LNU-FUZZY NETWORK AS A MATHEMATICAL ADAPTIVE MODEL OF A HYDRAULIC SYSTEM

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Model adaptive controllers such as Model Predictive Control or Model Reference Adaptive Control need a precise mathematical model of the controlled system adaptable in real-time. Systems consisting of a hydraulic 4-way proportional valve and a linear motor have non-linear behaviour such as hysteresis of and valve, death zone of a valve spool, time delay of a data transfer and control unit, dependence on coils temperature and oil temperature and nonlinear flow characteristics. This paper introduces modified Neuro-Fuzzy network as a mathematical adaptive model of a hydraulic system with above mentioned properties. The paper presents the basic architecture of Neuro-Fuzzy network which consists of artificial neural units a fuzzy layer and introduces modifications focused on identification. The basic real-time learning method such as Normalized Gradient Descent is introduced specially for the designed Neuro-Fuzzy Network. Identification and real time learning abilities of the model were tested on the hydraulic stand.

KEYWORDS

neuro-fuzzy network, 4-way proportional valve, adaptive model

1 INTRODUCTION

Systems consisting of a hydraulic 4-way proportional valve and a linear hydraulic motor are usually controlled by PID or their modifications. Designed controller has to fulfil requirements for the control criteria and also has to be designed with robust control for changing behaviour of the controlled system. Using classical control strategies can result in following:

- Each controller for each machine has to be set separately.
- The controller of machine has to be reconfigured during the machine lifetime.
- There are requirements for linearity of the systems components.

All above mentioned points increase the price of the machine or the price for their service.

That's the motivation for designing nonlinear adaptive controllers for hydraulic systems. Nonlinear adaptive controllers such as Model Predictive Control (MPC) [YANG 2016] or Model Reference Adaptive Control (MRAC) [HE 2012], [YANG 2011] are able to change their parameters during process according to changing systems behaviour. They are also able to partly calculate with nonlinear systems. Using nonlinear adaptive controllers is not meant to promise high precision of controlling but it promises low price of machines.

Nonlinear adaptive controllers need a precise mathematical model of the controlled system adaptable in real-time. This article presents the basic architecture of Neuro-Fuzzy network which consists of artificial neural units [YANG 2016],[GUPTA 2004] and fuzzy layer, and introduces modifications focused on identification of hydraulic systems. The basic real-time learning method such as Normalized Gradient Descent [BUKOVSKY 2016] is introduced specially for the designed Neuro-Fuzzy Network. Identification and real-time learning abilities of the model were tested on the hydraulic stand.

2 PROPERTIES OF 4-WAY PROPORTIONAL VALVE

One of the most important property of the valve is their flow characteristic, dependence of flow through the valve on the spool position or current to the coil. We expect that spool is much faster than the hydraulic motor so it is possible to neglect dynamic of the spool. The flow through the valve isn't directly proportional to the current in the coil for following reasons:

- Position of the spool depends on force-current characteristics of the coil and the temperature of the coil.
- The channel opening is not directly proportional to the position of the spool
- The flow depends on Bernoulli's equation
- The Figure 1 presents measured flow-characteristics of the valve.

There is obvious offset depending on minimum opening of the channels, hysteresis depending on the spool and the magnet friction and nonlinear characteristics.

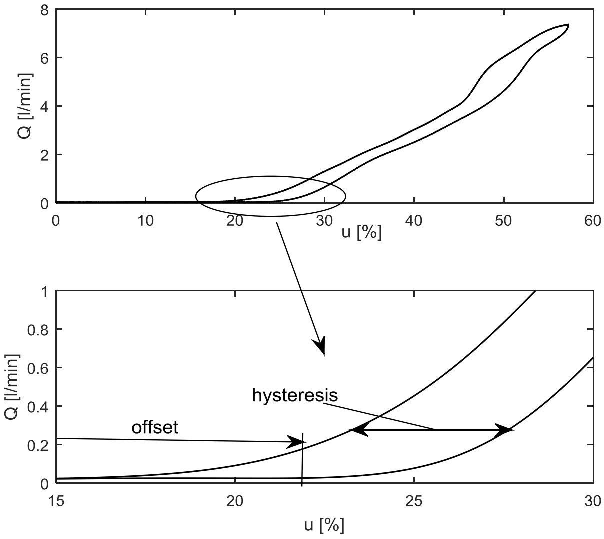

Figure 1. Current-Flow Characteristic of a Valve Hydraforce SP08-47C-Spool-Type, 4-Way, 3-Position, Closed Center

3 LNU-FUZZY MODEL

The main advantage of Artificial Neural Network is their universality of use and their ability to learn. But they are not as suitable for using in real-time process including in simple control units because they can be too large and their learning can be too computationally demanding. Fuzzy sets represent intuitive approach for when you one has mainly only theoretical or verbal knowledge. For example in our case: "The slope of the Current-Flow characteristic depends on actual current and its derivation." According that it is possible to build a space of fuzzy values. By combining the simplest neural model Linear Neural Units (LNUs) and output fuzzy layer a mathematical model was built with following advantages:

Even though the model is nonlinear it is linear according to LNUs weights, so it is possible to teach LNUs with simple optimization algorithms that search only for local minimums such as Normalized Gradient Descent (NGD).

The size of the model is smaller than neural networks with hidden layers

Building the model can be done intuitively according to technical knowledge of the system and it is also possible to use machine learning.

Linear Neural Unit (LNU) is the simplest HONU model [BUKOVSKY 2007]. The formula without activation function is following:

$$y_{i(k)} = \sum_{j=1}^{q} w_{i(k)} \cdot x_{i(k)} \qquad (1)$$

Where y_i is the neural output, $\mathbf{w}$ is a vector of neural weights. $\mathbf{x}$ is a input vector into LNU and for systems with 1 degree of freedom can be follows:

$$\mathbf{x}_{(k)} = \left[x_{1(k)}, \ldots, x_{n(k)}\right]^T$$
$$= \left[y_{(k-ny)}, \ldots, y_{(k-1)}, \Delta u_{(k-\tau-nu+1)}, \ldots, \Delta u_{(k-\tau)}\right]^T \qquad (2)$$

Where $\mathbf{y}$ is the vector of recent ny samples of piston position, $\Delta u_{(k)} = u_{(k)} - u_{(k-1)}$, $\mathbf{u}$ is the vector of recent nu samples of control input and τ is the input delay of the system. The reason why $\Delta\mathbf{u}$ is used here instead of $\mathbf{u}$ is in hysteresis. Hysteresis moves the absolute value of the input signal, but $\Delta\mathbf{u}$ is independent of that.

The slope of the Current-Flow characteristic depends on actual input, hence the fuzzy variable was chosen as the delayed input $u_{(k-\tau)}$. The space of the fuzzy variable is shown in **Chyba! Nenalezen zdroj odkazů.** where each of fuzzy set θ_i belongs to one of the LNU. The final built Neuro-Fuzzy model is in **Chyba! Nenalezen zdroj odkazů.**.

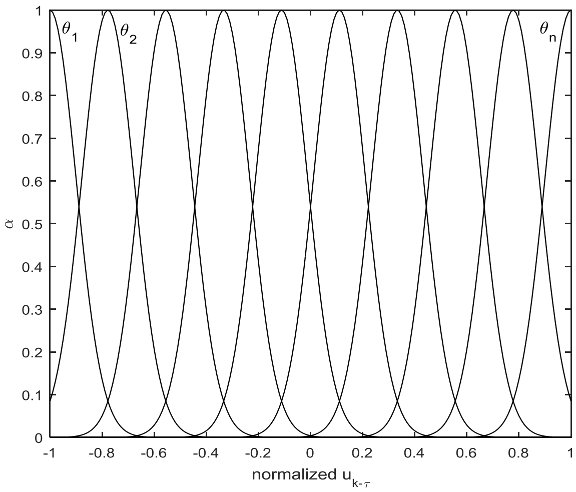

Figure 2. Fuzzy Sets

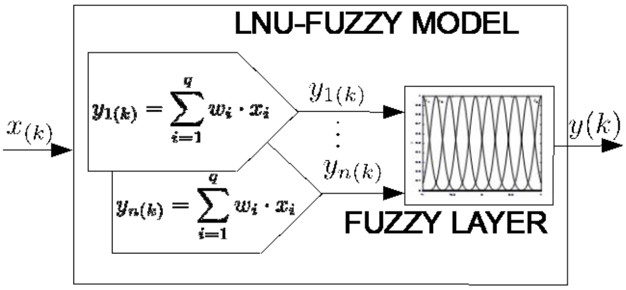

Figure3. LNU-Fuzzy Model

Fuzzy membership α_i to a given fuzzy set θ_i is calculated as follows:

$$\alpha_i = e^{-2 \cdot n^2 \cdot \left(\Delta u_{(k-\tau)} + S_i\right)^2} \qquad (3)$$

Where n the number of is fuzzy sets and S_i is the center position of the fuzzy set θ_i. The final output of the model is calculated as a center of maxim as follows:

$$y_{(k)} = \frac{\sum_{i=1}^{n} y_{i(k)} \cdot \alpha_{i(k)}}{\sum_{i=1}^{n} \alpha_{i(k)}} \qquad (4)$$

LNU-Fuzzy model given be (1),(2) and (4) can be rewritten to the matrix form as follows:

$$y_{(k)} = \boldsymbol{\alpha}_{(k)} \cdot \mathbf{W}_{(k)} \cdot \mathbf{x}_{(k)} \qquad (5)$$

Where the neural weights w_{ji} of the matrix $\mathbf{W}$ have to learn in real-time. For that Normalized Gradient Descent algorithm was chosen given by (6).

$$\mathbf{W}_{(k)} = \mathbf{W}_{(k-1)} - \mu_{norm(k-1)} \cdot \frac{\partial Q_{(k-1)}}{\partial w_{(k-1)}} \qquad (6)$$

$$Q_{(k-1)} = \frac{1}{2} e^2_{ref\,(k-1)} = \frac{1}{2}\left(y_{ref\,(k-1)} - y_{(k-1)}\right) \qquad (7)$$

Where Q is the cost function where e_{ref} is the reference error between real output of the system y_{ref} and the output from the model y. Putting (5) and (7) into (6) we get the following formula for weights adaption.

$$\mathbf{W}_{(k)} = \mathbf{W}_{(k-1)} + \mu_{norm(k-1)} \cdot e_{ref\,(k-1)} \cdot \boldsymbol{\alpha}^T_{k-1} \cdot \mathbf{x}^T_{k-1} \qquad (8)$$

According [3] and (7) is the normalized learning rate follows for this case:

$$\mu_{norm(k-1)} = \frac{\mu}{\varepsilon + \boldsymbol{\alpha}_{(k-1)} \cdot \boldsymbol{\alpha}^T_{(k-1)} \cdot \mathbf{x}^T_{(k-1)} \cdot \mathbf{x}_{(k-1)}} \qquad (9)$$

Where μ is the learning rate and ε is dumping small value.

4 IDENTIFICATION OF THE HYDRAULIC STAND

The experimental adaptive identification was tested on hydraulic stand shown in Figure 4 with hydraulic schema Figure 5. The lower hydraulic motor controlled by 4-way proportional valve in Figure 1 with the input signal u. The output signal was the position of the lower piston y. The upper hydraulic motor was used as a constant load controlled by using pressure reducing valve. This arrangement of two hydraulic motors against each other simulating a hydraulic press. Important settings of the hydraulic stand and LNU-Fuzzy model are in Table 1.

Learning rate	$\mu = 0.01$
y in $\mathbf{x}$	$ny = 20$
Δu in $\mathbf{x}$	$nu = 30$
Fuzzy sets	$n = 20$
Pressure 1	$p1 = 50[bar]$
Pressure 2	$p2 = 20[bar]$
Max. force V1	$F_{V1} = 1100[N]$
Max. force V2	$F_{V2} = 400[N]$
Max. speed	$v = 150[mm \cdot s^{-1}]$

Table 1. Hydraulic Stent and LNU-Fuzzy Model Settings

Figure4. Hydraulic Stand

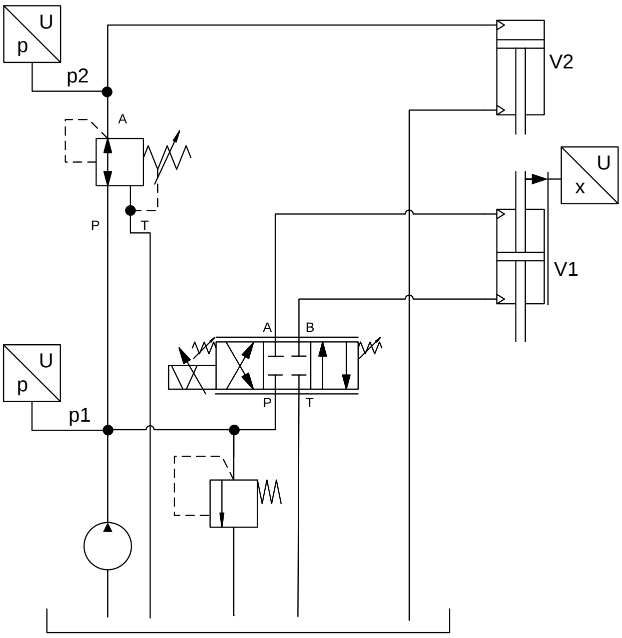

Figure5. Simplified Hydraulic Scheme

For identification 2 data sets were measured. Output data was compared with output from the model given as a prediction from the 0.2*s* data. The first data are from controlling without load and the LNU-Fuzzy model was pre-trained for it in **Chyba! Nenalezen zdroj odkazů.**. The second data was with the load and was tested if and how quickly is the model able to adapt to these changes. **Chyba! Nenalezen zdroj odkazů.** shows data with load and the model output trained on the data without load. The position of the contact of the pistons and higher inaccuracy of the model is visible.

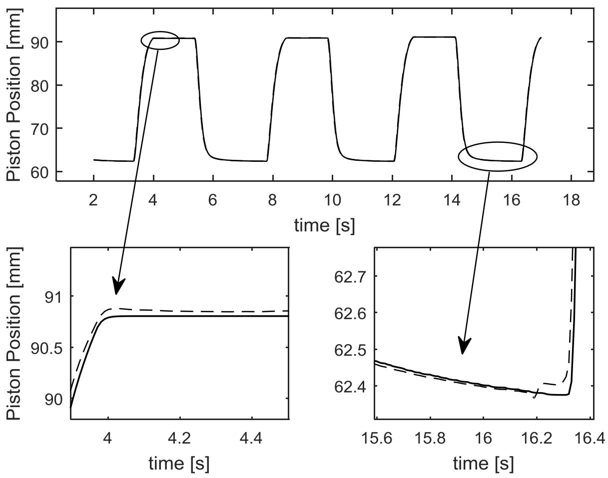

Figure6. Trained Model without a Load, - line reference data, -- line predicted output

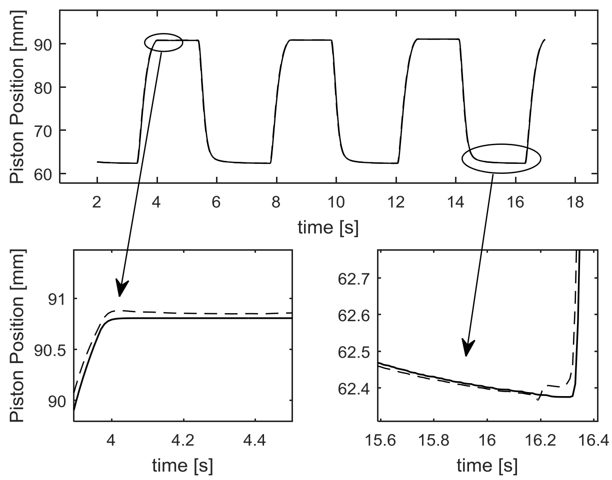

Figure7. Trained Model with a Load, - line reference data, -- line predicted output

Figure 8 shows model adapting to new data with load. Comparing Figure 7 and Figure 8 shows the ability to adapt to new data or new behaviour with load.

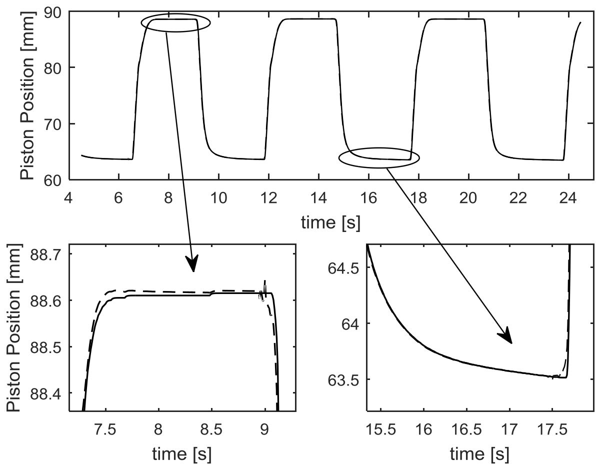

Figure 8. Adaptive Model with a Load, - line reference data, -- line predicted output

5 CONCLUSIONS

This article presented one of the options for identification of a hydraulic system consisting of a 4-way electromagnetic proportional valve and a linear hydraulic motor. Using Linear Neural Units and fuzzy sets a nonlinear model was built. The main reasoning for that is using adaptive controllers such as MPC or MRAC.

The article briefly introduces properties of a 4-way proportional valve which should be respected in the model. The article explained the basics of neural units and fuzzy sets and LNU-Fuzzy model was created. A specialized augmented Normalized Gradient Descent was used for LNU-Fuzzy model learning.

In the last section the LNU-Fuzzy model was used for identification and their retraining after changing the load on the stand simulating a machine press.

Using LNU-Fuzzy model as a model of hydraulic system brings following advantages:

- Model is adaptable during process and during lifetime of the machine and it's not necessary to retune it.
- Model is linear according to neural weights so it's able to learn by using simple local searching algorithms such as mentioned NGD.
- Model is not as big as universal neural networks with hidden layer or as a High Order Neural Units. Therefore it is more suitable for use in simple controllers.

Disadvantages of this type of modelling must be mentioned, and are following:

- The parameters of this type of the model don't have any real meaning such as dumping, stiffness or mass. If the model doesn't work or stops working flawlessly it is hard to tell the reasons why or where the problem could be. Another problem can be brought by real-time learning.
- For using in practise it should be ensured that the model can't be retrained to worse results.

REFERENCES

[Yang 2016] Yang, Y., Tan, S. C., Hui, A. S. Y. Adaptive reference model predictive control for power electronics. In: 2016 IEEE Applied Power Electronics Conference and Exposition (APEC): 2016 IEEE Applied Power Electronics Conference and Exposition (APEC). 2016, pp. 1169–1175.

[He 2012] He, Qiang. The design of model reference adaptive control. In: IET Conference Proceedings; Stevenage, United Kingdom: The Institution of Engineering & Technology, 2012 [vid. 2017-04-11]. ISBN 978-1-84919-537-9.

[Yang 2011] Yang, Y., Balakrishnan, S. N., Tang, L. and Landers, R. G. Electro-hydraulic piston control using neural MRAC based on a modified state observer. In: Proceedings of the 2011 American Control Conference: Proceedings of the 2011 American Control Conference. 2011, pp. 25–30.

[Gupta 2004] Gupta, Madan, Liang Jin a Noriyasu Homma. Static and Dynamic Neural Networks: From Fundamentals to Advanced Theory. B.m.: John Wiley & Sons, 2004. ISBN 978-0 471-46092-3.

[Bukovsky 2016] Bukovsky Ivo and Noriyasu Homma. An Approach to Stable Gradient Descent Adaptation of Higher Order Neural Units. IEEE Transactions on Neural Networks and Learning Systems. 2016 (DOI:10.1109/TNNLS.2016.2572310).

[Bukovsky 2007] Bukovsky, Ivo, Zeng-Guang Hou, Jiri Bila a Madan M. Gupta. Foundation of Notation and Classification of Nonconventional Static and Dynamic Neural Units. B.m.: IEEE, 2007, s. 401–407 [vid. 2016-03-13]. ISBN 978-1-4244 1327-0.

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