ISSN 1392-2114 ULTRAGARSAS, Nr.2(59). 2006.

Leakage diagnostics in pneumatic systems using transient patterns

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Abstract

Pneumatic cylinder leakage on-line diagnostics is considered in the paper. Flow and pressure transient patterns were recorded given various combinations of simulated leakage, working pressure and actuator load mass in the assembled testing bench. Search of diagnostic features applicable for leakage detection and estimation was performed among parameters of acquired data. Data-driven models were proposed for leakage detection and estimation irrespective of varying working conditions.

Key words: pneumatics diagnostics, leakages estimation, condition monitoring.

Introduction

Pneumatic actuators are widely used in automated industrial processes. Their technical conditions monitoring is one of measures towards implementation of predictive maintenance in a plant. As a result of long term operation connecting tubes, piston sealings and internal surfaces of a pneumatic actuator (in our study – pneumatic cylinder) wear out. This causes change of actuator speed, force and air consumption. All this together is regarded as performance.

Manufacturers of pneumatic components usually specify number of operation cycles, after which it is recommended to replace the component or its sealings. However, in every particular installation and working conditions leakages may appear and progress very specifically. Therefore, a diagnostic system capable of on-line monitoring of pneumatic actuator performance could be very valuable. Term "on-line" here refers to the monitoring mode without process line disassembly or stop and without introduction of special testing modes.

In our study we set a goal to investigate possibilities of implementing diagnostic system for actuator leakages detection and estimation. Some works in this field has already been published [1-5]. Most of these papers are concerned with application of static and timing process parameters. Since pneumatic actuator usually operates in a switching manner we step forward to search for applicable diagnostic features in the patterns of air flow and pressure transient processes. Transient process of air flow and pressure can be acquired using common industrial process transducers.

Approach of building data-driven diagnostic models

By the diagnostic model we denote relationship between set of directly measured process parameters and quantity describing fault, i.e. leakage. It is possible to measure patterns of air flow in the supply line and pressure at different points directly. All the patterns constitute set of features D_1, D_2, ..., D_n carrying information about the leakages in the cylinder. In the paper we consider three types of leakages [6]:

1. Cylinder extend line leakage;
2. Cylinder retract line leakage;
3. Cylinder piston sealing leakage.

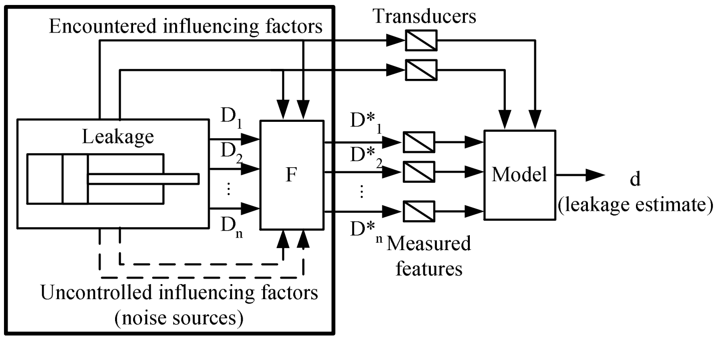

Fig. 1. **Leakage diagnostics scheme**

Diagnostic features are influenced by the working conditions of pneumatic system: working pressure, actuator load, throttle settings, tubing length, fluid temperature, etc. Thus, in fact one is only able to measure features D_1*, D_2*, ..., D_n*, that to some extent reflect not only leakage level but also set of working conditions parameters. Some of influencing factors can be measured directly, e.g. working pressure, but some can not, e.g. load mass. Therefore, diagnostic model must be built utilizing features D_1*, D_2*, ..., D_n* and encounter measured influencing factors (see Fig. 1). The effect of factors falling in to the group of uncontrolled, e.g. load mass, we treat as source of random noise.

Diagnostic model in principal could be derived by solving nonlinear differential equations describing operation of pneumatic system [7]. However, it is mathematically difficult to solve these equations, and they contain constants whose real values are seldom known in practice (dynamic and static friction coefficients, hydraulic friction coefficient, etc.) [8]. Therefore, we chose a data-driven model building based on learning. To generate data for data-driven model building typical pneumatic system (testing bench) "cylinder-control valve" was assembled.

In this investigation we assume tubing lengths and throttle settings are constant. Thus, the model will be adapted to the setup of pneumatic system by providing it with training data, acquired from real operating testing bench.

Experimental setup and data collection

Scheme of developed testing bench is shown in Fig. 2. Standard pneumatic cylinder with 80 mm stroke length and 32 mm piston diameter was used.

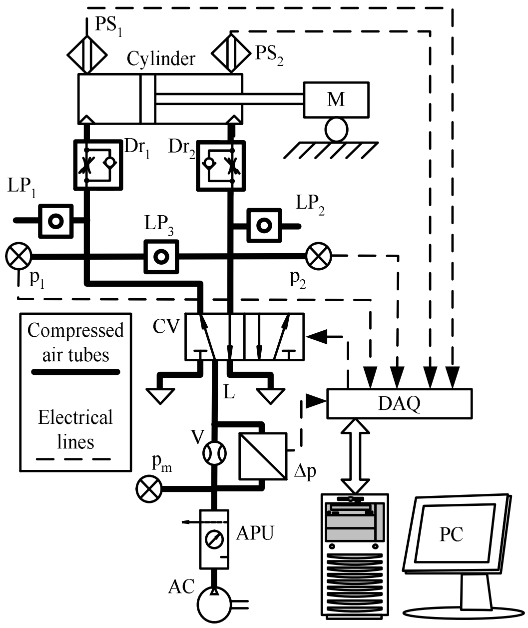

Fig. 2**. Setup of testing bench**

The testing bench consists of a pneumatic cylinder, control valve *CV*, one-way throttles Dr_1 and Dr_2, proximity switches PS_1 and PS_2, working pressure p_m, first and second cylinder chamber pressure p_1 and p_2 transducers, Venturi nozzle *V*, differential pressure Δp transducer, load mass *M*, air preparation unit *APU*, air compressor *AC*, computer *PC* with data acquisition board *DAQ* installed.

Patterns of flow $Q(t)$ (calculated from $\Delta p(t)$ patterns) and pressures $p_m(t)$, $p_1(t)$ and $p_2(t)$ were acquired together with valve control and proximity switches signals given all possible combinations of influencing factors and simulated leakage levels. Altered influencing factors were working pressure p_m=0.40, 0.45, 0.50 MPa and load mass *M*=0, 1, 2, 3, 4, 5 kg. Leakages were simulated using orifices of circular shape and known diameters: d_0 = 0.0 mm (no leakage), d_3 = 0.3 mm, d_5 = 0.5 mm and d_7 = 0.7 mm. They were introduced in the following places of the pneumatic system:

- leakage from the tube of first cylinder chamber to ambience – LP_1 (extend line leakage);
- leakage from the tube of second cylinder chamber to ambience – LP_2 (retract line leakage);
- leakage between cylinder chambers (through piston sealings)– LP_3 (piston sealing leakage).

Building diagnostic models

All acquired data were searched for features sensitive to leakage but invariant to influencing factors. Conducted investigation revealed two promising features for piston leakage diagnostics that can be extracted from flow pattern (Fig.3):

1. Magnitude *A* of initial cylinder operation phase [7]. It turned out to be insensitive to load mass.
2. Compressed air consumption *S*, calculated as integral under flow pattern in the fixed time interval T_1 to T_2. Here T_1 corresponds to the moment of control valve signaling, T_2 was chosen experimentally.

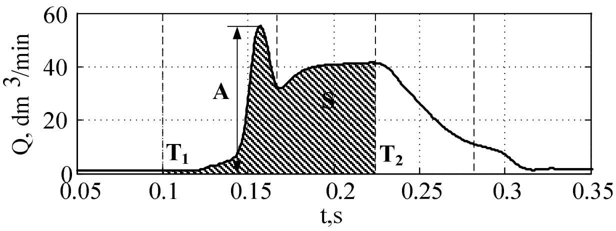

Fig. 3. **Selected diagnostic features: air flow amplitude *A* and compressed air consumption *S***

In a diagnostic system leakage (fault) may be characterized either by:

1) feature reflecting size of leakage and independent to influencing factors;
2) parameter directly characterizing fault, e.g. effective diameter of leakage orifice.

In the first case change of diagnostic feature *A* could be employed. Since *A* is dependant upon working pressure p_m that in real systems does not fluctuate in a wide range, it was assumed that dependence could be approximated using linear equation

$$A_0 = \alpha_0 + \alpha_1 p_m ,$$

here coefficients a_0, a_1 are determined by linear regression analysis provided learning data generated at different levels of working pressure and fault-free (no leakages) conditions. Any appeared change

$$\Delta A = A_0 - A_m$$

we attribute to the occurrence of piston leakage. Here A_m denotes value observed during monitoring. Variations of load mass *M* were treated like presence of random noise (see Fig.4). Indeed, scatter of values shown in the Fig.4 was due to load mass changes given fixed p_m. We can see, that increase of leakage LP_3 causes decrease of *A* which respectively means increase of ΔA. Influence of working pressure p_m upon A_0 is obvious but its influence upon ΔA is eliminated.

The second approach when leakage is characterized using effective diameter *d* is represented in the Fig. 5. To build a diagnostic model air consumption *S* change $\Delta S=S_0–S_m$ in respect to air consumption reference S_0 was estimated, setting all possible combinations of *d*=0.0, 0.3, 0.5, 0.7 mm, *M*=0 … 5 kg and p_m=0.40, 0.45 MPa.

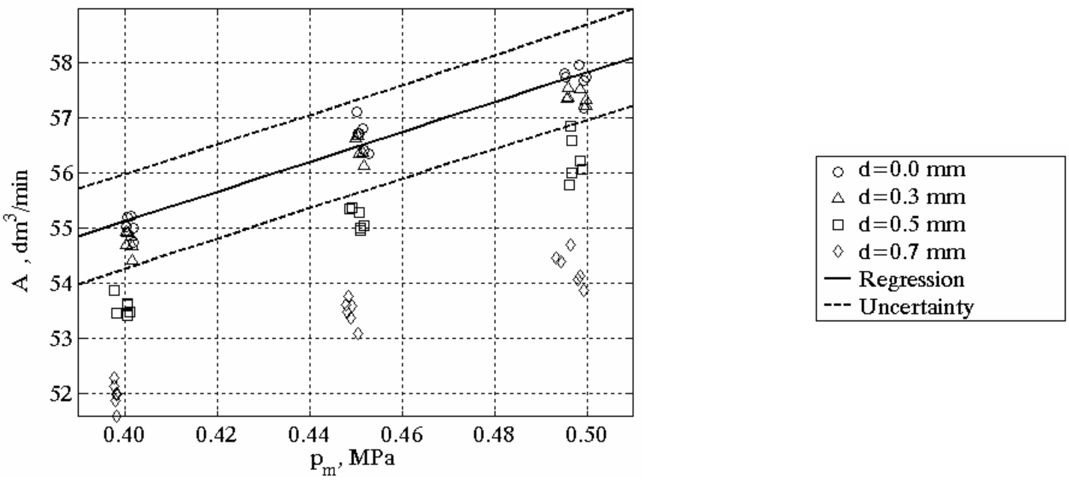

Fig. 4. **Dependence of feature *A* upon working pressure p_m and piston sealing leakage**

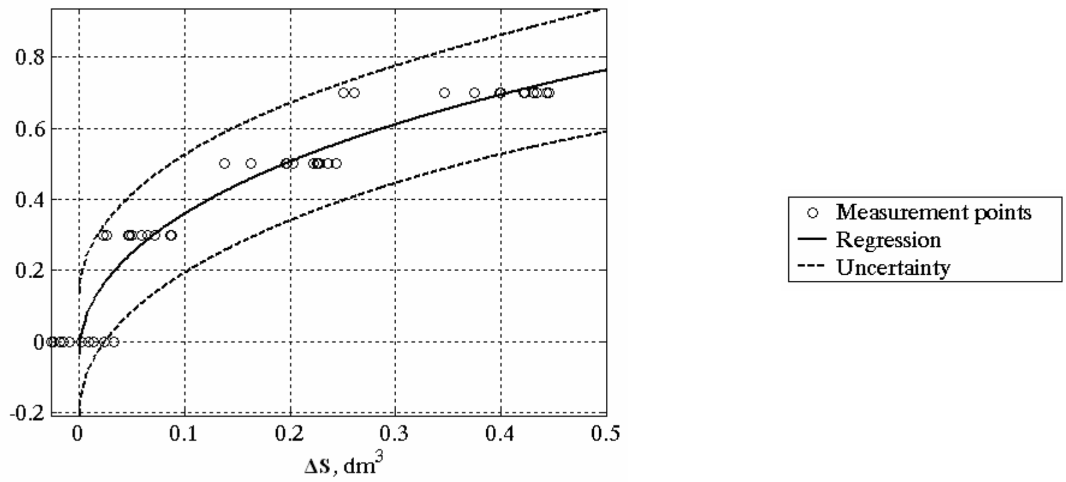

Fig. 5. **Dependence of increment of air consumption ΔS upon leakage LP_3 level**

Observing the data scatter plot (Fig. 5) the assumption was made about quadratic dependence

$$d = b_0 + b_1 \Delta S + b_2 \sqrt{\Delta S} \ .$$

Its coefficients were estimated using multiple regression analysis. Changes of p_m and M were attributed to the uncontrolled disturbances.

Leakages LP_1, LP_2 and LP_3 can be distinguished comparing diagnostic features in retract and extend subcycles [6]. It was found that diagnostic features ΔA and ΔS are affected: 1) during extend subcycle in case of LP_1 leakage; 2) during retract subcycle in case of LP_2 leakage; 3) during both subcycles in case of piston leakage LP_3.

Conditions with more than one simultaneous leakage have not been analyzed yet.

Conclusions

1. Pneumatic actuators diagnostic method utilizing dynamic air flow characteristics was proposed and analyzed. It enables online piston, extend line and retract line leakage level estimation and leaking unit identification in the pneumatic system.

2. Dynamic air flow pattern magnitude and air consumption over constant time interval were found to be most suitable diagnostic features for pneumatic cylinder piston, extend and retract line leakage estimation. Corresponding models utilizing these features were composed based on experimental data.

3. It was found that leakage appearing in the different places of pneumatic system affect the parameters of flow transients specifically. This could be used to identify system unit with leakage.

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Received 04 04 2006