TEM Journal. Volume 10, Issue 1, Pages 183-191, ISSN 2217-8309, DOI: 10.18421/TEM101-23, February 2021.

Diagnosis of Pneumatic Systems on Basis of Time Series and Generalized Feature for Comparison with Standards for Normal Working Condition

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***Abstract* – Faults are unwanted events in any industrial production system. Early detection and diagnosis of faults in automated systems is important in order to prevent equipment damage, loss of performance and profits. For this purpose, more and more sophisticated and complex systems for observation and monitoring of basic characteristics in automated processes are being built. Preconditions for increasing their efficiency are processing and analysis of process information is obtained through a significant number of sensors. For pneumatic systems in addition to the identification of certain faults that may affect the normal production process, it is important to consider the possibilities to improve their energy efficiency. In this regards, the work focuses on the detection of leaks. The fault detection is based on the measurement of the compressed air consumption at the inlet of the pneumatic module and synchronization with signal from the PLC to the valve, and controlled the pneumatic cylinder.**

The experimental study aims to develop methods for automatic detection and classification of leaks that may be used in machine learning algorithms.

***Keywords* – diagnosis, pneumatic systems, leakages detection, time series, feature, metric space, correlations.**

DOI: 10.18421/TEM101-23
https://doi.org/10.18421/TEM101-23

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Received: 04 December 2020.
Revised: 23 January 2021.
Accepted: 01 February 2021.
Published: 27 February 2021.

1. Introduction

Increasing of energy costs, efficiency requirements and awareness of climate change make energy efficiency a major challenge for industrial production systems.

For handling systems, pneumatic automation is an alternative to the traditionally limited electric motor and hydraulic technologies in most automated industries. Compared to electric motors and hydraulic, pneumatics is usually clean, reliable and easy to integrate. In addition, the pneumatic system can offer a high power/weight ratio and has great advantages in terms of initial investment of 10:1 over alternative technologies [2],[10].

According to various studies and studies worldwide, the percentage of electricity in the industrial sector used to produce compressed air varies between 5% in Japan, 10% to 15% in Australia and the EU, up to 30% in USA [1], and between 10% and 40% in China [7]. In some industries such as glass production and productions with a high degree of automation, this percentage reaches 45-50%.

Compressed air is known to be the most expensive energy media available in production facilities. Both, production companies and machine builders, are often surprised to learn that the average price of compressed air in the European Union is around 0,02 euro per $1m^3$.

Losses of compressed air are usually considered harmless and they are often underestimated as a waste of energy and resources. However, leaks, as the main source of losses, also impair the performance of the machine, as they change the main parameters of the drive mechanisms - power and speed during operation. The presence of leaks forces the compressor to operate at a higher load, producing more compressed air to compensate them.

In existing installations, leaks are the main cause of excessive compressed air consumption, sometimes over 50% of the compressed air produced [6].

In this context, the monitoring and diagnostics of the relevant parameters in compressed air systems has a high priority. More and more manufacturers of pneumatic elements and systems are focusing on product development aimed at optimizing and reducing compressed air consumption, reducing direct leakage losses, monitoring and managing compressed air consumption.

An example of this is the energy efficiency module developed by the Japanese corporation SMC, which limits the direct losses from static leaks in machines [14]. The module on Figure 1 can be mounted to a compressed air supply line of any pneumatic system.

Figure 1. SMC Energy saving module

The operation of the proposed solution is based on continuous measurement of the intake air flow. Based on these measurements, three levels of compressed air pressure are maintained: “normal”- when the system consumption is significant; “low pressure”- at reduced consumption, for short intervals (when the machine is in standby mode, waiting for charging or unloading) and “topping the supply of air to the machine” - during a long time of low consumption (end of the working cycle, prolonged stay for rest or change of operators). Such a solution, which is based on flow thresholds, could be improved by using an intelligent classifier that, based on flow data, classifies current system states that deviate from normal. In the event of a deviation from the norm, appropriate measures could be taken, such as notifying the machine operator or generating an alarm in the automated monitoring and control system.

A standard approach to developing a diagnostic algorithm is to create a model of the system behavior - for example through simulation or mathematical models. Mathematical modeling, in this case, is limited, especially in complex pneumatic systems, because it requires the creation of models of a large number of pneumatic components and takes in to account all relations in between.

Another possibility is the installation of multiple flow and pressure sensors along the pneumatic system. The collected time series data in combination with discrete signals from actuator autoswitches and PLC signals can be used for development of diagnostic algorithm.

In order to reduce measuring instruments, an approach of installing compressed air flow meters at the inlet of each machine and continuously monitoring of their readings is often used. In this way, the presence of leaks can be easily identified in the event of abnormally high consumption of the respective machine. However, identifying leak points is a time consuming task and involves relatively long machine downtimes.

The aim of this paper is to investigate the possibility of detecting and diagnosing leaks in different parts or components of the pneumatic system, based on processing and obtaining additional information from time series diagrams generated by flow sensor at the supply inlet and expanding the algorithm with data from available in the system sensors and discrete signals.

2. Theoretical Part

The use of time series diagrams, taking into account operating pressure and airflow, is a standard practice in the design and operation of pneumatic systems. The consumption time profile allows to analyze the quantitative consumption and compressed air demands in the installation over the time and to optimize the operation of the compressors, especially in the presence of large variations and periods with partial load. In most cases, this is done by measuring the inlet of the main compressed air highway over a wide time scale (eg. 24 hours)

In the present task a flow meter is used at the compress air supply inlet of the local production cell. The time diagrams characterize the consumption of each cycle of the process. In this way, the task of diagnosing and detecting leaks can be reduced to a task of analyzing time series (Figure 2).

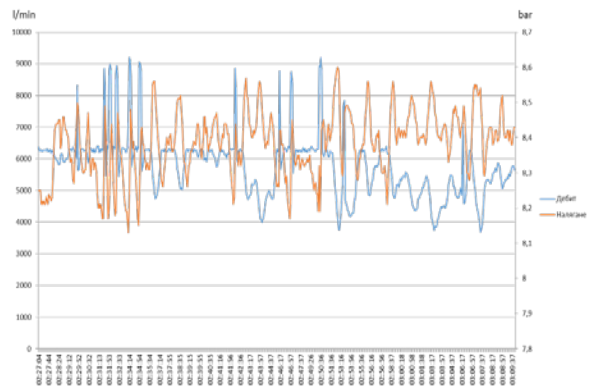


Figure 2. Flow and pressure time series

The time series similarity analyzing methods can be divided in three categories: direct, using original time series data; indirect with transformations (Fourier or wavelets transform, etc.); indirect, with metrics obtained from the original data (statistical moments, distances and others).

The direct use of primary information is appropriate in the case of small series (short processes or low-resolution timing diagrams). The use of additional transformations usually requires specialized software products.

This paper investigates the possibility of usage of metric characteristics in research of time series similarity. These metrics are widely used also for pattern recognition (prototypes comparison). More than 15 metrics which define the respective feature space are already known in literature. Majority of them are derivatives of classical distance metrics such as Euclidean Distance, Manhattan Distance, Mahalanobis Distance, etc. and improving their deficiency in particular cases. In this experimental study, limited numbers of such metrics are used.

2.1. Feature Fusion Based on Distance in Metric Space

2.1.1. Minkowski Distance

Minkowski Distance - D_{Mink} [5] is one of the most commonly used in clustering and classification tasks metric. Minkowski Distance between two time series $f^{p}(t)$ and $f^{q}(t)$ is defined by equation [3]:

$$D_{Mink} = \left(\sum_{t=1}^{N}\left|f_t^p - f_t^q\right|^r\right)^{\frac{1}{r}},$$

where: f_t^p and f_t^q are the values of time series f^p and f^q at the moment t;

N – number of records in the time series;

r - is integer number.

In most applications only values r=2 (Euclidean Distance), r=1 (Manhattan, or City-block Distance) and $r\rightarrow\infty$ (Chebyshev, or Maximum Distance) have been considered [3].

The main advantage of Minkowski Distances is that they are easy to calculate and interpret. In addition, standardized Minkowski Distances have been calculated [8], which take into account the number of samples. This allows time series with different lengths and missing values to be compared. For example, a calculated value of D_{Eucl}, based on only the real observations (N') in time series with missing data and subsequently dividing D_{Eucl} by N'.

One of the most important limitations of Minkowski Distances is that they do not take into account the nonstationarity of deviations or time cross-correlations in the data set [9]. As a result, the observations with the largest deviation (if not standardized) will dominate.

2.1.2. Canberra Distance

Canberra Distance (D_{Canb}) – examines the sum of series of a fraction differences between coordinates of a pair of objects.

$$\mathrm{D_{Canb}} = \sum_{t=1}^{N}\frac{|f_t^p - f_t^q|}{|f_t^p| + |f_t^p|}.$$

For close values in the series, the sums in the sum have minimal values.

D_{Camb} normalizes the scale of the deviations in the time series. This feature makes it suitable for a large span of values, which characterizes the flow diagrams of pneumatic systems with discrete-event action.

The distance is sensitive to a small change when both are coordinated close to zero [4].

2.2. Correlations

2.2.1. Pearson's cross correlation

The most know correlation measure is Pearson cross correlation coefficient

(D_{Pears}) [11], which defined the degree of linear relationships between two time series:

$$D_{\mathrm{Pears}} = \frac{\sum_{t=0}^{N-1}\left[\left(f_t^p - \bar{f}^p\right) * \left(f_{t-s}^q - \bar{f}^q\right)\right]}{\sqrt{\sum_{t=0}^{N-1}\left(f_t^p - \bar{f}^p\right)^2} * \sqrt{\sum_{t=0}^{N-1}\left(f_{t-s}^q - \bar{f}^q\right)^2}},$$

where: f_t^p and f_t^q are the values of time series f^p and f^q at the moment t;

N – number of records in the time series;

s – is the time lag between both series.

In case of s=0, the similarity between time series is assessed without taking into account the time lag.

As D_{Pears} is a measure of the linear relationship between time series and does not estimate the difference in time series values, amplitude scaling or translation does not affect the result. It does not take into account nonlinear dependences between the compared vectors.

2.2.2. Angular Separation correlation coefficient (D_{as}).

It represents cosine angle between two vectors.

$$D_{as} = \frac{\sum_{t=1}^{N} f_t^p \cdot f_t^q}{\left(\sum_{t=1}^{N} {f_t^p}^2 \cdot \sum_{t=1}^{N} {f_t^q}^2\right)^{\frac{1}{2}}}$$

D_{as} takes into account the degree of similarity of the profiles. Higher values of the angular separation coefficient indicate that the two objects are similar. The value of the angular similarity coefficient is [-1, 1].

3. Experimental Part

For the purposes of the experimental study, a model of a basic pneumatic module was used (Figure 3), and realized with conventional technical elements.

The used pneumatic elements are listed in Table 1.

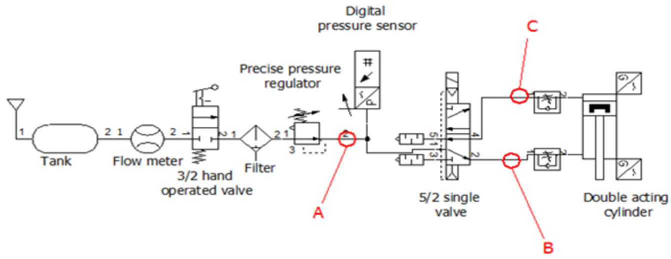


Figure 3. Experimental setup

Table 1. Equipment specification

N	Part Name	SMC Product Code	Q'ty
1	Air tank 10l, max. 2,0 MPa,	VBAT10AF-SV-Q	1
2	Digital Flow Switch without Monitor, 0.2 - 10 l/min,	PFM710-C6-F-N	1
3	2 port finger valve, Push-in Dm6-Push-in Dm6	VHK2-06F-06F	1
4	Air Filter, port size G1/8, max. operating pressure 1.0MPa,	AF20-F01-A	1
5	Precision regulator, port size G1/8, range 0.01-0.8 MPa,	IR1020-F01	1
6	Digital pressure switch with display,	ISE10-01-B-G	1
7	5/2 single solenoid valve 24V DC, push-in dia4,	SY3120-5LOU-C4-Q	1
8	One touch fitting, 2xpush-in dia4,	KGT04-06	1
9	Round cylinder ISO 6432, double acting, dia20, stroke125	CD85N20-125-A	1
10	Meter-out speed controller/check valve horizontal,	AS2201FG-01-04SA	1
11	Meter-out speed controller/check valve horizontal,	AS2201FG-01-04SA	1
12	Polyurethane tube dia4/2.5	TU0425BU-1	0,50
13	Polyurethane tube dia4/2.5	TU0425BU-1	0,30
14	Polyurethane tube dia4/2.5	TU0425BU-1	0,30
15	Auto Switch, LED 24 VDC, 0.5m lead wire	D-P5DW	1
16	Auto Switch, LED 24 VDC, 0.5m lead wire	D-P5DW	1
17	Silencer compact type, thread R1/8, synthetic material,	AN10-01	1
18	Silencer compact type, thread R1/8, synthetic material,	AN10-01	1

The experiment included 200 measurements of operating cycles: 50 measurements in the reference configuration (without leaks) and 50 measurements for three different situations of simulated leaks. Leaks are divided into two main categories:

- Static leaks: leaks, with high consumption, as they are either in the main lines or at the machine level in standby mode. In the first case, the losses are permanent. In the other - during the period of stay of the machine and when the actuator is in the initial position;
- Dynamic leaks, which are observed in the actuators (or more precisely in the system valve-fittings-tubes-speed regulator-actuator). When the system is in the initial state (for example, the cylinder has a retracted rod) these leaks are not observed. After switching the system (the cylinder has the rod extended) a leak appears. They are usually leaks caused by from broken actuator or manifold seals, but is often from a defective fitting or connection that is under pressure only in this position of the system.

On the test bench, the following three configurations are implemented (Figure 3):

- **Node A**: **static leak at the supply part of the system** - before the directional control valve, including the supply port of the valve;
- **Node B: static leak at the actuator part** - between the directional control valve and the cylinder, including leaks in the valve and leaks in the front seal of the cylinder;
- **Node C: dynamic leak** – between the directional control valve and the cylinder in the line of forward move, including leaks in the valve when it is switch in this condition.

The operating cycle data includes the status of the actuator end position autoswitches, the valve switching signal and the airflow values for the entire system. The sampling frequency is 10*Hz* (every 100*msec*). Each cycle starts with a 500*msec* pause (initial state of the system). After reaching the cylinder in the end position (at signal from the sensor) there is again a 500*msec* pause and return to the initial position.

The flow measurement at the inlet of the system is performed by means of a flow meter, in which the compressed air is forced to pass through the test compartment of the flow meter in order to ensure a laminar flow. This limits (changes) the flow characteristics, but since this change is the same for all measurements, it can be ignored. The flow meter - (PFM710, SMC) measures the mass of air passed in units of SLPM ("standard liter per minute"), a normalized value corresponding to the temperature 0°*C*, atmospheric pressure 1013*mbar* and atmospheric density 1.294 $kg{=}m^3$ [12].

For convenience, the inlet pressure of the system is fixed (5 *bar*) by means of a precise pressure regulator and sufficiently large tank is implemented. All leaks in the system are set to 1*l/min*.

4. Results and Analyzes

Visual analysis of time series charts in normal mode shows:

- The presence of stationary and random variations in the values of the supply pressure. In this case, the inlet pressure of the system is fixed by means of a mechanical precise pressure regulator with flow compensation. Stationary variations are the result of pressure drops in the supply line;
- Variations in the lengths of time series with a random character. They are equivalent to the speed of the process.
- Local variations are possible in certain segments of the process as a result of backlash, friction, etc.

Pre-processing of the data includes synchronization of the time series using the sensors and/or signals to the valve of the controlled cylinder. This is due to the inertia of the pneumatic systems, the different degree of air compressibility, as well as due to the fact that in the presence of leaks in any part of the system, the time for extending or retracting the cylinder rod is extended and this delay accumulates over time [15].

Figure 4 shows the averaged and synchronized time series of measurements of one cycle in each configuration.

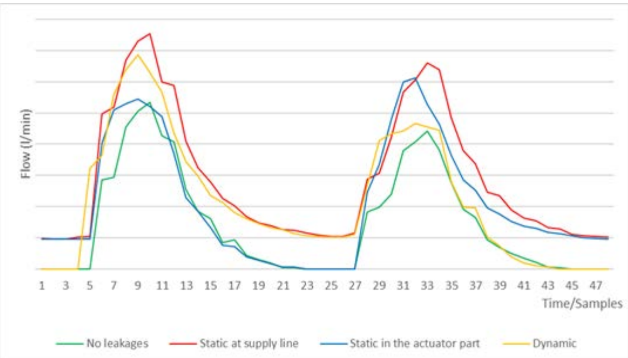


Figure 4. Average flow in one cycle for all configurations

For the compiled sample of experimental data, a quantitative analysis of the observed values with respect to the mean values of the time series of normal (no leakage) operation in different feature spaces was performed.

– *Pearson cross-correlation coefficient -* D_{Pears}

Figure 5 presents the results of the D_{Pears} calculation and normal distribution in all cases.

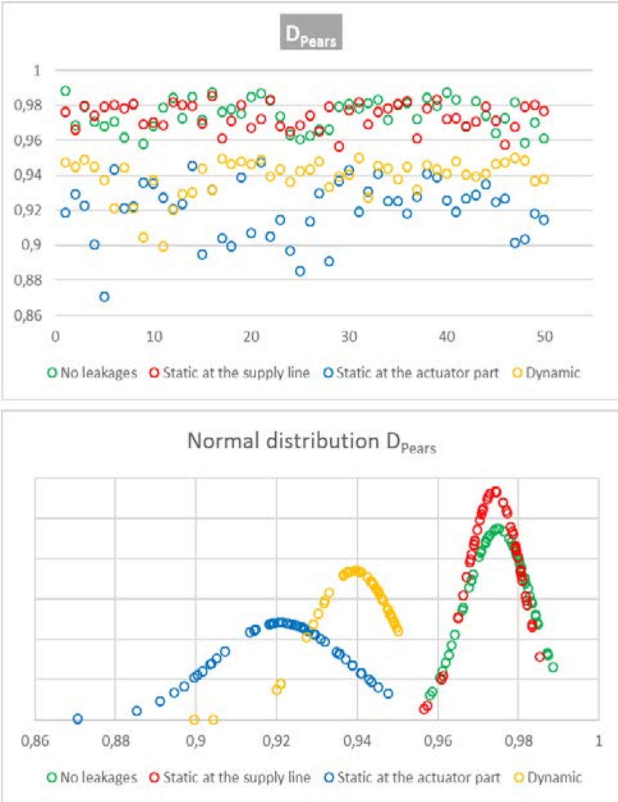
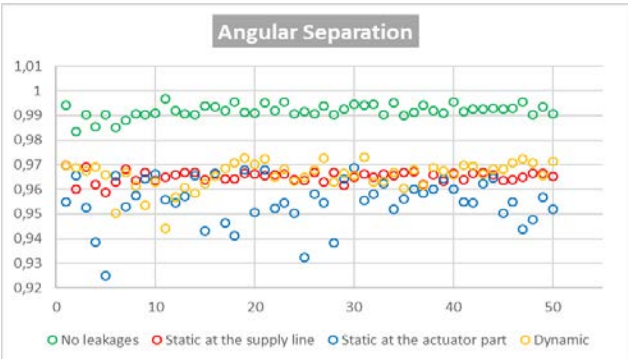


Figure 5. Pearson cross-correlation calculation and normal distribution in all cases

In case of static leak in the supply part of the system D_{Pears} have values > 0,96 which are close to the values in case of no leakages. The leakages in actuating part (after the directional control valve) decrease the value of D_{Pears}. Increasing the value of the leakage decreases the value of the D_{Pears}.

– *Angular Separation correlation coefficient (*D_{as}*)*

Figure 6 presents the results of the D_{as} calculation and normal distribution in all cases. D_{as} decreases in all three cases of leakage, which makes this metric suitable for detecting problems in the pneumatic system, but without being able to locate it.



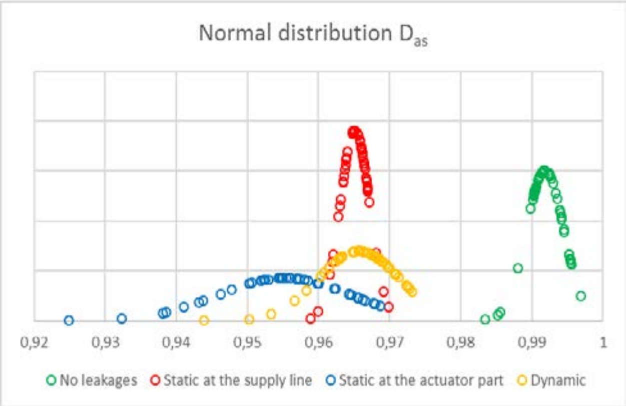


Figure 6. Angular Separation calculation and normal distribution in all cases

– *Minkowski Distance*

Two Minkowski Distances were used – Manhattan (Figure 7) and Euclidean Distance (Figure 8). As the power of r increases, the values from the different calculations converge and become indistinguishable.

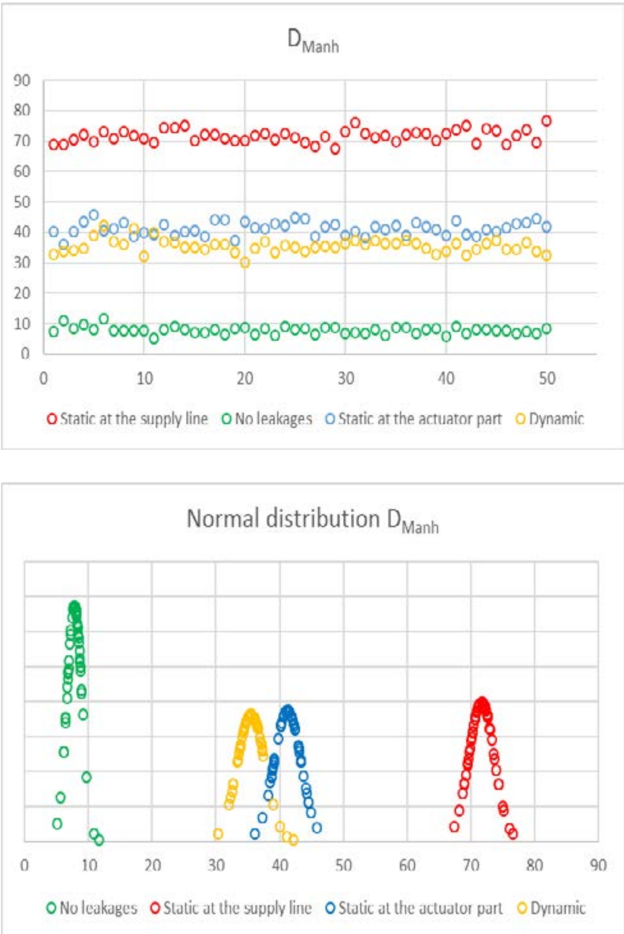


Figure 7. Manhattan Distance calculation and normal distribution in all cases

In this case the metrics are sensitive to the increasing of the amplitudes of the observed time series, i.e. if the size of the leaks increases, the distances will increase.

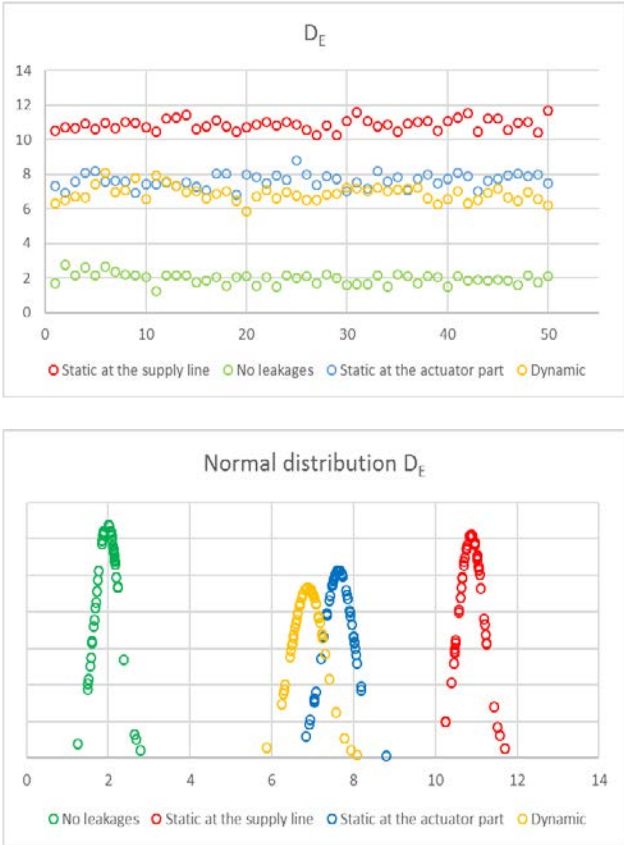


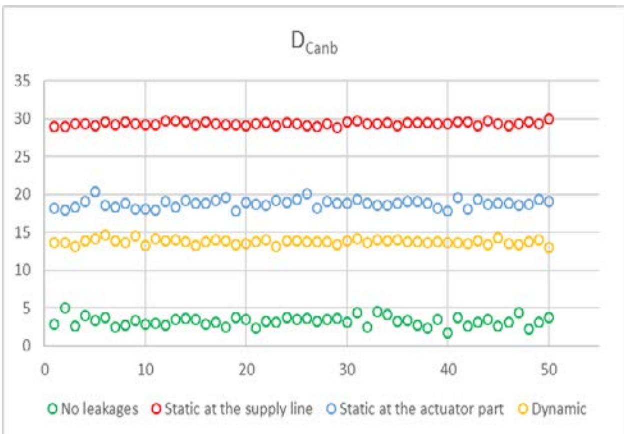
Figure 8. Euclidean Distance calculation and normal distribution in all cases

The distribution functions of the four classes of situations (Figure 7, Figure 8) show the possibility of their separation with the probability of errors in the classification of static and dynamic leakage after the valve.

– *Canberra Distance (D_{Canb})*

The results of the calculations and the normal distribution are presented in Figure 9.

The results show that the Canberra Distance clearly distinguishes leaks from the normal state and from each other, which makes this metric suitable for detecting and locating single leaks with a deterministic (threshold) separation function.



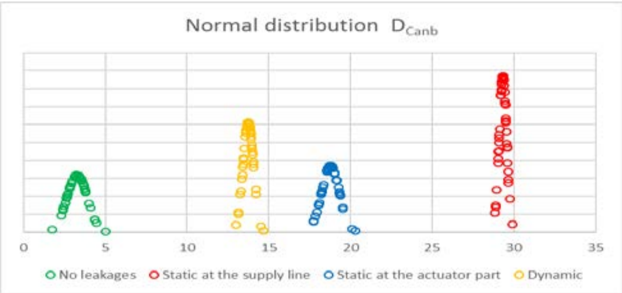


Figure 9. Canberra Distance calculation and normal distribution in all cases

– *Classification of two features*

The correlation coefficients applied above do not allow accurate classification of the leakages. Pearson's correlation does not provide information in the event of a static power leakage, and the angular separation coefficient, although giving a very clear idea of the problem, is not sufficient to determine whether the leakage is before or after the directional control valve.

The methods related to distance calculation have the main disadvantage that, although to varying degrees, they are influenced by the amplitude of the observed signal, i.e. by the size of the leak, which makes it impossible to accurately classify the type and location of the leak. This is most pronounced in the Minkowski Distances, where a dynamic leakage of 2*l/min* and a static leakage of 1*l/min* give similar results. At the Canbera Distance, this dependence is not so strong, but it still exists and this makes it impossible to distinguish a large leakage after the valve from a small leakage at the input.

With regards to above disadvantages, a variant of using two features for classification- Pearson correlation and Canbera Distance is proposed. Figure 10 shows the distribution of values in the space of these two features. Accordingly, the possible changes of the values are marked when the size of the leak changes. The results obtained show a clear separability as:

- D_{cc}<0,96, the leak is after the valve.;
- D_{cc}=>0,96 and C_a>5 the leak is on the supply line;
- D_{cc}=>0,96 and C_a<=5 there is no leak in the system.

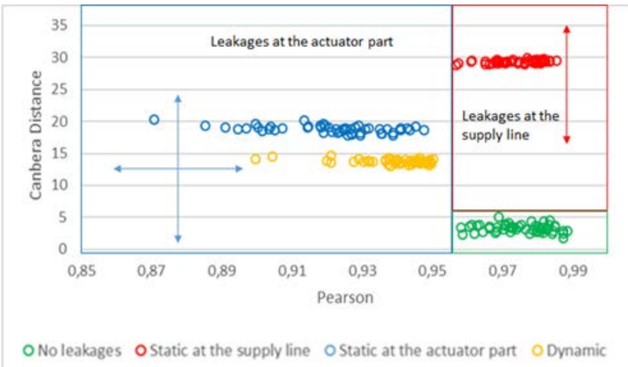


Figure 10. Two features classification

5. Consistent Approach in Examining the "Leakage/Measured Inlet Flow" Relationship

The operating cycle of the studied circuit can be divided into several steps, depending on the condition of the end position sensors, cylinder motion sensor, valve switching signal, valve position sensor, etc. depending on how many and what sensors are located in the system

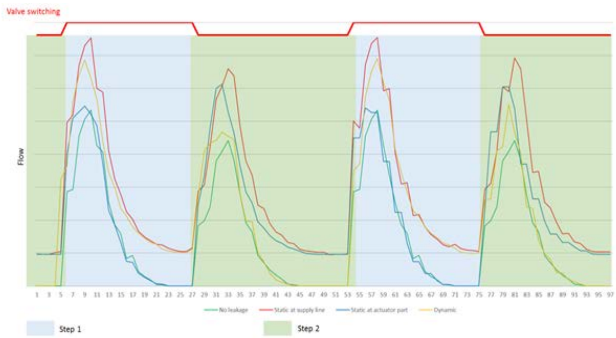


Figure 11. Dividing the operational cycle regarding the status of the end position autoswitch

A switching signal of a 5/2 single valve SY3120-5LOU was used to divide the cycle into steps (Figure 11). The data is time synchronized, taking into account the response time of the valve (20ms in 5bar) [13].

– *Using an indexed time series (logistic table)*

When one is detecting and diagnosing faults, it is convenient to form a logistic table consisting of given features of the parameters or processes to be diagnosed. The choice of features depends on the process and knowledge of the system based on the information collected.

In the case of pneumatic systems, this information could be collected from end switch sensors, flow meters, pressure sensors, valve switching signals, valve status sensors, etc. used in the system.

Suitable for the studied experimental model is the use of the readings of the flow meter at the input of the system and the switching signal of the directional control valve SY3120, taking into account the reaction time the valve for synchronization.

In Table 2 shows the dependence of the flow of compressed air on the three classes of leaks. The designation "0" corresponds to no influence, and "1" - increases the air consumption.

Table 2. The dependence of the flow of compressed air on the three classes of leaks

Flow / **Leakege**	Flow Step 1	Flow Step 2
No leakages	**0**	**0**
Static at supply line	**1**	**1**
Static after the valve	**0**	**1**
Dynamic after the valve	**1**	**0**

– *Canbera Distance*

Canbera Distance for each step is defined in below equations:

– For Step 1

$$DCanbS1 = \sum_{t=1}^{N} \left(\frac{|f_t^p - f_t^q|}{|f_t^p| + |f_t^p|} * d_t \right)$$

– For Step 2

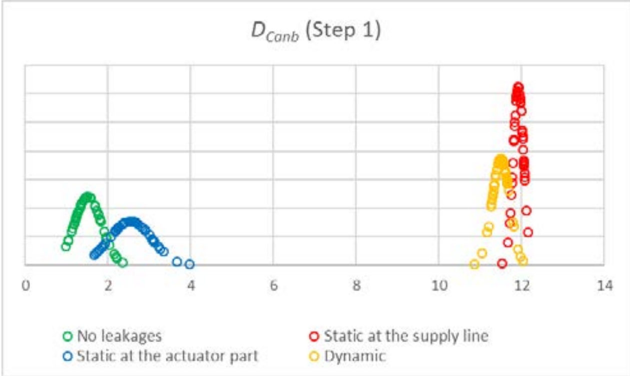
$$DCanbS2 = \sum_{t=1}^{N} \left(\frac{|f_t^p - f_t^q|}{|f_t^p| + |f_t^p|} * (1 - d_t) \right),$$

where: $d_t = [0,1]$ is the state of the signal from PLC that switch the valve.

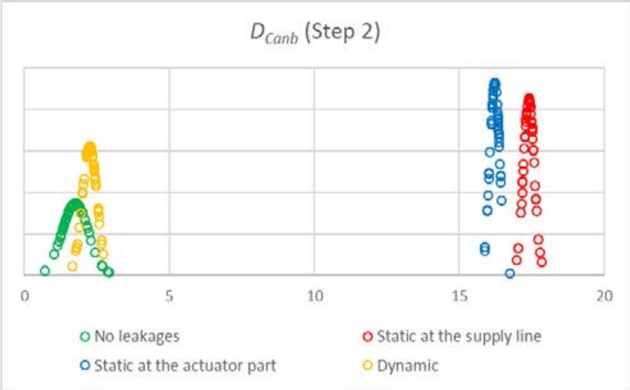
– *Results*

Dividing the duty cycle into sub cycles (steps) allows, applying only one metric to determine the location of the leak. This method eliminates the influence of leakage size.

The distribution functions of the calculated Canbera Distances for the three leakage classes and the non-leakage measurements are shown at Figure 12.



a)



b)

Figure 12. Canberra Distance normal distribution a) for Step 1, b) for Step 2

6. Conclusion

In modern automated systems, direct monitoring and rapid diagnostics are essential not only to limit unpredictable downtime, but also to optimize energy costs and reduce losses.

This paper discusses various possibilities for fault diagnosis (single leaks) in a basic and widely used in automation pneumatic system. Focusing on the prospects for building automatic diagnostic systems, the work is related to the initial stages of synthesis of image recognition algorithms.

To determine the characteristics of the system, one sensor was used to measure the flow rate and one signal from the PLC that implements the control of the circuit.

Based on experimental data, we presented estimates for the dividing classification relevance of classical metric distance.

The obtained results show the possibility of detecting leaks in two categories - on the supply line and after the distributor, by means of two features.

A concept for the use of a logistics table by two characteristics is also presented, with the help of which it is possible to classify each category of leaks, regardless their size.

The proposed methodologies and the obtained results are a prerequisite for their development for more complex industrial equipment including pneumatic systems.

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