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USING NEURAL NETWORKS AS A "BLACK BOX" APPROACH FOR SYSTEM MODELLING IN AUTOMOTIVE ENGINEERING

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Summary
This paper introduces using of neural networks for description of non-linear dynamic systems. Traditional "black box" methods can be used successfully either for modeling of non-linear static or linear dynamic systems. From the need for efficient description of non-linear dynamic systems (both frequency- and amplitude dependent), the need for new approach arises.
In human brain research simplified biological models of brain are used for testing of hypothesis about its function principles. These models have led to development of artificial neural networks, which can be used for data processing in different fields. Using neural networks it is possible to describe complex and unclear relationships for which is impossible to obtain an analytical solution. In turn, results achieved by using neural networks can be seen as a contribution to human brain researches.
Automotive shock absorber represents the example of history dependent, non-linear dynamic system. In this paper it has been modeled by establishing relationship between damping force and current as well as previous values of relative velocity. Description of system behavior is achieved by introducing a data set obtained from the test rig to neural network in a "training" cycle. As result, network will be able to predict output for any input data set, assuming appropriate learning pattern is used.

Key words:
neural network, black box, non-linear dynamic system, shock absorber

1. INTRODUCTION

Dynamic behavior of the motor vehicle is a result of interaction forces between vehicle and road surface and forces between elements of the vehicle (systems for suspension, steering, braking etc.). In order to describe vehicle dynamic behavior, knowledge about characteristics of elements, as well as connections between them, is needed.

A large number of significant parts and connections, but also high physical complexity level of some of them, make analysis of motor vehicles dynamics difficult. Conventional approach for such an analysis consists of mathematical modeling according to physical characteristics of system elements and connections. This approach gives good results for elements that are simple enough and can be therefore easily described.

In motor vehicles there is however a number of elements whose nature is too complex, or not known enough (like tires, shock absorbers, elastomeric bushings etc.) which makes using of conventional modeling approach difficult or impossible. Alternative way for modeling such an elements is using of so-called "black – box" approach. By this approach system or system element is described on the basis of empirical data so that a relationship between input and output is established, without taking into consideration of physical principles that cause this relationship.

By static systems relationship between input and output value is uniquely defined at any time point. In this case black – box modeling is usually made by assigning empirically obtained mathematical function, which can have a form of polynomial or spline, to an input – output relationship. By dynamic systems, output depends on current as well as past inputs, i.e. in general the present value of an element's output is a result of what has happened to the element in the past as well as what is currently affecting it [5]. Linear dynamic systems can be described by using Function Frequency Response (FRF), given by magnitude ratio between input and output and phase difference vs. stimulation frequency [1]. Regarding non-linear dynamic systems, there is no general modeling method that can successfully describe both non-linearity and dynamical aspects of a system behavior [5]. Therefore a need arises for alternative approaches by which this problem can be solved. In this paper a possibility of use of artificial neural network for modeling of vehicle shock absorbers as an example of non-linear dynamic system is examined.

2. ARTIFICIAL NEURAL NETWORKS

2.1. Function Principles of Human Brain

Basic tasks of human brain are acquisition, processing and response to stimulation signals [4]. Signals are received by sensors, i.e. sense organs (such as eyes, airs, skin...), then processed, and finally led to effectors (muscles and glands) as control signals if necessary. Simplified, a brain can be seen as a data handling unit, by which data processing is done by a great number of parallel connected processors, i.e. neurons (neural cells). Therefore, neurons are elementary units for data processing in human brain. The amount of neurons is about 10^{10}, with a possibility for 10^{14} connections between them. Data processing is done on the basis of existing patterns, which are saved earlier. At the birth there are no patterns present, i.e. neurons are not yet connected to each other. Establishing of a connection between neurons is needed for the response of the brain to the request of an environment. When response is successful, the connection is established permanently, i.e. saved, otherwise it disappears. In that way the behavior patterns arise and learning process is carried out.

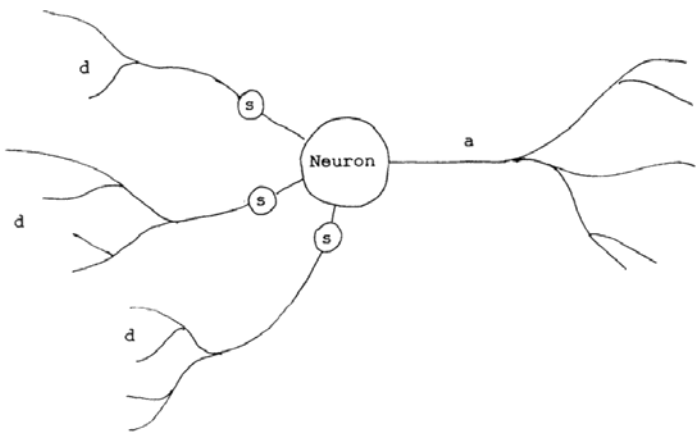


Figure 1: Neuron (a – axon, d – dendrite, s – synapse) [4]

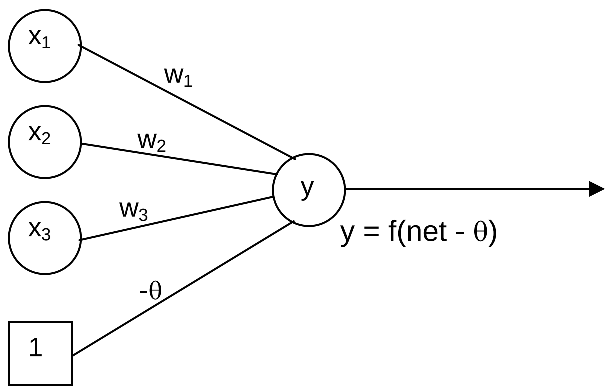
Neuron (figure 1), as processor, possesses input and output. Input signals are electro-chemical stimuluses, which come from other neurons or from sensors. They are led to the neuron by special links, dendrites. One neuron can have more inputs. If the total of all input signals exceeds certain threshold value, neuron becomes active.

In this case it sends an output signal through output link, so called axon. Axon can branch out, so that one neuron can send its output signal to more other neurons. End of each branch becomes than again a dendrite for the following neuron. Dendrites contain a special cell, called synapse. Synapse can increase or reduce level of incoming signal. A feature of synapse, which is important for learning process, is the possibility of changing its excitory or inhibitory effect through time. By learning a level of synaptic effect is varied until a satisfactory response to outer stimulus is achieved, and then saved.

Through such a configuration a well known features of human brain are achieved, for example a high level of flexibility, great adapting potential or ability for learning and generalization. Human brain can also successfully process uncomplete or unclear information, as well as the data containing small errors or noise. Artificial neural networks originate from an attempt to create ways for handling information in such a way, which can greatly help to solve different problems that cannot be solved with a present level of computer technology. They are used in variety of applications: pattern recognition (handwriting, speech, pictures), function approximation, representing of logical function, control and regulation processes etc.

2.2. Mathematic Description

As described above, neuron represents a processor with (possibly) more inputs (dendrites) and one output (axon). Signal level of dendrites can be increased or reduced by a synapse. Another feature of a neuron is its threshold value. This can be illustrated through figure 2:



x_1, x_2, x_3 – inputs
w_1, w_2, w_3 – synaptic (weight) coefficients
θ – threshold value

$net = \Sigma x_i w_i$

f – transfer function

$y = f(net - \theta)$ - output

Figure 2: Neuron with 3 inputs

Synaptic coefficients are also called “weight coefficients” or just “weights”. As seen on figure 2, a threshold value can be represented as a special input unit whose value is always 1 with weight $-\theta$. This threshold value is also called “bias”. State of a neuron is determined by a transfer function f, which can be a step function:

$$f(x) = \begin{cases} 1, & x > 0 \\ 0, & x \le 0 \end{cases} \quad \text{– step function (figure 3a)}$$

With such a transfer function a neuron can, as mentioned, have only two states, i.e. whether active or passive:

$net > \theta \iff x_1w_1 + x_2w_2 + x_3w_3 - \theta > 0 \Rightarrow f(net - \theta) = 1$ – active state
$net \le \theta \iff x_1w_1 + x_2w_2 + x_3w_3 - \theta \le 0 \Rightarrow f(net - \theta) = 0$ – passive state

Transfer function can also be continuous. In that case output of neuron can be any value from continuous spectrum. One of the most commonly used transfer functions is sigmoid function, whose output value can be between 0 and 1:

$$f(x) = \frac{1}{1+e^{-x}}$$ – sigmoid function (figure 3b)

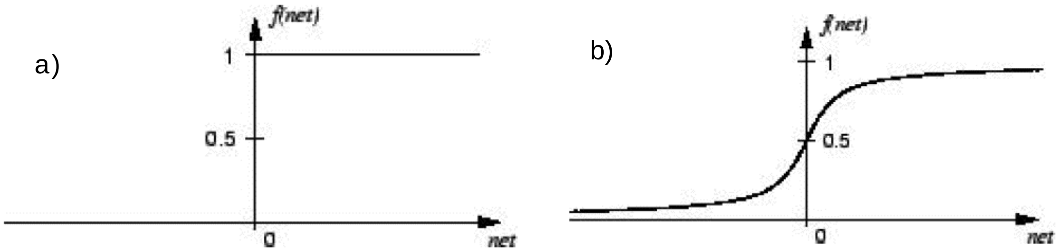


Figure 3: Step function (a) and sigmoid function (b) as neuron transfer functions in neural networks

Neural network consists of more neurons, connected to each other with parallel or series connections (figure 4) in described way.

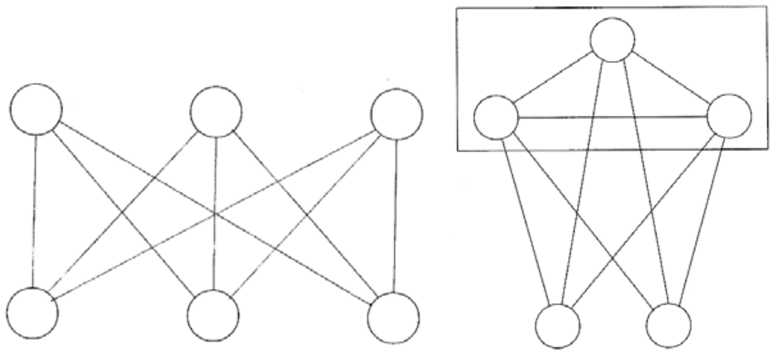


Figure 4: Examples of possible neural network configurations [4]

Neurons in the network are organized into different layers. Layer, which receives input from an outside, is called input layer, and the output of the network is obtained from an output layer. Between input and output layer can be a certain number of so – called hidden layers. Output of one layer represents an input for the following one. It has been proved that, theoretically, any shape of relationship between input and output can be depicted using maximum one hidden layer [4].

2.3. Learning in Neural Networks

Functional relationship y=f(x) is to be approximated by using neural network. Set of empirical data is required to carry out training process, in terms of having a set of input values (x_1, x_2,... x_i) to which appropriate output values (y_1, y_2,... y_i) are assigned. Here, x and y represent a vector values, i.e.:

$x = (x_1, x_2,... x_n)$

$y = (y_1, y_2,... y_m)$

This set of training data is called training pattern. Before the beginning of the training process, random numbers are assigned to the weight coefficients w_{ij} (j-th coefficient in i-th layer). In the next step a random pair of input and output vectors (x_k, y_k) is introduced to network. On the base of x_k and current values for weights w_{ij}, current network output o_k is calculated. This value is then compared to required value y_k:

$\Delta y_k = y_k – o_k$

On the basis of values Δy_{k1}, Δy_{k2}, ... Δy_{km} corrections of values for w_{ij} are made, i.e. calculations for Δw_{ij} are carried out:

$\Delta w_{ij} = f(y_{k1}, y_{k2},... y_{km})$

Function f can have different shapes [3,4,7], of which all are based on so-called “delta – rule” [4]:

$\Delta w_{ij} = \sigma \cdot x_i \cdot \Delta y_j$, $\sigma > 0$ – constant value

In order to optimize learning process, above expression can be modified by adding further parameters. At first, weight coefficients for links between output and precedent layer are changed, and then further toward links between input and first hidden layer. For that reason, this process is called "backpropagation", which is one of the most commonly used learning algorithms. Process is then carried out further, introducing different value pairs (x_k, y_k). On the basis of values for Δy_k, k = 1,2,...,i (i – number of present data values) the sum of square errors is calculated, which can be used as a criterion for ending of learning process. Another, more important criterion, is ability of the network for generalization. In order to determine such an ability, another set of data is needed, so – called validation data set. These data are not used in learning process, but for examining of how good the current network output is. Error of the validation data set vs. the number of training cycles is then observed. When this curve reaches its minimum, training process should be finished. If learning is carried out further, the error of validation set further increases, although the error of training set further decreases, though very slowly. This happens because the network fits to the noise contained in learning data [1]. Such a network is called "overtrained", as opposed to "undertrained" network, by which the training process was interrupted too early. When the training process is finished, network is available for further applications. With appropriate choice of training pattern, network will be able to depict learned functional relationship y=f(x) also for values which have not been used in training and validation process.

3. SHOCK ABSORBER AS NON-LINEAR DYNAMIC SYSTEM

Oscillations of motor vehicle caused by outer stimulation have a negative influence on vehicle dynamic behavior, which is caused by unfavorable distribution of wheels vertical loads [6] and wheel movements. Consequence of this is deterioration of vehicle's handling and stability, hence drive safety is endangered. Shock absorbers should damp oscillations by means of energy dissipation that happens due to viscous friction inside of the shock absorber. For the reason of simplicity, damping force is usual described as being directly proportional to relative velocity of shock absorber piston versus body. Such description corresponds to linear static system [1,5]. In reality, vehicle shock absorber is non-linear dynamic system by which output is a function of the current input as well as of past inputs. The curve of damping force vs. relative velocity exhibits hysteresis, which is a feature of history dependent system. The shape of hysteresis "backbone" indicates system non-linearity [5]. This can be seen on figure 5, on which shows damping force vs. relative velocity curve is frequency- i.e. history – dependent.

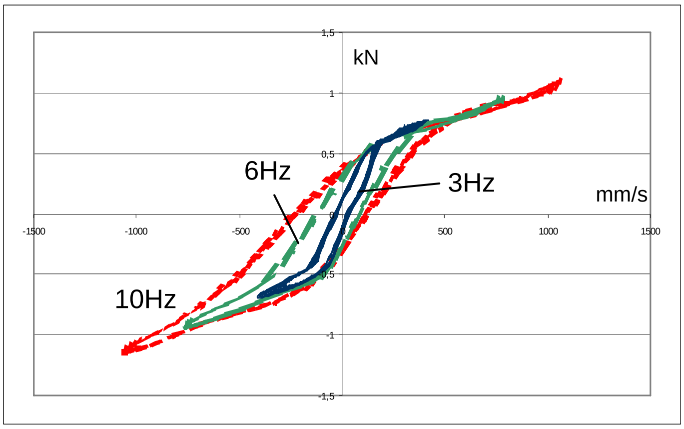


Figure 5: Damping force (N) vs. relative velocity for 3 different stimulation frequencies

Such response of shock absorber is result of a complex fluid flow, on which visco-elastic features of oil have a great influence. Visco-elasticity of hydraulic fluid is the most important feature that causes dynamic behavior of shock absorber to be history dependent [2]. Further, a non-linearity and noise are present, caused for example by hydraulic flow through a number of valves and narrow openings as well as by slip-stick effects at low velocities etc. These and other factors and their relationships are too complex to be described in analytical way, but also traditional black-box methods fail to give an appropriate modeling technique. In this paper, the possibility of exact modeling of shock absorber by using neural network is examined.

4. SHOCK ABSORBER MODELING BY USING NEURAL NETWORK

Because a behavior of a shock absorber is history dependent, it is assumed that dependence between damping force and relative velocity can be described as a function of current velocity and a number of discrete values of velocity in the past, i.e. in the following way:

$$F = F(v(t), v(t-\Delta t), v(t-2\cdot\Delta t), \ldots, v(t-n\cdot\Delta t))$$

Velocity values represent input values for the network. A number of past values considered, as well as the value for time interval Δt, must be at first chosen randomly or according to the experience, and later can be optimized experimentally for best results to be achieved. Here, following values will be assumed:

$$\Delta t = 0.01 \text{ s}, \ n = 7,$$

so that the total number of input neurons is 8, and history interval considered is 0.07 seconds. For hidden layer, a number of 10 hidden neurons is chosen. As only output value is damping force, output layer consists of only one neuron. All neurons of neighboring layers are connected to each other. The network is trained by using measured values of stochastic stimulation containing frequencies between 1 and 10Hz. As a validation set, a stochastic stimulation with frequency range 1 – 5Hz is used. After the training process is finished, another control is made by using the results of sinus stimulation on 5Hz with 20mm amplitude. Results are obtained on a test rig for a shock absorber used in vehicle Volkswagen Golf IV. The curves for damping force (N) vs. velocity (cm/s) are shown on figure 6. The training process is carried out by using SNNS, a computer program for handling neural networks.

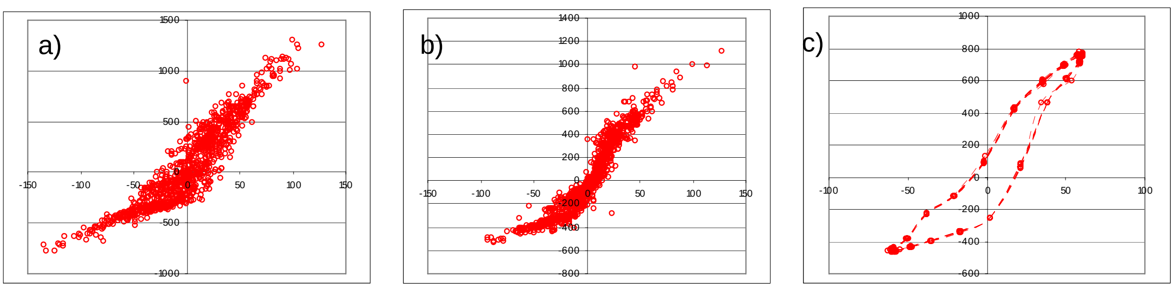


Figure 6: Damping force vs. velocity for training (a), test (b) and control (c) data

5. RESULTS

On a figure 7 a sum square error (SSE) of all three patterns vs. number of learning steps can be seen. SSE for both validation and control patterns reach their minimums at about 15,000 learning cycles. After that number is also obvious, that SSE of training cycles decreases very slowly, while SSE of the control set increases. At this point further overtraining occurs, so that the learning process should be stopped.

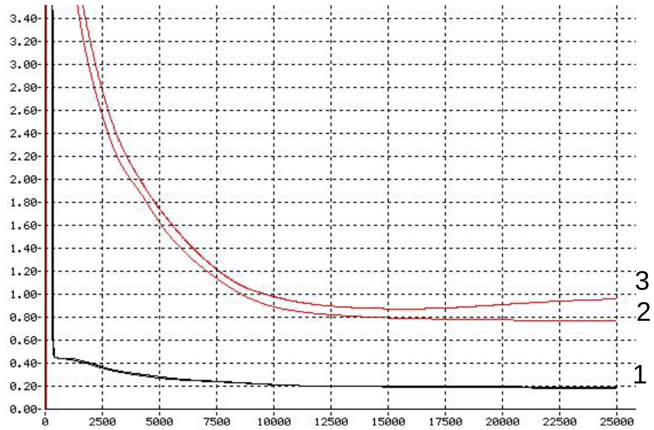


Figure 7: SSE of training (1), validation (2) and control (3) pattern vs. number of training cycles

Figure 8 shows measured values and prediction for the damping force of the neural network compared to each other for training (a), validation (b) and control (c) data sets, in the time domain. The measured data and the network prediction almost completely coincide with each other in the case of the training data set, which is shown on figure 8a. High level of coincidence is achieved also by validation set, which proves net's ability for generalizing (figure 8b). Deviation of a low level can be observed in several parts of the diagram. This diagram also contains parts in which very intensive dynamic variations of measured data occurs, which indicates that the data could contain noise. The prediction of the network smoothens the curve in these areas. Ability of the network to generalize is showed once again by using control data set (figure 8c). Although the network is trained by using stochastic pattern, the response of the shock absorber to harmonic stimulation is successfully described.

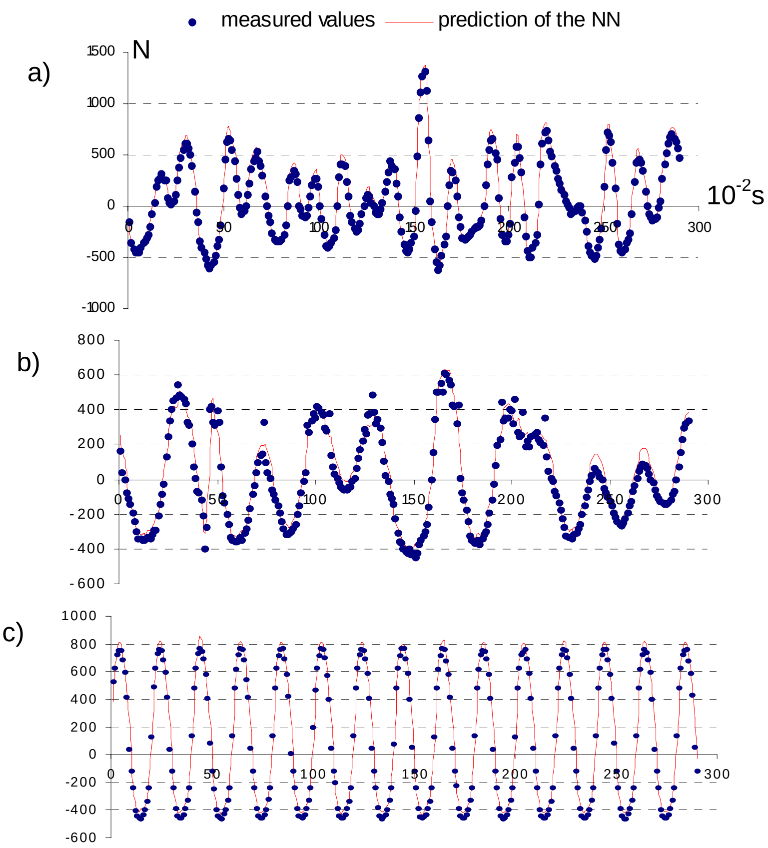


Figure 8: Comparation between measured data and prediction of the neural network for training (a), validation (b) and control (c) data set

6. CONCLUSIONS

The results show that the neural network can be, under certain circumstances, used for description of dynamic behavior of the shock absorbers. By using response of the shock absorber to stochastic stimulation as training data, the response to different stochastic stimulation is successfully described, as well as a response to harmonic stimulation. This proves that the network possesses generalizing ability, hence the “knowledge”, for the modeling of the shock absorbers.

For the final conclusions, it would be necessary to examine the results of the network for a wide variety of different stochastic and harmonic stimulation signals. A possibility of achieving better results by changing network configuration (a number of neurons in input and hidden layer, links between neurons, activation function) or by using different data set as a training pattern is to be examined, which can be done only by using experimental method. The influence of replacing conventional methods of shock absorber modeling with neural network approximation on the accuracy of the vehicle dynamic analysis should also be evaluated.

Further application of using neural networks in vehicle dynamics can be modeling of other complex elements vital for dynamic behavior of the vehicle, such as tires or elastomeric bushings of suspension linkages. In that way the entire suspension system could be modeled more exactly, improving overall accuracy of vehicle dynamic analysis.

REFERENCES

[1] Barber, Andrew: Accurate Models for Bushings and Dampers using the Empirical Dynamics Method, 14th European ADAMS Users' Conference, 1999.
[2] Bird, Robert Byron: Dynamics of Polymeric Liquids, Volume 1, John Willey & Sons Inc., USA, 1977.
[3] Braun, H., Feulner, J., Malaka, R.: Praktikum Neuronale Netze, Springer – Verlag Berlin Heidelberg, 1996.
[4] Kinnebrock, W.: Neuronale Netze – Grundlagen, Anwendungen, Beispiele, R. Oldenbourg Verlag München Wien, 1992.
[5] Palm, William John: Modeling, analysis, and control of dynamic systems, University of Rhode Island, USA, 1983.
[6] Reimpell, Jörnsen: Fahrwerktechnik: Stoßdämpfer, Vogel – Buchverlag Würzburg, Würzburg, 1983.
[7] SNNS User Manual, Version 4.2, University of Stutgart / University of Tubingen, http://www-ra.informatik.uni-tuebingen.de/SNNS/