MODELING AND PREDICTIVE ANALYSIS OF THE HYDRAULIC GEROLER MOTOR BASED ON ARTIFICIAL NEURAL NETWORK

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Abstract:

GEROLER hydraulic motors are known for their good value for money and their balance between simplicity, robustness, compactness, versatility and noise. Compared to axial hydraulic motors, GEROLER motors still represent a research area with the possibility of a significant contribution in terms of nonlinear dynamic behavior analysis. The aim of this research was experimental analysis of GEROLER motor dynamics at uneven load torque. Based on the obtained laboratory measurements, a black-box model for predicting the operating parameters using the artificial neural networks was developed. Two different neural network architectures were used: the simpler static multilayer feed-forward network and the more complex dynamic NARX neural network. From the obtained results, it appears that the multilayer feed-forward neural network provides acceptable results, while the dynamic NARX neural network provides more favorable results due to its flexibility in dealing with nonlinear dynamic systems. The research conducted represents a new approach for modeling and predictive analysis of the GEROLER engine.

1 Introduction

The historical development of the GEROLER hydraulic motor began with the research of rotary piston machines (ROPIMAs) [1], which represent volume displacement machines with chambers between a pair of counterparts, rotor and stator, also called "star" and "ring". The epitrochoidal profile is used for the profile of the star, while the profile of the ring is the envelope, which is the same design architecture used in the Wankel engine. The mentioned design, applied in the hydrostatic machines, results in higher power density and compact size of the hydraulic pumps and motors. The shapes of the star and the ring are constantly modified so that trochoidal and hypotrochoidal profiles can also be used for the star profile and enveloping curves for the ring profile. The main advantage of this design is the reduction of components and sealed elements compared to the design of a classic gear pump and motor. This results from the ratio between the number of lobes in the epitrochoidal profile and the number of lobes in the enveloping profile. In most cases, the star has one less bulge than the ring.

Modified epitrochoid created hydraulic motors, commercially known as ORBIT motors, which have a fixed star and/or ring, while the other parts rotate with orbital or planetary motion. This results in high torque and low speed, which are very important for low-speed high-torque (LSHT) motors. A similar design, commercially known as GEROTOR motors, has a fixed axis unit and both the star and ring rotate, as shown in Figure 1a. Pressurized working fluid flows into the motor chambers creating high pressure in one chamber and low pressure in another, which forms an imbalance of forces and the star begins to orbit. The star orbits multiple times for each complete single revolution within the ring. This design saves components and sealing

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elements, but on the other hand, ideal contact between the star and the ring simply cannot be achieved. The improved design of the GEROTOR motor is known commercially as the GEROLER motor (Figure 1b), in which rollers are arranged around the motor housing instead of the ring with the enveloping profile. This design reduces wear and friction and improves performance at low speeds.

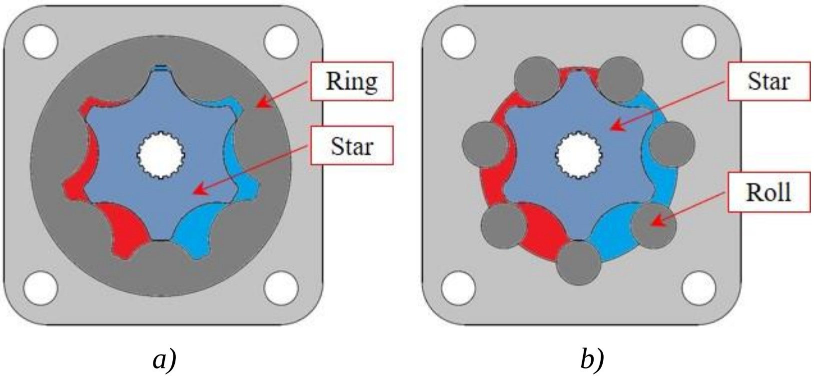


Figure 1. Working principle of: a) GEROTOR motor, b) GEROLER motor

Compared to the scientific studies of the other types of hydraulic motors, very few studies have been published about the GEROLER motors, which was analyzed in the article by Gamez-Montero et al [2]. One direction of GEROLER motor research is the development and improvement of ring and star profiles, so Colbourne [3] studied trochoidal curves and their envelopes, which may be applicable in hydraulic machines. Shung et al [4] used compact equations to describe the geometry of different trochoidal types. Maiti et al [5] studied trochoidal gears operating in a hydraulic motor and developed the torque characteristics, and the experimental results supported the theoretical predictions. The other direction of GEROLER motor research is mathematical and numerical modeling, so Stryzek [6] developed the first mathematical model of hydraulic machines with cycloidal gears, with parameter equations based on four geometrical parameters. Ivanović et al [7, 8] defined an analytical method for predicting the operating characteristics of GEROTOR machines. Mathematical models of contact forces and influence of backlash with numerical examples were presented. Ruvalcaba et al [9] developed a 3D method (CFD) for predicting the flow behavior of GEROTOR machines under different operating conditions by means of a computational fluid dynamics method (CFD) using the commercial program ANSYS FLUENT. It was shown that cavitation has a non-significant effect on the pump flow deficiency and that the tip to tip distance has a crucial effect on the flow efficiency. Gamez-Montero et al [10] presented a new boundary condition of a virtual wall that allowed the simulation of the tooth contact in the radial clearance between the teeth. The results showed good reliability in terms of analytical and experimental results. Researchers Castilla et al [11] and Gamez-Montero et al [12,13] presented a simulation of a mini-GEROTOR pump based on the open source tool OpenFOAM. The numerical results of flow rate and pressure were validated with experimental measurements on a newly fabricated prototype. Ding et al [14] presented a transient 3D model CFD for the GEROTOR engine using the commercial PumpLinx software. Also, Maili et al [15] performed CFD analysis to study the flow patterns of leakage phenomena in the ORBIT engine. Strmčnik et al [16, 17] described the GEROTOR hydraulic motor with a floating outer ring. Their study focused on the influence of the size of the holes in the valve plate, using high and low pressure chambers. The results showed that the highest overall efficiency was achieved by increasing the original hole diameter.

From the mentioned articles it can be concluded that the numerical model of the GEROLER motor is very complex, and most authors analyze models as white-box model with fully known mathematical equations or the CFD model. From the mentioned articles and available literature, it's also clear that the predictive model of the GEROLER motor using artificial neural networks hasn't been explored yet. Based on this fact, our research on modeling and predictive analysis of GEROLER motor using artificial neural networks has been conducted. Therefore, the objective of this research is to develop a predictive model with artificial neural networks using laboratory measurement data for non-uniform load torque, which is an extremely difficult operating condition for the motor.

The artificial neural networks (ANNs) present a model which is capable of processing information analogous to the activity of the human brain. The biological neural network consists of the body, axons, synapses and dendrites, which surround the neuron body. For the AAN, the biological neuron body is replaced by an adder, the dendrites become input signals, the output from the adder is an axon of artificial neurons, and the threshold value of biological neurons becomes the activation function [18]. The synapses of the biological neurons are replaced by the synaptic weight, which connects the artificial neuron with its environment. The output from the adder is the input in the activation function, which produces the output value of artificial neurons. The activation function can be linear where the output from the adder is multiplied by a certain factor (gain) or nonlinear where used: signum, sigmoid, threshold and hyperbolic and harmonic functions. The primary significance of an ANNs is its ability to learn from its environment, and to improve its performance through learning which is realized by interactive process of synaptic weights and bias level adjustments so the network becomes more knowledgeable about its environment after each iteration of the learning process. For the development of neural networks, it is necessary to organize neurons in layers and that each of them connects to synaptic weights. Three types of layers can be distinguished: the input, hidden and output layers of the neural network.

Two different types of ANNs were used to model the predictive model of GEROLER motor, the multilayer feed-forward neural network and the nonlinear autoregressive network with exogenous inputs (NARX). The multilayer feed-forward neural network is a static network consisting of multiple connected single-layer networks, which is a simpler design of the network, and it is used for analysis for modeling a dynamic system such as the GROLER motor. Dynamic neural networks are generally better than static networks (although they are more complex to learn) because their memory allows learning of sequential or time-varying data. The NARX dynamic neural network is a recurrent dynamic network with feedback connections that span multiple layers of the network. In the NARX model, the next value depends on the output signal and is fed back to previous values of the output signal and previous values of the independent (exogenous) input signal. The output is fed back to the input of the feed-forward neural network as part of the standard NARX architecture. Since the actual output is available while the network is learning, a serial-parallel architecture could be created using the actual output instead of the estimated output that needs to be fed back. This has several advantages: The input to the feed-forward network is more accurate, the resulting network has a pure feed-forward architecture, and static backpropagation can be used for learning. The input and output values of the GEROLER motor neural network model were measured on the real GEROLER motor under laboratory conditions.

2 Experimental investigation

The experimental measurements were carried out at the Laboratory for hydraulics and pneumatics at the Department of Mechanical Engineering Design, Faculty of Engineering University of Rijeka [19]. The laboratory hydraulic system for analysis the GEROLER hydraulic motor consists of a hydraulic power unit controlled with a programmable logic controller (PLC), a mechanical brake for generating the load torque and measurement equipment for measuring the pressure and temperature of the hydraulic oil and the rotational speed of the hydraulic motor shaft.

The laboratory hydraulic power unit consists of an electric motor connected to a constant displacement pump, an oil tank and filters. The hydraulic oil is supplied to the hydraulic motor through a directional control valve controlled by the PLC. The hydraulic motor was connected to a pressure relief valve, and the maximum pressure was set to 115 bar. The load torque is generated by a mechanical friction brake whose linings are released or tightened by screws. For this study, the mechanical friction brake and the bracket for the hydraulic motor were designed and fabricated, as shown in Fig. 2. The motor was connected to the brake by a rigid coupling so that no losses occur between the motor and the brake.

The Parker's SensoControl measurement equipment [20] was used to measure the pressure of the hydraulic oil in the high- and low-pressure motor chamber. Also, the rotational speed sensor was used to measure the rotational speed of the motor output shaft. The rotational speed sensor reflects a laser beam from the reflective tape placed on the shaft. Laboratory measurements were carried out with one, two, four, six and eight reflective tapes, and it was concluded that optimal results are obtained with four reflective tapes. The measurement results of the pressure and rotational speed of the hydraulic motor shaft are stored in the measuring instrument, which is capable of storing 256,000 measured values or points. The measurement uncertainty of the pressure sensors is less than 0,5% and the rotation speed sensor is less than 0,4% what is acceptable for conducted measurements.

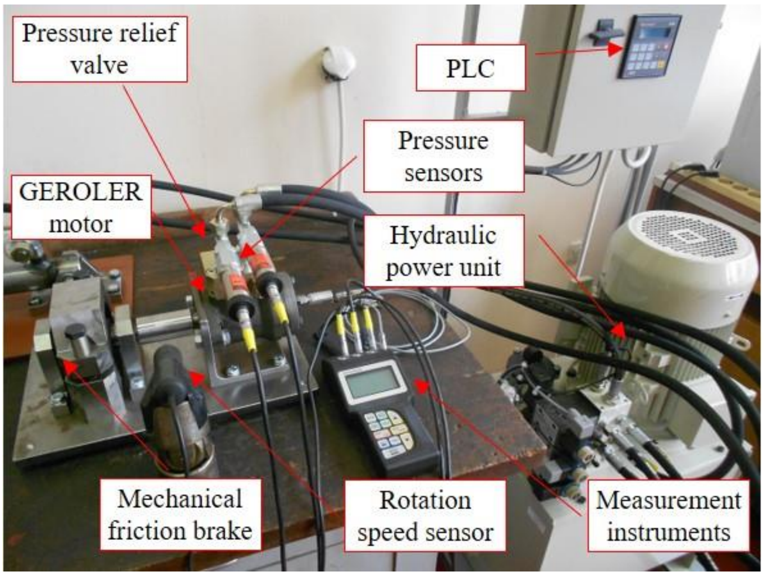


Figure 2. Laboratory hydraulic system for measuring the GEROLER motor operating parameters.

The first step of conducting the laboratory measurements is defining the output signal from PLC, which operated with directional control valve, i.e., the amount of flow into the GEROLER motor. During the experiment, the flow had constant value as a result of the constant displacement pump and rotational speed of electrical motor which amounted to 15 l/min. When the GEROLER motor started to rotate, the brake pads were released. By tightening the brake screws, the friction force between the pads and brake rotor increased, which resulted in an increase in the torque on the motor shaft and a decrease in the rotational speed. For the laboratory experiment, the GEROLER motor EPRM 50 from Lösi company was chosen [21]. The motor EPRM 50 has a displacement of 51.5 cm^3, maximum rotational speed of 775 min^{-1}, maximum load torque of 101 Nm and can operate up to a pressure of 140 bar.

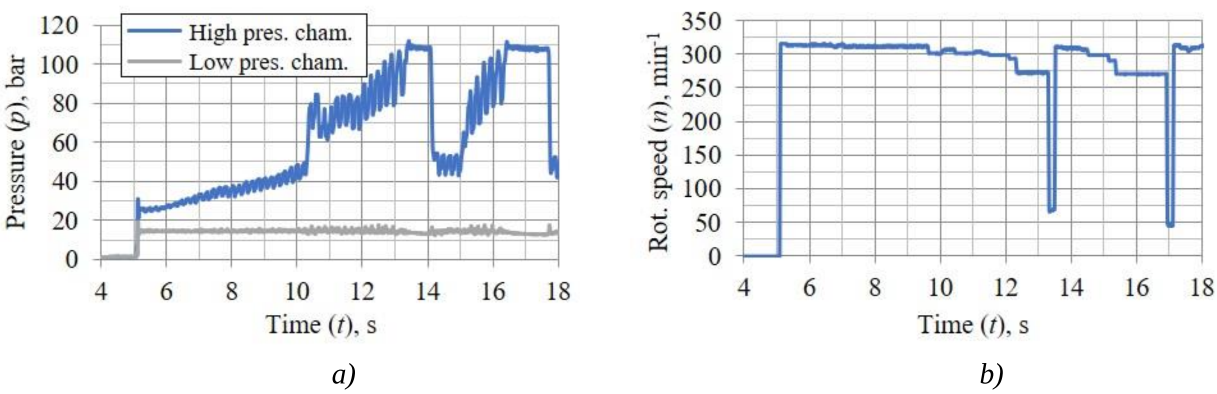


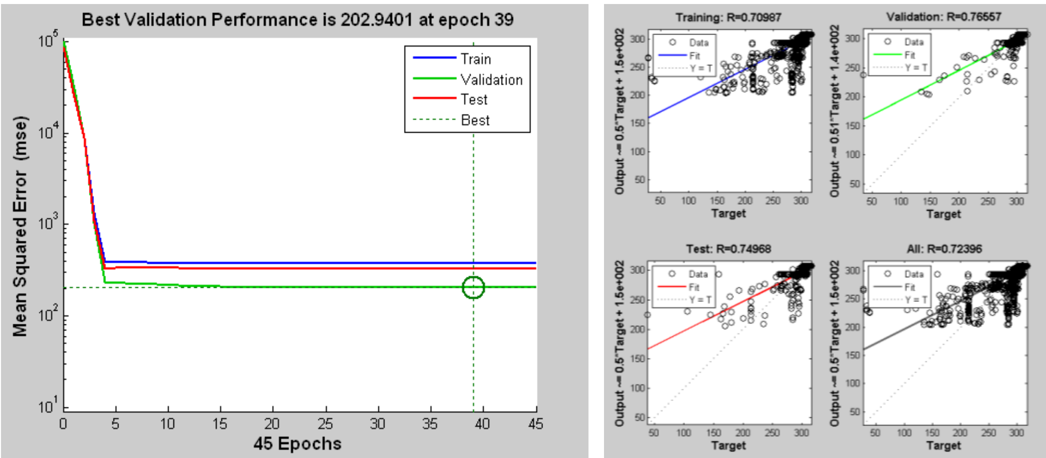
Figure 3. Measurement results of the hydraulic motor: a) pressure in the high- and low-pressure chamber, b) rotational speed.

The measurement results of the pressure in the high-pressure and low-pressure motor chamber are shown in Figure 3a, and from the results it can be concluded that the pressure changes depend on the braking torque. Thus, uneven braking of the hydraulic motor is followed by uneven high pressure, which initially increases due to the increased braking force, until the 13th second when the hydraulic motor has almost stopped and the pressure has reached the value of 110 bar, which is almost the maximum value set on the relief valve. Then the brake is released and the pressure drops accordingly. After 15 seconds, the pressure increases again due to the repeated increase of the braking force. Thus, the results indicate the validity of using the friction mechanical brake in the simulation of uneven torque loads that occur in real systems. The constant value of the pressure in the low-pressure chamber of the engine, about 14 bar, is the result of the open hydraulic circuit used in the laboratory hydraulic system. The measurement results of the engine speed are shown in Figure 3b. From the results, it can be concluded that as the torque on the brake, i.e. on the motor shaft, increases, the speed decreases. It can also be seen that the speed quickly drops to a value of about 50 rpm when the hydraulic motor has come to a virtual standstill.

The modeling and predictive analysis of the GEROLER motor using the black-box principle presupposes a predictive model based on input and output motor values, which are determined by experimental measurements. The input values of the black box are the measured values of the pressure drop in the hydraulic motor (difference of high and low pressure), and output values are values of the rotational speed. Therefore, the predictive model will determine the output value of the rotational speed depending on the input values of the pressure drop in the hydraulic motor.

3 Modeling of the GEROLER motor predictive model using the multi-layer feed-forward neural network and the NARX dynamic neural network

The predictive model with the multi-layer feed-forward neural network was made using the MATLAB software. After data collection through laboratory measurements and before using the data to learn the network, two steps must be performed. The data needs to be pre-processed and divided into three subsets. The first subset is the learning set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set, which monitors errors during the learning process. Finally, the third subset is used to test the neural network after learning with data unused for learning. After the data were collected, pre-processed, and divided, a multi-layer feed-forward neural network was created as a two-layer network with 20 neurons in the hidden layer. Accuracy falls with a decreasing number of neurons; however, increasing the number of neurons from 20 to 100 induced a slight increase in accuracy due to the saturation effect, but a large number of neurons requires long-term learning. The tangent sigmoid and linear functions were chosen as activation functions, while the Levenberg-Marquardt algorithm was used for learning due to its speed.



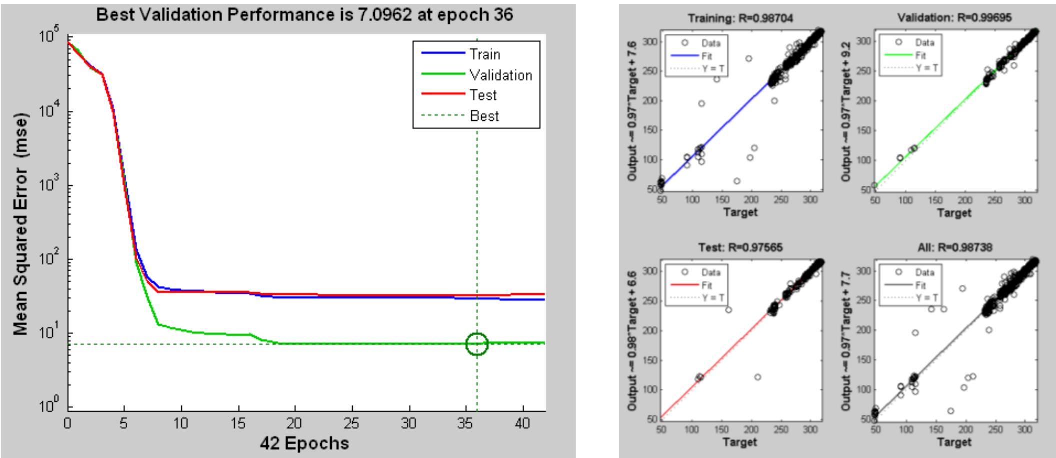
a) *b)*

Figure 4. The efficiency of multi-layer feed-forward neural network determined by: a) mean squared error, b) regression plot.

The efficiency of the network was evaluated by determining the mean square error for the learning (training), validation, and testing results. The resulting curves show that the network has been learned properly because the curves are very similar (Figure 4a). If the test curve begins to rise in comparison with the validation curve, the neural network will not work correctly. The next step in network validation is to create a regression plot, which shows the relationship between the outputs of the network and the targets (Figure 4b). The learning (training) data indicate good fit on this network, as the results show the value of R = 0.72, which is considered a high data correlation.

MATLAB was also used to create a predictive model of the GEROLER motor with a NARX dynamic neural network. As in the previous case, the input data is the pressure drop of the motor and output data is the rotational speed of the motor. The NARX dynamic neural network uses serial-parallel architecture for network learning and signal delay was defined after the input and output target data was loaded, so the learning for input and output data was commenced from the third value. The serial-parallel architecture has two inputs, input of measurement data and input of output target data. For network learning is using single input variable which is equal to the single output target data. After that, the network was closed in a feedback loop, which means that the output from the neural network is used as second inputs to the network. The dynamic neural network of NARX needs to be adjusted after creation, which finally in a two-layer network with 20 neurons in the hidden results layer; the Levenberg-Marquardt algorithm was again chosen for learning.

The efficiency of the network was evaluated by determining the mean square error for the learning, validation, and testing results. The results show that the network has learned properly because the curves are very similar (Figure 5a). Using the regressive analysis, it was determined that the NARX dynamic neural network achieved the correlation coefficient R = 0.98, which is a very high data correlation (Figure 5b).



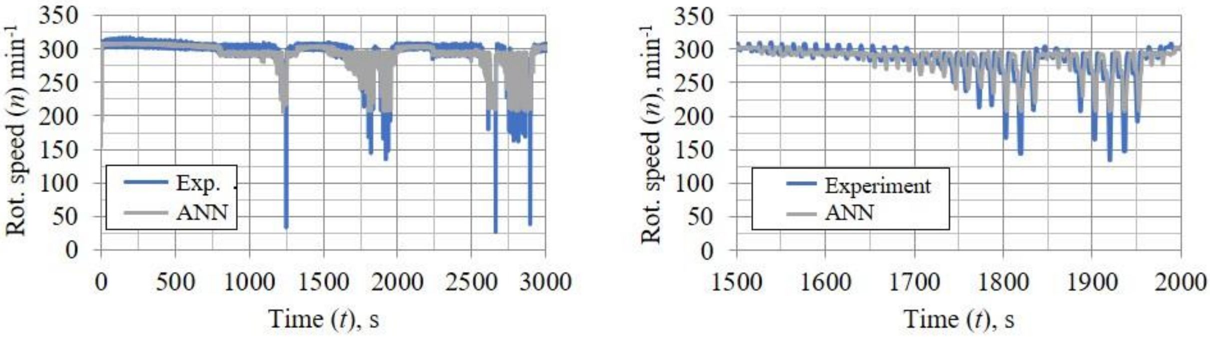
a) *b)*

Figure 5. The efficiency of the NARX dynamic neural network defined by: a) mean squared error, b) regression plot.

4 Results and discussion

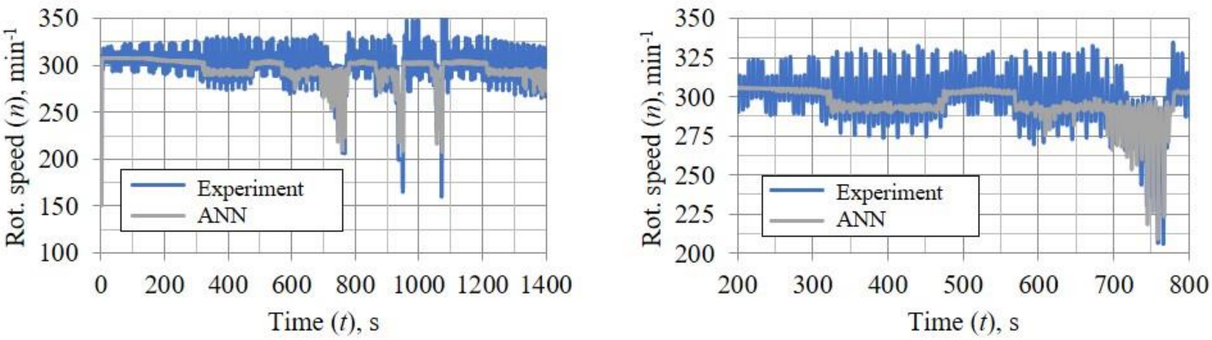
The results of the comparison of the rotational velocity by the modeled multilayer feed-forward neural network and the laboratory measurement used to learn the network are shown in Figure 6a and enlarged in Figure 6b. A good coincidence of the curves can be observed, except for a sudden drop in speed that occurs when the hydraulic motor almost stops. This can be explained by the lower values of the correlation coefficient at higher oscillations of the measured speed, which increases the error of the results.

The final test of the developed multi-layer feed-forward neural network was performed using the new pressure drop input data set. The comparison of the simulation results and new laboratory measurements data is shown in Figure 7a and enlarged in Figure 7b. It can be concluded that a very good fit of the resulting mean values was achieved. Larger oscillations of the measured rotational speed can be explained by larger braking forces compared to the previous measurements. Therefore, the simulation results do not oscillate as much as the measured data; however, the mean values have a good match. Therefore, the black-box predictive model of the GEROLER motor based on the multi-layer feed-forward neural network renders acceptable results.



a) b)

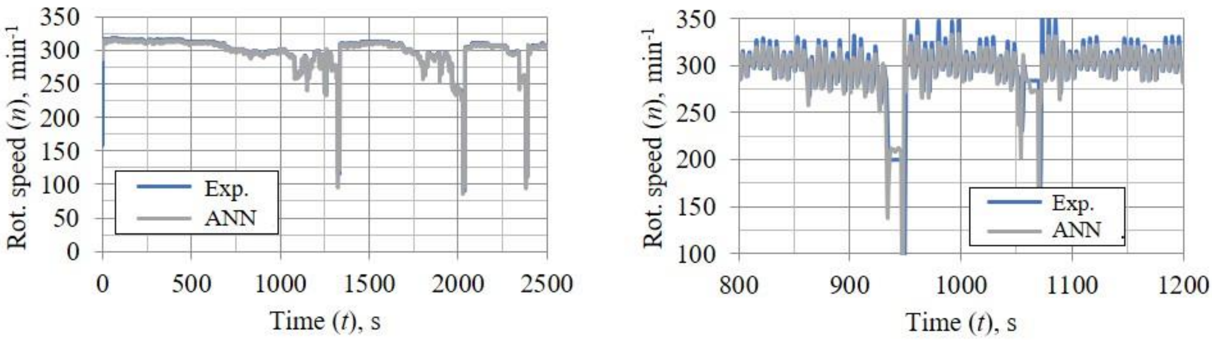
Figure 6. Results of the hydraulic motor rotational speed by the multi-layer feed-forward neural network for learning measurement data.



a) b)

Figure 7. Results of the hydraulic motor rotational speed by the multi-layer feed-forward neural network for new measurement data

After learning, the NARX dynamic neural network was implemented in two simulations. The first simulation was carried out for the learning data set (the results are shown in Figure 8a), and the second simulation was carried out for a new set of measured data (Figure 8b). The matching of the results is very good because the series-parallel configuration was used for one-step in-advance predictions.



a) b)

Figure 8. Results of the hydraulic motor rotational speed by the NARX dynamic neural network: a) for learning measurement data b) for new measurement data.

In the final step, the network was transformed into the original closed loop parallel form. Thus, the prediction is realized in several steps in advance. The NARX dynamic neural network with parallel closed forms was operated with a new set of measured data and the simulation results are shown in Figure 9. Based on the obtained results it can be concluded that the curves obtained by the dynamic simulation using the NARX neural network with closed loop parallel forms follow the mean curve obtained in laboratory measurements very well. The large braking force and measurement of motor speed using reflective tapes are the reason for high oscillations of measured rotational speeds. Since the NARX neural network has a parallel architecture with a feedback loop, the oscillation amplitude cannot be predicted but follows an average value, and therefore it has been proven to work properly.

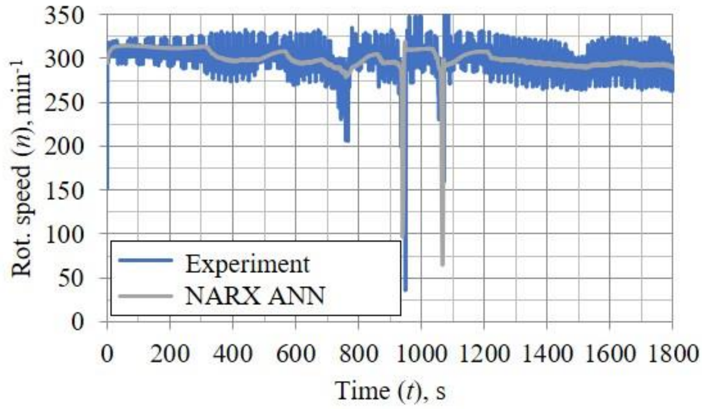


Figure 9. Results of the hydraulic motor rotational speed by the NARX dynamic neural network with the closed loop parallel form.

By comparing the results attained using the multi-layer feed-forward and NARX dynamic neural networks, it can be observed that the correlation factor for the series-parallel NARX network is larger, and the results of network learning are better. By transforming the NARX network to the feedback parallel form, the results correspond to the mean value of the measured speed. Thus, the general conclusion is that the multi-layer feed-forward neural network gives acceptable results, however the NARX dynamic neural network is more flexible and gives better results for solving nonlinear dynamic systems. In accordance with these results, the NARX dynamic neural network is appropriate for the simulation of the GEROLER motor.

5 Conclusion

The black-box model of the GEROLER motor was developed using artificial neural networks with the intention to predict the working parameters with an uneven load torque. The uneven load torque of the GEROLER motor was realized by a laboratory hydraulic system with a mechanical friction brake. The predictive model of the GEROLER motor was created using the multi-layer feed-forward neural network and the dynamic NARX neural network. Observing the results of rotational speed from the multi-layer feed-forward neural network and the laboratory measurement using for network learning, a good matching of results was achieved except in cases of sudden rotational speed drops. The reason for this is a short time interval, so the results obtained by neural network have not reached the target value. The multi-layer feed-forward neural network was finally tested with new input data of the motor pressure drop, which allowed very good matching of mean values. It can be concluded that the black-box model of the GEROLER motor based on the multi-layer feed-forward neural network offers acceptable results.

Because the multi-layer feed-forward neural network is a static network, and the GEROLER motor is a nonlinear dynamic system, the dynamic NARX neural network model was also developed. No allowed clipboard formats could have been pasted. Because of its parallel architecture with the feedback loop, the NARX neural network cannot predict the value of the oscillations, but the mean values are matching and the correct operation of the NARX neural network was proven. The general conclusion would be that the multi-layer feed-forward neural network provides acceptable results, but the NARX dynamic neural network gives more favorable results due to its flexibility in solving nonlinear dynamic systems such as the GEROLER hydraulic motor system.

Future research should focus on improving the laboratory hydraulic system with an electromagnetic brake that provides more precise definition of the non-uniform load torque, as well as new measurement devices to measure the torque and rotational speed. Implementation of the electromagnetic brake and torque transducer into the existing hydraulic laboratory system is currently underway. Also, future research should concentrate to modelling of predictive model using a deep neural network architecture.

References

[1] R. F. Ansdale, D.J. Lockley, "The Wankel RC Motor Design and Performance," *London Iliffe Books*, London, UK, 1968. *(Book)*

[2] P.J Gamez-Montero, E. Codina, R. Castilla, "A review of gerotor technology in hydraulic machines," *Energies*, vol. 12 iss. 12, 2019. Available: MSPI, http://www.mdpi.com [Accessed: 15 Feb. 2021]. *(Journal article)*

[3] J.R. Colbourne, "The geometry of trochoid envelopes and their application in rotary pumps," *Mech. Mach. Theoy.*, vol. 9, iss. 3-4, 1974, pp. 421–435. *(Journal article)*

[4] J.B Shung, G.R. Pennock, "Geometry for trochoidal-type machines with conjugate envelopes," *Mech. Mach. Theory*, vol. 29, iss. 1, 1994, pp. 25–42, Available: ScienceDirect, http://www.sciencedirect.com. [Accessed: 11 Feb. 2021]. *(Journal article)*

[5] R. Maiti, "Torque characteristics of epitrochoid generated orbital rotary piston type hydraulic motors," *Mech. Mach. Theory*, vol. 28. 1993, pp. 225–231. Available: ScienceDirect, http://www.sciencedirect.com. [Accessed: 11 Feb. 2021]. *(Journal article)*

[6] J. Stryczek, "Hydraulic machines with cycloidal gearing," *Arch. Bud. Mas.*, vol.43, 1996, pp. 29–71. *(Journal article)*

[7] L. Ivanović, D. Josifović, A. Ilić, B. Stojanović, "Analytical model of the pressure variation in the gerotor pump chambers," *Tech. Technol. Educ. Manag.* vol. 8, 2013, pp. 323–331. *(Journal article)*

[8] L. Ivanović, G. Devedžić, S. Ćukovic, N. Mirić, "Modeling of the Meshing of Trochoidal Profiles with Clearances," *J. Mech. Des.* vol. 134, iss. 4, 2012, Available: ASME, http://asmedigitalcollection.asme.org. [Accessed: 15 Feb. 2021]. *(Journal article)*

[9] M.A. Ruvalcaba, X. Hu, "Gerotor fuel pump performance and leakage study," In Proceedings of the *ASME 2011 International Mechanical Engineering Congress & Exposition*, Denver, CO, USA, pp. 11–17, Available: ASME, http://asmedigitalcollection.asme.org. [Accessed: 15 Feb. 2021]. *(Conference paper)*

[10] P.J Gamez-Montero, R. Castilla, D. del Campo, N. Ertürk, G. Raush, E. Codina, "Influence of the interteeth clearances on the flow ripple in a gerotor pump for motor lubrication," Proc. Inst. Mech. Eng. D, 2012, pp. 930–942, Available: SAGE journals, http:// journals.sagepub.com [Accessed: 15 Feb. 2021]. *(Journal article)*

[11] R. Castilla, P.J. Gamez-Montero, G. Raush, E. Codina, "Method for Fluid Flow Simulation of a Gerotor Pump using OpenFOAM," *J. Fluid. Eng.* vol. 139. iss. 11, 2017, Available: ASME, http://asmedigitalcollection.asme.org. [Accessed: 15 Feb. 2021]. *(Journal article)*

[12] P.J. Gamez-Montero, R. Castilla, A. Buza, M. Khamashta, E. Codina, "Numerical study in a mini trochoidal-gear pump with multi-meshing contact points," *In Proceedings of the ASME/BATH 2016 Symposium on Fluid Power and Motion Control, FPMC 2016*, Bath, UK, 2016. Available: ASME, http://asmedigitalcollection.asme.org. [Accessed: 15 Feb. 2021]. *(Conference paper)*

[13] P.J Gamez-Montero, R. Castilla, G. Raush, E. Codina, "Fluid Dynamic Efects of Interteeth and Sideway Clearances on a Mini Gerotor Pump using Dynamic Meshing Decomposition," *In Proceedings of the 11th International Fluid Power Conference*, Aachen, Germany, 2018. Available: RWTH Publications, http:// http://publications.rwth-aachen.de/ [Accessed: 11 Feb. 2021]. *(Conference paper)*

[14] H. Ding, X.J. Lu, B. Jiang, "A CFD model for orbital gerotor motor," *IOP Conf. Ser. Earth Environ. Sci*. vol. 15, 2012. Available: IOP science, http://www. iopscience.iop.org [Accessed: 11 Feb. 2021]. *(Conference paper)*

[15] R. Maiti, M.K. Das, V. Sahoo, K.C. Avula, A. Anukaran, V.P. Tolambia, A. Nag, "Leakage Past Active Contacts in Involute and Cycloidal Gear Hydrostatic Units," *In Proceedings of the 14th Scandinavian International Conference on Fluid Power*, 2015. *(Conference paper)*

[16] E. Strmčnik, F. Majdič, “The pressure and effciency characteristic of hydraulic gerotor motor with the floating outer ring,” *Tech. Gaz.* vol. 25, 2018, pp. 609–615. Available: Hrčak, http://hrcak.srce.hr [Accessed: 11 Feb. 2021]. *(Journal article)*
[17] E. Strmčnik, F. Majdič, “The improvement of the total effciency of the gerotor orbital hydraulic motor,” *In Proceedings of the 11th International Fluid Power Conference*, Aachen, Germany, 2018. Available: RWTH Publications, http:// http://publications.rwth-aachen.de/ [Accessed: 11 Feb. 2021]. *(Conference paper)*
[18] S. Haykin, Neural Networks, A Comprehensive Foundation, Ninth Indian Reprint, Pearson Education, Singapore, 2005. *(Book)*
[19] See http://www.riteh.uniri.hr/ustroj/zavodi/zks/laboratorij-za-hidrauliku-i-pneumatiku/
[20] See https://www.parker.com/literature/HPCE/New/CAT-4054-3-UK.pdf
[21] See https://www.losiuk.co.uk/