An experimental parameter estimation approach for an on-line fault diagnosis system

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1. Introduction

Electro-hydraulic systems are extensively used in applications of the automation technology from robotics and aerospace to heavy industrial systems and are becoming more complex in design and function. On-line diagnostic approaches for these systems have been considerably interesting for modern production technology as they play a significant role in maintenace of automation processes.

Modelling information involved in a diagnostic method is considered as a quite effective diagnostic technique and many approaches have been published for the automated industrial processes over the last years such as (Frank 1996, Gertler 1998, Zhou and Bennett 1998, Chen and Patton 1999, Patton, Frank and Clark 2000, Kinnaert 2003, Angeli 2008). Models that run in parallel to the dynamical industrial processes require parameter estimation methods that could respond effectively to time restriction situations.

Various parameter estimation methods have been applied for fault detection in dynamic systems including the use of system models linearized about operating points (Reza and Blakenship 1996), nonlinear parameter estimation (Marschner and Fischer 1997), least-square methods (Hjelmstad and Banan 1995), methods using observers (Drakunov, Law and Victor 2007) , Kalman filters (Chow et al 2007), expert systems (Isermann and Freyermuth 1991), neural networks (Raol and Madhuranath 1996), qualitative reasoning (Zhuang and Frank 1998) and genetic algorithms (Zhou, Cheng and Ju 2002).

For the most of these methods the need for highly accurate estimates of the parameters require high computational load and memory requirements that reduces the capability of the method (Chen 1995) for on-line estimation of the parameters and as consequence makes them less suitable for on-line systems. Additional difficulties are presented from the noise in the system or the noise by the measurements where most of the methods proposed for parameter estimation in non linear systems cannot be applied (Fouladirad and Nikiforov 2006, Tutkun 2009). On the other hand linearised models have difficulties in representing a wide range of operating conditions.

This Chapter describes a parameter estimation scheme which overcomes some of these difficulties. The method is particularly suitable for on-line fault diagnosis because of the low memory and computational load requirements and its capability to operate in parallel to dynamic industrial process for on-line fault diagnosis. For the development of the parameter estimation method the DASYLab data acquisition and control software was used. The proposed method is used for the estimation of parameter values that include uncertainty while other parameter values were estimated from analytical considerations. The developed mathematical model was incorporated in an on-line expert system that diagnoses real time faults in hydraulic systems.

2. The actual system and the variables of the system

A hydraulic system consists of various hydraulic elements connected with pipes and a hydraulic medium.

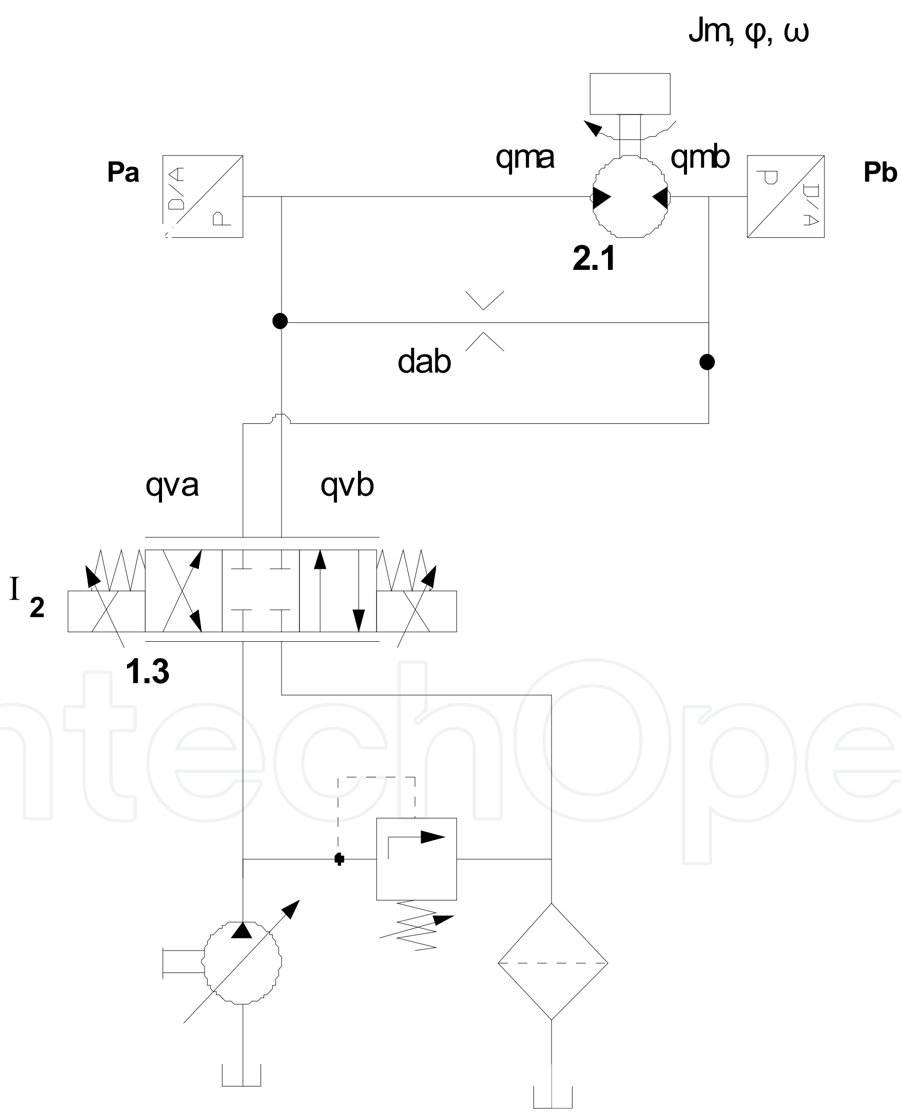

Fig. 1. A typical hydraulic system

A typical hydraulic system, Fig. 1, consists, besides the power unit, mainly of a proportional 4-way valve (1.3) and a hydraulic motor (2.1) with an attached rotating mass J_m. Assuming that the working pressure is constant, 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.

3. Operation of the system

The task of the actual system is to drive a hydraulic motor through a cyclical routine, which requires a high speed for a short time, and then return to a low speed.

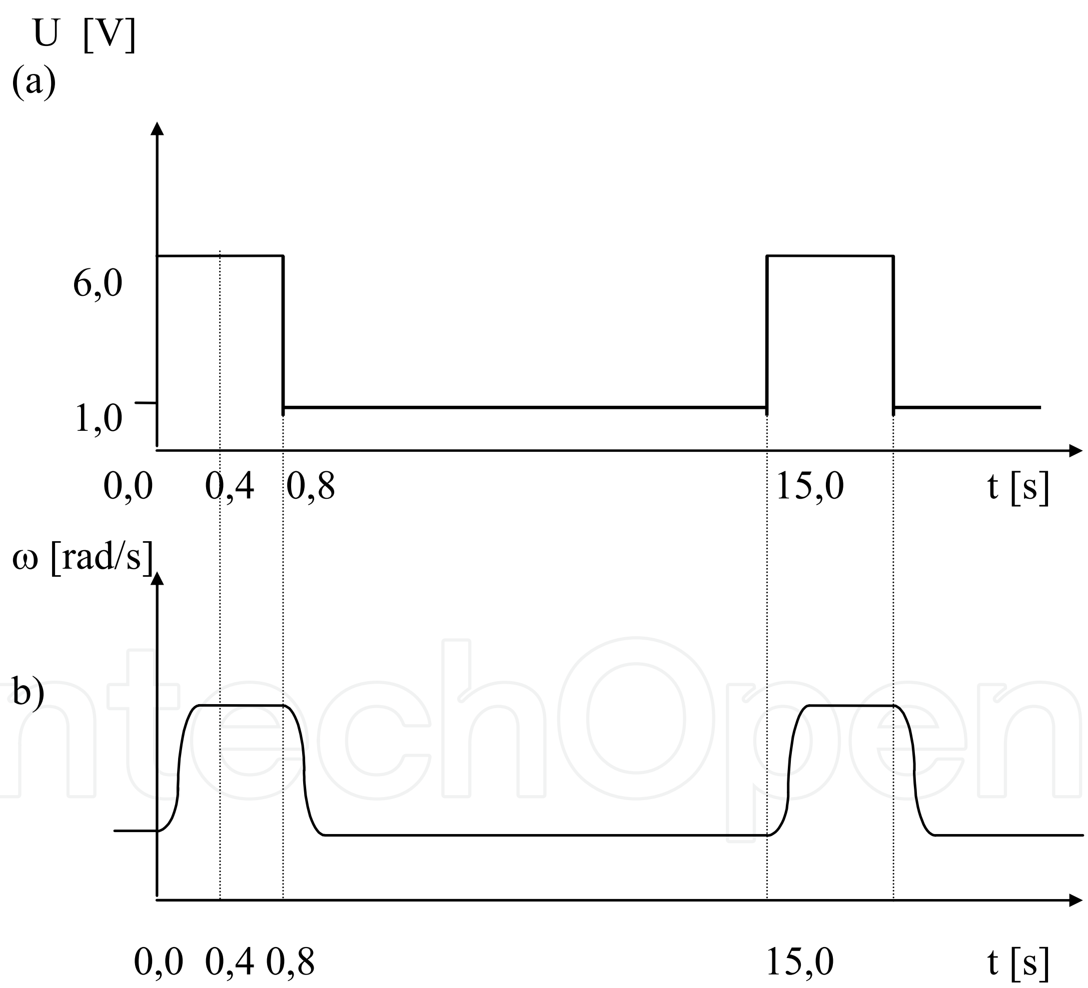

Fig. 2. Operation cycle of the system: (a) U - pulse; (b) Response of the hydraulic motor

To achieve this a typical input voltage is applied to the system as shown in Fig. 2. The speed of the hydraulic motor is proportional to the flow coming from the proportional 4-way valve and the displacement volume of the hydraulic motor. The flow is proportional to the input voltage to the amplifier of the proportional 4-way valve. The proportional 4-way valve is controlled by a periodically changed voltage value U. Fig. 2 shows the pulse waveform of the signal U to the amplifier of the proportional 4-way valve and the form of the corresponding waveform of the speed ω of the hydraulic motor.
On the normal operation the hydraulic motor takes approximately 0,4 s to change the speed from a low value corresponding to U=1 V to a high value corresponding to U=6 V. Any fault that occurs in the system can affect both the dynamic and the steady state of the system. Thus if data are taken over a period 0 to 0,4 s after having applied the change of voltage U both the dynamic and the steady condition should be determinable. In this work the positive response of the curve is used for the fault detection.

4. Estimation of the Uncertain Parameters

The simulation results depend on the values of the parameters. The model parameters are: the oil elasticity E, the volumetric efficiency η_v, the nominal flow of the proportional 4-way valve Q_{nv}, the nominal voltage signal to the amplifier of the proportional 4-way valve U_{nv}, the hydraulic motor displacement V_m , the oil volume in the pipes V_l , the moment of inertia J_m , the friction torque M_r, the system pressure p_0, the initial value of the command voltage to the amplifier of the proportional 4-way valve and the initial value of the rotation angle φ.
The parameter p_0 is the constant system pressure. The command value U_2 depends on the operating conditions. The parameters V_m , V_l and J_m are clearly determinable values depending on measurable physical characteristics of the system. The parameter U_{nv} is operation limit defined by the manufacturer. The parameters η_v and Q_{nv} are derivable from the manufacturer's data and their values are individually tested in the laboratory.
The parameters M_r (friction torque) and E (oil elasticity) are not easily determined from analytical considerations. For the determination of the value of these uncertain parameters the simulation for a set of values was performed, and the simulation results were compared with the corresponding measurements. The optimal values for M_r and E are the values that minimize the difference between the measurements of the actual system and the model. These values are estimated using the integral squared error (ISE) method. The determination of M_r is performed in relation to the commonly used range of values for the parameter E (oil elasticity including air) in order to determine more precisely the optimal value for both parameters. This process is extensively presented in following Sections 4.2 and 4.3.

4.1 The DASYLab software

As already mentioned, for the development of the proposed parameter estimation method the DASYLab software was used. The DASYLab (Data Acquisition SYstem Laboratory) is graphical programming software that takes advantage of the features and the graphical interface provided by Microsoft Windows. This software provides an "intuitive" operating environment, which offers data analysis functions, a high signal processing speed, an effective graphical display of results and data presentation possibilities. A measuring task can be set up directly on the screen by selecting and connecting modular elements which can then be freely arranged.

Among the module functions provided are A/D and D/A converters, digital I/O, mathematical functions from fundamental arithmetic to integral and differential calculus, statistics, digital filters of several types, logical connectors like AND, OR, NOR etc., counters, chart recorders, I/O files, digital displays, bar graphs, analogue meters and more.

With DASYLab it is possible to achieve high signal input/output rates using the full power of the PC. Special buffers with large, selectable, memory address ranges enable continuous data transfer from the data acquisition device through to the software. It obtains real-time logging at a rate of up to 800 kHz and real-time on-screen signal display at a rate of up to 70 kHz.

The worksheet displayed on the screen can be edited at any time. New modules can be developed and added, others can be moved to a different position or deleted. Dialogue boxes prompt for all the necessary parameters to be set for the experiment. By using the "Black Box" module it is possible to combine elements of the worksheet that are repeatedly required in the experiments, integrate them into a Black Box module and insert them into worksheets as ready-to-use units. The consequences of this are a saving of time and the simplification of the worksheets.

The maximum worksheet size is 2000 by 2000 pixels, and a worksheet can contain up to 256 modules. For most modules up to 16 inputs and/or outputs can be configured.

The acquired data and process results can also be saved to files so that they can be retrieved for further processing at a later time. Using DDE (Dynamic Data Exchange), data can be transferred directly to other Windows applications supporting the DDE protocol or applications with DDE capabilities may be used to start DASYLab and control it while running an experiment.

A worksheet can be created on the screen by selecting and connecting in a suitable way stored modules that represent a specific action. The modules are connected by data channels so that data can be transferred between them. The worksheet graphically displays on the screen the complete experiment setup or measurement procedure including all necessary modules and data channels.

A module represents a functional element in the experiment setup. The function symbolised by the modules comprises all the operations required for an experiment e.g. data acquisition (by a data acquisition board), signal generation (simulated by a software generator), data analysis, evaluation and processing (mathematics, statistics, control trigger and other functions), presentation on screen (display instruments) or export for documentation purposes (printer, metafile).

In the worksheet, modules are represented as complete symbols. These symbols display each module's name and the input and output channels that have been selected for it. A data channel is the connection between the output of a module and the input to another module. Data are transferred between the respective modules via these connections.

Modules are organised in module groups. A module group is made up of a number of modules providing similar functions. The available module groups are: input/output, trigger functions, mathematics, statistics, signal analysis, control, display, files, data reduction, special, and black box.

The overall data processing performance as well as the response time of the individual functions is determined by the experimental setup. In addition, the settings for the sampling rate, the block size, the analogue and digital outputs and the size of the driver buffer can be regulated by the experimental setup.

4.2 Derivation of the Integral Squared Error (ISE)

The estimation of the parameter value M_r is performed by measuring the integral squared error (ISE) between the measured and calculated signals over a period of time and looking for the minimum value of the ISE according to the following relations:

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

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

In principle, an optimum value for the friction M_r would exist if both integrals were at a minimum for this value.

The integral squared error is measured using the signal analysis capabilities of the DASYLab software by combining two DASYLab "experiments". The first “experiment”, Fig. 3, performs the control of the hydraulic system and the measurements under various operating conditions and updates the operational parameter values of the input files to the simulation program. In the second “experiment”, Fig. 4, the results from measurements and simulation are compared and processed. Between the two "experiments" the simulation program runs using the corresponding input data files with the updated parameter values. This method reduces the experimentation time considerably and allows us to perform experiments with a large variety of parameter sets.

The worksheet of Fig. 3 consists of three groups of modules. The module group A is responsible for the starting of the hydraulic system. The module group B is responsible for the control of the command voltage U_2. The module group C is responsible for the data measurement and storing for further processing by the second “experiment” (Fig.4).

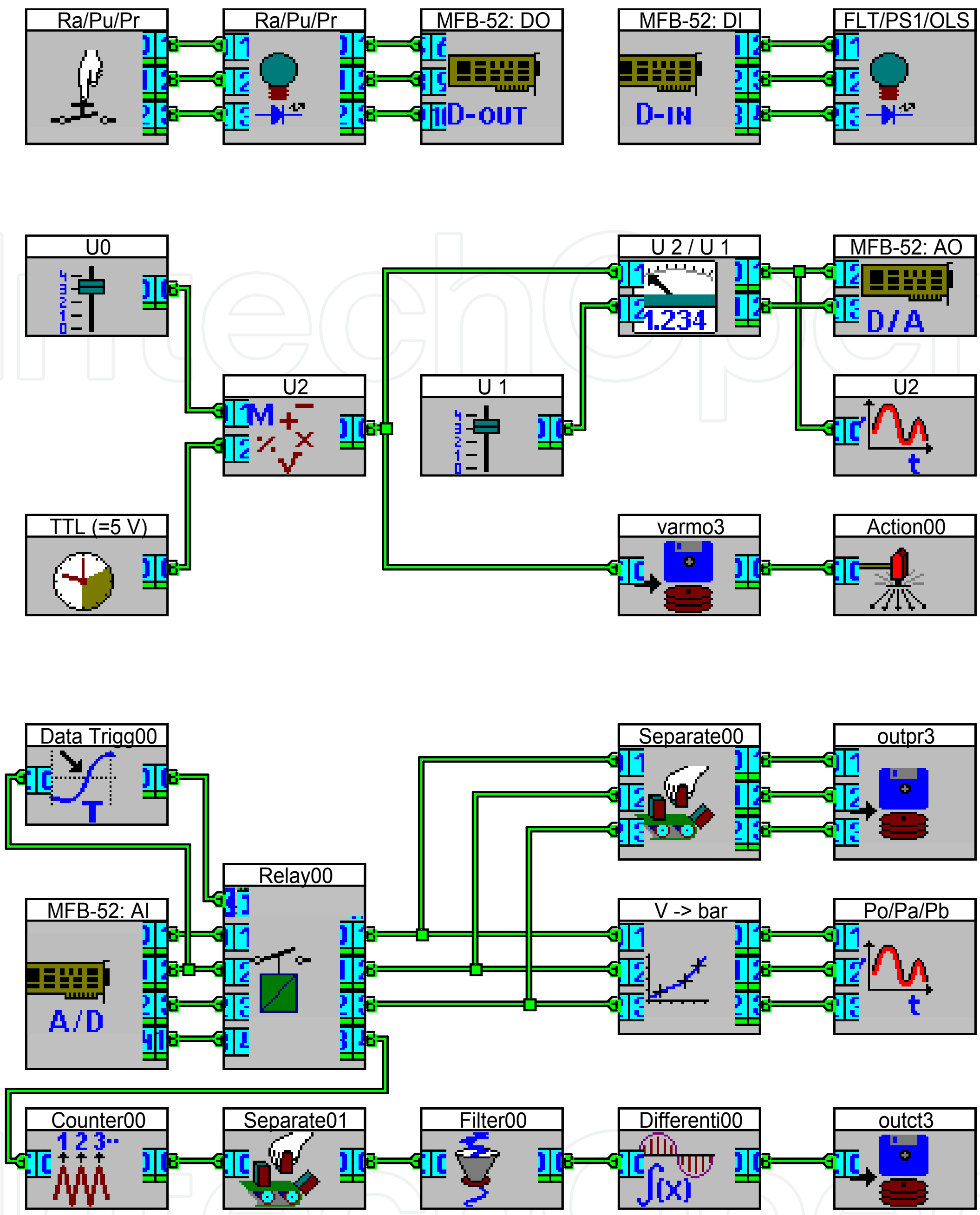

Fig. 3. Worksheet for experiment control and measurements

In the "experiment" of Fig. 3. the output from model (outmo3) and the output from measurements (oupr3) are compared. After this comparison of measured and calculated data, the integral squared error between them is derived using suitably formulated mathematical and statistical DASYLab modules.

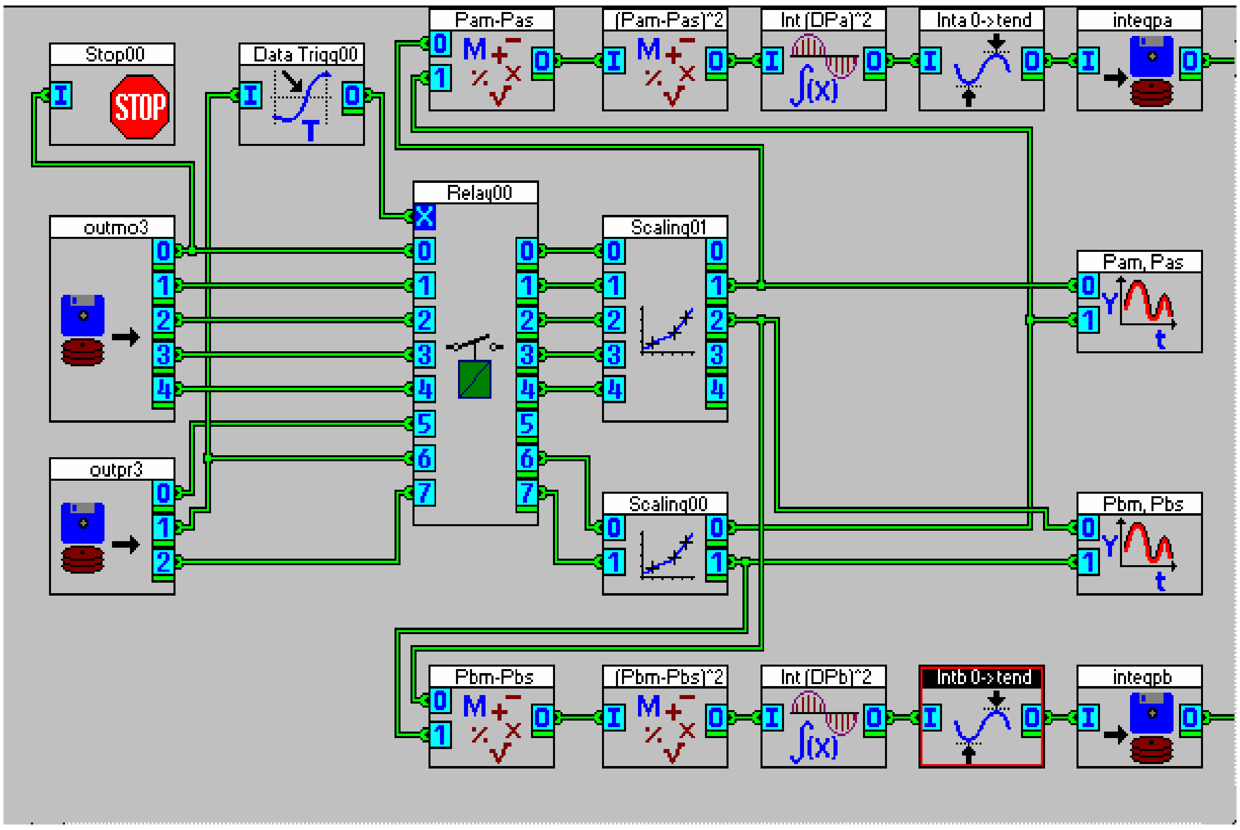

Fig. 4. Comparison of measured and calculated data and derivation of the integral squared error (ISE)

In this "experiment" the arithmetic module "Pam-Pas" calculates the difference between calculated and measured pressure p_a over the time period t = 0 to 0,4 s. The arithmetic module "(Pam-Pas)^2" calculates the square of the pressure difference.

The module " Int(DPa)^2" calculates the integral of (Pam-Pas)^2. The module "Inta0->tend" calculates the value of this integral in the time period t = 0 to tend (0,4 s). The result is the integral squared error over the observed period of time and is written to the file "integpa.asc", represented by the module “integpa”. This procedure is performed for a set of values near the expected value of the friction torque M_r and the result is appended to the data of the file "integpa.asc".

The processing of pressure p_b is performed in a similar way with the corresponding modules "Pbm-Pbs", "(Pbm-Pbs)^2", "Int(DPb)^2", "Int b 0 ->tend" and "integpb".

The files "integpa.asc" and "integpb.asc" together with the file "rm.asc", that contains the set of the M_r values, are processed by the "experiment" illustrated in Fig. 5, Section 4.3 for the estimation of the optimal parameter values.

4.3 Estimation of the optimal parameter values

The integral squared difference for the pressures p_a and p_b is the basis for the estimation of the best M_r value. In the DASYLab “experiment” of Fig. 5 the files “integpa” and “integpb” are graphically represented in relation to the M_r values and are processed for the determination of the optimal M_r value.

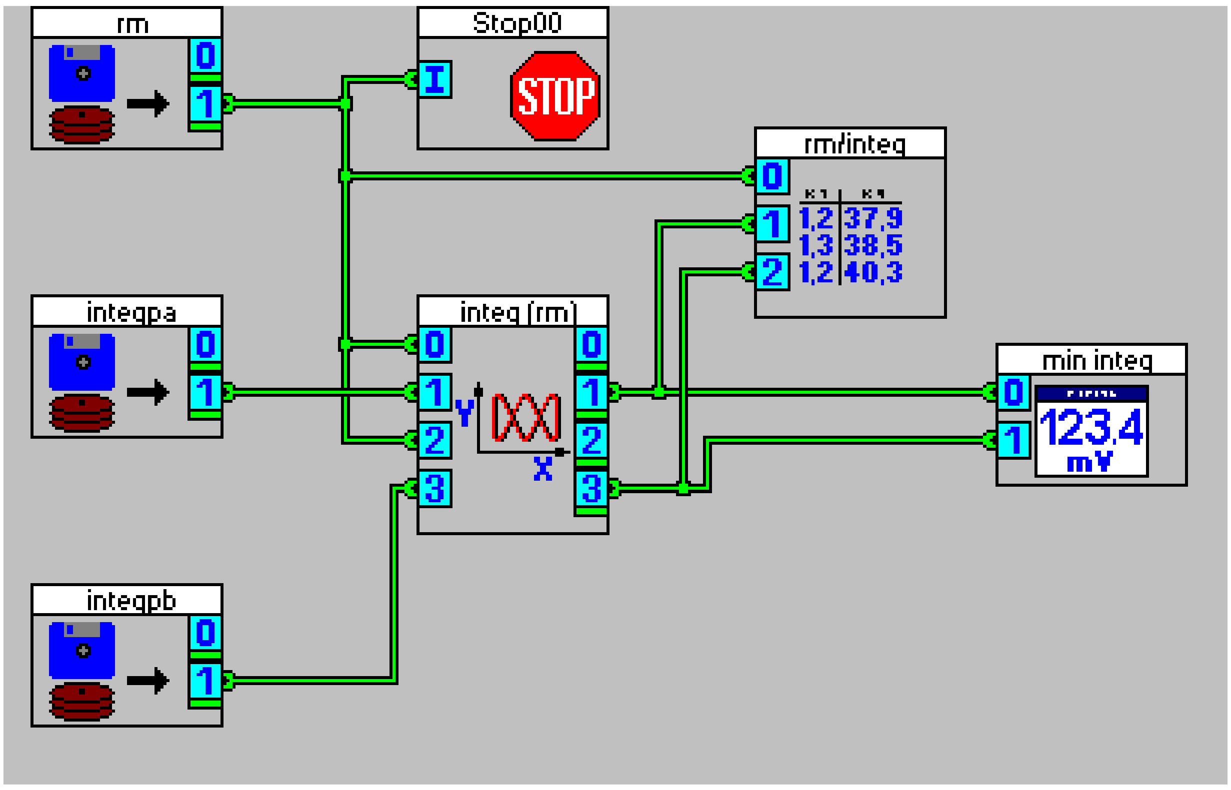

Fig. 5. Determination of the minimum integral squared error for pressures p_a and p_b

The module "integ(rm)" displays the integral squared error values for pressure p_a and p_b from the files "integpa" and "integpb" for various M_r values. The module "rm/integ" displays these values in a list form. The module "min integ" is a digital meter module that displays the minimum value between the integral squared error values of the list.

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/m^2 in the simulation, because these values lie near to the commonly used value for hydraulic mineral oil of 10^9 N/m^2.

The DASYLab "experiment" of Fig. 5 was performed for the pressures p_a and p_b with p_0 = 50 bar, U_2 = 6 V and oil elasticity values E = $0{,}90 \cdot 10^9$. N/m^2, E = $1{,}00 \cdot 10^9$ N/m^2 and E = $1{,}10 \cdot 10^9$ N/m^2. The results of the minimum integral squared error are plotted in Fig. 6.

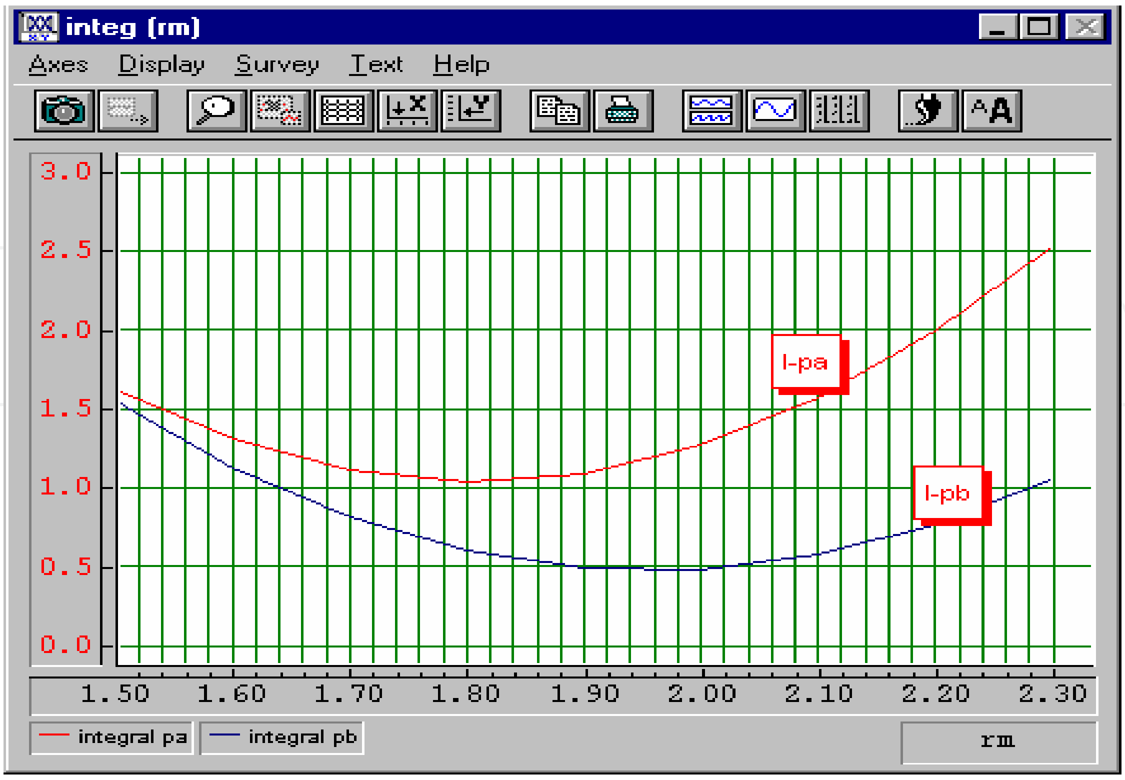

Fig. 6. The minimum integral squared error for pressure p_a and pressure p_b by p_0 = 50 bar, U_2 = 1 to 6 V and E = 0,90· 10^9 N/m²

In this Figure it is 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 N · m is taken for M_r.

The value 1,00 . 10^9 N/m² 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 . 10^9 N/m².

In order to test the performance of the model with the above estimated parameter values and to illustrate the changes of the pressure differences in relation to the operating parameters, the "experiment" of Figure 3 was used. The maximum differences of pressures p_a and p_b between measurement and simulation were calculated from the modules "Pam-Pas" and "Pbm-Pbs" for various command voltage values U_2 and various M_r values.

For comparison reasons the experimental results are summarised in Table 1, where the maximum pressure differences for the transient condition in relation to the command voltage values U_2 (5, 6 and 7 V) and the M_r values 1,70, 1,90 and 2,10 N.m are shown.

In this table, it can be observed that the maximum pressure differences from simulation and measurements are minimised for the estimated M_r value (= 1,9 N.m) while for other M_r values near to the estimated M_r value the differences increase.

Another observation is that all pressure difference values for the estimated M_r value 1,9 N.m are below the threshold which will be selected later as the criterion for the occurrence of a fault by the fault diagnosis process.

Deviation of Pa & Pb						
U2 [V]	1 to 5		1 to 6		1 to 7	
Mr [N.m]	DPa	DPb	DPa	DPb	DPa	DPb
1,70	3,3	2,8	3,1	2,6	3,2	2,7
1,90	3,1	2,6	2,9	2,4	3,0	2,5
2,10	3,4	2,9	3,2	2,7	3,3	2,8

Table 1. Experimental results of the pressure differences by various Mr values

5. Results of the Approach

The experimental work shows that the most accurate value for M_r is 1,9 N·m and the most accurate value for the oil elasticity E is 1,00 $.10^9$ N/m^2. From the experimental results it was observed that the deviation between the pressure curves from measurement and simulation was always lower than the threshold that will be defined for the occurrence of a fault in the fault detection process.

The behaviour of model and system using the estimated parameter values is illustrated in the diagrams of Fig. 7 where data from the simulation and from the data acquisition process are plotted on the same diagram. In these diagrams the high degree of approximation of the corresponding curves for the pressure p_a can be observed. Similar response for the pressure p_b and the angular velocity ω were observed.

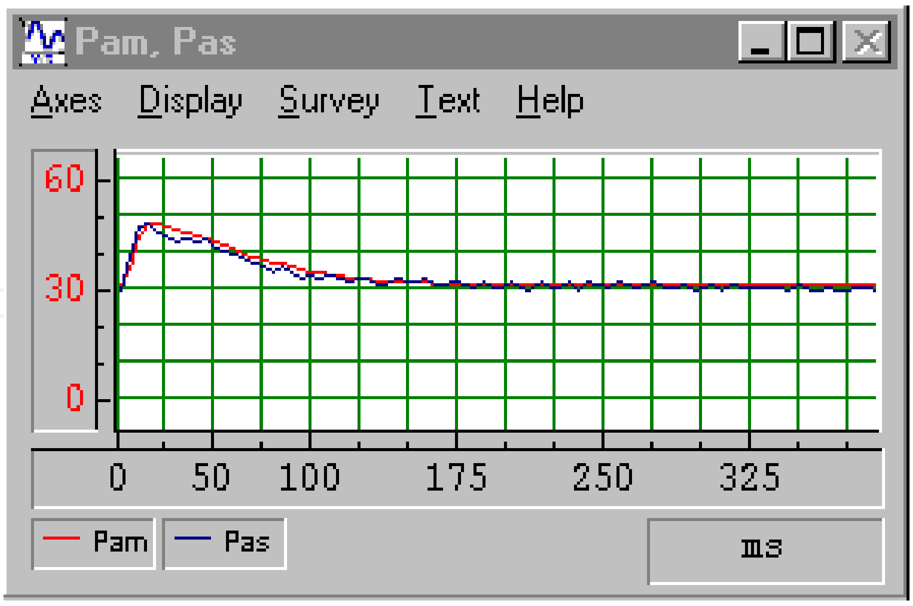

Fig. 7. Response of model and system regarding the pressure p_a by p_0 = 50 bar, U_2 = 1 to 6 V, E = 1,00 . 10^9 N/m², M_r = 1,9 N . m

6. Accuracy of the Diagnostic Results of the System

The effects of changes in parameter values on the simulation results were examined in order to test the performance of the system.

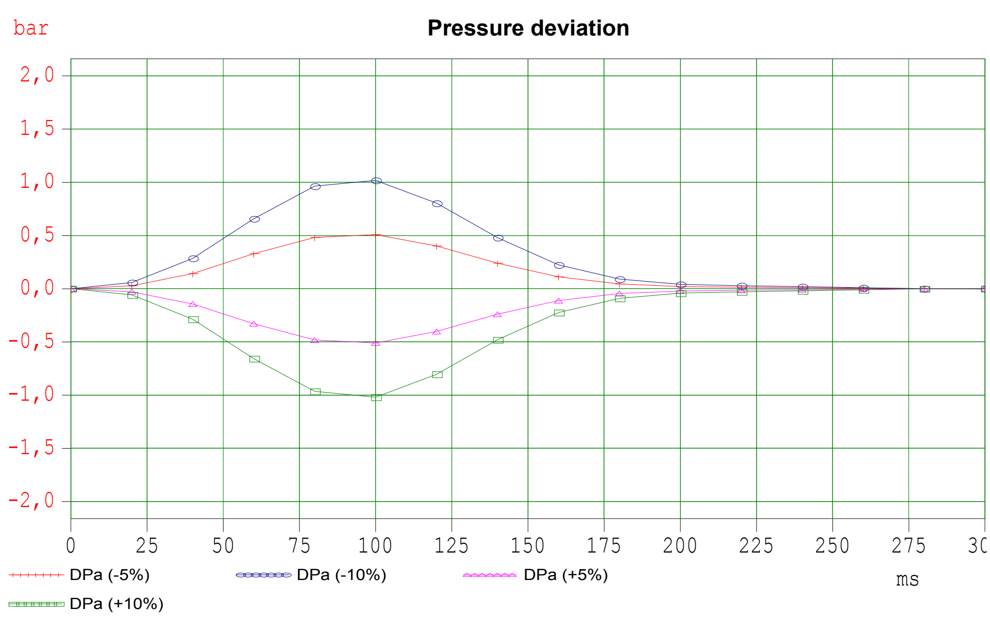

Fig. 8. Influence of a variation of ± 5 %, and ± 10% of the parameter J_m on pressure p_a.

The parameters, as the friction torque Mr, the moment of inertia Jm and the oil elasticity E were varied. For a variation of ± 5 %, ± 10 % and ± 20 % of these parameters the variation of the simulation results was observed and studied. As example, for the oil elasticity E the deviations of the simulation results for the above parameter changes are shown in Fig. 8. The maximum deviations are approximately 0,5 bar for a variation of ± 5 % and 1 bar for a variation of ± 10 %. These variations are acceptable for these systems and, in case, the specific should not affect the effectiveness of the fault detection. Observations indicated a similar effect for changes of the other parameters as well as on the pressure p_b.

7. Conclusion

Parameter estimation methods for real-time fault detection in dynamical systems are related to the effectiveness of the total diagnostic system. In this Chapter, a parameter estimation approach that uses low computational load and memory requirements has been presented which is also able to respond effectively to time restriction situations. The method has been applied to a dynamic drive and control system and has the capability to estimate on-line parameter values as well as to operate in parallel to the final real-time fault detection system. For the development of the parameter estimation method the capabilities of the DASYLab data acquisition and control software were used.

The final model, used by the fault detection system, is able to simulate quite precisely the actual behaviour of the physical system and can respond to the requirements of on-line performance. The experimental results provide evidence of the consistency degree between the behaviour of model and the system that makes the parameter estimation method particularly suitable for on-line fault diagnosis systems.

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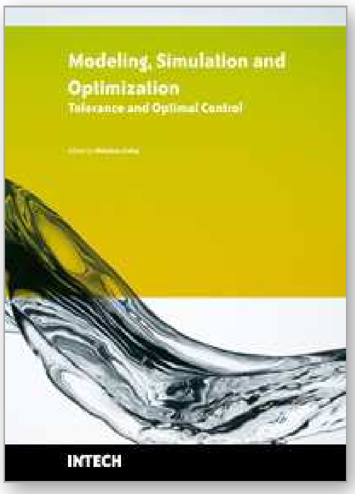

Modeling Simulation and Optimization - Tolerance and Optimal Control

Edited by Shkelzen Cakaj

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Parametric representation of shapes, mechanical components modeling with 3D visualization techniques using object oriented programming, the well known golden ratio application on vertical and horizontal displacement investigations of the ground surface, spatial modeling and simulating of dynamic continuous fluid flow process, simulation model for waste-water treatment, an interaction of tilt and illumination conditions at flight simulation and errors in taxiing performance, plant layout optimal plot plan, atmospheric modeling for weather prediction, a stochastic search method that explores the solutions for hill climbing process, cellular automata simulations, thyristor switching characteristics simulation, and simulation framework toward bandwidth quantization and measurement, are all topics with appropriate results from different research backgrounds focused on tolerance analysis and optimal control provided in this book.