

Analysis and Graphical Evaluation of Pressure Changes in Pneumatic Circuits for Industrial Applications

Marek Vagas^{*}, Ondrej Majercak^{}

Department of Industrial Automation and Mechatronics, Faculty of Mechanical Engineering, Technical University of Kosice, Letna 9, 042 01, Kosice, Slovakia, marek.vagas@tuke.sk, ondrej.majercak@tuke.sk

Abstract: Measuring and evaluating the condition of pneumatic systems (PS) is an important identification tool for many industrial applications. Therefore, this paper focuses on the detection of changes (faults) in these circuits by analysing system pressures. The proposed approach allows dynamic monitoring of the pressure profile when the run-in processes have an identical sequence (i.e. deviations and changes become steady at a specific frequency). The analysis performed and the subsequent graphical representation provide valuable insights into the running process for management. Proof-of-concept experiments are carried out with a sensor (AVENTICS) on a simple pneumatic circuit with constant motion, which serves as a sample example. Their results show the usefulness of this method, and the collected data will serve as a suitable basis for implementation in machine learning models.

Keywords: pneumatic systems, pressure changes (faults), filtering of unwanted states, failure detection

1. INTRODUCTION

Nowadays, the medium nonlinearity and the compressibility of pneumatic systems are mitigated by the use of servo valves and real-time computer control [1]. However, the consumption of the medium (air) is constantly increasing [2], which is crucial for continuous operation. Therefore, it is essential to continue optimisation processes and develop further saving methods that contribute to faster and more efficient fault diagnosis in pneumatic systems. With an appropriate diagnosis and a predictive approach, machine learning and the Internet of Things are proving to be reliable when considering the holistic cost-efficiency, simplicity, and accuracy of a given application (system). A study from 2023 shows that leak diagnosis (using the example of two parallel pneumatic cylinders) can also be implemented with a limited number of sensors [3]. In doing so, the authors used machine learning to identify system leaks. This opens the way for further affordable approaches and experiments. The typological research focused on monitoring sensor signals (pressure, flow, and others), which were processed and extracted to determine the exact cause and extent of leaks [4]. By combining predictive algorithms and modern sensor technologies, it is now quite efficient to detect and monitor the condition of individual pneumatic components. Meanwhile, the above combination has only used a minimum of sensors for speed and reliability measurements [5]. In addition, it should be noted that while experienced operators can easily identify and correct faults, they are limited in terms of both accuracy and efficiency.

Energy efficiency is a common deficiency in pneumatic systems. Leakages typically account for 10 % to 40 % of energy loss [6]. Subsequent leaks lead to a drop in system pressure, reduced functionality, shortened service life, and also impair product quality. From the above research, we can conclude that systems using minimal sensor technology can reduce maintenance costs, minimise downtime, and increase overall system efficiency, which is crucial for modern manufacturing processes [7]. Based on this research, the authors have chosen an approach that combines prediction, simplicity, and reliable identification.

2. RELATED WORKS

In their work, the authors [8],[9] confirm the growing research and application trend in the field of fast and effective fault diagnosis. They found that by focusing on the detection of system faults, it is now possible to monitor and identify air leaks in a high-quality measured pneumatic system. However, they used a methodological approach in which CO_2 emissions and noise levels (in dB) were measured using suitable ultrasonic devices. This means that the authors have provided a suitable comparison tool that will help save compressed air in a specific way. Compared to our solution, however, they used significantly more sensor technology in conjunction with a complex mathematical conversion of air leakage into flow. On the other hand, Caruana et al. [10], [11], [12] carried out an analysis of the sustainability of pneumatic systems in industry based on financial aspects, social impacts, and environmental effects.

They found that monitoring the compressed air and its possible leaks is a prerequisite for identifying and quantifying the overall performance of a given pneumatic system. They also carried out similar measurements to ours. However, unlike us, the authors used ultrasonic detectors, with which they were able to reduce losses by up to 32 % across the entire workplace.

However, in comparison to our approach, the authors measured and monitored an existing group of large compressor systems directly in the industry and evaluated the data obtained on their performance based on their energy consumption. Finally, the authors [13] confirm our approach in their latest research as they focus on calculating efficiency and identifying air leaks using the same application as we do (pick and place). However, they collect pneumatic data from two locations simultaneously and provide an alternative and systematic approach to investigate influences and identify potential faults. Nevertheless, they confirm our assumptions that the correct use of pressure data is necessary for the determination of fault characteristics.

3. SUBJECT & METHODS

The prediction of pneumatic systems is based on research aimed at detecting faults due to pressure changes. The underlying idea is to demonstrate the implementation of components that can detect the pressure on a model, provide an experimental example, and then train a model using this example. In the next step, the model is then able to identify faults and send information about its current state. Our measurement architecture is shown in Fig. 1.

A critical parameter to consider when applying this approach is the detection of leakage. The overall efficiency of a given compressor station η_{cp} depends on its design and typological structure. Conventional electrically driven compressor stations have an efficiency of 80 % to 96 %. Mathematically, it can be calculated as $\frac{P_2}{P_1} \times 100 \%$.

We therefore start from the basic consideration of pressure in a pneumatic circuit, where a distance y displaces the piston of the pneumatic cylinder while the air stream is forced into one chamber of the cylinder and the other chamber is directly exposed to the atmosphere [14]. The air pressure p in the circuit can be expressed with the ideal gas equation of state $p \times V = n \times R \times T$.

Where:

- p – pressure (Pa)
- V – volume (m^3)
- n – number of mols (mol)
- R – universal gas constant ($8.314 J K^{-1} mol^{-1}$)
- T – temperature in Kelvin (K)

Air pressure losses $\sum \Delta p$ can be expressed as a $\Delta p_1 + \Delta p_2$.

Where:

- Δp_1 – air pressure losses from the piping and individual components
- Δp_2 – air pressure losses due to failures, air leakages and pollutants (important for our case)

So, Δp_1 can be estimated as follows in (1):

$$\Delta p_1 = \frac{f \times L \times \rho \times v^2}{2 \times D} \quad (1)$$

Where:

- Δp – air pressure losses in (Pa)
- f – friction coefficient (depending on the surface and the flow)
- L – piping length (m)
- ρ – density (kg/m^3)
- v – air velocity (m/s)
- D – piping diameter (m)

Pressure changes in a pneumatic system indicate various problems, e.g. leaks in joint valves, component failure in the circuit, filter contamination, and malfunctions of control elements [15]. We can also calculate the air consumption Q (2) for a known system volume based on the pressure changes.

$$Q = \frac{V \times (p_1 - p_2)}{t} \quad (2)$$

Where:

- Q – air consumption in (m^3/s)
- p_1, p_2 – friction coefficient (depends on the surface and the flow)
- t – time in (s)

A speciality of the team of authors is the use of a basic pneumatic circuit as a demonstration example to verify the leakage and loss detection approach. The aim of this study is to determine the impact of faults on the system and its pressure conditions. The pneumatic circuit consists of a double-acting piston controlled by an electro-pneumatic 5/3 valve. The Siemens LOGO! circuit implements the control and information processing. The main component of our experimental analysis and subsequent evaluation of the pressure change in the circuits is a pressure sensor (AVENTICS) with an analogue output. Its resolution is $\pm\%$, with a working pressure of 0 – 10 bar, at a maximum power supply of 30 V.

The sensor is located in the input of the pneumatic circuit. This is mainly due to the current trends and methods, where the current authors in the field consider it essential to know (and measure) the individual changes at a specific input/output of the device (in our case, a piston). On the other hand, we were interested in know whether this measurement chain can also record pressure changes from a greater distance (as a high-quality sensor).

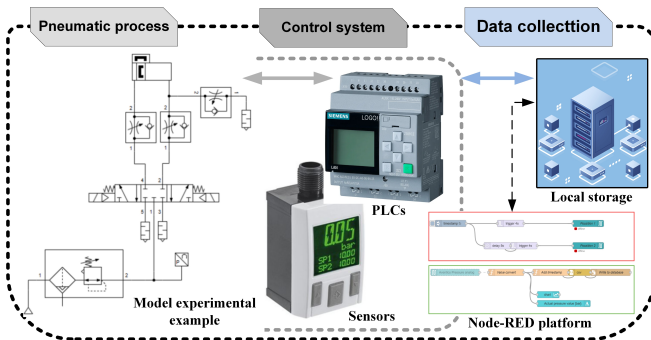


Fig. 1. Proposed procedure for measurement.

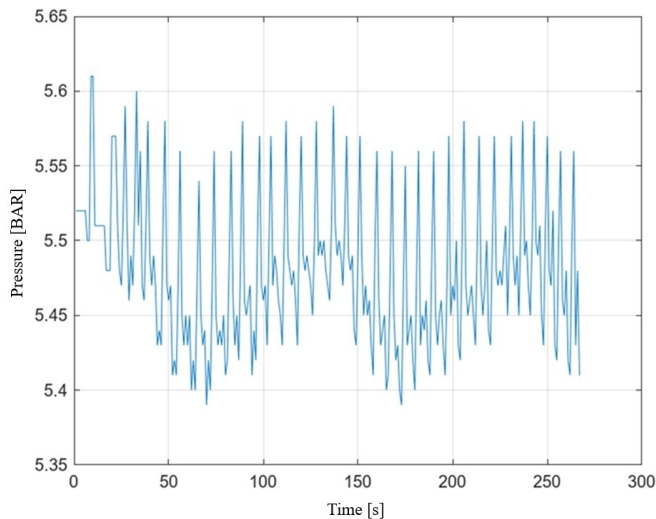


Fig. 2. Measurement of pressure changes in a pneumatic test system during standard operation.

The idea is to demonstrate the feasibility of detecting pressure changes in circuits with a single sensing element [16]. To collect, process, and evaluate the data from the basic pneumatic circuit, we developed a fundamentally simple IoT station using a PLC, the free Node-RED platform, and a Raspberry Pi. This solution was chosen due to the complexity, clarity of the collected data, and centralisation [17]. Also, in this way, we eliminated the need for additional pneumatic components (which increases the accuracy and efficiency of the measurement). The control was therefore implemented directly via Node-RED and the sensor data was collected directly at the same time.

4. RESULTS

The aim of these experiments was to analyse the pressure changes in the measured system and their subsequent graphical representation in order to demonstrate the usefulness and cost-effectiveness of our solution. The type of measurement procedure started with the analysis of the pressure under closed valve conditions (to simulate a fault condition in a pneumatic circuit). Further measurements were performed when the given (fault) valve was open, simulating small leaks of the medium from the measuring system [18]. The last case was the complete opening of the (fault) valve, which was intended to simulate a faulty condition (of the component(s) in the system).

With regard to the control of entire system, it was important to ensure the steady state of the system pressures, which can be achieved by using the operating pressure in the measured circuit (6 bar). Other research experiments by other authors also worked with the same medium pressure. In addition, a programme that stopped the pneumatic piston in each position for one second ensured the stability of the measurement process and controlled it. It ensured the steadiness of the process and the regularity of the operation of the entire pneumatic system without further (unwanted) movements.

Monitoring and data acquisition were analysed under steady-state system pressures. The data acquisition and the analysis of the collected data were solved by creating the corresponding variables using the Node-RED platform. We created a block that normalised the data, but most importantly assigned a timestamp and wrote it to the database we created. The created time variables controlled the cycle of the pneumatic piston movement from the extended to the retracted position. We then analysed the database and processed the measurement results graphically [19].

A. Case 1

The first experiment analysed the pressure changes during standard operation of the pneumatic test measuring system. The initial condition was that the simulated fault (using the valve) does not occur and the valve is closed throughout the measurement. We therefore verified and assumed the optimum condition at the workplace.

As can be seen from the flow in Fig. 2, we can recognise the start-up of the medium in the measuring system in the initial phase of the measurement process (within about 0.5 s). However, in the next phase, the pressure stabilises between 5.45 and 5.55 bar. The next phase shows both the steadiness of the pressure and its maximum value, which is 6.06 bar. The average pressure values in the tested pneumatic measuring system are 5.48 bar with 756 data points. In the next step of this experiment, we filtered, analysed, and cleaned the collected data. These processes were carried out using the efficient MATLAB software tool Data-Cleaner. The results support the assumption that no pressure change occurs in a pneumatic system with a no-fault condition, i.e. that the pneumatic system is steady over a given measured time frequency (with Median = 5.475 and Standard Deviation = 0.043829). Further detailed results and the settings of the evaluation process are shown in Table 1, Case 1.

B. Case 2

The second target experiment analysed the pressure changes during operation with minor (negligible) leakages or losses in the pneumatic test measuring system. In this case, it was assumed that the simulated failure (using the valve) manifests itself to a small extent, i.e. the failure valve is open. We verify whether a given measurement chain can detect small pressure changes (leaks) and maintain the regularity of the process cycle (programme run and compliance with the time constants). As can be seen from the flow in Fig. 3, the process is highly irregular; nevertheless, some regularity curves can still be determined for both the process and the programme run.

The different phases of the measurement process are unsteady and exceed the usual pressure values of 5.36 – 5.56 bar for the same amount of data. The next step was to re-filter the data record it using the same software tool (mentioned above). The results show that despite the small simulated fault (smaller leakage range = minor fault), some regularity can be observed in the cycle and in the system. Table 1 (Case 2) contains further detailed results and settings of the evaluation process.

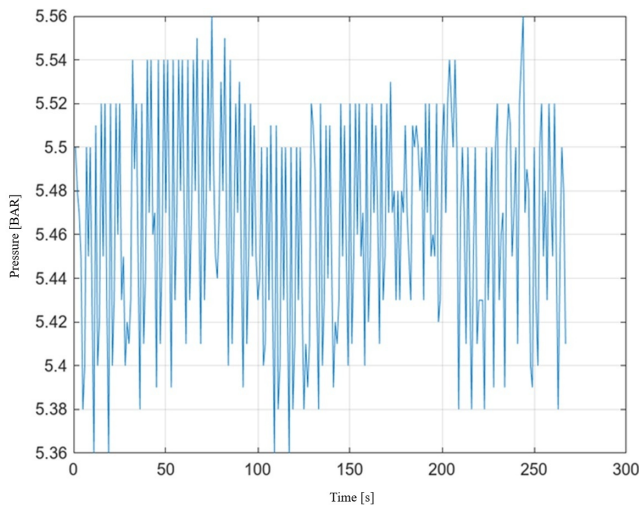


Fig. 3. Measurement of pressure changes in a pneumatic test system during a slight pressure leak.

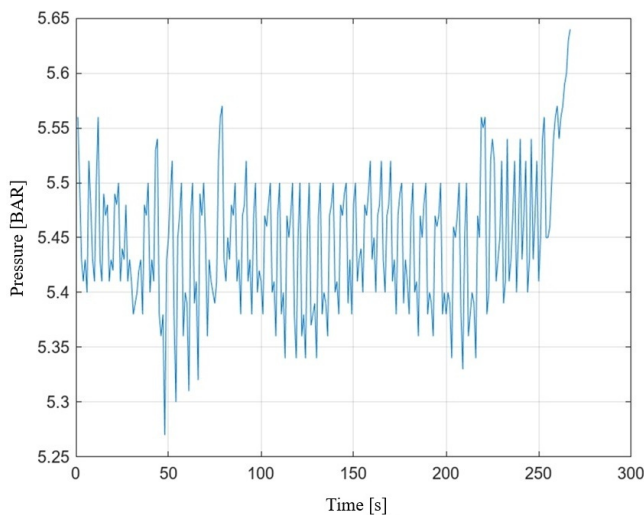


Fig. 4. Measurement of pressure changes in a pneumatic test system during a significant pressure leak (fault).

C. Case 3

The last target experiment analysed pressure changes when a fault (leakage of medium pressure) was fully manifested in the pneumatic test measuring system. The input condition is that the simulated fault (using the valve) is manifested at full maximum (the fault valve is fully open). We verify the extent to which the developed measurement chain can detect, display and evaluate this intervention in the pneumatic system. The process is irregular, as can be seen from the waveform in Fig. 4. No dependency can be observed or detected, and this condition remains despite the application of data filtering. The different phases of the measurement process are irregular to the maximum extent possible and exceed all standard pressure values (5.3 – 5.65 bar) for the same amount of data.

5. DISCUSSION & CONCLUSIONS

By implementing this approach, we wanted to analyse, visualise and evaluate the condition of the selected pneumatic system and identify its states.

The experiments were based on the methodological assumption that the change in pressure allows reliable identification of even small leaks in the medium (system failures). Furthermore, the usefulness of our example is documented by the fact that with this approach we can also detect the location of the medium leakage. The experimental results show that under ideal conditions in a pneumatic circuit there is a regular frequency of process activity that can be easily identified. In the following steps, we solved the problem of collecting, sorting, and filtering the collected data, which is another excellent basis for implementing a machine learning model. Data filtering was performed using different smoothing methods (available in the Data-Cleaner tool).

Table 1. Evaluated and data processing-based MATLAB Data Cleaner tool.

#	Case 1	Case 2	Case 3
Data type	Double	Double	Double
Unique values	34	32	32
Has duplicates	True	True	True
Is sorted	False	False	False
Missing count	0	0	0
Min	5.425	5.41	5.38
Max	5.61	5.56	5.59
Mean	5.4813	5.4703	5.4402
Median	5.475	5.47	5.435
Mode	5.49	5.47	5.43
St. deviation	0.043829	0.026314	0.035574

Note: *Unique values*, *Missing count* in (times);
Min, *Max*, *Mean*, *Median* and *Mode* in (bar).

A common feature of these smoothing methods (tools) in MATLAB is the removal of outliers or missing values from the acquired data. These include, for example, the Moving Mean, the Gaussian filter, the Local Linear Regression, or Robust Lowes. For our purposes, we ultimately processed the data using the Gaussian filter as we found that this method produced the smoothest signal with less blurring. This is because the tool processes the data based on weights given by the Gaussian distribution, which means that points that are closer together have a greater influence (in terms of the principles of the Gaussian curve).

However, when evaluating and monitoring slow or nonlinear processes, it would be more advantageous to process the data using the Robust Lowes tool, for example. With this type of data processing, the weights are recalculated in each iteration. Points that stand out strongly are given a low weight. The result would be a smooth and realistic trend, but this processing method is the most computationally intensive. In general, we can say that by using these tools and data processing methods, we have effectively cleaned, pre-processed, and formatted the acquired data. This gives us a better overview of the results obtained (readability and understanding).

The aim was to detect the process cycle in the measured pneumatic system as accurately as possible, removing noise and short-term fluctuations. On the other hand, we try to emphasise longer-term trends and cycles in these data by using the mean trend.

When comparing different smoothing methods, we obtained very similar results. They differ slightly, but the key comparison is the smallest Standard Deviation and the number of Unique Values (*in times*). Therefore, further research will be directed in this direction. The authors want to jointly test the hypothesis that a model trained in this way can reliably identify and document pneumatic system failures in various industrial applications. Our analysis has shown that the measured variations in the pressure waveforms for different types of failures have specific characteristics that can be easily recognised using advanced machine learning algorithms.

Thus, with this approach, we can detect failures at an early stage and provide an educated guess as to the extent of a leak or other anomaly. Our experimental work has also been improved by discovering that some types of failures cause repeated pressure changes at well-defined intervals, making them easier to identify. Initial tests have shown that this solution can be extended to monitoring more complex systems, such as those with multiple valves or cylinders. In addition, the experimental results show the potential to use the data to continuously monitor the system status in realtime, thereby increasing the overall reliability of the process.

The results form a solid basis for the further development of software tools for predictive maintenance. By integrating these models into control systems, timely warnings of pressure changes could be generated to indicate component failures or wear. This functionality would significantly reduce maintenance costs and minimise downtime associated with unexpected outages. In addition, automated monitoring and diagnostics support the long-term sustainability and optimisation of pneumatic systems in a production environment. The measurement process has shown that by combining precise pressure sensors and advanced algorithms we can gain a deeper understanding of the dynamics of a given pneumatic system. On this basis it is possible to adapt the maintenance frequency to the specific conditions of a particular operation. This inevitably leads to more efficient planning of maintenance interventions. In summary, this approach can effectively contribute to optimising the diagnosis and maintenance of pneumatic systems. It opens up the new possibilities for the modernisation of industrial technology.

ACKNOWLEDGMENT

This work was supported by the Slovak grant agency VEGA under grant No. 1/0169/22 New methodics approaches to data from automated and robotized workplaces.

REFERENCES

- [1] Pandian, S., Takemura, F., Hayakawa, Y., Kawamura, S. (2002). Pressure observer-controller design for pneumatic cylinder actuators. *IEEE/ASME Transactions on Mechatronics*, 7 (4), 490–499. <https://doi.org/10.1109/TMECH.2002.805624>.
- [2] Unger, M., Radgen, P. (2018). Energy efficiency in compressed air systems – a review of energy efficiency potentials, technological development, energy policy actions and future importance. In *Proceedings of the 10th International Conference on Energy Efficiency in Motor Driven Systems*. Luxembourg: Publications Office of the European Union, 207–233. ISBN 978–92–79–79364–6. <https://doi.org/10.2760/345473>.
- [3] Feng, B., Liu, Z., Zhang, H., Fan, H. (2024). Research on the measurement system and remote calibration technology of a dual linear array camera. *Measurement Science Review*, 24 (3), 105–112. <https://doi.org/10.2478/msr-2024-0015>.
- [4] Borg, M., Refalo, P., Francalanza, E. (2024). Pneumatic fault monitoring and control for sustainable compressed air systems. *Procedia CIRP*, 122, 217–222. <https://doi.org/10.1016/j.procir.2024.01.032>.
- [5] Shi, Y., Cai, M., Xu, W., Wang, Y. (2019). Methods to evaluate and measure power of pneumatic system and their applications. *Chinese Journal of Mechanical Engineering*, 32, 42. <https://doi.org/10.1186/s10033-019-0354-6>.
- [6] Wang, Z., Yang, B., Ma, Q., Wang, H., Cariveau, R., Ting, D., Xiong, W. (2023). Facilitating energy monitoring and fault diagnosis of pneumatic cylinders with exergy and machine learning. *International Journal of Fluid Power*, 24 (4), 643–682. <https://doi.org/10.13052/ijfp1439-9776.2442>.
- [7] Abela, K., Refalo, P., Francalanza, E. (2022). Analysis of pneumatic parameters to identify leakages and faults on the demand side of a compressed air system. *Cleaner Engineering and Technology*, 6, 100355. <https://doi.org/10.1016/j.clet.2021.100355>.
- [8] Cagman, S., Soylu, E., Unver, U. (2022). A research on the easy-to-use energy efficiency performance indicators for energy audit and energy monitoring of industrial compressed air systems. *Journal of Cleaner Production*, 365, 132698. <https://doi.org/10.1016/j.jclepro.2022.132698>.
- [9] Dindorf, R., Wos, P. (2021). Universal programmable portable measurement device for diagnostics and monitoring of industrial fluid power systems. *Sensors*, 21 (10), 3440. <https://doi.org/10.3390/s21103440>.
- [10] Caruana, L., Refalo, P. (2018). Sustainability analysis of a compressed air system. In *Engineering Sustainability & Sustainable Energy 2018 (ESSE'18) Conference*. ISBN 978-99957-853-2-1.
- [11] Mousavi, S., Kara, S., Kornfeld, B. (2014). Energy efficiency of compressed air systems. *Procedia CIRP*, 15, 313–318. <https://doi.org/10.1016/j.procir.2014.06.026>.
- [12] Gauchel, W., Streichert, T., Wilhelm, Y. (2020). Predictive maintenance with a minimum of sensors using pneumatic clamps as an example. In *12th International Fluid Power Conference*. Technische Universität Dresden, 175–183. <https://doi.org/10.25368/2020.81>.

- [13] Borg, M., Refalo, P., Francalanza, E. (2024). Fault condition indicators along the demand side of a sustainable compressed air system. *Procedia CIRP*, 126, 283–288. <https://doi.org/10.1016/j.procir.2024.08.340>.
- [14] Zhu, H., Wang, Z., Wang, H., Zhao, Z., Xiong, W. (2023). Leakage fault diagnosis of two parallel cylinders in pneumatic system with a minimal number of sensors. *Electronics*, 12 (15), 3261. <https://doi.org/10.3390/electronics12153261>.
- [15] Xu, M., Wang, H., Wang, Y., Tian, H. (2023). Design and experimental study of a probe for crankshaft full-automatic measuring machine. *Measurement Science Review*, 23 (2), 72–79. <https://doi.org/10.2478/msr-2023-0009>.
- [16] Li, X., Kao, I. (2005). Analytical fault detection and diagnosis (fdd) for pneumatic systems in robotics and manufacturing automation. In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2517–2522. <https://doi.org/10.1109/IROS.2005.1545573>.
- [17] Krejčí, J., Babiuch, M., Babjak, J., Suder, J., Wierbica, R. (2023). Implementation of an embedded system into the internet of robotic things. *Micromachines*, 14 (1), 113. <https://doi.org/10.3390/mi14010113>.
- [18] Kundu, P., Cohen, I., Dowling, D. (2011). *Fluid Mechanics*. Academic Press, ISBN 978-0123821003.
- [19] Dindorf, R., Takosoglu, J., Wos, P. (2023). Review of compressed air receiver tanks for improved energy efficiency of various pneumatic systems. *Energies*, 16 (10), 4153. <https://doi.org/10.3390/en16104153>.

Received May 12, 2025
Accepted July 28, 2025