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NEURAL NETWORK CONTROLLER FOR FAULT DETECTION AND MONITORING OF A CLOSED-LOOP COMPACT HYDRAULIC DIRECT DRIVE SERVOMECHANISM

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Abstract: *This paper delves into the development and implementation of a neural network controller devised for the purpose of fault detection and monitoring within a compact closed-loop direct-drive hydraulic servomechanism. The primary function of this servomechanism is to swiftly and precisely adjust the force produced by a single-rod double-acting hydraulic cylinder. The monitoring system, integrated with neural networks, is configured to oversee three pressure transducers, the system's command input, and the resultant force output. This configuration enables the generation of continuous error values, specifically adapted to prevalent faults often encountered within such servomechanisms. One notable aspect of this research lies in the ability to generate variable error values that serve as predictive indicators, forecasting potential future system malfunctions in accordance with the principles of predictive maintenance aligned with the paradigm of Industry 4.0. The research and development presented in this paper offer a significant advancement in the field of fault detection and predictive maintenance for hydraulic servomechanisms, catering to the demands of Industry 4.0. By leveraging neural networks to analyze and interpret continuous error values, this approach enables the pre-emptive identification of potential faults, ensuring proactive maintenance interventions. The system's capability to predict potential failures in advance is a pivotal step toward ensuring increased operational efficiency, reduced downtime, and improved reliability within industrial settings adopting compact closed-loop direct-drive hydraulic servomechanisms.*

Keywords: *Neural network, fault detection and monitoring, predictive maintenance, closed-loop, hydraulic direct drive servomechanism, Industry 4.0.*

1. Introduction

Industry 4.0 and predictive maintenance. The spectacular increase in the scientific and technological level of production led to a new form of known development named Industry 4.0, which is the fourth Industrial Revolution (see fig. 1), and was introduced in 2011 by a group of German scientists [1].

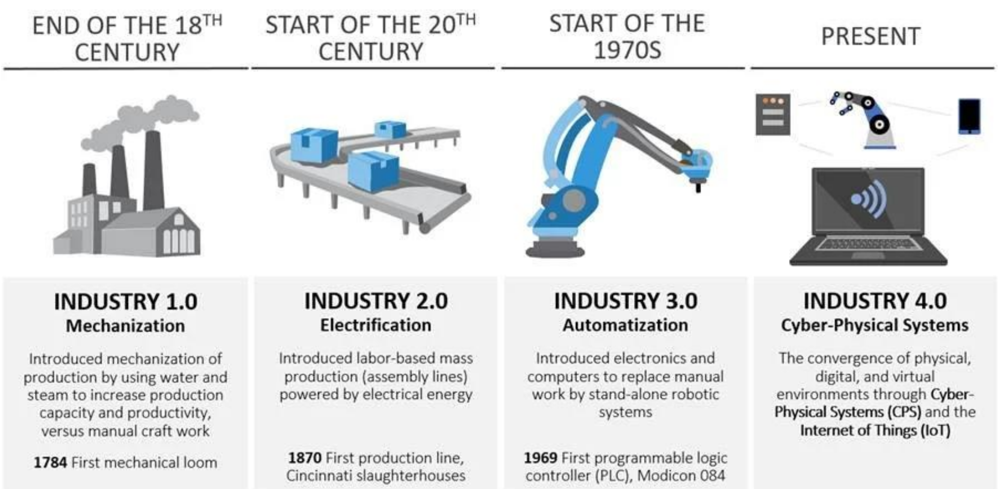

Fig. 1. The 4 major Industrial Revolutions [2]

This industrial revolution also started from the finding that, for several decades, manufacturing was transferred to Asia, so that today the question arises of the reindustrialization of Europe, for a sustainable development. The problem of the technical-economic development of countries is not only in Europe, but is felt in many countries of the world where it has acquired all kinds of names, among which one can mention IIC in the USA, Industrial Value-Chain Initiative in Japan, Industry of the Future in France, but also a similar initiative in China [3].
The main pillars of the Industry 4.0 are (see fig. 2):

- Advance human-machine interface
- Big data
- Internet of things (IoT)
- Data analysis
- Augmented Reality (AR)
- Digital to real life
- Smart sensor

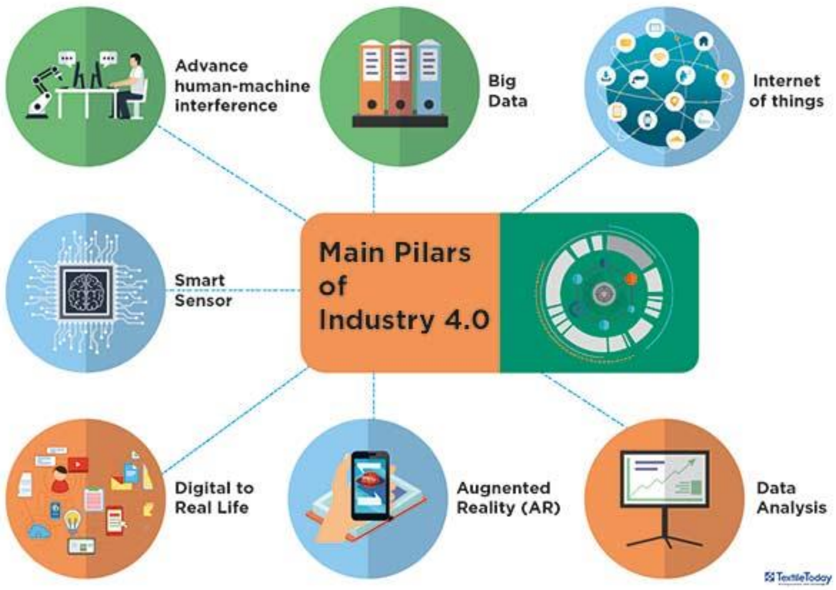

Fig. 2. Main pillars of Industry 4.0 [4]

This concept introduces for the first time the principle of Smart Factory (see fig. 3), where all systems are interconnected with the help of network, and can provide data for all the department in the factory, which reduces time and it is cost efficient. The data provided in the Intelligent Factory can be about a certain process carried out by a system, or about the state of the system itself, and this type of factory comes with a lot of changes compared to the traditional factories.
One of the aspects that changes in the Smart Factory is that of maintenance [5]. In general, the maintenance is calculated for a certain number of operating hours of the equipment and to be able to achieve it, it is necessary to stop work on the equipment in question for the entire maintenance period; even if at the time scheduled for the maintenance the factory urgently needs that equipment to work, it cannot do that.
Therefore, together with this concept of Industry 4.0, the concept of predictive maintenance [6] is also introduced. Predictive maintenance [7] is carried out by introducing into the system some sensors placed on different equipment that can ‘tell’ the maintenance teams at any time the state of the system and which of the components monitored by the sensors show signs of fatigue or failure, so that the competent department can know in advance when they need to intervene.
Even more, thanks to the continuous harsh surveillance of the system made by the sensors, one can work with the equipment in question until the moment when they are almost at the upper limit

of the optimal functioning range before the appearance of a major fault. Of course, this type of operation is only recommended in case of emergencies, when the factory really needs for that equipment to work, otherwise it is recommended that the maintenance be done in advance.

Fig. 3. Smart Factory - Graphic illustration of the concept [8]

A decade after its introduction, the concept of Industry 4.0 has gained global scope and is the dominant concept in the digital transformation of the industry. By combining results-based research and practical industry experience, progress has been made in implementing the concept and new areas of action have been identified from a technological and application-oriented perspective. Industry 4.0 is human-centered and is the basis for innovative business models and agile forms of organization.
At this moment, in industry IoT and cyberphysical production are a reality in newly built factories and the connectivity of machines has been improved in existing factories.
Currently, there are six new megatrends (see fig. 4) that will influence the development of the next 10 years: industrial AI, edge computing up to edge cloud, 5G in the factory, teams of robots, autonomous intralogistics systems and trustworthy data.
These things allow the creation of an innovative digital ecosystem that allows long-term adaptability in a volatile economic and geopolitical environment.

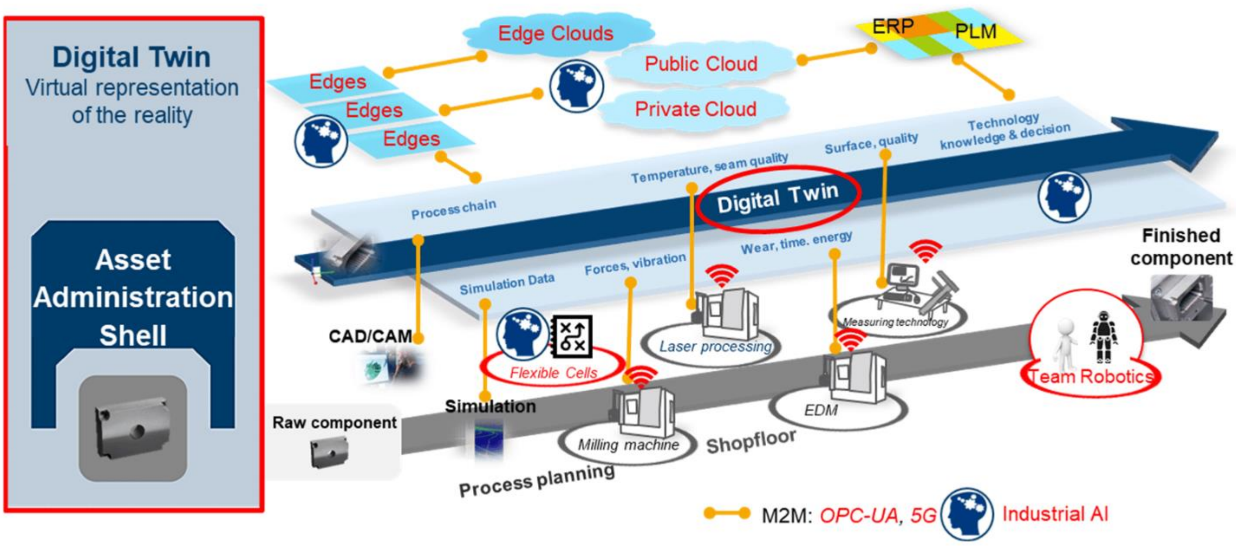

Fig. 4. Megatrends for the next level of Industry 4.0 [8]

Neural network in Industry 4.0. In today's era of Industry 4.0, where automation and smart manufacturing processes are revolutionizing industrial operations, the need for efficient fault detection and predictive maintenance systems has become paramount. The integration of advanced technologies and intelligent systems is no longer a luxury but a necessity to ensure seamless, reliable, and cost-effective industrial processes. In this context, this scientific paper delves into a groundbreaking development that interlaces the power of neural networks [9] with the intricacies of a closed-loop compact hydraulic direct drive servomechanism to create a novel approach for fault detection and monitoring.

This paper paves the path to reshaping the way industries approach maintenance and efficiency in the Smart Factory defined by the Industry 4.0 concept.

The servomechanism at the heart of this research plays a pivotal role in swiftly and precisely adjusting the force generated by a single-rod double-acting hydraulic cylinder, making it indispensable in a variety of industrial applications. However, the very complexity of these systems also renders them susceptible to various faults and malfunctions, leading to reduced operational efficiency and increased downtime.

To address these challenges, the paper introduces an innovative monitoring system that harnesses the capabilities of neural networks [10]. This system is meticulously designed to oversee critical components of the hydraulic servomechanism such as the pump, cylinder or the system filter by including three pressure transducers. The system's command inputs, and the resultant force output, are also collected by the neural network. By continuously monitoring and analyzing data from these components, the neural network-based controller can generate error values that are specifically designed to prevalent faults that often afflict hydraulic servomechanisms. What sets this research apart is its ability to generate variable error values, transforming them into powerful predictive indicators. These indicators, in line with the principles of predictive maintenance, have the potential to forecast future system malfunctions. This proactive approach holds significant promise for industrial settings, as it empowers maintenance teams to address issues before they escalate into critical failures. Consequently, the integration of neural networks into this context paves the way for more efficient, cost-effective, and reliable industrial processes. This research is a clear manifestation of how the interlacing of advanced technology and engineering ingenuity can transform the industrial landscape.

This paper unfolds at the intersection of multiple critical domains. It combines the intricate engineering of a compact hydraulic direct drive servomechanism with the cutting-edge power of neural networks. Furthermore, it aligns itself with the overarching principles of Industry 4.0, where the digitalization of industry is ushering in a new era of intelligent, interconnected manufacturing processes. As we progress further into this digital age, the significance of such research cannot be overstated, as it holds the potential to drive progress and innovation in the industrial sector.

In the following pages, the authors delve deeper into the specific components of the neural network controller, its integration with the servomechanism, the methodologies used for fault detection, and the generation of predictive indicators. This paper represents a significant advancement in the realm of fault detection and predictive maintenance for hydraulic servomechanisms, ultimately catering to the demands and expectations of Industry 4.0. By leveraging the capabilities of neural networks to analyze and interpret continuous error values, this approach not only identifies potential faults but also enables pre-emptive maintenance interventions, a pivotal step toward ensuring increased operational efficiency, reduced downtime, and improved reliability within industrial settings that rely on compact closed-loop direct-drive hydraulic servomechanisms. Below, the authors reveal the intricate details of this groundbreaking research, offering insights that have the potential to reshape the future of industrial maintenance and operation. The utilization of neural networks in Industry 4.0 exemplifies the intersection of cutting-edge technology and the demands of modern industrial processes. This integration not only facilitates efficient fault detection but also aligns with the overarching principles of the fourth industrial revolution, promoting intelligent, interconnected, and agile manufacturing systems. As industries continue to evolve in this digital age, the role of neural networks in optimizing processes and ensuring reliability becomes increasingly indispensable.

2. Material and Method

The present section unveils the foundation of the neural network controller's development for fault detection in a hydraulic servomechanism. Fig. 5 provides a snapshot of training data in both tabular and graphical formats, crucial for the network's learning.

	A	B	C	D	E	F	G	H	I	J	K	L
1	Pressure_P1	Cavitation_B1	Pressure_P2	Cavitation_B2	Pressure_P3	Clogged_filter	Force_1	Overload	P1/P2_ratio	Volumetric_losses_B2_to_B1	P2/P1_ratio	Volumetric_losses_B1_to_B2
2	bar	0 .. -1	bar	0 .. -1	bar	0 .. 200 %	N	+100 .. -100 %	-	0 or 1	-	0 or 1
3	0.00	0.00	0.00	0.00	0.00	0.00	160000.00	100.00	0.00	1.00	6000.00	0.00
4	0.10	0.00	0.10	-1.00	0.02	0.40	159680.00	99.60	0.02	1.00	59.35	0.00
5	0.20	0.00	0.20	-0.90	0.04	0.80	159360.00	99.20	0.03	1.00	29.79	0.00
6	0.30	0.00	0.30	-0.80	0.06	1.20	159040.00	98.80	0.05	1.00	19.87	0.00
7	0.40	0.00	0.40	-0.70	0.08	1.60	158720.00	98.40	0.07	1.00	14.90	0.00
8	0.50	0.00	0.50	-0.60	0.10	2.00	158400.00	98.00	0.08	1.00	11.92	0.00
9	0.60	0.00	0.60	-0.50	0.12	2.40	158080.00	97.60	0.10	1.00	9.92	0.00
10	0.70	0.00	0.70	-0.40	0.14	2.80	157760.00	97.20	0.12	1.00	8.50	0.00
11	0.80	0.00	0.80	-0.30	0.16	3.20	157440.00	96.80	0.13	1.00	7.43	0.00
12	0.90	0.00	0.90	-0.20	0.18	3.60	157120.00	96.40	0.15	1.00	6.60	0.00
13	1.00	0.00	1.00	-0.10	0.20	4.00	156800.00	96.00	0.17	1.00	5.93	0.00
14	1.10	0.00	1.10	0.00	0.22	4.40	156480.00	95.60	0.19	1.00	5.39	0.00
15	1.20	0.00	1.20	0.00	0.24	4.80	156160.00	95.20	0.20	1.00	4.94	0.00
16	1.30	0.00	1.30	0.00	0.26	5.20	155840.00	94.80	0.22	1.00	4.55	0.00
17	1.40	0.00	1.40	0.00	0.28	5.60	155520.00	94.40	0.24	1.00	4.22	0.00
18	1.50	0.00	1.50	0.00	0.30	6.00	155200.00	94.00	0.25	1.00	3.94	0.00
19	1.60	0.00	1.60	0.00	0.32	6.40	154880.00	93.60	0.27	1.00	3.69	0.00
20	1.70	0.00	1.70	0.00	0.34	6.80	154560.00	93.20	0.29	1.00	3.47	0.00
21	1.80	0.00	1.80	0.00	0.36	7.20	154240.00	92.80	0.31	1.00	3.27	0.00
22	1.90	0.00	1.90	0.00	0.38	7.60	153920.00	92.40	0.32	1.00	3.10	0.00
23	2.00	0.00	2.00	0.00	0.40	8.00	153600.00	92.00	0.34	1.00	2.94	0.00
24	2.10	0.00	2.10	0.00	0.42	8.40	153280.00	91.60	0.36	1.00	2.80	0.00
25	2.20	0.00	2.20	0.00	0.44	8.80	152960.00	91.20	0.37	1.00	2.67	0.00
26	2.30	0.00	2.30	0.00	0.46	9.20	152640.00	90.80	0.39	1.00	2.55	0.00
27	2.40	0.00	2.40	0.00	0.48	9.60	152320.00	90.40	0.41	1.00	2.44	0.00
28	2.50	0.00	2.50	0.00	0.50	10.00	152000.00	90.00	0.43	1.00	2.34	0.00
29	2.60	0.00	2.60	0.00	0.52	10.40	151680.00	89.60	0.44	1.00	2.25	0.00
30	2.70	0.00	2.70	0.00	0.54	10.80	151360.00	89.20	0.46	1.00	2.16	0.00

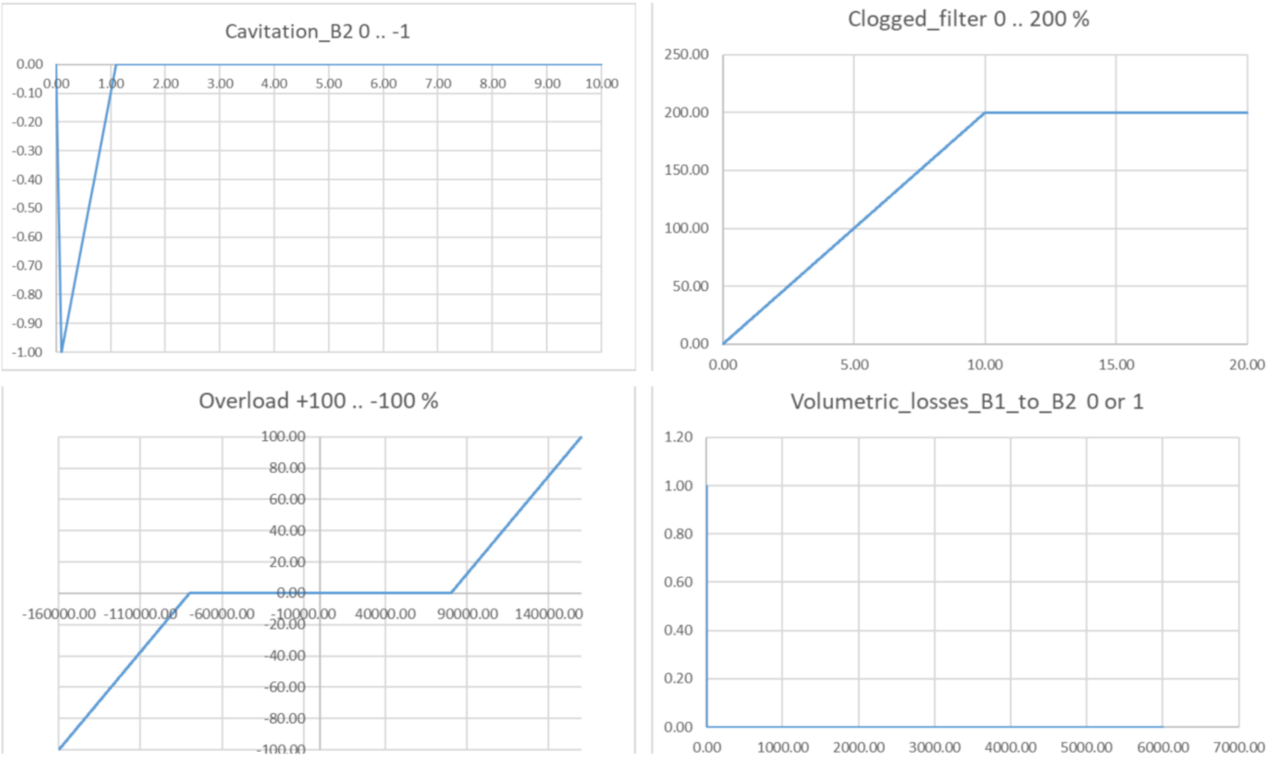

Fig. 5. Sample of data used for training and validation of neural network - tabular and graphical form

Fig. 6 reveals the data headers governing training and validation, offering transparency into the parameters guiding the network's adaptation. These visuals not only anchor the discussion but also emphasize the meticulous approach to training and validation processes, crucial in achieving precision in fault detection within the complexities of Industry 4.0 context.

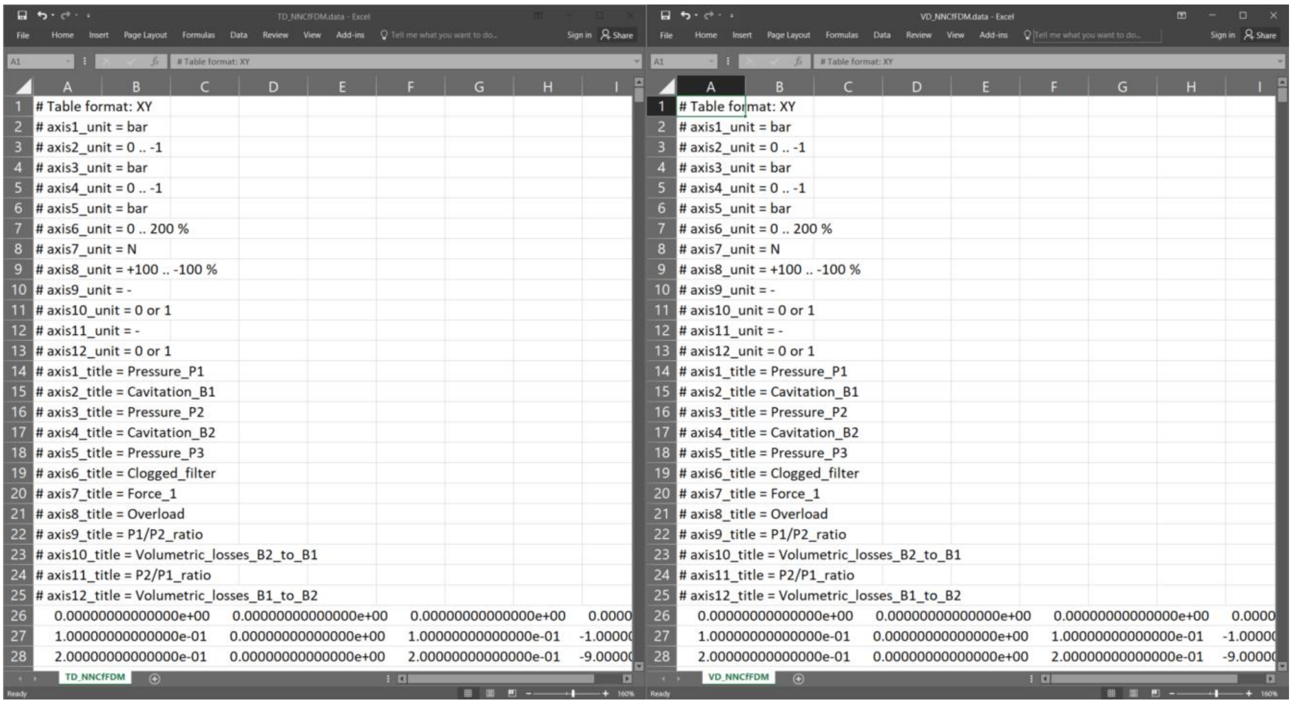

Fig. 6. Data headers of training and validation data

Fig. 7 and Fig. 8 serve as visual representations of the neural network builder, displaying the training and validation data for the newly developed neural network. These figures offer a clear depiction of the two distinct datasets employed in the training process and highlight the 12 variables crucial to the neural network's configuration. The visuals provide a tangible glimpse into the intricacies of the data sets, enabling the identification of key components essential for the network's learning and subsequent application in fault detection within the closed-loop compact hydraulic direct drive servomechanism.

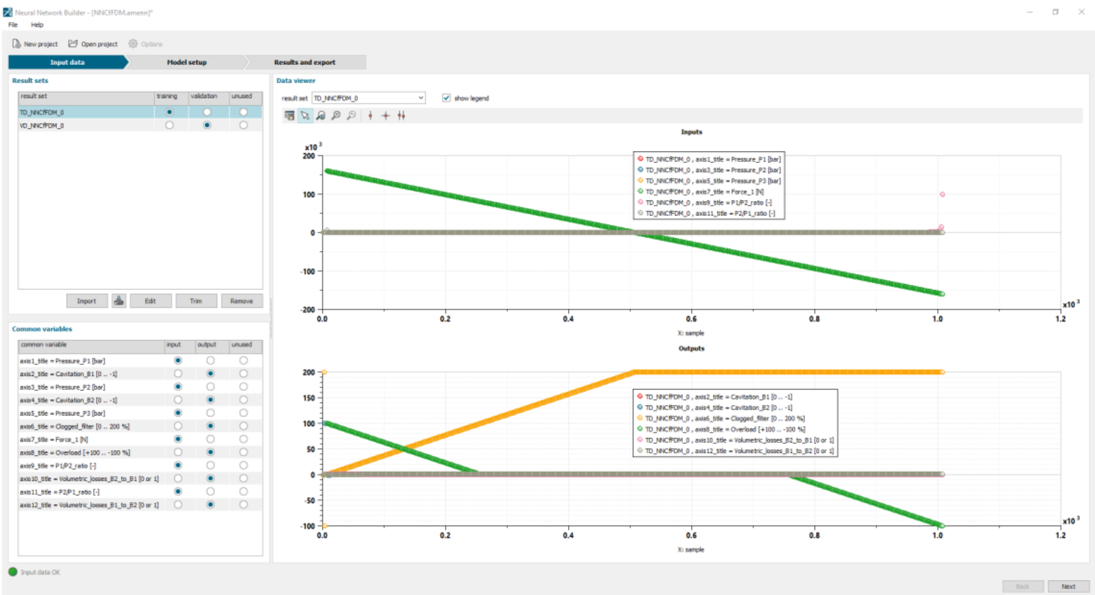

Fig. 7. Input of training data in neural network builder

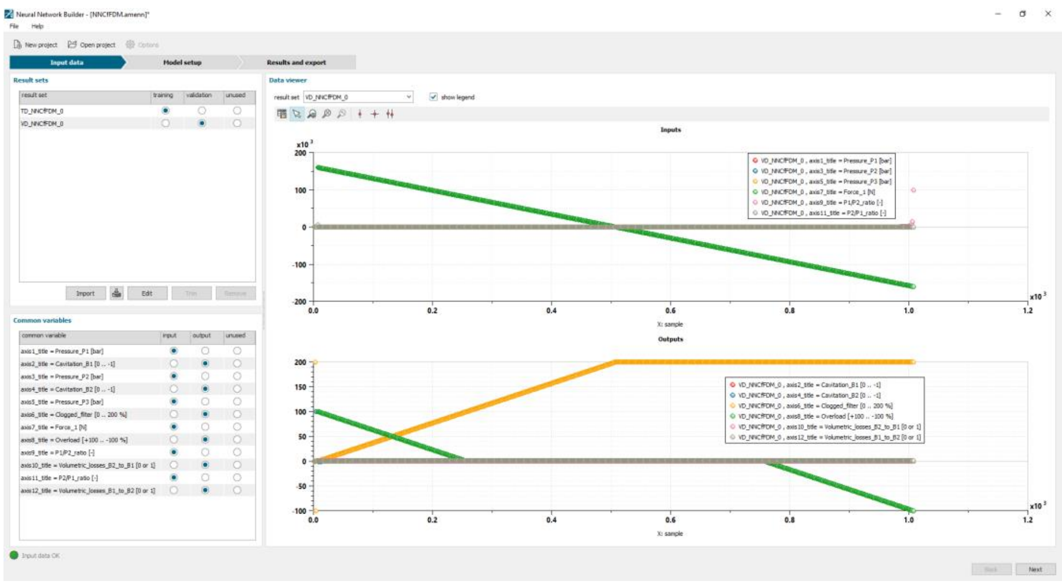

Fig. 8. Input of validation data in neural network builder

Fig. 9 shows the training of the neural network, the training parameters and the variables of the network.

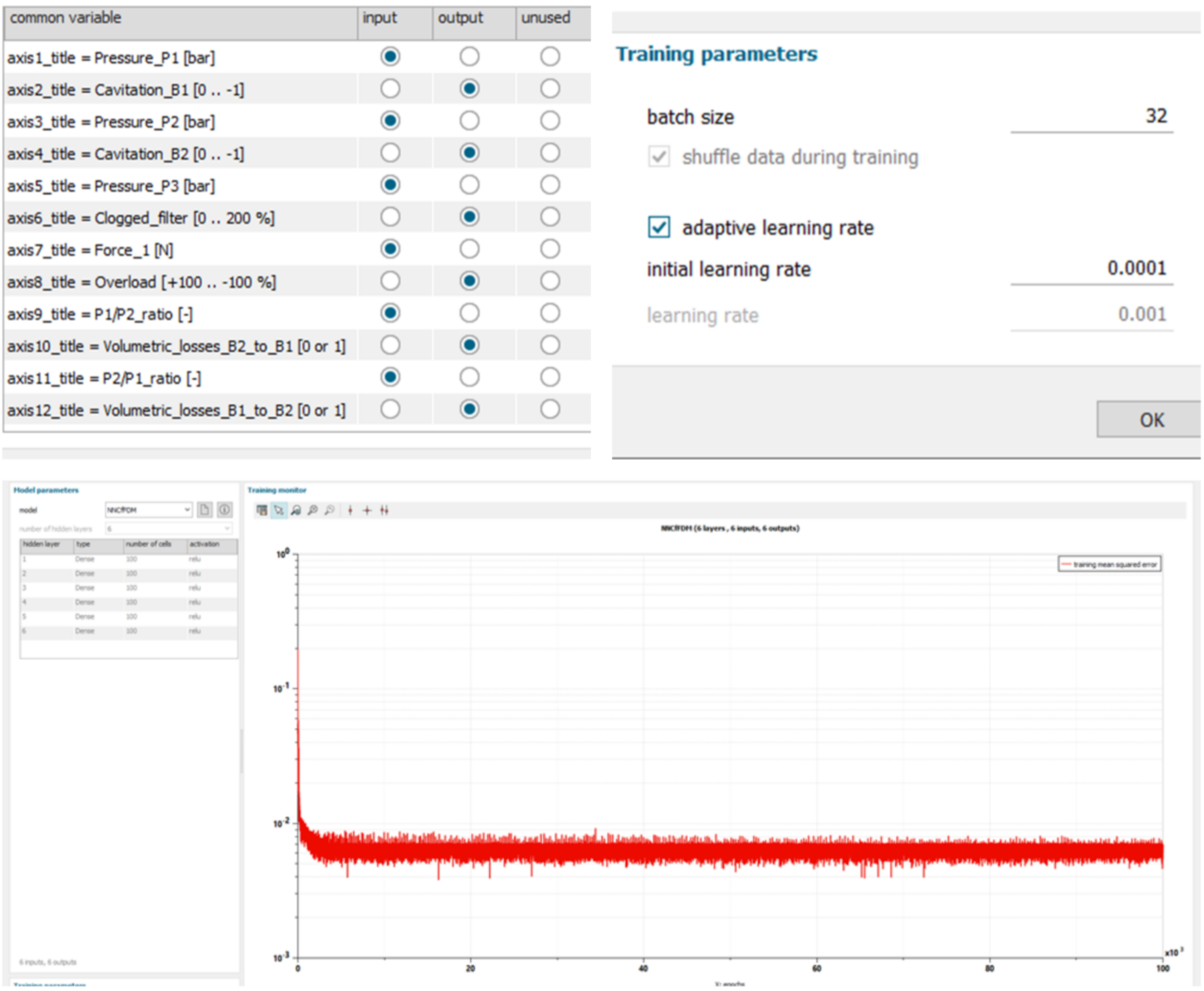

Fig. 9. Neural network training, training parameters and network variables

According to Fig. 10, after the 100000 training epochs the mean square error has a value of 0.007.

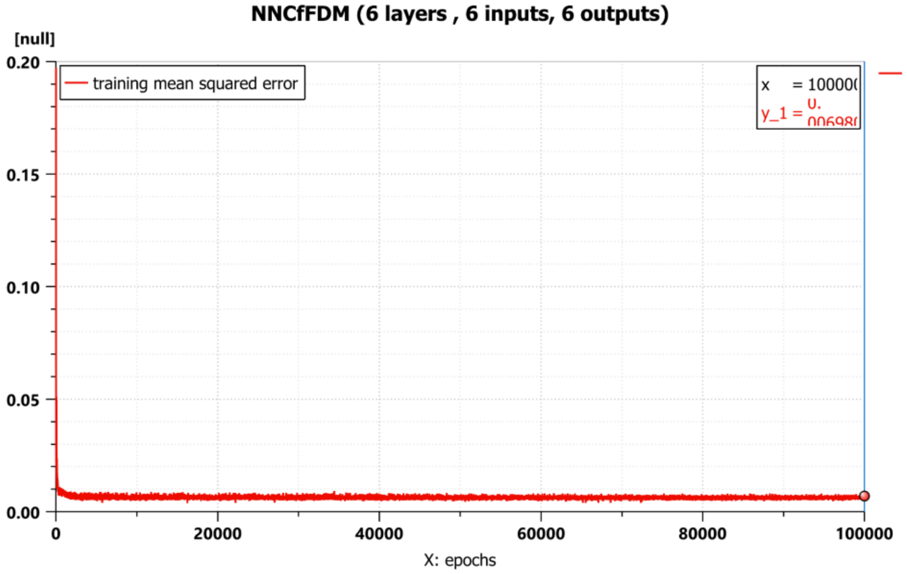

Fig. 10. Training mean square error

The results of the neural network training can be seen in Fig. 11, which shows 4 of the 6 outputs of the neural network.

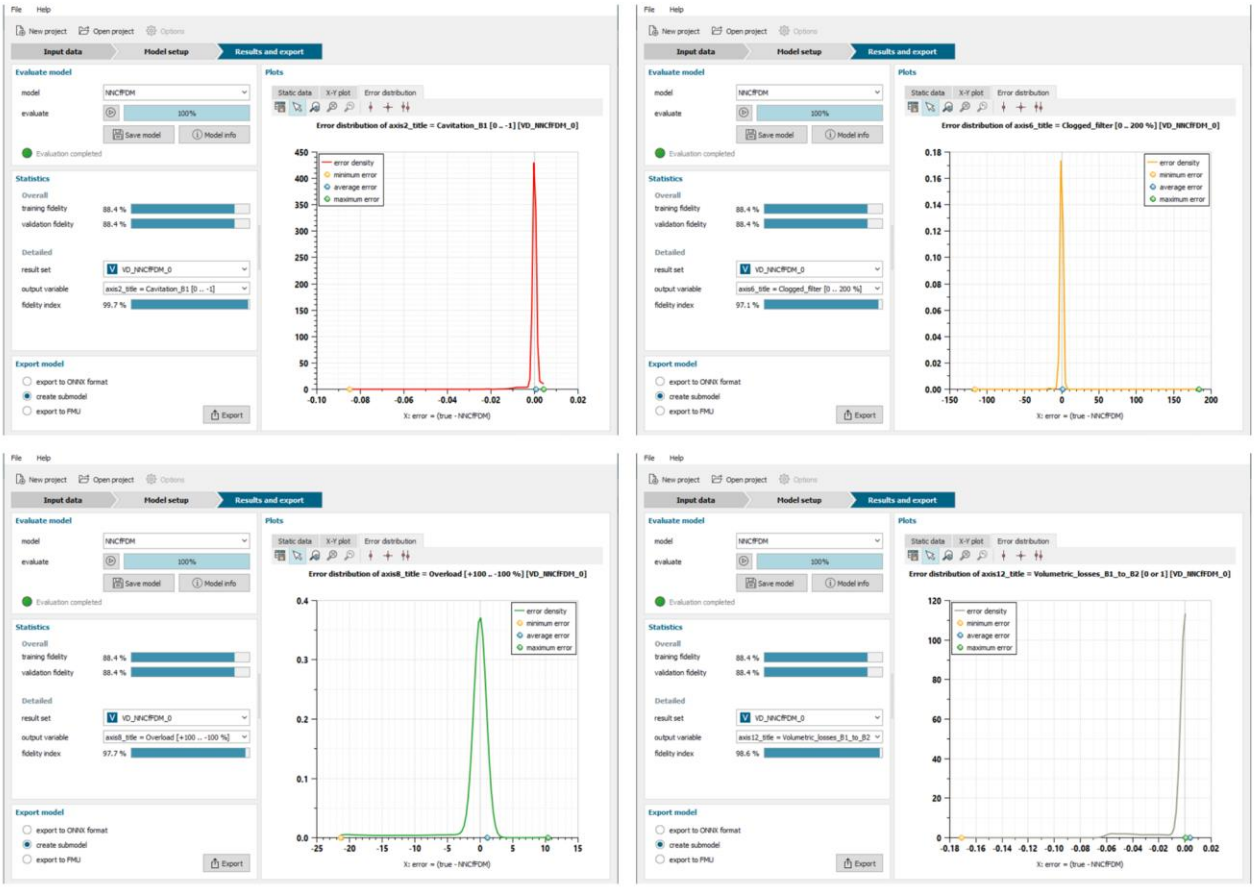

Fig. 11. Results of neural network training

In Fig. 12, the model manager of the neural network discloses, revealing essential parameters and training outcomes. Noteworthy metrics include a training fidelity of 88.4% and a matching validation fidelity. The training process, spanning 5661 seconds, demonstrates the model's robustness. The neural network configuration comprises six deep layers, each containing 100 neurons, using the rectified linear unit (ReLU) type activation. These parameters summarize the neural network's structure and its ability in learning from the provided datasets, crucial for effective fault detection in the closed-loop compact hydraulic direct drive servomechanism.

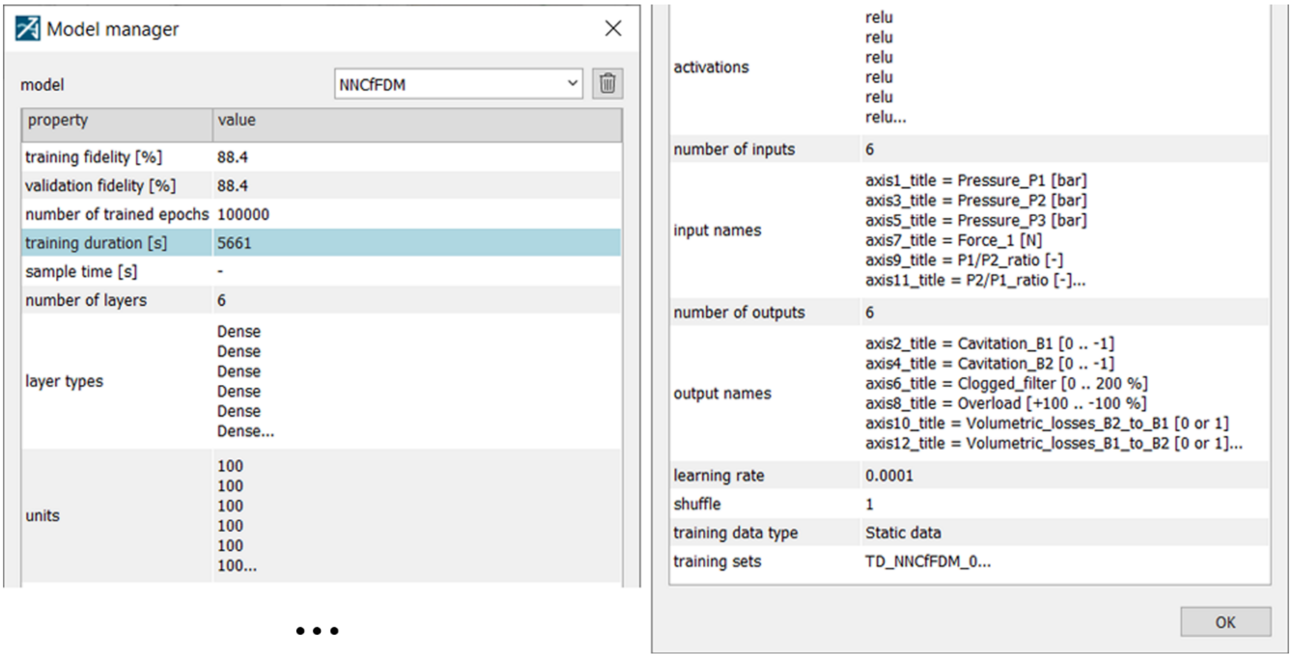

Fig. 12. Model manager of the neural network

At the end of the neural network training and validation process, the network model was saved as a submodel (see Fig. 13) to be used later.

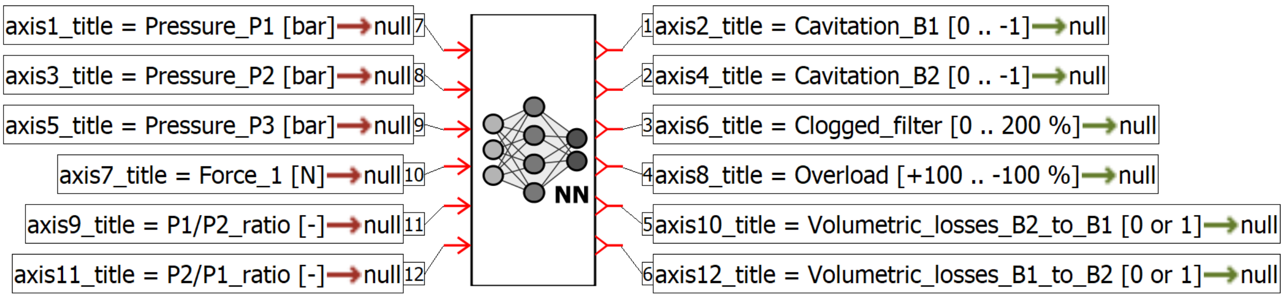

Fig. 13. The neural network submodel

The neural network was integrated into the simulation model shown in Fig. 14, which is composed of a closed-loop compact hydraulic direct drive servomechanism and neural network controller for fault detection and monitoring. The parameters of the components are also presented in the same figure.
System operation: The chirp command signal is sent to the PID controller that continuously adjusts the flow rate of the servopump so that the force generated by the hydraulic cylinder is always as close as possible to the commanded one. The values of the 3 pressure transducers (one of which is differential) and one force transducer are monitored by the neural network that processes them and signals if a malfunction occurs in the system.

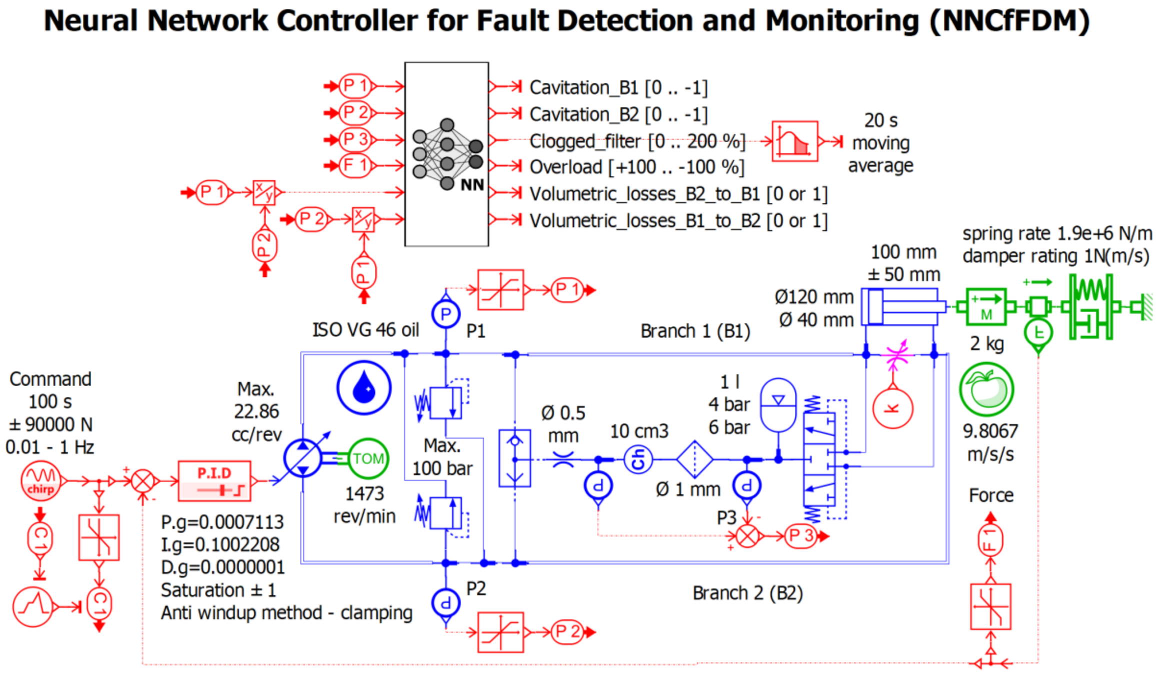

Fig. 14. The simulation network of a closed-loop compact hydraulic direct drive servomechanism

3. Results

In this section, the results of the numerical simulation are presented in three sets (Figs. 15 - 17); the simulation was conducted in the scope of the developing a neural network controller for fault detection and monitoring in the closed-loop compact hydraulic direct drive servomechanism.

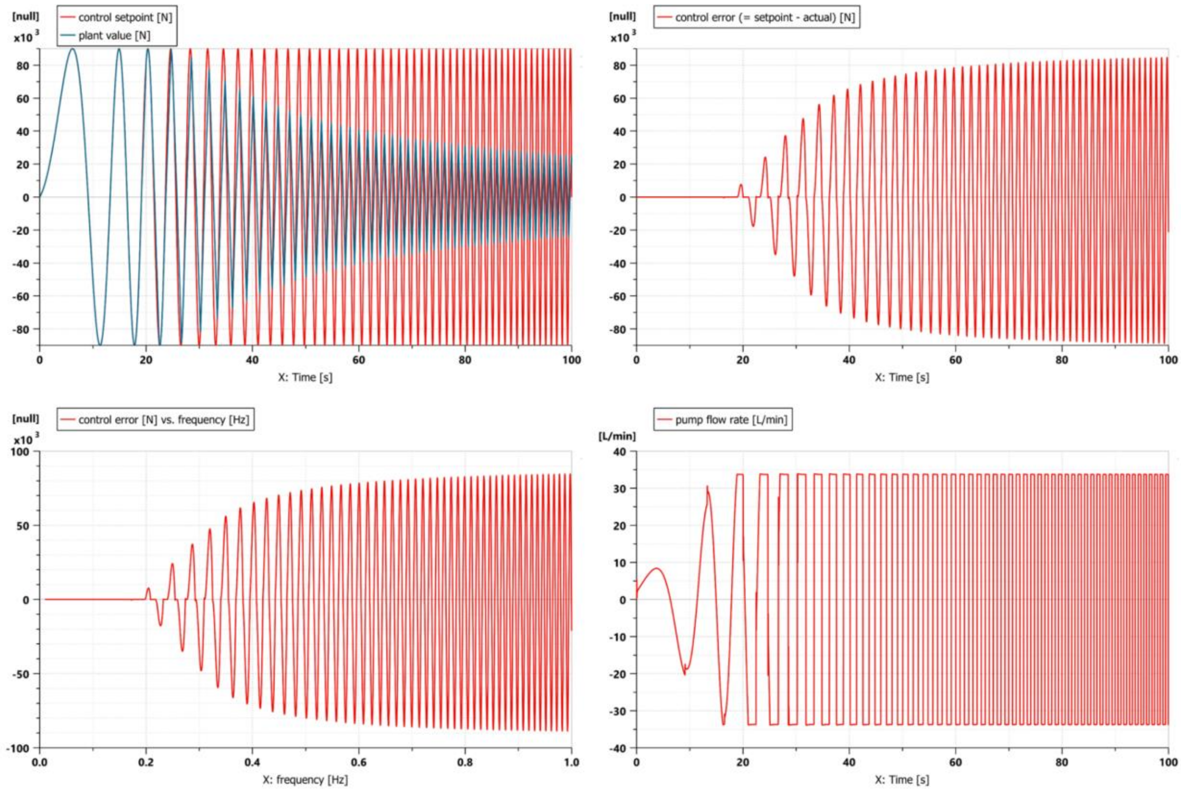

Fig. 15. Results set 1

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In Fig. 15, the upper left corner illustrates the control setpoint curve (desired force) alongside the plant value (achieved force). This graphical representation provides a visual comparison between the intended force output and the actual force achieved by the system. On the right side of this graph, the instantaneous variation of the control error is presented, offering insights into how the control error evolves in real-time. Moving to the lower left graph, the instantaneous adjustment control error versus frequency of the control signal is depicted. This section of the figure provides a detailed examination of how quickly and accurately the system responds to changes in the control signal frequency and system limits. The dynamic variation of the servopump flow rate is then showcased on the right side of this graph, shedding light on the real-time adjustments made to the flow rate of the servopump in response to the dynamic requirements of the system; the value of the generated force decreases with the increase of the command frequency.

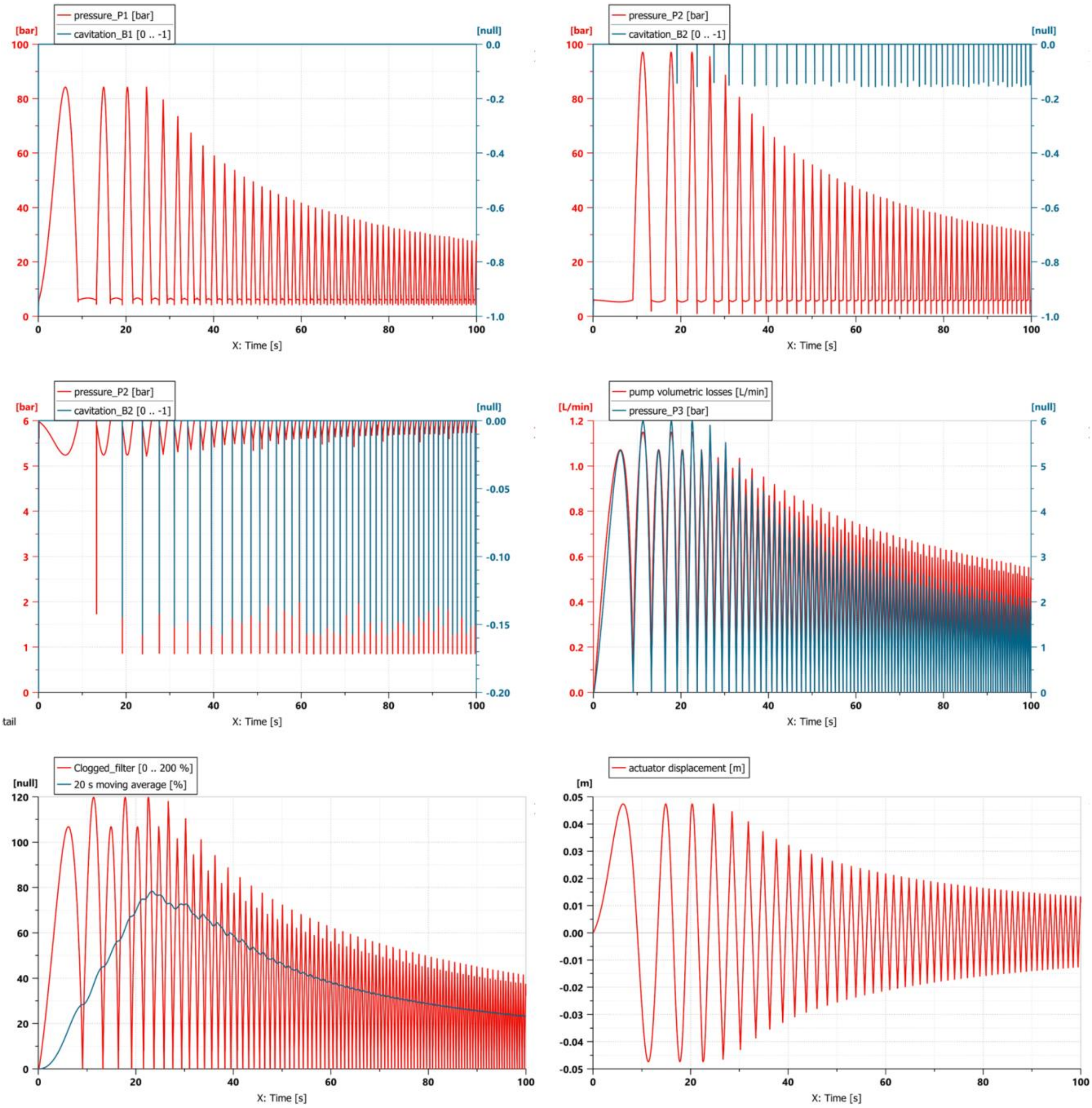

Fig. 16. Results set 2

Fig. 16, the top row of graphs presents an overview of the pressures within the two branches of the transmission. The detailed left-center graph provides a closer view, revealing a drop in pressure below atmospheric pressure specifically on branch B of the transmission; this phenomenon is further corroborated by the neural network's indication, represented by the blue curve, aligning with the observed drop in pressure. The right-center graph in the same row focuses on volumetric losses of the servopump and the resulting pressure drop attributed to these losses on the oil filter. The lower left graph captures the neural network response to this pressure drop (on the oil filter), and an average of these values is also included for a clearer representation. Finally, the graph in the lower right corner shows the movement of the actuator whose movement amplitude decreases with the increase of the command frequency.

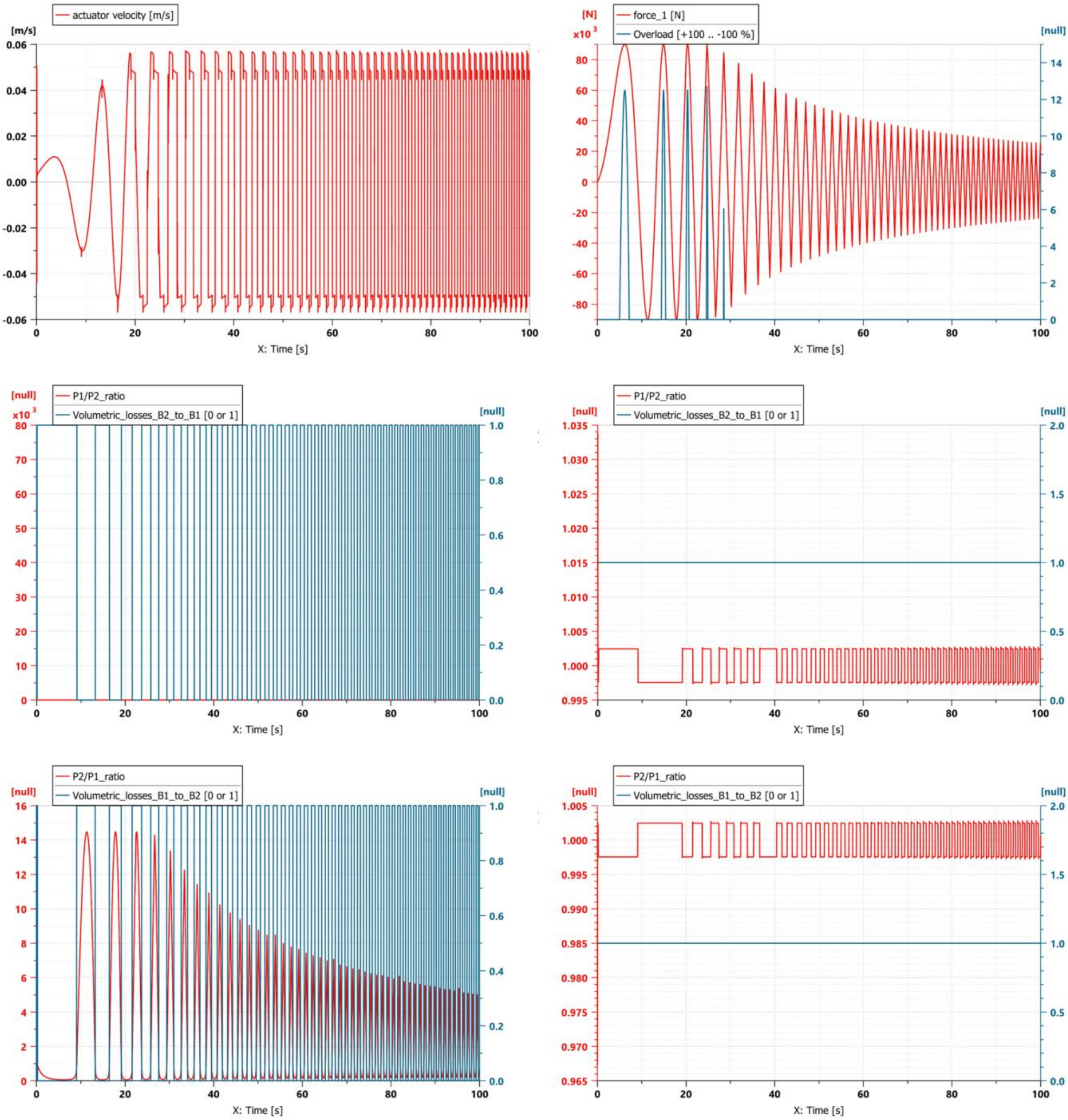

Fig. 17. Results set 3

In Fig. 17, the upper left column features a graph illustrating the time variation of the velocity of the hydraulic actuator. To the right of this graph, the force generated by the hydraulic actuator is presented in red. Additionally, the overload is signaled by the neural network and is represented by a blue curve, indicating a value of 12% of the nominal force, which is 80000 N. The graphs in the center and bottom left further delve into the response of the neural network to small volumetric losses. On the other hand, the graphs in the center and bottom right depict the neural network's response to large volumetric losses, simulated through the use of a throttle that short-circuits the hydraulic cylinder ports.
In summary, the current chapter underscores the effectiveness of the neural network controller in fault detection and monitoring for a closed-loop compact hydraulic direct drive servomechanism. Through meticulous development and numerical simulations, the research demonstrates the controller's robust performance across various scenarios. The ability to generate continuous variable error values, serving as predictive indicators, stands out as a proactive tool for preemptive maintenance interventions. These findings not only present the functioning of hydraulic servomechanisms but also exemplify the integration of cutting-edge technology (neural networks) in addressing the complexities of modern industrial processes within the context of Industry 4.0, setting the stage for further discussion and implications in subsequent research.

4. Conclusions

• The integration of a neural network controller in a closed-loop compact hydraulic direct drive servomechanism marks a substantial advancement in the realm of fault detection and predictive maintenance. This approach addresses the inherent complexities of industrial processes, providing a proactive solution to potential faults.
• The research showcases the meticulous development and training of the neural network controller, with a focus on achieving precision in fault detection within the context of Industry 4.0. The presented results demonstrate the effectiveness of the neural network in monitoring critical components and generating predictive indicators, aligning with the demands of smart manufacturing.
• The ability to generate continuous variable error values and transform them into predictive indicators sets this research apart, offering a valuable tool for preemptive maintenance interventions. The neural network's capacity to forecast future system malfunctions contributes significantly to increased operational efficiency, reduced downtime, and improved reliability in industrial settings.
• The numerical simulations presented in the results section provide a comprehensive overview of the neural network controller's performance in different scenarios, including variations in control error, pressure drops, volumetric losses, and actuator movements. These simulations validate the practical applicability and robustness of the developed neural network.
• As industries continue to evolve in the digital age, the role of neural networks in optimizing processes and ensuring reliability becomes increasingly indispensable. The research not only contributes to the specific domain of hydraulic servomechanisms but also exemplifies the broader intersection of cutting-edge technology and the demands of modern industrial processes, in line with the principles of Industry 4.0.

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