CO-OPERATING EXPERT KNOWLEDGE AND ARTIFICIAL NEURAL NETWORKS FOR FAULT DIAGNOSIS OF ELECTROHYDRAULIC CYLINDER POSITION CONTROL SYSTEMS

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ABSTRACT

Results are presented from a study of leakage losses from a position control system and the resulting knowledge that may be incorporated into an on-line expert system for fault diagnosis. The use of a minimum number of sensors results in leakage and position error data that have limitations for multiple-fault situations. It is then shown how the application of an artificial neural network can give additional confidence to a fault assertion, and results are shown for a number of leakage conditions.

KEY WORDS

Fault diagnosis, Artificial intelligence, Electrohydraulics

INTRODUCTION

Fault diagnosis of fluid power systems is receiving a growing interest by industry, particularly in large manufacturing plant, as experienced by the authors. In this respect research and development at Cardiff has concentrated on leakage detection due to its immediate impact on both machinery down-time and environmental issues. An approach is required that can handle potentially a large amount of data, on-line, and from a range of sensors typically pressure, flow rate, temperature and position. In addition, fault diagnosis is often required to be component specific, or at the very least subsystem-specific. This inevitably requires sensors to be placed within the appropriate fluid power circuit and often not in the ideal place due to operating constraints, particularly vibration and temperature in heavy process industries. Large knowledge bases are therefore rapidly acquired for even the most simple of circuits, and some examples may be found in earlier work by the authors which has considered both motor and cylinder drives

[1,2,3]. The open-loop cylinder drive with flow metering discussed in [3] particularly highlights knowledge base complexity where using an expert system approach to identify 10 different types of fault in lines, actuator, and a flow control valve. An alternative approach is to use Failure Modes and Effects Analysis, whereby primitive relations between quantities, smaller than, greater than, etc., are used to deduce the effect on other component characteristics within the system [4,5]. This is still a complex operation, particularly for multiple faults, and it has been established that qualitative reasoning algorithms are not suitable for FMEA, although they may have a role in fault diagnosis [6]. It is then proposed that systems simulation, particularly for steady-state conditions, may be utilised in an automated FMEA approach. Artificial Neural Networks are showing promise for describing the behaviour of hydraulic circuit components and also for fault classification [7,8,9]. An advantage is that network training is

undertaken using real data, admittedly for the appropriate fault conditions, although experience is also suggesting that a knowledge of system dynamics is useful in establishing the network topology.

Continuing work by the authors, and being discussed here, is concerned with closed-loop position control of a loaded hydraulic cylinder, and appropriate leakage faults are first assessed via an expert system approach. Additional information on position error is then considered, together with a fault assessment using a trained artificial neural network to support the conclusions obtained from the expert system approach.

KNOWLEDGE ACQUISITION

Previous work [2,3] has shown how an expert system shell may be utilised to on-line diagnose leakages on an open-loop cylinder drive incorporating a directional control valve. In this study a servovalve is used for conventional closed-loop position control of a cylinder with a force-dominant load as shown in Fig.1.

Fig.1 Hydraulic circuit diagram of the test rig

Two flow meters were placed adjacent to the servovalve output ports and the electrical signals together with those from each pressure transducer, cylinder position, and the control error signal were connected via a data acquisition card to a microcomputer incorporating an expert system software package. In addition the control signal was generated by the microcomputer such that a completely automated fault diagnostic system could be developed. In the context of leakage flow detection, i.e. from both lines and across the cylinder piston seal, knowledge may be acquired from the following sources:

- i) step response dynamics
- ii) displaced volumes during step response test
- iii) steady-state position error
- iv) steady-state characteristics utilising flow rates.

The first approach utilising the transient response to a step input is of little value for a cylinder drive with negligible inertia effects as in this case. The response is a first-order characteristic which undergoes a negligible change when faults are introduced. Hence time series analysis techniques do not produce significant changes in coefficients to be used for diagnostic purposes. The displaced volume concept first developed in [2,3] is a powerful approach to leakage detection whereby the flow continuity equations for the cylinder, combined with a derived third equation, are transformed to a set of rules embedded within an expert system.

The first control action was therefore to initiate a step change in position of typically 20 mm and take 30,000 samples of two flow rates, two pressures and one position transducer. This procedure occurred in two seconds, and both extending and retracting steps were used. Displaced volumes are calculated from flow rate integration, these being V_1 and V_2 from flow meter 1 and flow meter 2. The theoretical displaced volumes A_1s and A_2s are known, where A_1 and A_2 are the cylinder cross-sectional areas and s is the known stroke change. A truth table for extending only will then appear as shown in Table 1.

Support for the single-fault classification case may be obtained from consideration of the steady-state position errors which must exist in the presence of leakage. More specifically, unique combinations of position error when extending and retracting may be obtained when the load force is above a value to ensure that the pressure differential changes sign for the two cases. In the present system this occurred for a load pressure of 60 bar, and some measurements are shown in Fig.2 for both extending and retracting cases. From Fig.2 it is deduced that unique error trends exist for developing simple faults, the increasing or decreasing trends being indicated in Table 2.

It will also be seen from Fig 2 that a tolerance band of 10mV (0.23 mm) is introduced to allow for the practical variation in the error characteristics due to temperature effects and servovalve spool underlap effects.

THE INTEGRATION OF ARTIFICIAL NEURAL NETWORKS FOR FAULT CLASSIFICATION

An MLP network was trained for a range of leakage flow single fault and multiple fault conditions. This was achieved again by direct computer control by demanding a constant actuator velocity over the full stroke and in both directions. Actuator position was found to have little advantage as training data and hence four inputs were used, two flow rates and two pressures. One hidden layer with 6 neurons only was

Table 1 Truth table for leakage faults when extending

Equation used	Condition	
	Known parameters	
A	1	$V_1 > A_1 s$
	2	$V_1 < A_1 s$
	3	$V_1 = A_1 s$
B	4	$V_2 > A_2 s$
	5	$V_2 < A_2 s$
	6	$V_2 = A_2 s$
C	7	$V_1 - V_2 > A_1 s - A_2 s$
	8	$V_1 - V_2 = A_1 s - A_2 s$
	9	$V_1 - V_2 < A_1 s - A_2 s$

Outcome	Classification
147	Multiple faults including internal leakage (-)
148	Internal leakage (-)
149	Calibration drift
157	Multiple faults
158	Internal leakage (+/-)
159	Calibration drift
167	Line 1 leakage
168	Calibration drift
169	Calibration drift
247	Calibration drift
248	Calibration drift
249	Calibration drift
257	Multiple faults including internal leakage (+)
258	Internal leakage (+)
259	Calibration drift
267	Calibration drift
268	Calibration drift
269	Calibration drift
347	Calibration drift
348	Calibration drift
349	Calibration drift
357	Line 2 leakage
358	Calibration drift
359	Calibration drift
367	Calibration drift
368	No Fault
369	Calibration drift

Fig.2 Position errors for different single-leakage conditions

found to be adequate and the output layer had 3 neurons having states of either 0 or 1 to indicate no fault or fault respectively. Leakage flow rates used for training were typically between 0.5-1.0 l/min, and fault detection rates were extremely high for the higher flow rates. A summary of the network performance is given in Table 3.

Table 2 Error trends for single fault conditions

Fault	Error (0.023 mm/mV)	
	Extending mV	Retracting mV
none	-17 → -20	-7 → -11
line 1	increase	increase
line 2	decrease	decrease
internal	increase	decrease

Table 3 ANN fault classification, trained network

Fault	Outputs			% Success
	1	2	3	
no fault	0	0	0	76
line 1 leak	1	0	0	91
line 2 leak	0	1	0	85
internal	0	0	1	97
line 1 + line 2	1	1	0	96
line 1 + internal	1	0	1	89
line 2 + internal	0	1	1	90

Table 3 indicates the average success over a number of trials. The percentage of correct diagnoses for the single -fault cases is 87% and 92% for the multiple-fault cases.

THE CO-OPERATING APPROACH - SOME RESULTS

Single-fault situations present little problem and, following step response stimulation, the displaced volume method is first used with separate diagnoses for extension and retraction. A typical result for line 2 leakage is shown in Fig.3 where it can be seen that the leaked volumes are only 0.01L and 0.02L when extending and retracting, and occurring over just 2 seconds. Both steady-state errors have decreased and confirm line 2 leakage as indicated in Table 2. Running the neural network, following the stimulated open-loop response over full stroke, gave a correct diagnosis percentage score of 99% for the test data only.

Consider next a multiple-fault case and in particular simultaneous leakage in lines 1 and 2. The measured data shown in Fig 4 indicates internal leakage from

steady-state position errors, but the exact cause cannot be deduced via the expert system rule base. The suggested action is then to "click" the neural network button on the screen which automatically triggers the constant-velocity, full-stroke, open-loop response. The data is then applied to the neural network and the prediction is shown in Fig.4, which indicates an 82% confidence that the multiple fault case is attributable to lines 1 and 2.

CONCLUSIONS

The displaced volume method has been found to be reliable for the closed-loop case and with only 20 mm changes in position, with excellent results being obtained for leakage flow rates down to 0.5L/min and for position change intervals of 2 seconds. the steady-state error method is a useful addition, but is sensitive to changes in temperature of the order $\pm 5^{\circ}\text{C}$. Support from an ANN was found to give very encouraging results using flow rates and pressures from both lines. The network could not be trained from the closed-loop response data, and it was found necessary to utilise effectively the open-loop response at constant velocity and over the full stroke. All three approaches gave the best predictions using both extending and retracting data, and valid only for the specific load conditions used to obtain both the expert system and ANN training data.

Fig.3 A practical result for line 2 leakage

Fig.4 A practical result for multiple faults

REFERENCES

1. Creber, D. J. and Watton, J. Development of a Low Cost Expert System Shell for Condition Monitoring of Fluid Power Systems. Proc. 9th International Fluid Power Symposium, Cambridge, 1990, pp.281-291. STI, Oxford.
2. Stewart, J. C. and Watton, J. Fault Diagnosis of a Cylinder Drive using On-line Expert System Techniques. Proc. 10th International Fluid Power Symposium, Brugge, 1993, pp 277-280. Mechanical Engineering Publications Ltd., London.
3. Watton, J., Lucca-Negro, O., and Stewart, J.C. An On-line Approach to fault diagnosis of fluid power cylinder Drive Systems. Proc. IMechE, Journal of Systems and Control Engineering, Vol. 208, 1994, pp.249-262.
4. Atkinson, R. M. et al. Automated Fault Diagnosis for Hydraulic Systems, Part 1: Fundamentals. Proc. IMechE, Journal of Systems and Control Engineering, Vol. 206. 1992, pp. 207-214.
5. Hogan, P.A. et al. Automated Fault Diagnosis for Hydraulic Systems, Part 2: Applications. Proc. IMechE, Journal of Systems and Control Engineering, Vol. 206, 1992, pp.215-224.
6. Bull, D, R. et al. Approaches to Automated FMEA of Hydraulic Systems. Hydraulic Systems Design for the Future Seminar 9, Paper C505/9/099, pp.1-8, Aero Tech '95, Birmingham, UK.
7. Xue, Y. and Watton, J. A Self Organising Neural Network Approach to Data-based Modelling of Fluid Power Systems Dynamics using the GMDH Algorithm. Proc. IMechE, Journal of Systems and Control Engineering, Vol. 209, 1995, pp.229-240.
8. Darling, J. and Tilley, D. G. Progress Towards a General Purpose Technique for the Condition Monitoring of Fluid Power Systems. IMechE Seminar on Aerospace Hydraulics and Systems, London, 1993, pp.47-55.
9. Naylor, J. B. Fault Diagnosis of a Fluid Power System using a Neural Network Approach. M.Sc. Thesis, School of Engineering, University of Wales Cardiff, 1993.