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NEURAL NETWORK MODELING OF THE SEMI-ACTIVE MAGNETO-RHEOLOGICAL FLUID DAMPER

MODELOWANIE NEURONOWE PÓŁ-AKTYWNEGO TŁUMIKA MAGNETOREOLOGICZNEGO

A b s t r a c t

The paper describes model of a semi-active damper based on Magneto-Rheological Fluid (MRF). This model is constructed in a neural networks (NN) system. Such a solution is used because of nonlinear character of the MRF damper elements. The result of research and calculations exposes ways to solve problems connected with this kind of modeling processes. In the final part of the paper, the authors compare results of the NN model verification process with real MRF damper force to velocity characteristics. The article is a complete description of nonlinear model construction with usage of Radial Basis neural Networks (RBN).

Keywords: neural network model, magneto-rheological fluid, semi-active damper

S t r e s z c z e n i e

W artykule opisano model tłumika pół-aktywnego opartego na płynach magneto-reologicznych (MR). Model ten zbudowano za pomocą sieci neuronowych. Ze względu na nieliniowy charakter tłumików MR zastosowano modelowanie neuronowe tłumików. Na podstawie badań zaprezentowano sposoby rozwiązywania problemów związanych z tego rodzaju modelowaniem. W końcowej części artykułu autorzy porównują w procesie weryfikacji charakterystykę siły do prędkości wynikłą z symulacji modelu neuronowego z charakterystyką rzeczywistego tłumika MR. Artykuł stanowi kompletny opis konstrukcji modelu tłumika MR za pomocą sieci neuronowej o podstawie radialnej.

Słowa kluczowe: model neuronowy, płyn magneto-reologiczny, tłumik pół-aktywny

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1. Introduction

Nowadays, modeling processes are used in advanced researches. The main idea in those processes is to create a model as similar to the real object as possible. Science gives us many new modeling solutions, such as Neural Networks (NN) modeling. Those NN systems can describe many types of objects, both linear and nonlinear. A capability to self-adapt and even learn is their advantage. For Magneto-Rheological Fluid (MRF) damper characterization simple dynamic models may be created like for example in Milecki's work [1]. Such model creation may be complicated. From this reason, many researchers use methods that are more advanced, such as NN modeling. Patel and Dunne [2] describe in literature, the possibilities of passive damper modeling for various temperature variable. They used NARX model to realize it. Xia [3] shows effects of elaboration on an inverse model of MRF damper with NN usage. Such kind of NN model may be used for control signal estimation for a concrete MRF damper force signal. These literature positions are base for research continuation for concrete MRF damper model. This model is based on Radial Basis Networks (RBN) in MATLAB-Simulink® program.

1.1. A description of the real semi-active MRF damper

A Magneto-Rheological Fluid (MRF) damper is a semi-active element of a car suspension system. This element makes possible the regulation of the damping coefficient in the above-mentioned system. A very important element of the semi-active damper construction is the MRF valve represented in Figure 1.

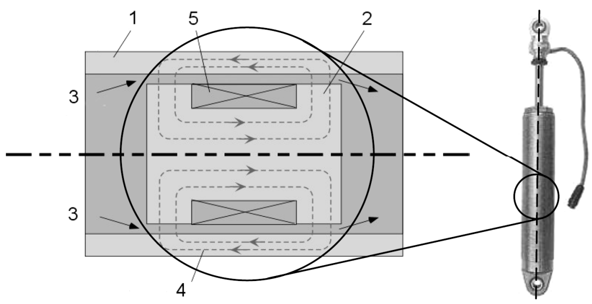

Fig. 1. Simple axis-symmetric MRF valve: (1) – tube of piston (steel); (2) – piston (steel); (3) – MRF flow; (4) – magnetic field; (5) – inductor coil

Rys. 1. Prosty osiowo-symetryczny zawór magneto-reologiczny (MR): (1) – cylinder (stal); (2) – tłok (stal); (3) – przepływ płynu MR; (4) – pole magnetyczne; (5) – cewka indukcyjna

In a magnetic field, MRF (3) flows through a circular gap between the steel tube of piston (1) and piston (2), which is also made from steel. The stiffness and viscosity of this MRF is changed by the alteration of the magnetic field (4) intensity, which is emitted by inductor coils (5). Steel elements are used here as a core of the electromagnet. The MRF character varies from the consistency of oil to frozen nut butter consistency according to the magnetic field changes [4]. The real dampers are nonlinear objects and from this reason they require advanced modeling methods.

1.2. Possibilities of the neural network modeling

Neural Networks (NN) are usually associated with artificial intelligence but in contemporary science they are used also in modeling and approximation processes. The simplest solution is to use a classical identification process but it gives the model as a linear transfer function and it is not as good and fast solution as an NN approximation. Another good feature of a NN system is the possibility of adaptation in a very short time for simple nonlinear systems [5].

2. System Description

The Neural Networks (NN) modeling process needs data from a real object. In this case it is a MRF damper described by a force-velocity set of characteristics dependent upon the current intensity of the control system [6]. The above-mentioned data should be prepared for use in the NN learning process to optimize learning effects. The set of characteristics is the basis of the NN model construction. These are physical characteristics of the real MRF damper CARRERA™ Magneto Shock™ [7]. There are also nonlinear static characteristics of force-velocity (where a positive force corresponds to a positive velocity deformation). These characteristics describe the relationship between three quantities, namely:
a) damper piston collapse-rebound velocity [m/s],
b) electrical current intensity of the damping coefficient control signal [mA],
c) damper reaction force [N].

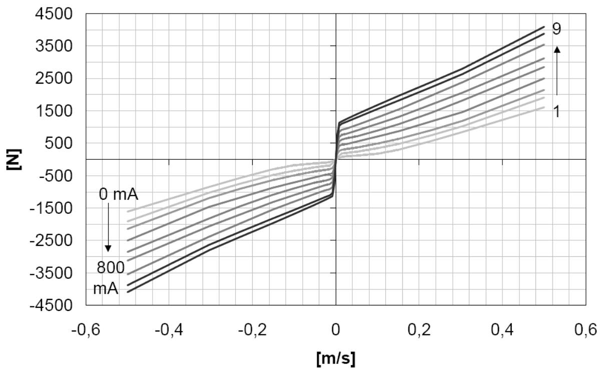

Fig. 2. The nonlinear characteristics of the MRF damper [6]

Rys. 2. Nieliniowa charakterystyka tłumika MR [6]

These characteristics are the basis to construct the NN model of the semi-active damper. They are examined by computer application and prepared by this application for the NN model construction.

In the modeling process the MATLAB-Simulink® package was used. This program let us use many cases of NNs [8]. The case described in this paper appears to be the most interesting of them and the most useful for this task. Radial Basis Networks (RBN) were chosen because of their advantages in semi-active damper modeling. RBNs consist of two layers: a hidden radial basis layer and an output linear layer. The first layer consists of many radial neurons. An ideal situation exists when the number of neurons equals the number of measurement points. The second layer usually consists of one linear neuron (Fig. 3).

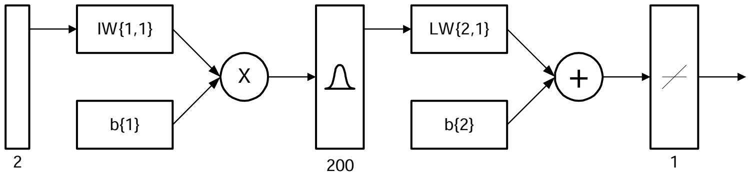

Fig. 3. The structure of the radial basis network system:
IW – input weight matrix, LW – layer weight matrix, b – bias vector

Rys. 3. Struktura sieci neuronowej o podstawie radialnej:
IW – macierz wag wejścia, LW – macierz wag warstwy wewnętrznej, b – wektor odchyleń

Bias vector values are the same for all radial basis neurons in the MATLAB® application. As the 'bias', authors describe a coefficient of the radial function shoulders gradient. To improve the properties of the network, the different bias values for single neurons are used. An ideal situation also exists when the number of neurons equals the number of measurement points, in the first layer case. In practical situations the computational power of the computers should be taken into consideration. In this case a fewer number of the first layer neurons could be the best. It allows the simulation to proceed much faster without losing too much information about real object, in the NN model.

2.2. Real neural networks solutions in the MATLAB-Simulink® application

In the NN model that is created, 781 points are used for description of the object, but a NN model with 200 neurons in the hidden layer was chosen. This kind of model works faster, as it was said in previous section. In the MATLAB-Simulink® application many NN modeling procedures are prepared, but they have a general character. This character became more detailed in the research described in this paper. It means that the RBN created Matlab function allowed us to use only one bias to the whole NN. In a NN with different bias values for each neuron the exact object description is needed. In this case, the bias values were chosen, and they depended on parts of the characteristics that were related to particular neurons. For this reason, three values were used, namely: $b_1 = 0.000438$, $b_2 = 0.00167$ and $b_3 = 0.000238$ (see Table 1). The first value was used for the wings of the characteristic. It describes values between –0.5 and –0.02 m/s or between 0.02 and 0.5 m/s. The second value was used for the part of the characteristic of the near right of zero velocity values. It describes values between 0 and 0.02 m/s. The third value was used for a part on the near left of zero velocity values. It describes values between –0.02 and 0 m/s. A 3-dimensional characteristic of such NN model is shown in Figure 5.

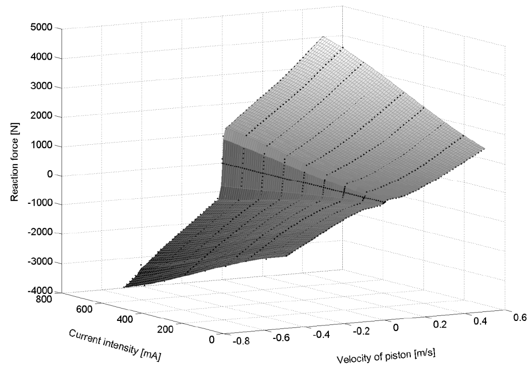

Fig. 4. The nonlinear 3-dimensional characteristic of the NN model of the MRF damper

Rys. 4. Nieliniowa trójwymiarowa charakterystyka neuronowego modelu tłumika MR

To improve precision in the zero velocity points the added points for zero velocity were set. The usefulness of that operation will be justified in the next section. Parameters b_1, b_2 and b_3 were chosen in the research process. To find the most optimal NN model 10 models were examined with usage of criterion described by Equation 1. The bias parameters of these models are shown in Table 1.

Table 1

Results of the minimal L value searching

No.	b1	b2	b3	L
1	0.000555	0.000278	0.003330	14881
2	0.000555	0.000238	0.001110	13888
3	0.000555	0.000208	0.001665	23412
4	0.000416	0.000278	0.001110	9995
5	0.000416	0.000238	0.001665	10791
6	0.000416	0.000208	0.003330	9784
7	0.000333	0.000278	0.001665	7204
8	0.000333	0.000238	0.003330	35267
9	0.000333	0.000208	0.001110	13687
10	0.000438	0.000238	0.001665	6456

The formula of the criterion is as following:

$$L = (1-\lambda)\cdot\sum_i (y_i - \hat{y}_i)^2 + \lambda\cdot\sum_i (y_i'')^2 \tag{1}$$

where:

λ – weight coefficient for two elements of the criterion,
y – model output value,
$\hat{y}$ – expected value.

As it is exposed in Equation 1, the criterion consists of two modules [9]. The first describes how close the model points to the measurement points are. The second, if it is minimal, tells the observer that oscillates in the model output are small or there are no oscillates. This is very important in this concrete case. During the tests, the multimodality of the error criterion function was empirically found. It caused an unsuccessful result of the optimal parameters determination with classical experiment theory methods. For this reason the model with the L minimal value was chosen, simply from the Table 1.

2.3. The problems that draw attention in neural network modeling

In the MRF damper modeling process, the researcher can observe three main NN modeling problems. They are described in the three subsections presented below.

2.3.1. First problem

For NN systems data points should be located evenly for the best effect of approximation. For this reason a result of approximation would be the best. In this concrete situation the collapse-rebound velocity (x-axis in Fig. 5) is multiplied by 50,000. After NN created the velocity, this input must also be multiplied by 50,000. The current intensity (y-axis in Fig. 5) is multiplied by 1000 and also current intensity input in the final model has to be multiplied by 1000.

2.3.2. Second problem

In the modeling process of the MRF damper there is one serious problem. If collapse-rebound piston velocity in the real MRF damper is equal zero the reaction force is also equal zero. In other words current intensity in the damper coil is the only factor of the damping coefficient, which changes.

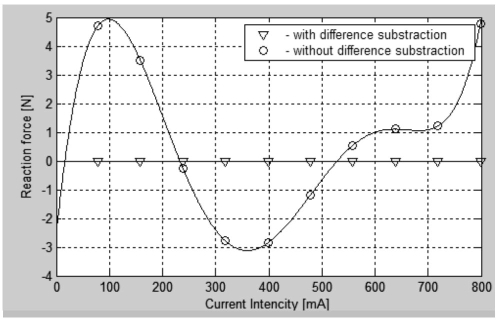

Fig. 5. Problem of non-zero force value with zero rebound-collapse velocity value with changing current intensity

Rys. 5. Problem niezerowej wartości siły dla zerowej wartości prędkości ugięcia odbicia przy zmiennym natężeniu prądu sterującego

This factor cannot generate any force without collapse-rebound velocity. In the NN modeling process this important feature of the real damper may be lost. It is possible that

some current intensity values will generate some force value. To avoid this problem in the NN model few solutions are used, namely:
a) increase a number of the zero force points for zero velocity values (Fig. 5),
b) improve the precision of the damper characteristic measurement method,
c) subtract the difference between force value for zero velocity value and an expected force value (It is good for small difference) (Fig. 6).

If these three operations are conducted, the model accomplishes zero force value in zero velocity state with minimal change of the whole model.

2.3.3. Third problem

The third problem is connected with wave structures that appear in the middle part or in whole characteristic of the damper model.

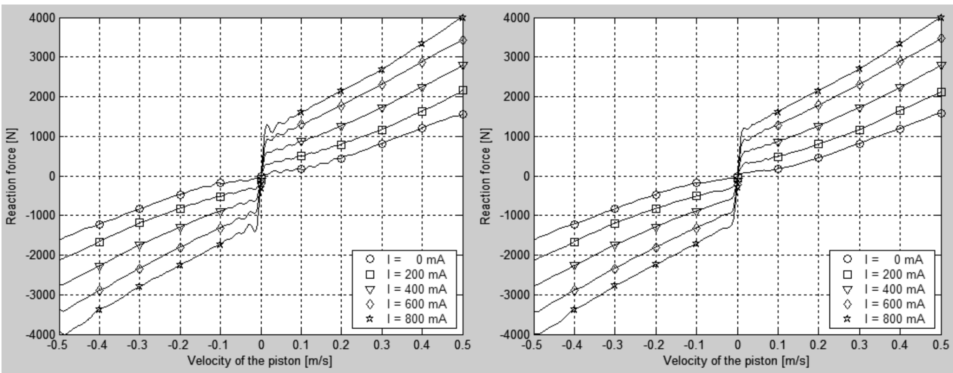

Fig. 6. NN model characteristics with the same bias coefficient for all neurons and after its diversity

Rys. 6. Charakterystyka modelu NN przy jednakowej wartości odchylenia oraz po jej zróżnicowaniu

There are two reasons of this problem:
a) Too few neurons in the model, which can be corrected by increasing their number,
b) The necessity of the bias vector diversity near the characteristic bend points.

In the left part and in the right part of Fig. 7 the models' characteristics with 200 neurons are shown. The right part model is described in section 2.2. The left side model presents typical model, which is produced in MATLAB® application. It has the same bias values for all neurons, namely 0.0004757. Then it can be seen that wave structure appears. In above cases the bias values are established in experiments.

3. NN Model Verification

The NN model was verified on few chosen 'force to velocity' characteristics of the real object. The comparison of the real model's measurement points and the output signal of the NN model during the simulation process are shown in the picture below. For the creation of the NN model, five characteristics of current intensity were used for values: 0 mA, 200 mA, 400 mA, 600 mA, 800 mA. Both the measurement points and the NN characteristics were examined for selected current intensity values, namely: 100 mA, 300 mA, 500 mA, 700 mA (Fig 7).

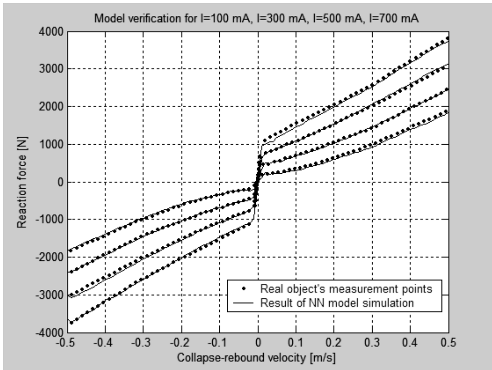

Fig. 7. Comparison of the NN model output and the real object measurement points

Rys. 7. Porównanie wyników symulacji modelu neuronowego oraz pomiarów obiektu rzeczywistego

The verification process shows that the NN is able to reconstruct completely unknown portions of characteristics based on similar characteristics. As it is shown in Fig. 8 the NN model results are very close to the results of the real MRF damper. In addition, researchers can observe that the NN model preserves the nonlinear character of above-mentioned damper characteristics. During the test a second kind of verification process was used, namely the random choice of measurement points to be used in verification process.

4. Conclusions

The NN systems are very good tools to quickly build correct models of real objects. The most important variables are connected with problems: how many neurons should be used and what bias values should be established for concrete model. The number of neurons should not be too big, because the computation time could increase to much. This means that it should not exceed number of measurement points. In the NN modeling process researchers should remember the problems described in section 2.3 to maximize the model's effectiveness. This model NN could become an element of more complicated complete physical models of the automotive vehicles.

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