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An approach to pneumatic cylinder on-line conditions monitoring

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1. Introduction

Linear pneumatic cylinder or drive is one of the most often used actuators in various production, assembly and conveyance units. As a result of long term operation, sealings of a cylinder wear out and this causes appearance of internal leakages. Leakages may become the reason for:

1. degradation of cylinder performance (force and speed decrease, change of timing parameters);
2. increase of compressed air consumption.

Cylinder manufacturers usually specify the number of operation cycles or the mileage for component or its sealing replacement. However, in every particular installation and working conditions cylinder leakages may progress dissimilarly.

Leakages are among the most important factors describing technical conditions of a cylinder. Therefore, following tasks are raised for a cylinder diagnostics:

1. leakage localization;
2. leakage level estimation.

Though the problem of pneumatic and hydraulic components condition monitoring is not new, constant interest and research activities in this field were observed over the last decade. Scientific articles mainly seek to propose methods for fault detection and identification (estimation) of pneumatic systems and components. Pneumatic and hydraulic cylinders [1-5], pneumatic servo-motors [6], digitally controlled valves [7] were most often considered among the objects of monitoring. Faults in these systems are sealing leakages [1, 3-5, 6, 8, 9], friction increase [2, 10] and other malfunctioning [6]. Development of new sensors for process data acquisition [4, 11] as well as obtained data processing in order to recognize the fault and estimate its level [3-6, 9] are described in references. Signals gathered for the fault detection can be separated to the high frequency vibrations (acoustic emission) [3, 8, 11] and low frequency patterns such as pressure, flow, timing parameters, etc. [2, 4-6, 7, 9, 10, 12, 13]. Despite the origin of physical measured signals their further processing is usually applied. It involves feature extraction and feature mapping to the space of faults. Applications of various classification methods such as neural networks [5, 7, 9, 10, 13], vectorized maps [4, 12], bond graphs [6], genetic programming [2, 8], etc. were presented in the papers.

It has to be mentioned that the reliability of solutions offered by these mathematical tools are strongly dependant on the successful selection of input features that are extracted from original sampled signals. The so called diagnostic features selection is done in the research stage and requires understanding of mechanical processes running in a pneumatic system [14,15]. Some authors also discover influence of possible diagnostic features characterizing operation of a pneumatic cylinder on the features of the other cylinders in a pneumatic system composed of several pneumatic components [16].

The diversity of reported approaches makes us think that the final reliable and suitable solution for pneumatic components conditions on-line monitoring has not been found until now. Therefore, the goal of our investigation is to perform a search of diagnostic features and methods that could be utilized for the on-line condition monitoring by means of estimation of a pneumatic cylinder leakages using only common industrial process sensors such as air flow, pressure transducers and proximity switches.

2. Pneumatic cylinder and typical pneumatic system

Several leakage appearance locations can be distinguished in a typical pneumatic cylinder construction:

1. between chambers of an actuator (piston seal);
2. from retract chamber to the ambience (end seal, wiper seal);
3. through the tube connection ports (extend, retract ports).

Measurement of pressure in the selected points is common in pneumatic systems. Operation of a system could be monitored using industrial air flow meters as well. For indication of an actuator piston end position, typically magnetic proximity sensors are used. Seeking to detect and estimate leakage levels it is not enough to observe pressures, air flow and time intervals between proximity switches discrete signals, but it is also necessary to know an algorithm or model that transforms directly measured parameters to leakage estimates.

A pneumatic cylinder starts its working cycle on triggering of the control valve. At the moment of triggering, transient flow and pressure processes can be observed in connecting tubes. We will call flow and pressure time domain signals flow and pressure patterns. The shape and parameters of these patterns depend on leakage. Other system parameters and settings such as working pressure, actuator load, length of connecting tubes, throttles position, etc. make influence on them too.

The testing bench was assembled in order to investigate the influence of leakages and secondary factors on directly measured transient processes of air flow and pressure. The acquired experimental data are used for the search of diagnostic features.

3. Experimental setup

Schematics of the built testing bench is shown in the Fig. 1.

The testing bench consists of the pneumatic cylinder with the diameter of 32 mm, stroke of 80 mm length, 5/2 type control valve CV, one-way throttles Dr_1 and

Dr_2 to control cylinder piston movement velocity, tubing L whose length can be changed during the experiment, magnetic proximity sensors PS_1 and PS_2, working pressure p_0 transducer, the first and the second cylinder chamber pressure p_1 and p_2 transducers respectively, Venturi nozzle V, differential pressure Δp transducer, load mass M, simulated leakages between the actuator chambers LP_3 and to the ambience LP_1 and LP_2, computer that controls the testing bench. All signals were sampled with the sampling frequency F_S =3 kHz. The pneumatic valve was controlled using discrete outputs of the multifunctional data acquisition board DAQ. Type of the air compressor used is Jun-Air 6-15.

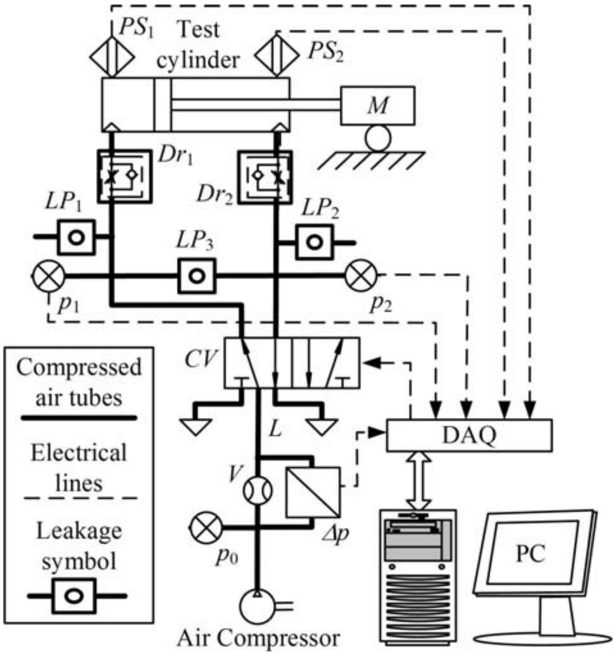

Fig. 1 Scheme of testing bench

Compressed air flow Q was calculated using the measured differential pressure Δp and the working pressure p_0 according to expressions given in [17]. Air compressibility was taken into account. The Venturi nozzle was calibrated in five points in the range of Reynolds number from 1200 to 15000 by the accredited laboratory.

Table 1

Leakage flow rate through the leakage orifices

d, mm	p_0, MPa	Q, dm^3/min	U, dm^3/min
0.3	0.28	0.08	0.06
0.5	0.28	0.83	0.05
0.7	0.28	1.99	0.05

Leakages LP_1, LP_2 and LP_3 were applied in the positions, shown in the Fig. 1 using orifices of circular shape and known diameters. Compressed air flow rates (leakage rates) Q through these orifices are given in the Table 1. The compressed air flow rate uncertainty U is evaluated statistically taking repetitive measurements and calculating 95% confidence interval of the average value.

4. Data acquisition and preprocessing

Selected values of working pressure, load mass and leakage levels were set during the data acquisition. The pneumatic actuator was operated for 10 cycles for each set of settings. One cycle consists of extend and retract subcycles. The following experimental data were recorded during these 10 actuator operation cycles: $\Delta p_j(t_i)$, $p_{0j}(t_i)$, $p_{1j}(t_i)$, $p_{2j}(t_i)$, $PS_{1j}(t_i)$, $PS_{2j}(t_i)$, $V_j(t_i)$, $j = 1, \dots, 10$. Having pressures $\Delta p_j(t_i)$ and $p_{0j}(t_i)$ the corresponding flow rate pattern $Q_j(t_i)$ was calculated. Then synchronous averaging was applied on the extend subcycle flow rate and pressure patterns. Prior to the synchronous averaging patterns were synchronized according to the rising edge of the proximity sensor PS_1 signal. The retract subcycle patterns were averaged in the same way, except the synchronization was done on the rising edge of the PS_2 signal.

In the following we will omit the word averaged though all later considered flow and pressure patterns are assumed averaged as explained above.

5. Search for diagnostic features and algorithms

5.1. Parameters of air flow rate and pressure patterns

Air flow rate and pressure patterns of extend and retract subcycles are of similar shape, though some of their parameters may differ, because of unequal working cylinder volumes and effective piston areas. Taking this into account, extend and retract subcycles are averaged separately.

According to the physical model of a pneumatic cylinder operation, three phases may be distinguished: initial (phase I), movement (phase II) and final (phase III) [18]. It makes sense to consider separate phases of a cylinder operation subcycle, because physical processes, taking place during these phases are of different nature. For instance, in the phase I piston does not move and thus load mass does not influence patterns of the flow rate and the pressure.

The following factors influencing pressure and air flow rate dynamic characteristics were investigated using the above described testing bench:

1. leakage LP_1, LP_2 and LP_3 level and position;
2. working pressure, p_0 = 0.30, 0.35 and 0.40 MPa;
3. load mass, M = 0, 1, 2, 3, 4 and 5 kg;
4. connection tubing L length;
5. settings of throttles Dr_1 and Dr_2.

Parameters of the dynamic flow rate and the pressure processes that were apparently affected by considered leakages and secondary factors are pictured in Fig. 2. In the Table 2 dependencies between pattern parameters and influencing factors are labeled. “+” sign in a cell of the table denotes monotonic dependence between value of the parameter corresponding factor. “*” denotes non-monotonic dependence and “-“ denotes absence of correlation between the parameter in the respective row and the factor in the respective column. We call monotonic dependence the one showing only increase or only decrease of the parameter value through all the range of influencing factor levels independent to the values of other factors.

Nonmonotonic dependence on the other hand is characterized at least by one of the following features: 1) the pattern parameter increases in one range of influencing factor, but it decreases in another range, 2) character (increase or decrease) of the dependence changes in accordance to the values of other factors.

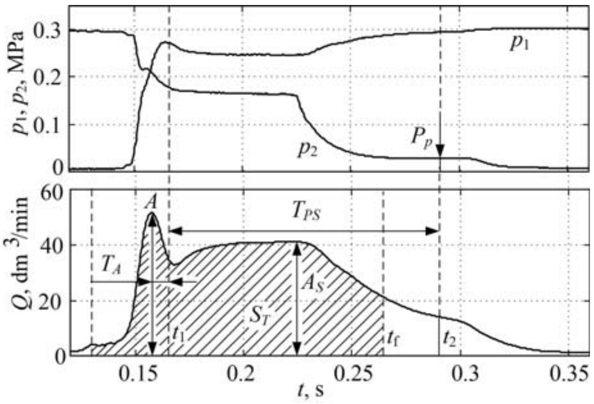

Fig. 2 Parameters of flow rate and pressure patterns

Table 2
Dependence between measured parameters and influence factors

Parameter x_i	Factor						
	Leakage location			p_0	M	Dr	L
	LP_1	LP_2	LP_3				
A_1	+	–	+	+	–	–	+
A_2	–	+	+	+	–	–	+
A_{S1}	+	–	*	–	+	+	+
A_{S2}	–	+	*	–	+	+	+
S_{PS1}	+	–	+	–	*	+	+
S_{PS2}	–	+	+	–	*	+	+
S_{T1}	+	–	+	–	*	+	+
S_{T2}	–	+	+	–	*	+	+
P_{P1}	–	–	+	+	+	–	–
P_{P2}	–	–	+	+	+	–	–
T_{PS1}	+	–	–	–	+	+	+
T_{PS2}	–	+	–	–	+	+	+
T_{A1}	–	–	–	–	+	–	+
T_{A2}	–	–	–	–	+	–	+

Parameters given in the Table 2 are called diagnostic features and are defined as follows (subscript denotes subcycle: “1” – extend subcycle, “2” – retract subcycle):

- A – magnitude of phase I;
- A_S – magnitude of phase II;
- S_{PS} – compressed air consumption in phase II, $S_{PS1} = \Delta t \cdot \sum_{i=1}^{N} Q_i$, where Δt is the sampling period, N is the number of samples in the time interval from t_1 to t_2; t_1 corresponds to the moment of proximity switch PS_1 signal edge, while t_2 corresponds to the moment of PS_2 signal edge;
- S_{T1} – compressed air consumption over fixed interval; start of the interval is the control valve signal while the duration is selected experimentally and kept constant despite the real phase II duration, i.e. cylinder operation conditions (load, pressure, etc.). The end moment of the interval is noted by t_f in the Fig. 2;
- P_p – residual pressure at the end of the phase II;
- T_{PS} – duration of the phase II;
- T_A – duration between the phase I magnitude position and the start moment of the piston movement, which corresponds to the rising edge of the respective proximity sensor signal.

Due to the jittering effect of proximity sensor air consumptions S_{PS1} and S_{PS2} exhibit larger variation than air consumptions S_{T1} and S_{T2}.

In the Table 2 we show that the leakage LP_1 affects extend subcycle parameters A_1, A_{S1} and S_1 but does not affect corresponding parameters of retract subcycle patterns. The leakage LP_3 on the other hand affects parameters of both subcycles.

Most of the parameters are influenced by secondary factors. Some of secondary factors, such as throttles settings and tubing length often remain unchanged after pneumatic system is installed and tuned. Therefore, values of these factors could be assumed constant during the monitoring stage. It is of importance that diagnostic system could adapt itself to particular settings of throttles and tubing characteristics. On the contrary, it would not be correct to assume stability of working pressure and load mass. The load mass may vary in each subcycle. Working pressure may also fluctuate as a result of the compressed air source adjustment by plant personnel.

Inadequacy of modeling the cylinder leakages by orifices connected as shown in the Fig. 1 can result in absolute measured parameters values changes compared to those caused by the real internal leakages. However, this will not affect principals of the bellow described diagnostic methods, since they are based on the comparison of refeerence and monitoring values of the diagnostic features.

5.2. Building a diagnostic model

We have found it difficult to select a flow rate or pressure pattern parameter independent upon secondary factors. Therefore, we need to transform one or several directly measured parameters into derived diagnostic feature $y*$, that is independent on secondary factors. The output of the diagnostic model could be:

1. Modified air flow rate or pressure pattern parameter having eliminated the influence of secondary factors, such as, for instance, working pressure;
2. A parameter of cylinder physical model that characterizes the level of a fault, e.g. the diameter of an effective leakage orifice;
3. Measurable parameter that directly characterizes fault level. In a case of leakage this could be an increase of air consumption, compared to the air consumption observed in reference conditions, i.e. conditions without any leakage.

Anyhow the derived diagnostic feature will need to be related to directly measured parameters with an expression

$$y* = F\left(x_1, x_2, \ldots, x_n, b_1, b_2, \ldots, b_m\right) \quad (1)$$

where x_i, $i = 1, \ldots, n$ is directly measured flow rate or pressure pattern parameter, b_j, $j = 1, \ldots, m$ is the model parameter.

Having the specification data of pneumatic components and tubing lines one may attempt to derive expression (1) using equations of fluid dynamics. Unfortunately, these nonlinear differential equations are difficult to solve and include various parameters that are seldom known in practice. These are dynamic friction coefficient, line losses coefficient, etc. [18].

An alternative approach is to derive empiric expression (1) using measured training data. This way we can compose the so called "data-driven" model. Training data are composed of a group of points (y_k*, x_{1k}, x_{2k}, …, x_{nk}), $k = 1, \ldots, K$ measured at various possible working conditions. K is the total number of training points. In this approach structure of the model is kept known and coefficients b_j are estimated in a manner to optimally fit the model (1). The criterion for optimality is a minimized mean square error. The goal of training or more precisely derivation of a coefficient estimates is to adapt model (1) to the particular configuration of a pneumatic system that involves tubing lines length, settings of throttles, cylinder type, etc. Other factors such as working pressure and load mass will enter the model directly or indirectly in a form of independent variables x_i. An example of an indirect case could be load mass, whose value usually is unknown during operation. Therefore, some flow rate or pressure parameter reflecting load mass must be included into the model (1).

In references [7, 12, 13] their authors attempt to derive dependence (1) using artificial neural networks. In these publications a larger variety of fault types and a larger variety of directly measured parameters are considered. In our investigation we focused mainly on the problem of leakage LP_3 detection and its level estimation. Let us take a closer look to the examples of each type of derived diagnostic feature:

1. change in the initial phase (phase I) magnitude;
2. parameter of the physical cylinder model, that characterizes effective leakage orifice diameter;
3. increase of compressed air consumption over the defined part of subcycle.

5.3. Change in the initial phase magnitude

The parameter A depends on working pressure p_0 but not on the load mass M. What is said concerning A_1 can equally be applicable for A_2. Thus, further we deal only with A_1. Pressure p_0 in real systems does not fluctuate in a wide range. Taking this into account, we assume that the dependence between A_1 and p_0 is linear

$$A_1 = b_0 + b_1 p_0 \tag{2}$$

The estimates of coefficients b_0 and b_1 may be obtained using regression analysis. The value of A_1 calculated from Eq. (2) is the expected initial phase flow rate pattern magnitude when working pressure is p_0 and leakages are absent (reference conditions). The difference $\Delta A = A_1 - A_{1m}$ between magnitude A_{1m} measured in monitoring stage and expected magnitude A_1 may be an indication of the occurred leakage. Fig. 3 presents experimental data that shows the feature A_1 dependence on pressure p_0 when the leakage LP_3 was absent and later three specified leakage levels were introduced (see Table 1).

Eq. (2) represents the initial phase magnitude dependence upon working pressure when leakage is absent. Conditions at the absence of leakage are called reference conditions. After the further investigation it was found that adequacy of the model (2) can be improved using second order polynomial instead of the linear model. However, in such a case training data must be collected by setting at least three different pressure levels for the derivation of coefficients b_0, b_1 and b_2 estimates. In the case of a linear model only two levels of independent variable p_0 are sufficient.

It is easy to notice that the larger leakage LP_3 was introduced the smaller the value of A_1 or respectively larger value of ΔA_1 was observed. We approximate the dependence of experimental A_1 samples on the working pressure by the linear function at each fixed leakage level (see Fig. 3). Then one may see that lines corresponding to the different leakage levels can be held parallel. This way the change ΔA_1 does not depend on working pressure p_0 and ΔA_1 is an instance of derived feature $y*$ that characterizes leakage LP_3. Differently from A_1 it is not sensitive to working pressure p_0.

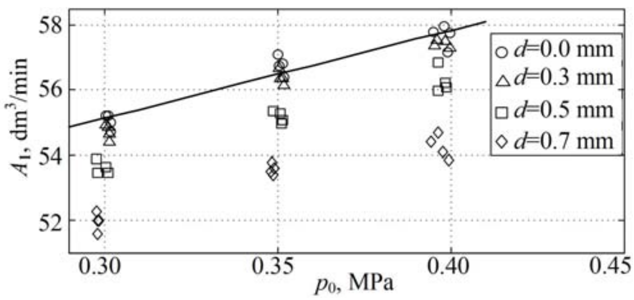

Fig. 3 Dependence of the phase I flow rate pattern magnitude A_1 on working pressure p_0 and piston sealing leakage LP_3. Measurements of the magnitude were made at four different load mass values M = 0, 1, 3, 5 kg

The drawback of diagnostic feature ΔA_1 is that particular leakage level will be difficult to track from the value of ΔA_1. Therefore, threshold of a diagnostic rule must be set, based on the experience of experts. For example, one could offer to consider leakage LP_3 significant, when ΔA_1 exceeds some percentage from the value of A_1 that was observed in reference conditions.

5.4. Effective leakage orifice diameter

Seeking to determine effective leakage orifice diameter d from directly measured parameters we could use working pressure p_0 and initial phase magnitude A_1. We have made an assumption that the dependence between d and these two parameters is linear

$$d = b_0 + b_1 p_0 + b_2 A_1 \quad (3)$$

To find the estimates of coefficients b_0, b_1 and b_2 values of the orifice diameter d = 0.0, 0.3, 0.5, 0.7 mm, the working pressure p_0 = 0.30, 0.35, 0.40 MPa and the load mass M = 0, 1, 3, 5 kg were alternated. Magnitude A_1 was measured each time after setting all combinations of d, p_0 and M values. Fig. 4 presents family of lines calculated using model (3) together with experimental data used to derive estimates of the coefficients of the model.

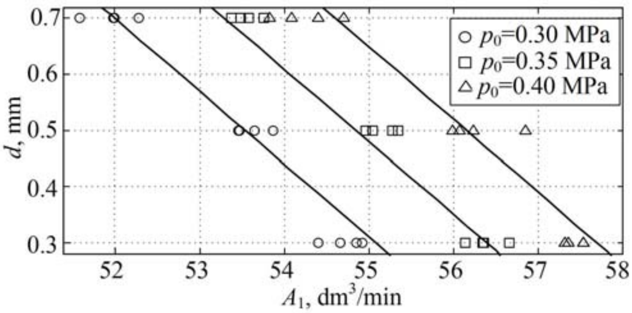

Fig. 4 Prediction of the leakage LP_3 effective orifice diameter d using model (3)

Effective diameter of leakage orifice is not difficult to interpret and it could be used to characterize leakage level. However, in this approach it is always necessary to collect experimental training data at several levels of the artificially introduced leakage. This, of course, can be carried out only having laboratory facilities but hardly in field conditions.

5.5. Increase of compressed air consumption

It is possible to estimate compressed air consumption by integrating flow rate pattern over the defined time interval.

Compressed air consumption is influenced by the load mass M. However, load mass measurement during pneumatic system operation is hardly possible. We have noticed from the experimental data that load mass size is strongly correlated with the time interval T_A (see Fig. 2). In the Fig. 5 dependence between M and T_A is presented at two different pressure p_0 and all leakage LP_3 levels. We see that T_A may be utilized to indirectly estimate load mass of the cylinder. This way, it is reasonable to consider dependence of the air consumption and easy measurable T_A instead of load mass M.

In the (a) and (c) subplots of the Fig. 6 dependences of the air consumptions S_{T1} (extend subcycle) and S_{T2} (retract subcycle) on T_{A1} and T_{A2} respectively are shown at different leakage LP_3 levels and all working pressure levels.

In a case of leakage absence we have approximated dependence of S_{T1} upon T_{A1} by the following second order polynomial function

$$S_{T1} = a_0 + a_1 T_{A1} + a_2 T_{A1}^2 \quad (4)$$

An expression analogous to Eq. (4) may be written for S_{T2} dependence on T_{A2}.

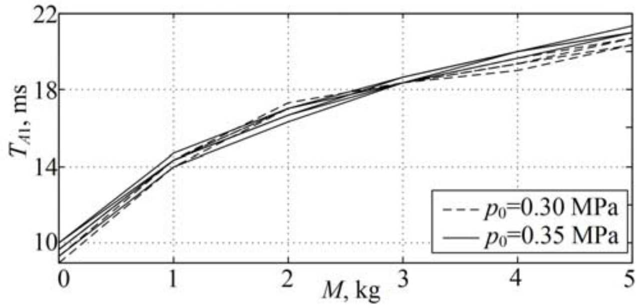

Fig. 5 Dependence between T_{A1} upon load mass M at different leakage LP_3 and working pressure p_0 levels

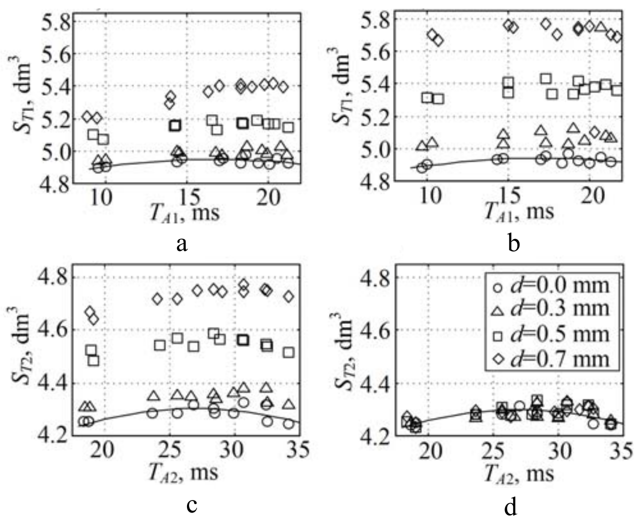

Fig. 6 Dependence of the air consumption on parameters T_{A1} and T_{A2} at different leakage LP_3 (a) and c)) levels and at different leakage LP_1 (b) and (d)) levels

Utilizing measured T_{A1} and using Eq. (4) we can calculate the expected air consumption. If measured air consumption exceeds the expected one, this may be an indication of leakage presence. The difference between measured and expected air consumptions may be used to characterize the leakage level.

We assume that S_{T1} does not depend on T_{A1} or load mass if the range of load mass variation is narrow. This way leakage detection and estimation will become straightforward since derivation of the model (4) will not be necessary. In this approach the expected air consumption would be simply equal to the consumption observed in reference conditions.

Dependence of S_{T1} on T_{A1} and dependence of S_{T2} on T_{A2} at different leakage LP_1 levels are presented in subplots (b) and (d) of the Fig. 6. It is interesting to notice that the value of S_{T2} is not influenced by the leakage LP_1

level, though value of S_{T1} is influenced. Hence, by comparing changes of S_{T1} and S_{T2} over their reference values we gain principal possibility to distinguish the type of appeared leakage.

7. Conclusions

Internal leakages of pneumatic cylinder may be monitored without interruption of its normal operation (online). In this paper several methods were suggested for piston sealing leakage level estimation by directly measuring dynamic flow rate patterns in the compressed air supply line. These methods are based on the comparison of diagnostic feature value measured during monitoring over its observed value in reference conditions. Because it is difficult to find a parameter sensitive only to the leakage, a model or algorithm that allows predicting the reference value is required. The reference value must be predicted taking into account current working conditions that in general may not be identical to those present in reference conditions.

It was found that useful diagnostic features for the above problem solution are: 1) flow rate pattern magnitude of the initial cylinder operation phase, i.e. prior to its movement start, 2) air consumption over the defined period of the cylinder operation subcycle.

Leakage may also be characterized by the effective diameter of leakage orifice. A method of indirect orifice diameter estimation using working pressure and flow rate pattern magnitude of initial cylinder operation phase was presented.

We have found it difficult to detect piston sealing leakage bellow 0.3 mm of effective orifice diameter despite the considered method, because the values of diagnostic features were very close to their values in reference conditions. Leakages with effective orifice diameters 0.5 mm and 0.7 mm were detected reliably.

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PNEUMATINIO CILINDRO BŪSENOS DARBO METU STEBĖSENOS METODAS

R e z i u m ė

Straipsnyje pasiūlytas pneumatinio cilindro nuotėkių aptikimo ir lygio įvertinimo metodas, taikomas nepertraukiant normalaus cilindro darbo režimo. Atlikti eksperimentiniai tyrimai matuojant oro srauto ir slėgio pereinamąsias charakteristikas bei cilindrą valdančios sklendės ir galinių stūmoklio padėčių jutiklių signalus. Remiantis išmatuotais signalais buvo atlikta diagnostinių požymių, nešančių informaciją apie nuotėkio vietą ir jo lygį, paieška. Nustatyta, kad oro srauto ir slėgio charakteristikos yra įtakojamos ne tik nuotėkių, bet ir kintančių darbo sąlygų, t. y.

darbinio slėgio, apkrovos masės, jungiančiųjų oro tiekimo linijų ilgio, droselių nustatymo ir t. t. Straipsnyje pateikiami analizuoti nuotėkio aptikimo ir jų lygio įvertinimo diagnostiniai modeliai, invariantiški minėtoms kintančioms cilindro darbo sąlygoms.

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AN APPROACH TO PNEUMATIC CYLINDER ON–LINE CONDITIONS MONITORING

S u m m a r y

A method of pneumatic cylinder leakage on-line detection and level estimation is considered in the paper. Air flow rate and pressure patterns together with control valve signals and proximity sensors feedback signals are measured in the conducted experimental tests. Search of features applicable for the leakage detection and estimation was carried out. Air flow rate and pressure patterns are influenced not only by leakages, but also by working conditions that embody system working pressure, load of the cylinder, characteristics of tubing, flow throttles settings, etc. Data-driven models and methods of their composition are proposed in order to enable leakage detection and measurement independent from varying working conditions.

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ОПЕРАТИВНЫЙ МЕТОД ДЛЯ МОНИТОРИНГА ТЕХНИЧЕСКОГО СОСТОЯНИЯ ПНЕВМАТИЧЕСКОГО ЦИЛИНДРА

Р е з ю м е

В статъе рассматривается метод для обнаружения утечки и оценка ее уровня в пневматическом цилиндре (он-лайн). Динамические процесы потока сжатого воздуха и давления вместе с сигналами распределительного клапана и сигналами обратной связи датчиков положения были измерены экспериментально. Используя экспериментальные данные был произведен поиск диагностических признаков, применимых для обнаружения утечки и оценки ее уровня. На параметры динамических процесов влияют не только утечки, но также и рабочие условия, которые характеризуются рабочим давлением системы, нагрузкой цилиндра, особенностями соеденительных линий, настройкой дроселей, и т.д. В работе предложены диагностические модели и методы их составления, которые позволяют обнаружить утечки и измерить их уровень независимо от изменения рабочих условий.

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