A data array generating algorithm for diagnosing a hydraulic system using machine learning methods based on a virtual model

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***Abstract*—The existing systems for diagnosing and monitoring complex technical systems are based on machine learning methods which require acquisition and processing of large amounts of information. Generating data based on virtual simulation is preferable in comparison with the experiment since it not only takes less time, but also allows you to model faults that are difficult or impossible to implement with the test bench. However, this requires the development of a model of the diagnostic object adequate to real processes, as well as the processing and classification of the received information. Based on the dynamic processes modeling in the power supply subsystem of the fluid power system of an engineering complex in a fault-tree and faulty states, we have developed an algorithm for generating a data array used in machine learning for diagnosing faults. As a result of virtual modeling in SimulationX, we have calculated transients according to the main parameters of the power supply subsystem adequate to the experimental data. The developed algorithm for the processing and classification of transients allows the formation of training samples under various technical conditions of the system. The published material may be useful for specialists engaged in developing methods for monitoring and diagnosing fluid power systems of energy and engineering complexes based on machine learning methods.**

Keywords—diagnosing, fluid power system, virtual simulation, data, verification, machine learning.

I. INTRODUCTION

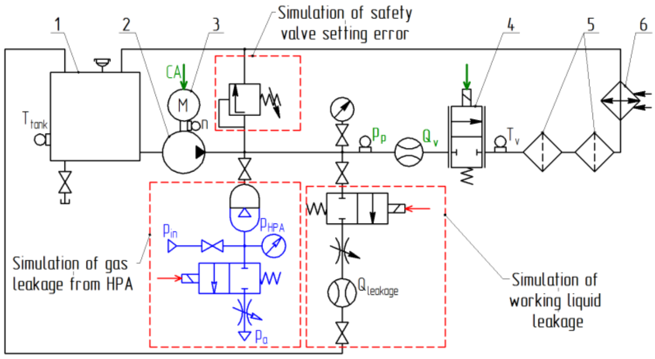
Fluid power systems (FPS) are widely used in various industries due to their advantages: high speed, high specific power, high efficiency and gain, a possibility of continuous stepless control [1]. FPS often perform key functions as a part of complex engineering units which makes ensuring their reliability a highly relevant task. In these conditions, on the one hand, an integrated approach is needed to ensure a high level of reliability of the FPS at the design and production stage, while on the other hand, one will require strict observance of the rules and norms of their maintenance and repair. It is the operational reliability that plays a key role in ensuring the reliability of the FPS, the high level of which is achieved, first of all, by applying modern approaches based on machine learning methods [2-10]. These methods make it possible to implement a proactive approach enabling us to detect a possible failure in advance at the stage of their initiation, as well as to predict the dynamic pattern of changes in the technical condition of the system.

For implementing machine learning methods, it is necessary to have appropriate data arrays - training samples, compiled on the basis of the simulation of dynamic processes in hydraulic systems or their experimental studies in fault-free and faulty states under control and disturbing input. The first method based on modeling the processes in systems is preferable, especially when practising machine learning methods, as it allows to quickly change the data arrays taking into account the type, number and installation locations of the sensors of the measured parameters in them and to optimize the accuracy of recognition of existing faults. Another advantage of this method is the possibility of simulating almost any faults in the system under study, e.g., friction or the spool valves characteristics inside the units which are difficult to be simulated experimentally. However, it should also be borne in mind that the virtual model of the FPS must correspond to the real system and the more accurately it is made, the higher the accuracy of the diagnosis result. To do this, it is necessary to carry out experimental studies to verify the adequacy of the mathematical model of the FPS. Studies on the formation of training samples for diagnosing by machine learning methods are rather insufficiently presented in the technical literature which, apparently, is associated with the multidisciplinary nature of the problem of electro-hydromechanical units of the fluid power system. The aim of this work is to present an algorithm for generating training samples of FPS which can be used to create systems for diagnosing them using machine learning.

II. DEVELOPING A SIMULATION MODEL OF THE FPS POWER SUPPLY SUBSYSTEM TAKING INTO ACCOUNT THE TYPICAL FAULTS

A. Description of the circuit diagram

Fig. 1 shows a schematic diagram of a typical power supply subsystem of an engineering unit [11]. The task of the power supply subsystem is to ensure the supply of the working fluid with the required parameters to the executive subsystem. To simulate the operation of the executive subsystem, a proportional distribution valve 2/2 is used. The power supply subsystem under consideration takes into account the typical faults in the form of a violation of the tightness of the gas cavity of the hydro-pneumatic accumulator (HPA), leakage of the working fluid in the pressure line at the pump outlet, and pressure relief valve wrong settings that are represented by the corresponding simulators.



1 - tank; 2 - gear pump; 3 - electric motor; 4 - proportional directional control valve 2/2 - simulator of the executive subsystem (disturbing effect); 5 - hydraulic filters; 6 - heat exchanger; CA - a signal for controlling the frequency of the pump drive rotation (control action on the FPS subsystem)

Fig. 1. A schematic diagram of the FPS power supply subsystem taking into account the typical faults.

The system in good condition operates as follows. The working fluid from the tank forcibly or by gravity enters the pump inlet while the pump driven by rotation from the electric motor pumps the working fluid into the pressure line and then into the system. The HPA reduces pressure pulsations from the pump and increases the compliance capacity of the system. The pressure relief valve protects the pump from excess pressure above the permissible value due to the working fluid bypass to drain acting as an overflow valve. Ensuring the purity of the working fluid and maintaining the temperature is carried out respectively by hydraulic filters and heat exchangers. The 2/2 proportional distribution valve provides an imitation of the “loading” of the power supply subsystem by changing the area of the passage section. For example, with a reduction in the flow area, an increase in the pressure of the working fluid takes place in the pressure line and a decrease in the pump performance due to an increase in internal leaks in it also takes place. A further decrease in the cross-sectional area of the proportional distributor leads to a further increase in pressure in the system and the opening of the pressure relief valve to bypass a part of the liquid flow to the drain. An increase in the power lost in the throttling sections of the subsystem of the FPS is accompanied by an increase in the temperature of the working fluid and, as a result, a change in its viscosity and density. Using a heat exchanger allows you to maintain the temperature of the working fluid in the required range. The pre-charge pressure of the HPA provides a quick transfer to the operating pressure in the FPS. At a sudden actuation of the proportional directional control valve 2/2, the dynamic processes in the FPS change smoothly when the pressure in the system is higher than the HPA charging pressure due to the flexibility of its gas cavity.

Methods of mathematical and physical modeling can be used to conduct analysis of processes in order to identify defects and faults in the system. To diagnose the system requires the accumulation and processing of a large amount of information, so the use of physical modeling of the object in this case becomes difficult. Mathematical modeling of dynamic processes in a system based on the equations of the laws of mechanics, hydrodynamics, electromagnetism, etc. in high-level software will allow to obtain the necessary amounts of data which can be further used to train neural network models and create systems for diagnosing and monitoring the state of the FPS on their basis.

B. Developing a simulation model in SimulationX

Simulation of dynamic processes in the FPS power supply subsystem taking into account characteristic faults is performed in SimulationX. This software is an interdisciplinary software package for modeling, simulation, analysis and virtual testing of complex mechatronic systems [12]. The development of a simulation model in SimulationX takes place by connecting and combining finished blocks (models of devices and units) into a network. Models of various devices in SimulationX depending on their functional purpose and application are combined into libraries (hydraulics, pneumatics, mechanics, physical signals, electrics, electronics, magnetism, vehicles, internal combustion engines, vibration analysis, acoustics, thermal processes, system reliability analysis, etc.). As a result of using these ready-made elements and models of devices, the development of an entire system takes place much faster in comparison with the compilation of models of elements and units of systems and calculations by algebraic and differential equations, especially when it comes to complex multicomponent and interdisciplinary systems.

When developing a simulation model of the power supply subsystem under consideration, we used elements of the hydraulics, pneumatics, mechanics, and electrics libraries. The appearance of the obtained simulation model is presented in Fig. 2 [11].

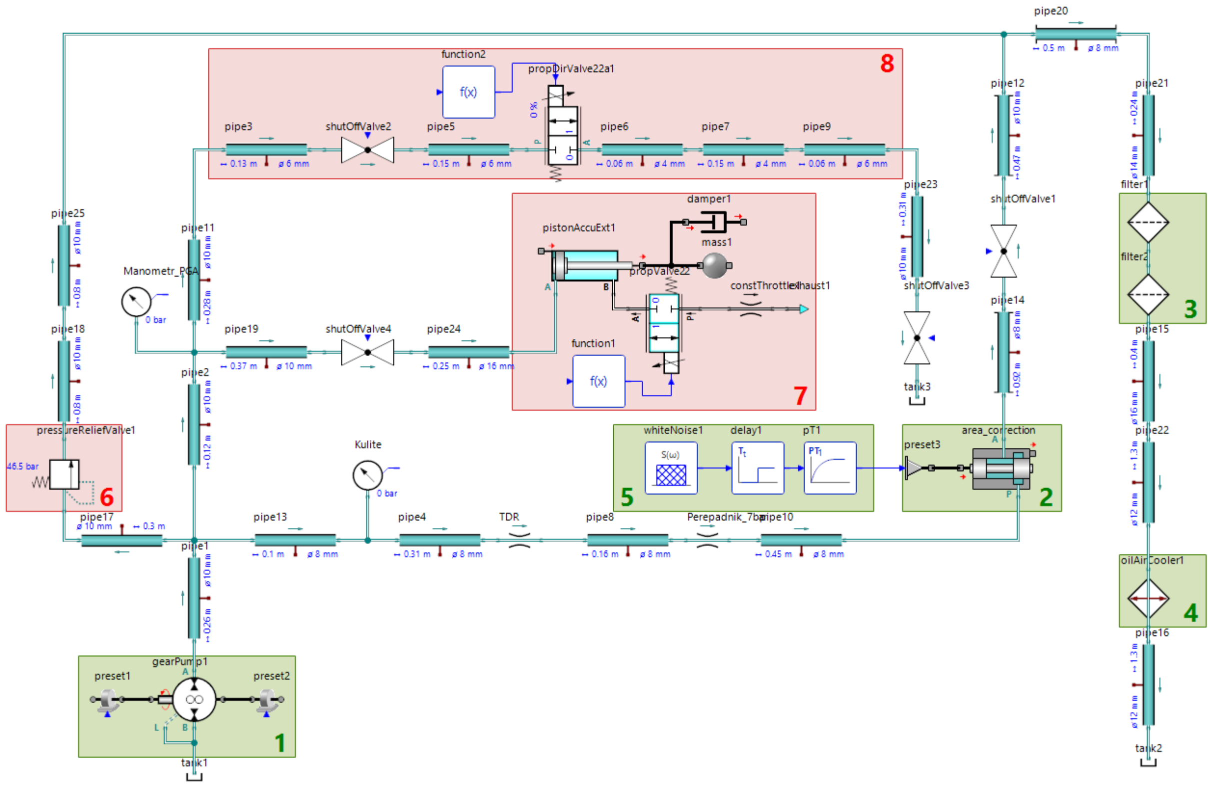
C. Faults simulations

Two methods can be used when simulating faults. The first is to change the parameter or characteristics of the element during the integration process. In this case, the required law of the change is recorded in the window with its parameter value. For example, to simulate a fault of a pressure relief valve based on the "Pressure Relief Valve" model in order to change the elastic properties of a spring in the field of the "Static Pressure Behavior" parameter characterizing the slope of the flow-differential characteristic of the pressure relief valve in the control mode, a function of the following form can be recorded [12]:

$$p = p_0 (1 - r_0 \cdot I)^{n \cdot \mathrm{scale}}, \tag{1}$$

where p_0 is the initial value of the parameter; r_0 is the prefactor defining maximal reduction; I is the error rate; *scale* is the scale ratio.

The second method is to create a faults simulator from blocks, e.g., it can be used to simulate a HPA faults. When creating a simulator of a HPA faults in the form of a gas leak, the "Piston Accumulator" model is used as the base element. In this case, the gas cavity of the element is connected to the atmosphere through a pneumatic distributor and an adjustable throttle, the passage section of which determines the rate of the gas leakage. When modeling a HPA fault which manifests itself in the form of an error of its pre-charging, one can use the standard "Accumulator" model as the basic element. Moreover, to simulate this fault, it is sufficient to change the initial value of the precharge at the initial moment of integration time. However, it should be noted the differences between the considered faults in the HPA. When simulating a HPA faults in the form of a HPA pre-charging error based on the "Accumulator" model, the gas cavity is not connected to the atmosphere but remains airtight. However, while modeling a fault in the form of a gas leak, e.g., as a result of wear of the seals, the cavity is depressurized, and in this case the standard "Accumulator" model can no longer be applied.



1 - pump with drive; 2 - proportional 2/2 distributor; 3 - hydraulic filters; 4 - heat exchanger; 5 - the proportional distributor control unit; 6 - KP settings error simulating block; 7 - HPA gas leakage simulating block; 8 - working fluid leakage from the pressure line simulating block

Fig. 2. SimulationX simulation model of the FPS power supply subsystem taking into account faults.

III. Theoretical Studies of the Dynamic Processes in the FPS Power Supply Subsystem Taking into Account Typical Faults

One of the typical faults of the system under consideration is an inadequate functioning of the HPA. Fig. 4 and 5 show fragments of transients in pressure and flow rate of the working fluid in the power supply subsystem in good condition and with a fully discharged HPA. To simulate this fault, before starting to calculate the model, we set the pre-charge pressure of the HPA to zero. The calculation results are obtained by changing the flow area of the proportional directional control valve according to a random law with a uniform distribution (Fig. 3).

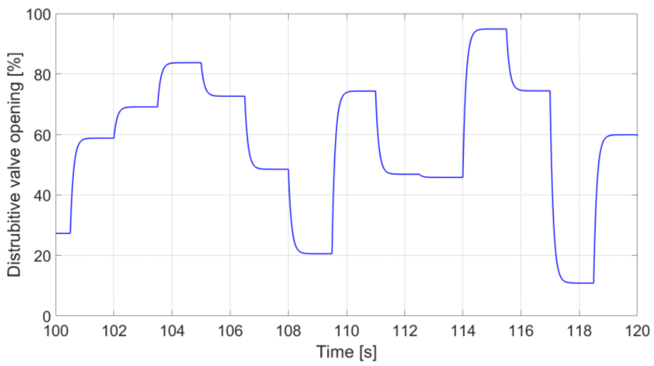


Fig. 3. Transients of the change in the relative area of the proportional valve 2/2 flow cross-section for the cases of simulating the FPS power supply subsystem in fault-free and faulty conditions.

Analysis of the graph in Fig. 4 shows that when the valve is opened by more than 50%, there is a decrease in the flow rate of the working fluid in a system with a discharged HPA in relation to a fault-free working system due to the lack of an additional fluid flow from the HPA.

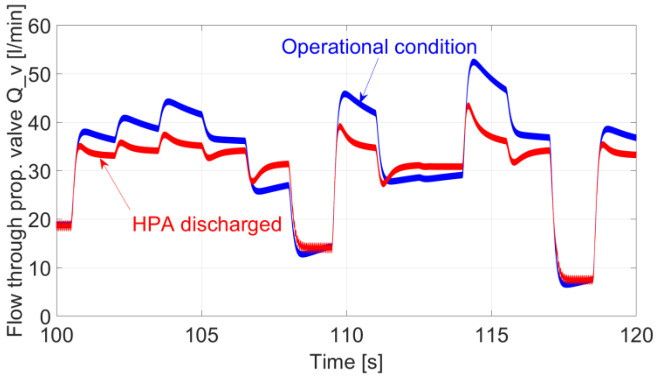


Fig. 4. Transients of a change in the flow rate of the working fluid through the valve for a fault-free and faulty FPS subsystem.

In a power supply subsystem with a discharged HPA, more abrupt (spasmodic) changes in pressure occur as a result of the change in the flow area of the distributor compared to a fault-free state which is explained by a decrease in the system compliance capacity (Fig. 5). In addition, an increase in pressure pulsations when opening the pressure relief valve can be noted, which is associated with fluctuations in its shut-off and control element.

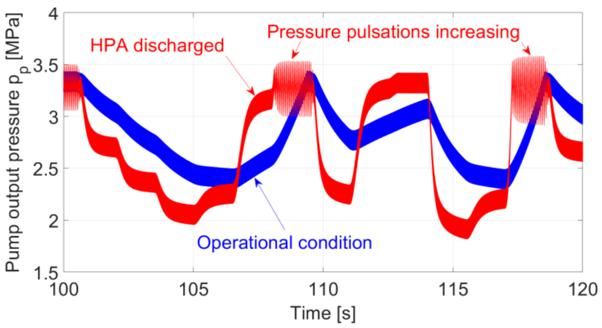


Fig. 5. Transient pressure changes at the pump outlet for a fault-free and faulty FPS.

The analysis of the results presented above shows that the considered fault has a significant effect on the characteristics of the heterostructure: the amplitude of the pulsations of the parameters grows and their gradients increase. The preparation of the training samples consists of the formation of arrays of relative deviations of the parameters of the FPS power supply subsystem in a fault-free and faulty states in a wide range of changes in the control and disturbing input.

IV. Verification of the Mathematical Model of the FPS Power Supply Subsystem Taking into Account the Typical Faults

Verification of the simulation model is carried out by comparing the calculated and experimental data obtained under identical conditions for the power supply subsystem in a fault-free and faulty conditions: temperature of the working fluid is 50 C; electric motor rotation frequency is 2500 rpm [13]. To simulate the operation of the executive subsystem, a proportional valve distributes a signal in the form of random numbers in the range from 2 to 4 V with a uniform distribution. The period of a stepwise changing signal is 1.5 s. Parameters are measured with a sampling frequency of 5 kHz which allows to record pressure pulsations as a result of the gear pump operation. The constraint when setting the sampling frequency in this case is the hardware capability in terms of memory storage and the speed of the information transfer.

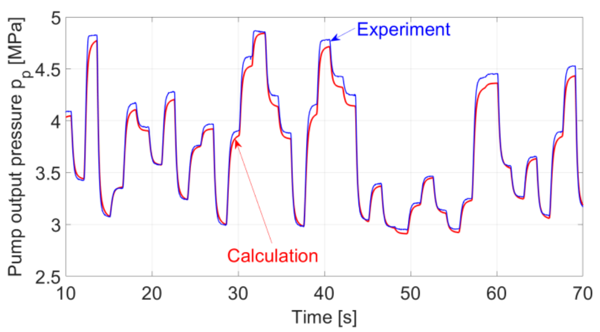


Fig. 6. Comparison of the calculated and experimental data, pressure by the pump outlet pressure for a fault-freet and faulty FPS.

The main source of experimental data generation is the measuring and control part which includes sensors, actuators, valves, I/O modules, National Instruments cRIO 9023 real-time controller. It preprocesses the experimental data: analog-to-digital conversion, filtering, high-speed record. It also provides data visualization and control of actuators, valves and distribution valves. Based on the results of the data processing, time series arrays are generated in a digital form, they are transmitted in real time for state analysis and are additionally recorded and used to verify the model. Fig. 6 shows the graphs of transient changes in pressure at the pump outlet obtained for the power supply subsystem with an operable and discharged HPA.

From the analysis of the results it follows that the difference between the calculated and experimental data obtained for the case under consideration does not exceed 5%.

V. Training Samples Algorithm

Generating training samples in the form of arrays of the parameters values of the power supply subsystem obtained in its various states is an important step in the development of diagnostic systems since it directly affects the accuracy of classification. The formation of training samples can be represented in the form of an algorithm, the main stages of which are: virtual modeling, storage, processing and transmission of the received data to the hardware and software complex of the diagnostic system for the purpose of machine learning. An important component of the presented algorithm is the need to correct modeling conditions in order to improve the classification accuracy (Fig. 7).

To obtain the training samples as a result of calculation, arrays of pressure and flow rate values from time are written into a text file. The number of arrays depends on the number of faults intensity levels. In order to increase the efficiency of the training the neural network models, additional manipulations with the obtained data may be included, as well as filtering or superimposing the noise.

VI. Conclusion

Diagnosing the technical condition of the fluid power systems using machine learning methods is impossible without generating training samples which can be obtained by simulating electro-hydromechanical processes or conducting experimental studies in high level software. The first method is preferable, especially when practising machine learning methods, because it is less time- and labour-consuming and you can quickly classify the data obtained by type, installation location and number of sensors, sampling frequency of temporary implementations, their sample sizes and other parameters. However, it is necessary to be confident of the adequacy of the hydraulic system model to real processes. The experimental method of generating training samples for practising machine learning methods is more time- and labour-consuming and it is advisable to apply it even during operation of the FPS.

The proposed algorithm for generating and correction of training samples based on the simulating electro-hydromechanical processes in SimulationX, as further studies have shown, provides recognition of the system faults using machine learning methods.

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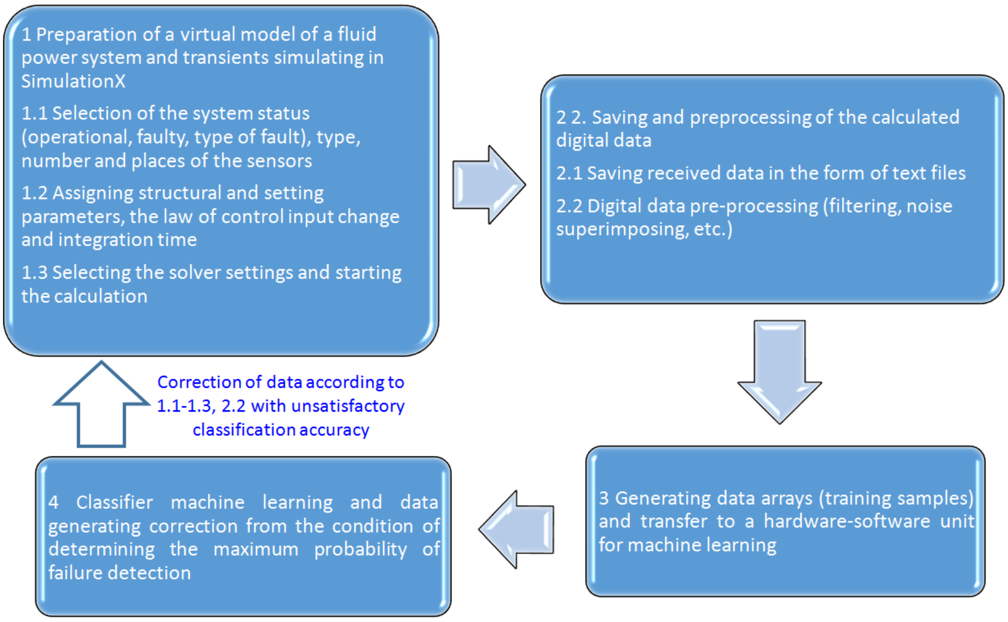

Fig. 7. Generating and correcting algorithm for the training samples.

References

[1] J.L. Johnson, "Introduction to Fluid Power," Cengage Learning, Inc. Florence, United States, 2001.

[2] L.A. Wen, X. Li, L. Gao, Y. Zhang, "New Convolutional Neural Network Based Data-Driven Fault Diagnosis Method," IEEE Transactions on Industrial Electronics, vol. 65, no. 7, pp. 5990-5998, 2018.

[3] P. Athanasatos, D. Koulocheris, Th. Costopoulos and V. Spitas, "Experimental Verification of Fault Predictions in High Pressure Hydraulic Systems," Modern Mechanical Engineering, vol. 4, pp. 67-83, 2014.

[4] R. Ahmed1, M. El Sayed, S.A. Gadsden, J. Tjong and S. Habibi, "Automotive Internal Combustion Engine Fault Detection and Classification using Artificial Neural Network Techniques," IEEE transactions on vehicular technology, vol. 64, no. 1, pp. 21-33, 2015.

[5] H. Wang, T. Chai, J. Ding and B. Martin, "Data driven fault diagnosis and fault tolerant control: Some advances and possible new directions," Acta Autom. Sinic, vol. 35, no. 6, pp. 739-747, 2009.

[6] V.Venkatasubramanian, R. Rengaswamy, K. Yin and S. Kavuri, "A review of process fault detection and diagnosis—Part I: Quantitative model-based methods," Comput. Chem. Eng., vol. 27, no. 3, pp. 293-311, 2003.

[7] H. Li, Z. Tian and H. Yu, "Baohua Xu Fault Prognosis of Hydraulic Pump Based on Bispectrum Entropy and Deep Belief Network," Measurement science review, vol. 19, no. 5, pp. 195-203, 2019.

[8] Y. Lei, W. Jiang, A. Jiang, Y. Zhu, H. Niu and S. Zhang, "Fault Diagnosis Method for Hydraulic Directional Valves Integrating PCA and XGBoost," vol. 7, no. 9, pp. 1-18, 2019. DOI: 10.3390/pr7090589.

[9] Z. Yao, Y. Yu and J. Yao, "Artificial neural network–based internal leakage fault detection for hydraulic actuators: An experimental investigation," Proc IMechE Part I: J Systems and Control Engineering, vol. 232, no. 4, pp. 369-382, 2018.

[10] O. Ritter, G. Wende, R. Gentile, F. Marino, A. Carlo Bertolino, A. Raviola and G. Jacazio, "Intelligent Diagnostics for Aircraft Hydraulic Equipment," European conference of the prognostics and health management society, 2018.

[11] A.M. Gareev, A.G. Gimadiev, A.V. Nikonorov and D.M. Stadnik, "Datasets gathering for hydraulic systems technical diagnosis using machine learning methods," Collection of abstracts of ITNT, 2020.

[12] Official web-site of SimulationX [Online]. URL: https://www.simulationx.com/.

[13] A.M. Gareev, P.I. Greshnyakov, A.V. Nikonorov, A.G. Gimadiev and D.M. Stadnik, "Experimental study of the effectiveness of the method for diagnosing electro- hydromechanical systems with consideration for the dynamics of processes based on a neural network basis," Collection of abstracts of ITNT, 2020.