network to specific cases of training data compilation (greater numbers of neurons in the hidden layer).

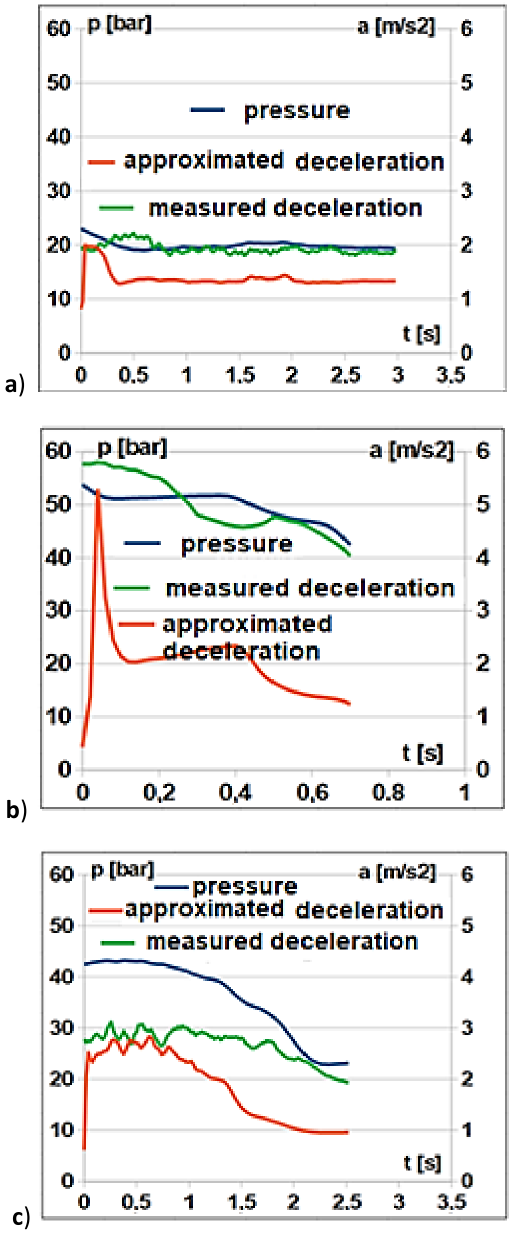


Fig. 4. Results of mapping the neural deceleration with the use of Bayesian regularization and 5 neurons in the hidden layer: a) inhibition waveform 2, b) inhibition waveform 3, c) inhibition waveform 4

The number of neurons and the neural network training algorithm, which ensured the greatest efficiency of its operation, were used to map the deceleration values for the subsequent analyzed braking processes. The results of the analysis are shown in Figure 4. For each run, the input and output values shown in Figure 2 were used, in accordance with the previously discussed methodology for the runs shown in Figure 3. Braking processes characterized by greater irregularities and greater dynamics result in much greater requirements for a neural network. For the shortest and most dynamic braking process – process 3 - the average value of the neural mapping error is the highest and amounts to approximately 0.6. In the case of the braking process with the introduced defect - loss of brake fluid - for pressure values up to about 1 second, the accuracy of reproducing the deceleration is significantly higher than for the rest of the process (Fig. 4 c). This fact is caused by a slight variation of pressure up to about 1 second and its more rapid changes after exceeding this time. The braking process, for which the results of the deceleration mapping are shown in Figure 4 b, is characterized by the regular nature of changes in the initial pressure values, for which the neural network mapped the deceleration values. In his case, it is visible that the deceleration values for the initial pressure values are overestimated, which results from the instability of the neural mapping algorithm at the initial moment.

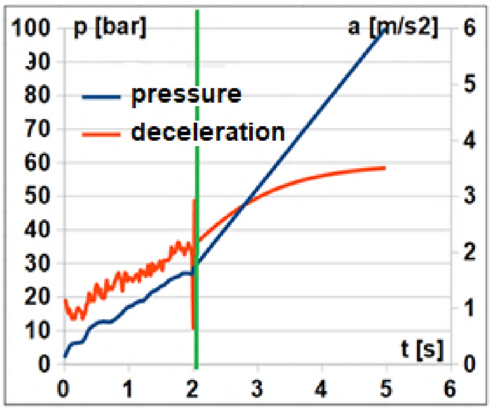
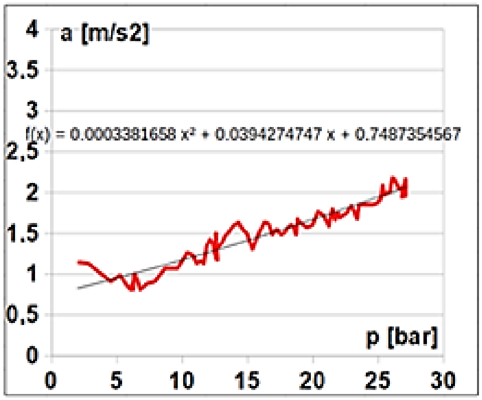


Fig. 5. Test braking process 1- Time deceleration and pressure waveforms for the input data and the results of neural mapping of the deceleration for new pressure values

The next step of the analysis is to check which step of changing the pressure values for which the neural network maps the deceleration values will ensure the accuracy of this mapping at a sufficient level from the point of view of the brake system diagnostics. In order to illustrate this task, the effectiveness of mapping the deceleration values for pressures greater than the largest value contained in the set used as input set (derived from the real braking course) and increasing with a step of 0.48 bar per 0.02 seconds was checked. The value of the pressure increase step determines the size of the output data, which, apart from the rapid change in pressure, also affects the effectiveness of the braking deceleration approximation. When the amount of output data is greater, the efficiency decreases. The input and output data are located on the left and right sides of the green line in Figure 5, respectively. Advantageous for diagnostics (ensuring its uniqueness) is the fact of the established character of the mapped braking deceleration, which is the result of the fixed (linear) nature of the pressure change, for which the discussed values are decelerations have been mapped.



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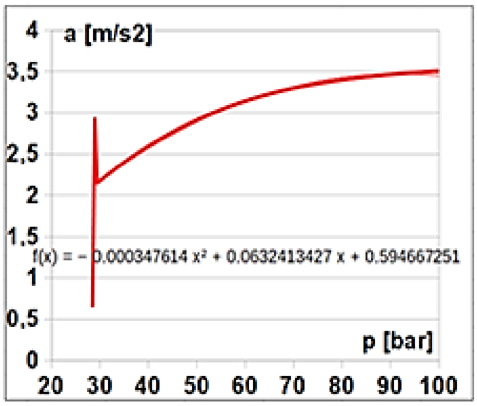

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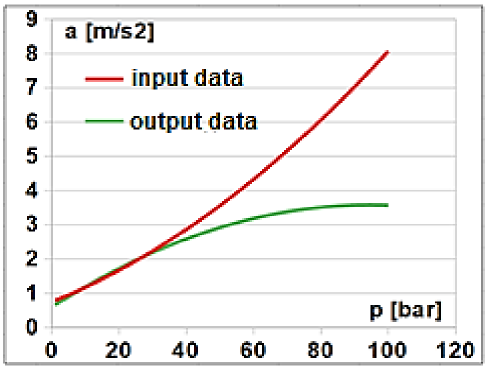
c) 

Fig. 6. Dependencies of braking deceleration on the pressure in the braking system, related to the verification of the neural network operation presented in the previous figure: a) for input data, b) for output data, c) comparison of the deceleration-pressure relationship, which are the results of the input data approximation and output

In order to verify the effectiveness of the network, in the case shown in Figure 5, a comparison was made of the dependence of the braking deceleration on the pressure in the brake system, which were created with the use of 2nd degree approximation polynomials, which approximate the input data (Fig. 6 a) and the output data (Fig. 6 b). These polynomials were used to calculate the deceleration value for pressures from 1 to 100 bar. The results of these calculations are shown in Figure 6 c. The green line marks the data obtained using the approximation polynomial of the neural mapping results, while the red line shows the calculations using the polynomial approximating the input data for the neural network. The more precise the neural mapping is the more the waveforms of both polynomials overlap. Due to this fact, in Figure 6 c the area of increased accuracy of the neural mapping is observed from the initial values of the braking pressure to about 35 bar. It results from the fact that it is a pressure range close to the pressure range included in the input data for the neural network.

The fact of the increased accuracy of the neural mapping of the deceleration values for the input pressure values that differ slightly from the input values was used to attempt to improve the efficiency of the formulated neural network. Its efficiency was checked in mapping the deceleration values for input pressures, increased linearly by 0.01 bar for each successive element of the output data set (pressure values for which the network represented the braking deceleration values). However, in view of the discussed steps of changing the output pressures, their 100-element set is characterized by a pressure change of 1 bar. From the point of view of the diagnostics of the brake system, it is advantageous for the neural network to represent the deceleration values for a wide range of pressures - for example from initial values to 100 bar. In the case of the adopted step of increasing the pressure in the output data set (0.01 bar for each element), increasing the number of elements of the output pressure set so that they cover the discussed, exemplary range of diagnostically favorable pressures, causes a significant increase in the number of elements of the output set in relation to the number of elements of the input set. This is a disadvantageous situation from the point of view of the effectiveness of the neural network. In order to limit it, it has been proposed to use a neural network that operates in a computational loop.

In the first step of its operation, we use as input data for the neural network 100 points with the values of pressure and the corresponding braking deceleration, obtained on the basis of the research braking process. As the output set of pressures for which the network maps the deceleration values, we use 100 values increased with a step of 0.01 bar starting from the last pressure value from the input set. The deceleration values obtained as a result of the operation of the neural network in the discussed first loop step are used to create the input set for the neural network in the next loop step. Then the input set consists of the pressure values with the corresponding deceleration values, which were the input values in the previous loop step (test results) and the output pressure values from the previous loop step (100 values increments of 0.01 bar) with the corresponding deceleration values obtained as a result of the operation of the neural network in the previous loop step. The pressure output values for which the neural network represents the deceleration values in this second loop step are again 100 pressure values, increased by 0.01 bar starting from the last set pressure value for this loop step. In accordance with the methodology discussed in the example of two steps, subsequent loop steps are carried out until the output set contains the pressure values for which the braking deceleration informs about the extremely intense braking efficiency (e.g. 100 bar). The use of loop in question is the use of a neural network to build an input set for the same network for further steps of its operation. Thus, the accuracy of mapping the decelerations for new pressures in the next loop step depends on the accuracy of mapping the decelerations for the pressures in the previous loop step. Using the discussed loop, on the one hand, we provide favorable conditions for the neural mapping of decelerations (a small difference of output pressures from the last pressure value from the input set), and on the other hand, we eliminate the risk of using the output set, which is much larger than the input set. It is the size of the input set that increases, while the output set contains 100 data points at each step of the loop. Thus, as the successive loop steps are performed, the effect of the deceleration and pressure values obtained from the measurements on the neural network mapped decelerations is less and less at the expense of the greater and greater effect of the deceleration values along with their corresponding pressure, which are the output data sets of the previous loop execution steps.

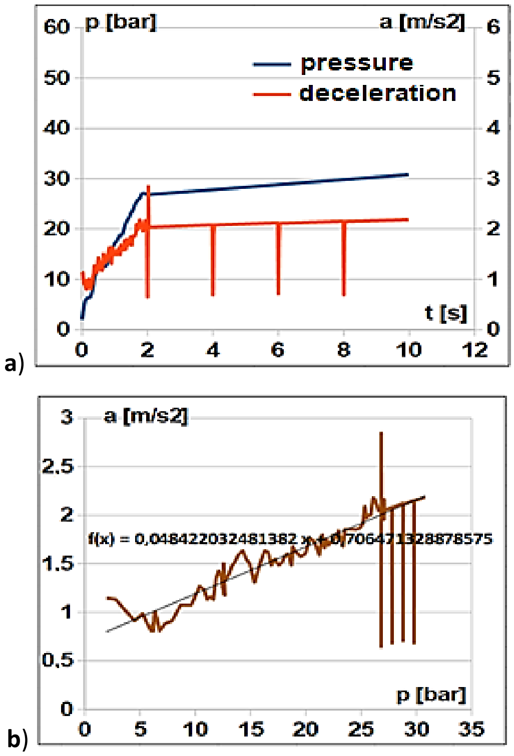


Fig. 7. Neural network operation loop for input data related to the 1st test braking process: a) deceleration and pressure time courses for input and output data, b) dependence of the deceleration on the braking pressure for input and output data

The figure above shows the results of the operation of the previously discussed neural mapping loop on the example of the braking process, which was characterized by the mildest character among the waveforms used for the analysis. 4 steps of loop operation have been carried out. Figure 7 a shows the time histories of the braking pressure and deceleration of the vehicle. The values of the pressure in the braking system for the range from 2 to 10 seconds are the values for which the neural network mapped the car decelerations in the individual operating loops. The values of the deceleration mapped in individual loops were shown on the time course of the deceleration also in the range from 2 to 10 seconds. According to the discussed methodology of creating a loop, the results of the previous loop (100 points of dependence of the mapped deceleration on the given pressure) were added to the input data set for the next loop. The low deceleration values at the limits of the values for individual loops are observed in the time course of the braking deceleration. This fact results from the instability - the operation of the neural network in the initial moments. The fact that the deceleration values mapped for the initial pressure values in consecutive calculation loops is not much greater than the deceleration values mapped for the final pressure values in the previous calculation loops (excluding the underestimation of decelerations resulting from the network instability at the ends of the loop). The linear nature of the waveform mapped by the deceleration neural network for the linearly increased pressure is maintained. Figure 8 b shows the dependence of the braking deceleration on the pressure in the braking system, which includes the data presented in Figure 8 a. For pressures up to about 27 bar, it includes the test results used as input data for the neural network in the first loop of its operation. The rest of it is the dependence obtained as a result of the implementation of individual loops of neural mapping. The premise proving the reality of the deceleration values mapped by the neural network is the fact that this part does not differ significantly from the simple one, constituting a linear approximation of the whole deceleration-pressure characteristic.

The neural network, operating in a loop, was also used to approximate the deceleration-pressure relationship on the basis of the course of braking with a defect (significant loss of brake fluid) (Fig. 8).

The data presentation is analogous to that shown in Figure 8.

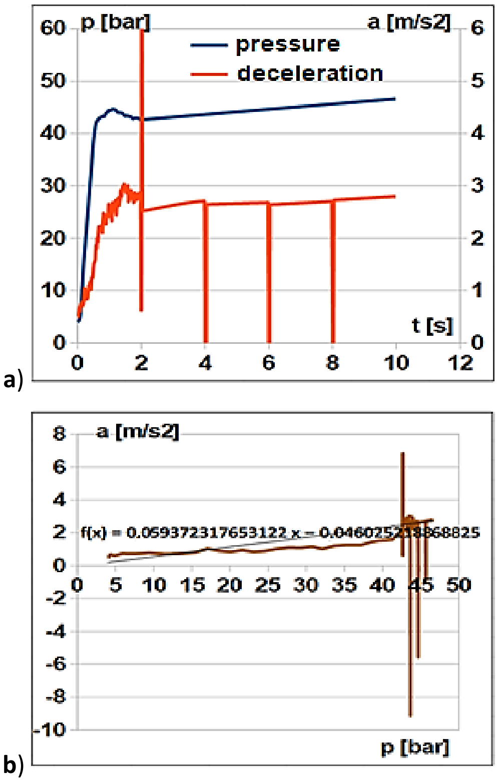
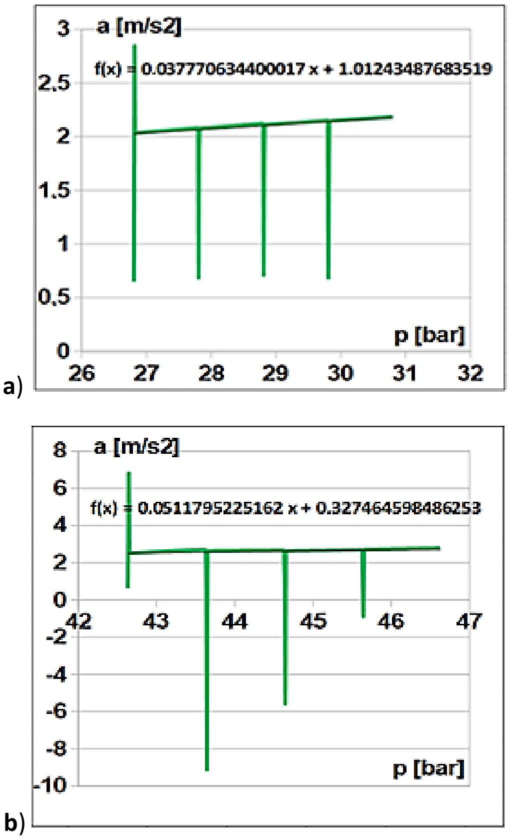


Fig. 8. The use of the neural mapping loop for the test braking 4 run: a) deceleration and pressure time runs for input and output data, b) dependence of the deceleration on the braking pressure for input and output data

The described braking process was characterized by greater abruptness compared to the previously analyzed braking process. The values of the braking pressure, which are the input data from the tests (from 0 to 2 seconds in Figure 9 a), reached the values up to about 45 bar, while in the previously discussed braking process the maximum was about 27 bar. In view of the conditions of more rapid braking, the neural network operating in the loop showed worse accuracy of operation compared to its application in the previously discussed braking process. This fact is evidenced by the differences in the slope of the fragments of the time course of the deceleration, which are the result of the neural mapping in individual loops (Fig. 8 a). The ambiguity of the deceleration-pressure relationship (Fig. 8 b) in the range from about 42 bar results from the fact that most of the pressure values for which the deceleration mapping using the neural network was requested are smaller than the highest pressure value included in the input data for the first implemented neural network loop (pressures up to 2 seconds). Another factor increasing the discussed ambiguity of the deceleration-pressure relationship is the scatter of test results, caused by the suddenness of the braking process.

An analysis of the possibility of using the discussed method of approximation of the deceleration-pressure relationship to signal weakening of the vehicle brakes was carried out. This analysis consisted in comparing the results of the linear approximation of the deceleration-pressure relationship, which was the result of the neural mapping for the course with the brake failure (Fig. 9 b) and without failure (Fig. 9 a) in the same range of braking pressures. The results of the comparison are shown in Figure 9 c. If the approximation of the deceleration-pressure relationship is correctly sensitive to the weakening of the brakes, then the approximation line for the failed braking run should be below the approximation line for the faultless braking run in Figure 9 c.



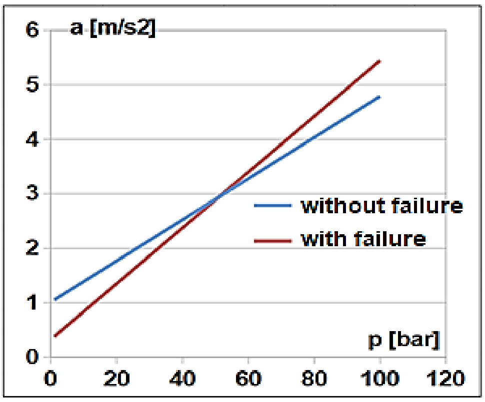
c) 

Fig. 9. Comparison of the results of the operation of the neural mapping loop: a) results of the operation of individual loops for test braking 1, b) results of the operation of the neural network in individual loops for the test braking 4, c) comparison of the deceleration-pressure relationship, resulting from the linear approximation of the results the operation of the neural mapping loop

This situation occurs for the braking pressure range up to about 50 bar, which results from the fact that the braking pressure values in this range are values that were included in the input data set and the output data set for which the neural network mapped the deceleration values. Higher pressures were not subject to the operation of the neural network. Thus, there is a premise to conclude that if the operating loop of the neural network was conducted for a wider range of pressures, the approximation straight line for the deceleration - pressure relationship obtained at that time would be characterized by a smaller slope. Then, for the most part, it would be under the simple approximation deceleration-pressure relationship for the brakes in the state of technical efficiency.

Conclusions

The analysis carried out in the work allows to draw a conclusion about the legitimacy of using an artificial neural network to approximate the parameters of the braking process in terms of increasing the effectiveness of the braking system diagnostics. In the case of verification of the neural network, representing the braking deceleration values for the pressure values coming from the actual braking process, the accuracy was achieved at the level of 20%, when it was requested to map the deceleration values for pressures with values not exceeding the values of the input pressures and the input data to the neural network from in-service braking processes with moderate abruptness. This accuracy results from the analysis of the value of the defined indicator-error of the neural mapping. In the case of using such step values of the pressure change, for which we want to map the deceleration values so that the pressure reaches 100 bar while maintaining the number of input data equal to the number of output data, the situation dramatically worsens. The accuracy of the neural mapping of the deceleration values is so small that the obtained deceleration-pressure relationship is not suitable for use in the diagnostics of the braking system. Hence, a loop-based neural network was used, the accuracy of which is promising.

The possibility of introducing linearly increasing pressure values for which it is desired to represent the deceleration value is an advantageous issue from the point of view of brake system diagnostics. Under these conditions, the neural network returns deceleration values that are also close to linear. Thus, the linearity of the deceleration-pressure characteristic obtained favors the unambiguity of its comparison with the reference characteristics and the uniqueness of the assessment of the technical condition of the brakes on this basis.

There are a number of activities that must be carried out in order to formulate a comprehensive solution for a diagnostic brake system monitor, using the approximation application of an artificial neural network formulated in the paper. It is necessary to conduct a wide range of experimental tests that will allow formulation of the conditions that should be characterized by the braking process so that the approximation of the braking process parameters on its basis would allow for the diagnostics of the braking system with the appropriate accuracy. It is necessary to formulate a methodology for determining the parameters of the braking process, related to road conditions and the condition of the vehicle (including its weight). These parameters should be taken into account when assessing the technical condition of the braking system. In order to do this, a classifier should be formulated, assigning the dependencies between the extortion of the braking system and the response to the excitation to specific states and faults of the braking system. It is also necessary to develop the approximation model so that it is possible to diagnose the brakes associated with the individual wheels of the vehicle.

WYKORZYSTANIE METOD SZTUCZNEJ INTELIGENCJI W ANALIZIE WYNIKÓW BADAŃ OPÓŹNIENIA HAMOWANIA POJAZDU W DIAGNOSTYCE UKŁADU HAMULCOWEGO POJAZDU SAMOCHODOWEGO

W artykule przedstawiono koncepcję wykorzystania sztucznej sieci neuronowej do aproksymacji parametrów opisujących proces hamowania pojazdu z punktu widzenia zastosowania tej metody w diagnostyce układu hamulcowego. Do aproksymacji zależności opóźnienia hamowania od ciśnienia w układzie hamulcowym wykorzystano sztuczną sieć neuronową nieliniowej autoregresji. Skuteczność sieci neuronowej sprawdzono w zależności od liczby neuronów w jej warstwie ukrytej oraz zastosowanego algorytmu uczenia. Działanie sieci neuronowej zostało zweryfikowane na podstawie rzeczywistych procesów hamowania Skody Octavii, realizowanych z różną dynamiką, przy różnych masach samochodów i różnych ciśnieniach w oponach. Po weryfikacji sieci neuronowej posłużono się nią do aproksymacji wartości opóźnienia hamowania dla wartości ciśnień przekraczających te występujące w zbiorze danych wejściowych. Działanie to pozwala na analizę możliwości uzyskania przez pojazd opóźnienia hamowania, co kwalifikuje jego układ hamulcowy jako sprawny. Przeanalizowano dwie koncepcje wykorzystania sieci neuronowej do rozwiązania tego problemu. Wyciągnięto wnioski związane z zasadnością rozwoju omawianych metod.

Słowa kluczowe: opóźnienie, diagnostyka, pojazd samochodowy, sztuczna inteligencja, układ hamulcowy

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