

An Experimental Parameter Validation Approach

C. Angeli - A. Chatzinikolaou

Abstract - The development of model-based fault detection methods for engineering systems requires a high degree of consistency between the behaviour of mathematical model and the actual system in order to produce reliable results. It means that the mathematical model must be very accurate. Due to the usually complicated equations describing the dynamic behaviour of these systems, some parameters can be roughly estimated based on the steady-state analysis. It is necessary to use alternative approaches that optimise the parameter values and make them more accurate. This paper presents a parameter validation approach that can be used in the case of incomplete information of the system state and improve the quality of a model. The approach is used for the determination of the acceptable deviation limits between model and system.

Keywords - Modelling, Simulation, Fault detection, Parameter Validation.

I. Introduction

Models that are used as a part of fault detection methods should describe the dynamics of the system as accurate as possible using suitably selected mathematical relations and parameter values. In model-based fault detection, faults are detecting by setting a threshold on a residual generated from the difference between measurements and estimates of these measurements. When a fault occurs, the deviation from zero is such that the new condition can be distinguished from the fault free working mode. The role of the decision system is to determine whether the residuals differ significantly from zero and to decide which is the possible faulty component.

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Model-based fault diagnosis for dynamical systems is a well established approach and a lot of research work has been published over the last years such as [1], [2], [3], [4], [5], [6].

Difficulties with model based fault detection methods arise from the fact that the accuracy of the measurements needed to calculate the evolution of faults should be of high quality. In addition, use of model-based methods may require assumptions about the process that are not valid, such as the assumption that the process is linear as well as that the influence of noise and disturbances to the fault detection process is of minor importance.

The parameter estimation methods for dynamical systems are particularly important for the effectiveness of the total diagnostic system as they are associated with the normal and abnormal system operation. Parameter estimation techniques for fault detection in dynamic systems include [7], [8], [9].

This paper presents a parameter validation scheme that can represent the system dynamics and can be used in case of incomplete information on the system state. This system is used for the determination of the acceptable deviation limits between the behaviour of model and measurement results so that a stable diagnostic system can be established.

The paper is organized as follows: Section 2 presents the variables and parameters of the model. Section 3 focuses on the estimation of parameter values, while Section 4 presents the parameter validation process and the justification of the results. Finally, Section 5 includes concluding remarks. Recent research work in diagnostic procedures for fluid power systems includes [10], [11], [12], [13].

II. Parameters and Variables of the Model

The variables of the system are following: The pressure at the port A of the hydraulic motor p_a , the pressure at the port B of the hydraulic motor p_b , the rotation angle of the motor shaft φ , the angular velocity ω , the flows

q_{va} and q_{vb} through the A and B ports of the proportional 4-way valve, the flows q_{ma} and q_{mb} through the ports A and B of the hydraulic motor, the input current to the proportional valve I_2 or the corresponding voltage to the amplifier of the proportional valve U_2 .

The parameters are: (p_0) System pressure, (I_2) Input current to the proportional 4-way valve, (Q_{nv}) Nominal flow of the proportional 4-way valve, (V_m) Displacement volume of the hydraulic motor, (V_l) Pipe volume between valve and motor, (M_r) Mechanical friction torque, (J_m) Moment of inertia, (P_{np}) Nominal pressure of the proportional pressure valve, (η_v) Volumetric efficiency of the fluid, (E) Modulus of elasticity, (U_2) Command voltage to the amplifier of the proportional 4-way valve and (U_{nv}) Nominal voltage of the amplifier.

III. Estimation of the Parameter Values

The parameter values oil elasticity E and the friction torque M_r include uncertainty. The friction torque M_r includes the mechanical friction and the torque loss caused by the pressure losses that have to be subtracted from the theoretical motor torque.

The determination of the uncertain parameters values M_r (friction torque) and E (oil elasticity) was performed after the simulation for a set of values near the estimated. The simulation results were compared with the

corresponding measurements. The optimal value for M_r was determined in relation to the commonly used range of values for the parameter E in order to achieve more accurately the optimal value for both parameters. This determination was performed by measuring the integral squared error (ISE) between the measured and calculated pressure signals over a period of time and looking for the minimum value of the ISE according to the following relations:

$$I_a = \int_0^{t_{end}} (p_{am} - p_{as})^2 \cdot dt = F_a(M_r) \rightarrow \min$$

$$I_b = \int_0^{t_{end}} (p_{bm} - p_{bs})^2 \cdot dt = F_b(M_r) \rightarrow \min$$

The optimum value for the friction M_r would exist if both integrals were at a minimum for this value.

In order to estimate an accurate value for the parameter E this procedure was performed for oil elasticity values of $0,90 \cdot 10^9$, of $1,00 \cdot 10^9$ and $1,10 \cdot 10^9$ N/m² in the simulation, because these values lie near to the commonly used value for hydraulic mineral oil of 10^9 N/m² if we consider the elasticity of the included air.

For $p_0 = 50$ bar, $U_2 = 6$ V and oil elasticity values $E = 0,90 \cdot 10^9$ N/m², $E = 1,00 \cdot 10^9$ N/m² and $E = 1,10 \cdot 10^9$ N/m², the results of the minimum integral squared error are plotted in Figure 1.

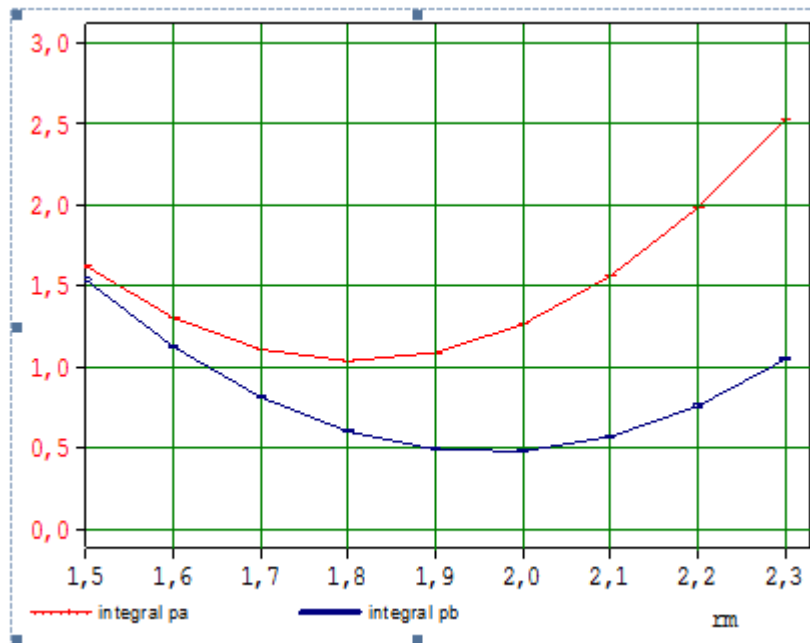


Figure 1. The minimum integral squared error for pressure p_a and pressure p_b by $p_0 = 50$ bar, $U_2 = 1$ to 6 V and $E = 0,90 \cdot 10^9$ N/m²

In this Figure it can be seen that the value $M_r=1,8$ minimises the difference between measured and calculated pressure p_a and the value $M_r = 2,0$ minimises the difference for the pressure p_b . Therefore the average value of $1,9 \text{ N} \cdot \text{m}$ is taken for M_r . The value $1,00 \cdot 10^9 \text{ N/m}^2$ for the oil elasticity parameter E is also the most accurate, because for a slightly lower and a slightly higher E value the minimum values of the Integral Squared Errors of the pressure differences are higher than for $E = 1,00 \cdot 10^9 \text{ N/m}^2$.

IV. Experimental validation results

To examine the effects of changes in parameter values on the simulation results the parameters for the friction torque M_r , the moment of inertia J_m and the oil elasticity

E were varied. For a variation of $\pm 5 \%$, $\pm 10 \%$ and $\pm 20 \%$ of these parameters the variation of the simulation results was observed and the differences are illustrated.

Regarding to the friction torque, the results of the simulation for the above parameter variations together with the measurement result are shown in Figure 2. The deviations of the pressure curves are shown in Figure 3.

These deviations are less than 0,5 bar for a variation of $\pm 5 \%$, less than 1 bar for a variation of $\pm 10 \%$ and less than 2 bar for a variation of $\pm 20 \%$. The performance of the fault detection system should not be affected by these individual variations because the maximum deviation of the model from the measurement results is less than the threshold 5 bar that is taken for a fault criterion.

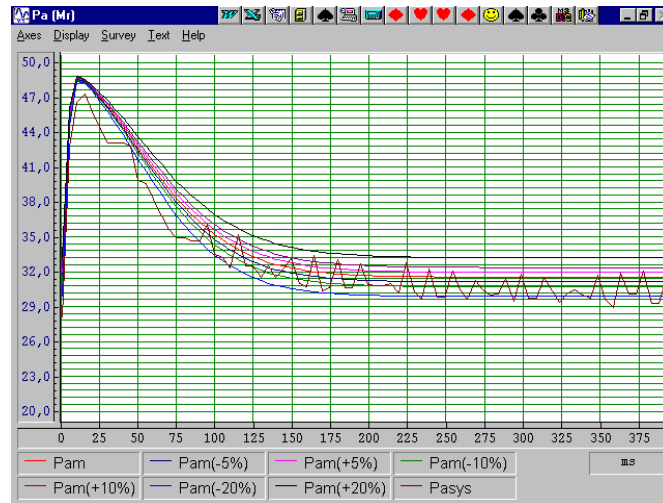


Figure 2. Influence of a variation of $\pm 5 \%$, $\pm 10 \%$ and $\pm 20 \%$ of the parameter M_r on the pressure p_a .

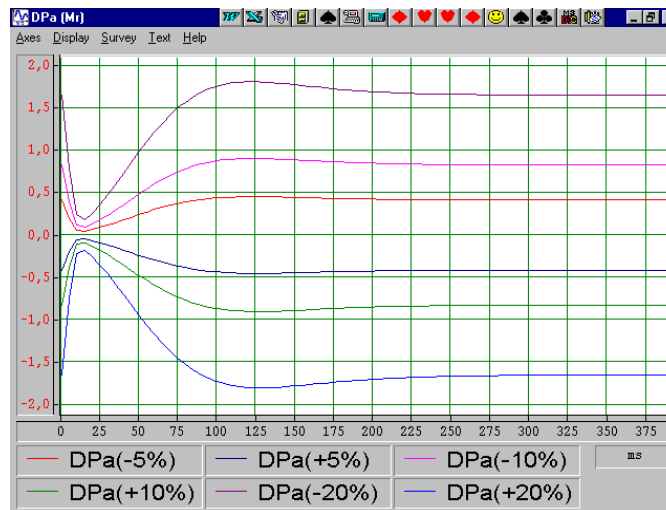


Figure 3. Deviations of pressure p_a by a variation of the parameter $M_r \pm 5 \%$, $\pm 10 \%$ and $\pm 20 \%$.

The influence of the same parameter variations on pressure p_b was found to be similar to that for the pressure p_a .

For the oil elasticity E the deviations of the simulation results for the above parameter changes are shown in

Figure 4. These deviations are also less than 0,5 bar for a variation of $\pm 5\%$, less than 1 bar for a variation of $\pm 10\%$ and approximately 1,5 bar for a variation of $\pm 20\%$.

The influence on the performance of the fault detection method is unimportant.

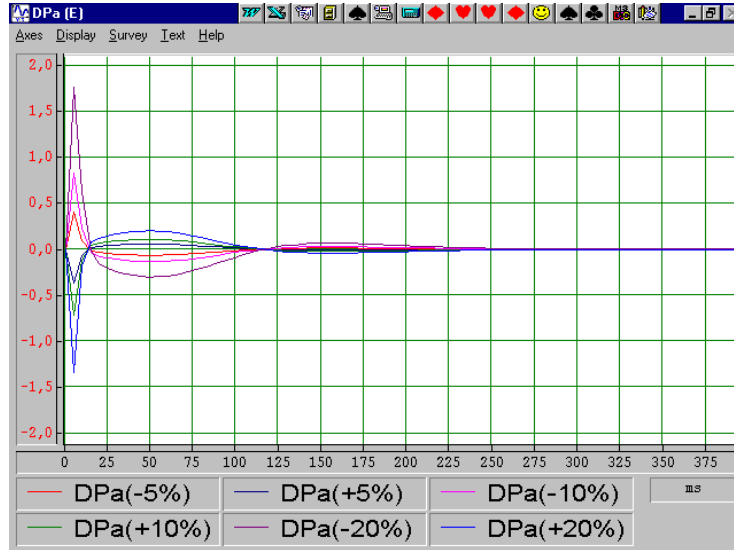


Figure 4. Influence of a variation of $\pm 5\%$, $\pm 10\%$ and $\pm 20\%$ of the parameter E on pressure p_a

In Figure 5 the effect on pressure p_a by simultaneously changing the parameters of the friction torque M_r by

10%, the moment of inertia J_m by 5% and the oil elasticity E by 10% is shown. The result is the curve Pa' .

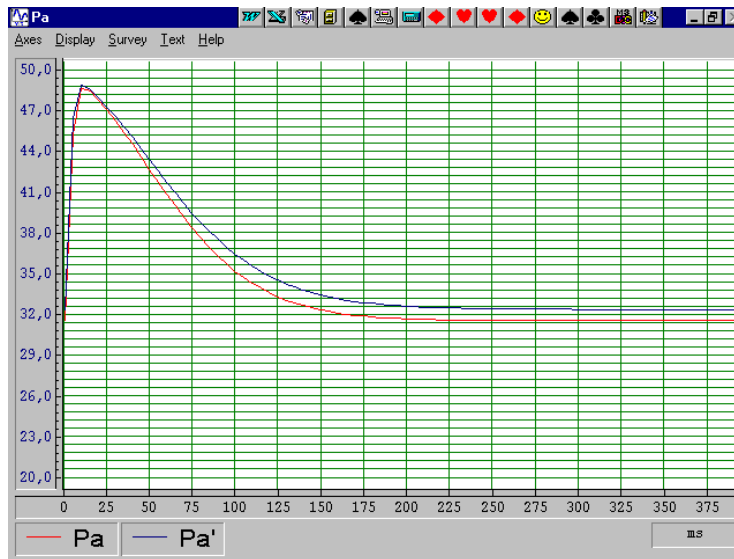


Figure 5. Influence on pressure p_a by a parameter change 10% for M_r , 5% for J_m and 10% for E .

The influence of these parameter changes on pressure p_b was found to be similar to that for the pressure p_a .

Thus, it can be concluded that a small spread of the parameter values does not affect the result of the simulation and consequently the performance of the fault detection method because a deviation of 5 bar is required to predict faults and all the adobe deviation are less than 2 bar. In consequence the variation of the parameter would not affect the fault detection system.

V. Conclusion

This paper describes an experimental validation approach of a model for a hydraulic drive system so that the final model can represent efficiently the system's dynamics. Laboratory testing provide evidence for the reasonable consistency between the performance of model and system. It is experimentally proved that the pressure deviations are less than 2 bar even for a variation of $\pm 20\%$ of the uncertain parameters so that the performance of the fault detection system should not be affected by these individual variations because the maximum deviation of the model from the measurement results is less than the threshold 5 bar that is taken for a fault prediction.

The main benefits of implementation of such a kind of experimental procedure for the evaluation of the performance of a diagnostic system lies on the higher degree of accuracy, quality, reliability and efficiency of the diagnostic conclusions as well as the higher degree of safety for the actual environment of a production plant when the diagnostic system is operating in a real working environment.

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