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FDI by Parameter Estimation Based on CLFRT

Ferreiro García Ramon and Manuel Haro Casado
Department of Ingeniería Industrial, Universidade da Coruña, ETSNM,
C/Paseo Ronda 51, 15011 A Coruña, Spain

Abstract: Most of non-linear type one and type two control systems suffers from lack of detectability when model based techniques are applied on FDI tasks. This research is centered on a strategy based on Closed Loop Frequency Response Test (CLFRT) to estimate plant parameters which includes massive neural networks based functional approximation procedures. Nominal plant parameters are matched against on-line estimated parameters on a parity space approach. The strategy to carry out this task consists in developing a fault tolerant data acquisition strategy to achieve a database to be used in neural networks training. Proposing and implementing a methodology to estimate plant parameters by functional approximation based on backpropagation neural networks.

Key words: Backpropagation, conjugate gradient, fault detection, fault isolation, frequency response, neural networks, parameter estimation

INTRODUCTION

Safety in process industry can be strongly related to the detection and isolation of the features indicative of changes in the sensors actuators or process performance. In using model-based approaches, when the models describing the process are accurate, the problem of fault detection may be solved by observer-type filters. These filters generate the so-called residuals computed from the inputs and outputs of the process. The generation of these residual signals is the first stage in the problem of Fault Detection and Isolation (FDI). To be useful in the FDI task, the residuals must be insensitive to modeling errors and highly sensitive to the faults under consideration. In that regard, the residuals are designed so that the effects of possible faults are enhanced, which in turn increases their detectability. The residuals must also respond quickly. The residuals are tested in order to detect the presence of faults. Various FDI methods have been previously reported, such as the papers of (Willsky, 1976; Isermann, 1984; Frank, 1987a; Gertler, 1998; Patton and Chen, 1991). Among the classic books on the subject are those of (Himmelblau, 1978; Pau, 1981; Basseville, 1986).

Model based fault detection methods: Fault detection methods based on process and signal models include actuators, processes and sensors for which inputs and output variables must be precisely measured. Such methods deal mainly with parameter estimation, state observers and parity equation methods. If measuring system fails, fault detection methods based on the use of input/output measurements yields ambiguous and/or erroneous results.

A lot of research on model based fault detection methods has been carried out during the last three decades. In this study a brief list on process model based fault detection methods is given:

- Fault detection with parameter estimation (Gertler, 1988)
- Equation error methods
- Output error methods
- Fault detection with state-estimation.
- Dedicated observers for multi-output processes.
- State Observe, excited by one output (Clark, 1978a).
- Kalman filter, excited by all outputs (Mehra and Peschon, 1971).
- Bank of state observers, excited by all outputs (Willsky, 1976).
- Bank of state observers, excited by single outputs (Frank, 1987a)
- Bank of state observers, excited by all outputs except one (Frank, 1987a).
- Fault detection filters for multi-output processes (Beard, 1971).
- Fault detection with parity equations (Isermann, 1984; Gertler, 1991; Patton and Chen, 1994).
- Output error methods.

Corresponding Author: Ramón Ferreiro García, Department of Ingeniería Industrial, Universidade da Coruña,ETSNM, C/Paseo Ronda 51, 15011 A Coruña, Spain

- Polynomial error methods.
- Fault detection using analytical redundancy (Ragot *et al*., 2000).
- Static analytical redundancy.
- Dynamic analytical redundancy.

No general method exists for solving all FDI cases. Successful FDI applications are based on a combination of several methods. Practical FDI systems apply analytical redundancy using the so-called first-principles like action-reaction balances such as mass flow rate balance, energy flow rate balance, force/torque/power balances and commonly, the mathematical balance of any cause-effect equilibrium condition.

As stated before, diagnosing techniques previously mentioned, when applied to non-linear type one and type two processes, suffers from lack of detectability. With regard to residuals, they are the outcomes of consistency checks between the plant observations and a mathematical model. The three main ways to generate residuals are parameter estimation, observers and parity relations. For parameter estimation, the residuals are the difference between the nominal model parameters and the estimated model parameters. Derivations in the model parameters serve as the basis for detecting and isolating faults.

In most practical cases the process parameters are partially not known or not known at all. Such parameters can be determined with parameter estimation methods by measuring input and output signals if the basic model structure is known. There are two conventional approaches commonly used which are based on the minimization of equation error and output error. The first one is linear in the parameters and allows therefore direct estimation of the parameters (least squares) in non-recursive or recursive form. The second one needs numerical optimization methods and therefore iterative procedures, but may be more precise under the influence of process disturbances. The symptoms are deviation of the process parameters. As the process parameters depend on physically defined process coefficients, determination of changes usually allows deeper insight and makes fault diagnosis easier (Isermann, 1984). These conventional methods of parameter estimation usually need a process input excitation and are especially suitable for the detection of multiplicative faults. Parameter estimation requires an input/output correct measuring system. Some drawbacks of such methods are:

- The possibility of faulty measuring signals, an unknown model structure or the necessity of an on-line excitation of the input signals.

Goals to be achieved: Afore-mentioned diagnosing techniques, when applied to non-linear type one and type two processes, has the disadvantage of lack of detectability. Consequently, the following work will be pointing towards other useful alternatives. This research is focused on the problem of fault detection, fault isolation and fault estimation by a novel parameter estimation method associated to residual generation on the basis of parity space approach. The proposed parameter estimation method is based on functional approximation techniques implemented with Backpropagation Neural Network (BPNN) even under a faulty measuring system.

The main tasks to be carried out are: Develop a fault tolerant data acquisition method by means of CLFRT to achieve a consistent database Develop a neural network based structure to increase the accuracy and/or of process parameters to be estimated.

ON CLFRT TECHNIQUES

This study is focused on the problem of fault detection, fault isolation and fault estimation on the basis of parameter estimation by functional approximation implemented with backpropagation neural networks associated to frequency techniques on nonlinear type one and type two systems, for which serious problems with detectability exist.

Among the most important work carried out on frequency techniques is (Eugene, 2002; Lucas *et al*., 1996) where a collection of computer programs for aircraft system identification is described and demonstrated. The programs, collectively called System Identification Programs for AirCraft, or SIDPAC, were developed in MATLAB® as m-file functions. In Brian and Mark (1999) it is reviewed all of the main topics associated with experimental modal analysis (or modal testing), including making FRF measurements with a FFT analyzer, modal excitation techniques and modal parameter estimation from a set of FRFs (curve fitting). In Douwe and Paul (1998) a method is considered for the identification of linear parametric models based on a least squares identification criterion that is formulated in the frequency domain. Nevertheless, mentioned methods, when based on parameter estimation techniques are affective if measuring system operates free of faults. That means, measurement equipment operates without drift errors. Consequently, when the possibilities of sensor drift errors exist, a method called CLFRT described below is proposed.

Process characteristics based on frequency response: Frequency response is understood as the gain and phase response of a plant or other unit under test at all frequencies of interest. Although the formal definition of frequency response includes both the gain and phase, in common usage, the frequency response often only implies the magnitude (gain). In this study phase response must be considered.

The frequency response H(f) is defined as the inverse Fourier Transform of the Impulse Response h(τ) of a system.

$$H(f) = \int_{-\infty}^{\infty} h(\tau)e^{-j2\pi f\tau}d\tau \tag{1}$$

Frequency response measurements require the excitation of the system with energy at all relevant frequencies. The fastest way to perform the measurement is to use a broadband excitation signal that excites all frequencies of interest simultaneous and use FFT techniques to measure at all of these frequencies at the same time. Noise and non-linearity is best minimized by using random noise excitation, but short impulses or rapid sweeps (chirps) may also be used. The selected excitation signal for this study is of the type given as

$$f(\omega t) = \sum_{i=1}^{n} A_i \mathrm{Sin}(\omega_i t) \tag{2}$$

with three relevant frequencies (n = 3) and same amplitude yielding

$$f(\omega t) = A_1\mathrm{Sin}(\omega_1 t) + A_2\mathrm{Sin}(\omega_2 t) + A_3\mathrm{Sin}(\omega_3 t) \tag{3}$$

Excitation function can be applied simultaneously or sequentially. Obviously, when excitation signals are applied simultaneously, the CLFRT is faster than sequentially because the solution provided by applying the FFT algorithm uses only a computational phase.

When the desired resolution bandwidth of interest is less than about 100 kHz, the fastest way to measure the frequency response functions is to use FFT based techniques as it is done in this study.

For proper measurement, it is also important to take into account the nature of the type of signals that we are dealing with.

As a rule of thumb, if there is a given percent distortion or noise in the system, the error will be of the same order of magnitude. The output must be statistically correlated to the input. This assumption is normally true in high fidelity analog systems. However, in mechanical systems, as well as systems with complex transmission mechanism and/or with digital encoding, echo cancelling

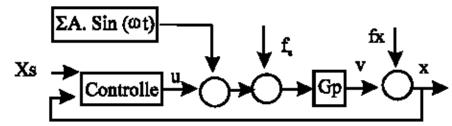


Fig. 1: Structure of the CLFRT

and other adaptive techniques, this assumption may not be fulfilled. To account for all of the above, it can be used digital signal processing techniques. In this research FFT is to be applied.

The output of a stable nonlinear system under the effect of a sinusoidal continuous disturbance consists in a steady-state oscillation about an equilibrium point and still be considered stable. Such an oscillation similar to a limit cycle is a periodic though not sinusoidal oscillation whose amplitude $|G|_\omega$ and phase ϕ_ω is dependent only upon the magnitude of the input and the characteristics of the system.

When stationary processes are under consideration, the technique does provide a useful tool for the process parameter changes detection as shown in this work. If a change in the characteristic values of the frequency response (amplitude and phase) is observed, this means that some parameters of transfer function has changed. The method requires a sine generator added to a closed loop controller as shown in Fig. 1.

It follows that if any change in system parameters takes place, then the magnitude and phase, will change also. This property is expressed as:

$$(|G|_\omega, \phi_\omega) = f(P_i); \quad i = 1, \cdots M \tag{4}$$

With P_i the system parameter set. So that, the condition to asseverate system parameter invariance which means to confirm that no parameter has changed is

$$(|G|_\omega, \phi_\omega) = f(P_i) = |G|_{\omega N}, \phi_{\omega N} \tag{5}$$

Where $|G|_{\omega N}$ and $\phi_{\omega N}$ are the nominal amplitude and phase respectively corresponding to the nominal parameters set P_{iN}.

It should be noted that Eq. 3 and 4 give us approximate values for $|G|_{\omega N}$ and $\phi_{\omega N}$ because the measuring system introduces an additional error into the system which must not be relevant. However, for most systems, the approximation is close enough for engineering purposes.

Nevertheless, when a system transfer function is influenced by any auxiliary or external variable, (variables different of the input/output of the transfer function), they should be taken into account. As consequence of the existence of such variables, (3) can be rearranged as follows:

$$(|G|_{\omega}, \phi_{\omega}) = f(P_i, V_i) \tag{6}$$

If a sinusoidal function of amplitude A inserted in parallel with a feedback controller is forced to change its frequency to a new value, then a different pair of amplitude and phase as frequency response is achieved. Such idea is expressed as

$$\begin{aligned} &A_1, \omega_1 \Rightarrow (|G|_{\omega 1}, \phi_{\omega 1}) \\ &A_2, \omega_2 \Rightarrow (|G|_{\omega 2}, \phi_{\omega 2}) \\ &\vdots \\ &A_n, \omega_n \Rightarrow (|G|_{\omega n}, \phi_{\omega n}) \end{aligned} \tag{7}$$

for identification pourposes the amplitude of the excitation signal can be salected such that $A_1 = A_2 = \ldots A_n$ yielding

$$\begin{aligned} &A, \omega_1 \Rightarrow (|G|_{\omega 1}, \phi_{\omega 1}) \\ &A, \omega_2 \Rightarrow (|G|_{\omega 2}, \phi_{\omega 2}) \\ &\vdots \\ &A, \omega_n \Rightarrow (|G|_{\omega n}, \phi_{\omega n}) \end{aligned}$$

Consequently, the application of (5) yields

$$\begin{vmatrix} (|G|_{\omega 1}, \phi_{\omega 1}) \\ |G|_{\omega 2}, \phi_{\omega 2}) \\ \vdots \\ (|G|_{\omega n}, \phi_{\omega n}) \end{vmatrix} = f(P_i, V_i) \tag{8}$$

Expression (7) states that any pair of amplitude and phase is function of the complete set of plant parameters and related external variables (coupling variables).

Independence of output sensor error (drift)

Theorem I: Magnitude and phase of a frequency response measured under sensor drift is not altered due to such fault.

This theorem applied to the CLFRT means that the magniude and phase of the frequency response of a closed loop controlled system excited by the manipulated variabale doesn't depend on the output measuring system performance due to constant drift.

Proof: Given the closed loop system shown in Fig. 1 based on a SISO case and assuming that f_x is an addictive fault to the output (a constant drift on output measuring variable x) and asumming that such fault doesn't introduce any additional time lag on the system, real amplitude of output is such that

$$x = y + f_x \tag{9}$$

the limit values of output response are

$$x_2 = y_2 + f_x \tag{10}$$

$$x_1 = y_1 + f_x \tag{11}$$

the value of the output range is such that

$$x = x_2 - x_1 = (y_2 + f_x) - (y_1 + f_x) = y_2 - y_1 \tag{12}$$

From Eq. 11 follows that drift based output sensor faults doesn't affect the measured output along its full range.

Advantages of the method: This method has several distinct advantages over conventional parameter estimation methods:

- It doesn't depend on the output measuring errors (drift of system output sensors)
- No a priori knowledge of the system parameters is needed. The method automatically results in a sustained oscillation at the excitation frequency of the process. The only parameter that has to be specified is the frequency and amplitude of excitation signal.
- It is a closed loop test, so the process will not drift away from the setpoint. This is precisely why the method works well on highly nonlinear processes. The process is never pushed very far away from the steady-state conditions.

Applying CLFRT on parameter change detection: Intuitively, the set of parameters P_i of a non-structured process model which is not affected by external variables can be associated to a set of data like ultimate frequency response data (amplitude and phase) by means of the CLFRT described in last section. This idea is described with the Fig. 2.

To fulfill the requirements for training a feedforward backpropagation neural network, a database relating plant parameters P_{ij} and the associated pairs of (amplitude

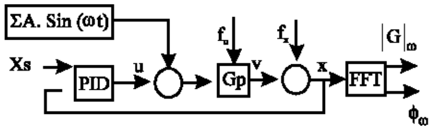


Fig. 2: Frequency response measuring using FFT

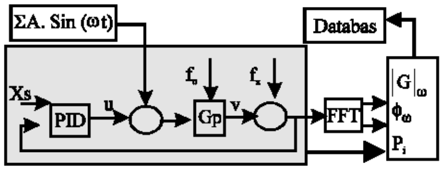


Fig. 3: CLFRT to achieve the necessary data to be used in NN training

andphase) must be achieved using the data structure described by (7). Such pairs of ultimate values corresponding to actual plant parameters are nominal ultimate values if and only if, plant parameters are nominal. In this situation it is assumed a fault free plant operation mode. Figure 3 shows the implementation of CLFRT to achieve the actual demanded data.

When an CLFRT is applied on a real time process, the functional relation of every data set is subjected to the functional scheme

$$f(P_1, P_2, \cdots P_{M-1}, P_M, |G|_\omega, \phi_\omega) \qquad (13)$$

Where the process variables don't influence the HB test, being P_1, P_2, .. P_M the plant parameters and amplitude and phase are the outputs of CLFRT.

The simplest idea to identify only one parameter consists in applying a functional approximation technique based in the use of backpropagation neural networks properly trained as shown in Fig. 4. Figure 4 illustrates the case of a plant with unknown model structure and three (but could be any other quantity) accessible (known by any means) parameters P_1, P_2 and P_3.

The general procedure to achieve a database useful to train the neural network based parameter estimator, consists in the following tasks described in Fig. 5:

- Application of the CLFRT and record the data relating the plant parameters with the pairs of amplitude and phase.
- Generation of the neural network structure (number of hidden layers and the number of neurons per layer).
- Training the neural network with the achieved data using the appropriate algorithm to achieve accurately

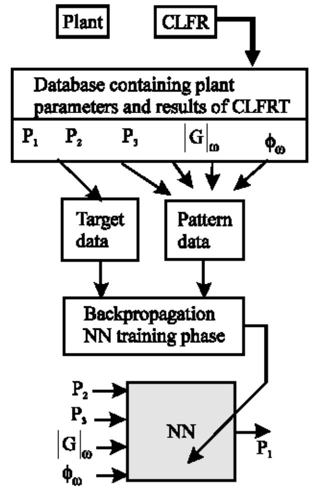


Fig. 4: Tasks involved in achieving a neural network parameter estimator

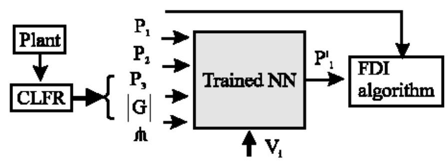
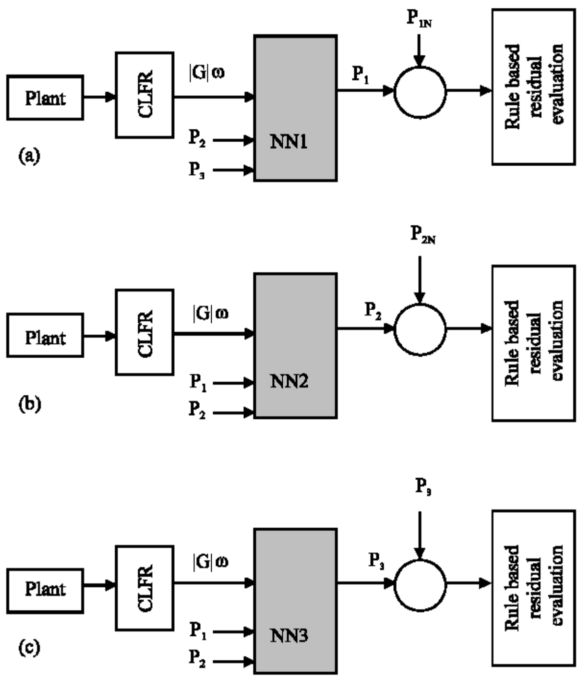


Fig. 5: Scheme of parameter estimation and diagnostic tasks

a functional approximator which will operate as a plant parameter estimator.

Figure 5 shows a parameter estimator or functional approximator, which consists in a trained neural network as shown in Fig. 4, ready to identify a plant parameter, P_1, when real time or actual data is applied to the inputs. So that, the tasks necessary to identify a unique plant parameter, requires again the on line CLFRT to obtain the actual pair of magnitude and phase. By introducing such actual values including the rest of known parameters and related variables (if is the case) to the neural network inputs, it yields at the neural network output, the actual value of the plant unknown parameter. The accuracy in the value of the estimated parameter is crucial because it will be immediately applied into a parity space approach, which is the core of the diagnostic tasks.

Let's assume that no external or coupling variables excites the transfer function. In such situation, an inherent property of functional approximation is the loss of output data accuracy as the number of parameters to be estimated increases with respect to the total number of function parameters. Let a function relating the plant parameters with the pair of magnitude and phase by applying an CLFRT be expressed as:



$$f(P_1, P_2, \cdots P_{M-1}, P_M, |G|, \phi) \qquad (14)$$

Fig. 6: Estimation with two known parameters of three. (a), estimation of parameter P_1 with (P_2, P_3) known. (b), estimation of parameter P_2 with (P_1, P_3) known. (c), estimation of parameter P_3 with (P_1, P_2) known

then, the idea for achieving more accurate parameters in the identification task is expressed as follows:
being

$$P_1 = f(P_2, \cdots P_{M-1}, P_M, |G|, \phi) \qquad (15)$$

and

$$P_1, P_2 = f(\cdots P_{M-1}, P_M, |G|, \phi) \qquad (16)$$

then, follows that the results of the estimation task using a backpropagation neural network trained by means of the conjugate gradient algorithm with the same data, achieves more accurate results in the case described by expression (14) than in the case described by expression (15). Consequently, the accuracy in the estimation of plant parameters can be improved by increasing the number of accessible plant parameters considered into the functional description of the plant with respect to the number of parameters to be estimated.

According last asseveration, the comparison of Fig. 6 and 7 shows such concept. Thus, in Fig. 6 it is shown an example of the case where for every neural network based parameter estimator, only a parameter is estimated. In this case a process described by a structured model with three parameters (P_1, P_2, P_3) is considered. Consequently, the pair of remaining non estimated parameters must be well known. In Fig. 7 it is shown the case where for every parameter estimator, two parameters are estimated assuming a considerable reduction in the estimates accuracy. In the Table 1 it is shown the arrangement of data achieved by applying the CLFRT on the considered process f ($|G|$,ϕ, P_1, P_2, P_2) represented in Fig. 6 and 7, respectively.

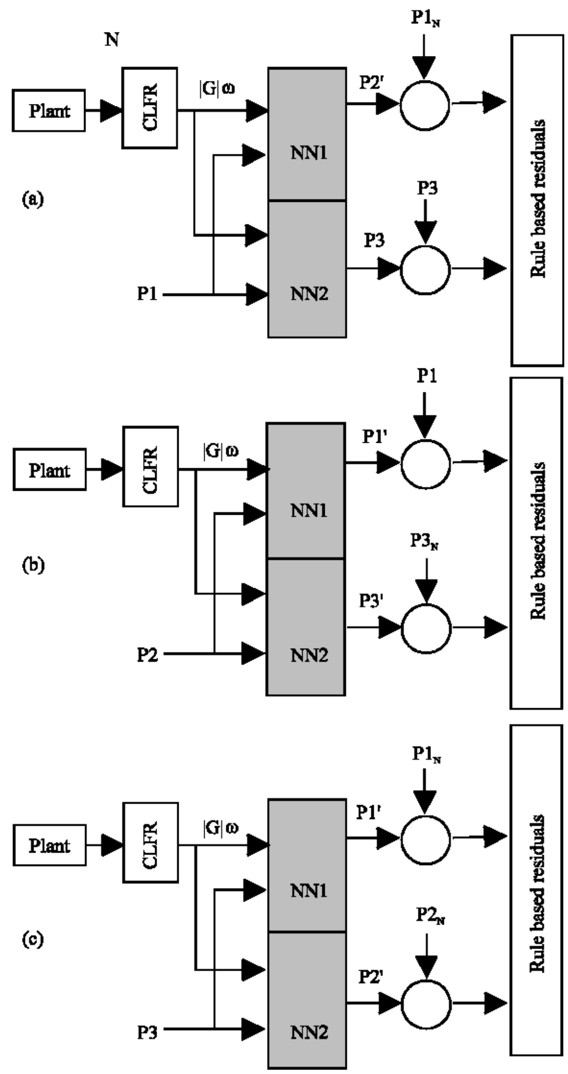


Fig. 7: Estimation with one known parameter of three. (a) parameter P_1, (b), parameter P_2, (c) parameter P_3

Implementation of the FDI method on a servomotor

System description: This study deals with the implementation task concerning to FDI on a pilot servomotor using parameter estimation by means of proposed techniques. The servo under study is specially

Table 1: Data structure for nn training

Figure	Pattern data	Target data
6	$\|G\|, \omega$, P2, P3	P1
	$\|G\|, \omega$, P1, P3	P2
	$\|G\|, \omega$, P1, P2	P3
7(a)	$\|G\|, \omega$, P1	P2, P3
7(b)	$\|G\|, \omega$, P2	P1, P3
7(c)	$\|G\|, \omega$, P3	P1, P2

Table 2: CLFRT characteristics

	$\|G\|_{\omega 1}, \phi_{\omega 1}$	$\|G\|_{\omega 2}, \phi_{\omega 2}$	$\|G\|_{\omega 3}, \phi_{\omega 3}$	Kp, Ti Td
cps	0.6	1	1.4	16, 63, 5
cps	0.8	1.2	1.6	16, 63, 5
cps	1	1.4	1.8	16, 63, 5

designed to research the effect of variations on inertia load and viscous friction load. It consists in a Variable Speed Drive (VSD) responsible of supplying variable energy to an AC motor. The AC motor drives both, a variable inertia load and an electric brake, mechanically coupled on the motor shaft as shown in Fig. 8. Such servo-system installation is equipped with measurement instrumentation to record the necessary process variables including supply voltage, variable friction emulated by the brake, by measuring the supply current I_L. Inertia load is computed by measuring the rotating mass attached to the motor shaft.

In the notation used in Fig. 9, Km is the proportional constant relating the torque developed with an input or control voltage e_c generated by the VSD. B_m is the constant that relates the back e.m.f. with the shaft speed. J_N and B_N are the inertia and viscous friction of the motor at zero external load. K is a constant relating brake torque with the shaft speed and supply current I_L. An approach to the servo linear transfer function is achieved from the block diagram of Fig. 9, yielding

$$\frac{\theta}{e_c} = \frac{K_L Km}{s\left[(J_N + J_L)s + B_N + B_m Km + I_L K\right]} \tag{17}$$

The modus operandi of any AC motor coupled to external loads is inherently nonlinear, where its model may result non-structured, due to the nonlinear nature of internal and external loads, including inertia and friction. The method studied in this research project is especially designed to non-linear and non-structured systems.

For research or experimental purposes, inertia and friction loads will be changed by means of varying J_L and I_L, respectively.

Achieving a database: In order to achieve a consistent database, a series of CLFRT relating the relevant plant parameters such as inertia load J_L and load friction (not necessary viscous friction) I_L, are performed. Input data for CLFRT are the exciting frequencies, known plant parameters and PID parameters, as shown in Table 2.

The achieved database contains the inputs (actual plant parameters, J_L, I_L) and outputs of CLFRT tests ($|G|_\omega$, ϕ_ω) as function of input frequencies shown in Table 2. Under such conditions, a database shown in Table 3 of Appendix I was achieved.

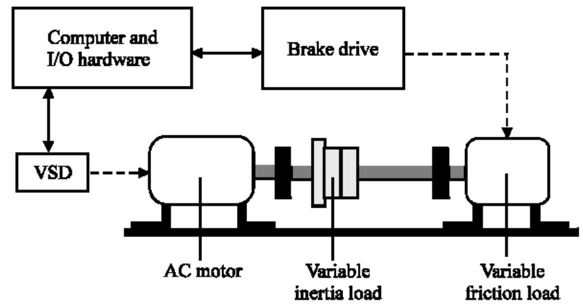


Fig. 8: Lab-servo scheme

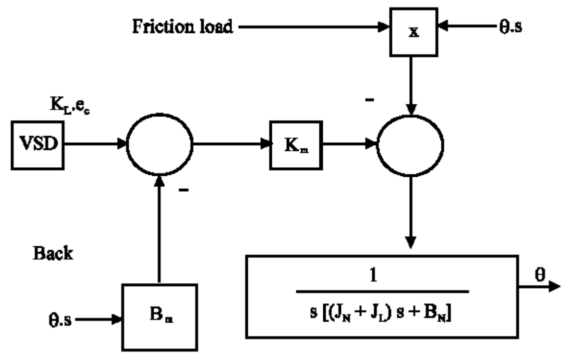


Fig. 9: Block diagram of a linearized servomotor depicted with Fig. 8

Using the database data: The results of a consistent database like those of Table 3 are used in backpropagation neural network training phase. The training algorithm selected is the conjugate gradient Fletcher-Reeves implemented on the Neural Network toolbox of Matlab under off-line training sessions. Consequently, the selected neural network architecture is defined by means of the Matlab expression:

net = newff(minmax (p), [10, 10, 1], {'tansig','tansig','purelin'},'traincgf')

which consists of a feedforward Backpropagation NN trained with, traincgf algorithm.

After several training sessions with different data structures from the database in Table 3, some of the training results are shown in Table 4.

MSE is an acceptable performance index to evaluate the accuracy of the estimates in the training results as shown in Table 4. By comparing the values of rows

Table 3a: Database data

J/10	B	Mag1	Fase1	Mag2	Fase2	Mag3	Fase3
4	1	0.630947	-90.6335	1.85844	-151.137	1.34405	-202.767
4	1.5	0.577644	-82.4399	1.47806	-137.228	1.19672	-190.562
4	2	0.624697	-79.9567	0.715435	-112.035	1.07464	-181.289
4	2.5	0.340753	-69.0807	0.776777	-108.933	0.973985	-173.917
4	3	0.50778	-75.5674	0.31516	-86.8589	0.803768	-165.696
8	1	3.74226	-133.783	1.86431	-195.39	0.800792	-233.477
8	1.5	2.9606	-121.859	1.70908	-185.509	0.785869	-227.676
8	2	2.43303	-112.493	1.56625	-177.454	0.768264	-222.395
8	2.5	2.00016	-104.434	1.43569	-170.567	0.749173	-217.57
8	3	1.49718	-96.0878	1.24458	-163.255	0.72928	-213.104
12	1	3.43234	-158.421	1.36418	-211.309	0.546214	-242.902
12	1.5	2.97064	-147.013	1.32754	-204.959	0.544649	-240.099
12	2	2.64801	-138.778	1.28451	-199.406	0.54196	-237.331
12	2.5	2.38695	-132.139	1.23916	-194.481	0.538541	-234.617
12	3	2.17022	-126.589	1.19347	-190.024	0.534575	-232.033
16	1	2.92106	-171.336	1.04037	-218.568	0.405086	-244.309
16	1.5	2.66564	-162.378	1.0374	-214.639	0.405052	-242.515
16	2	2.4814	-155.682	1.02794	-211.136	0.404214	-241.159
16	2.5	2.31698	-149.825	1.01309	-207.541	0.403332	-239.867
16	3	2.17202	-144.651	0.995596	-204.217	0.402578	-238.676

Table 3b: Database data

J/10	B	Mag1	Fase1	Mag2	Fase2	Mag3	Fase3
4	1	2.6746	-125.297	1.79022	-180.629	0.989218	-221.14
4	1.5	1.77295	-110.39	1.49478	-167.237	0.916567	-210.166
4	2	0.695943	-97.7064	0.996662	-153.567	0.849307	-201.419
4	2.5	0.573386	-94.1128	1.06923	-149.306	0.789635	-194.282
4	3	0.546804	-93.0729	0.485661	-126.711	0.737531	-188.299
8	1	2.61474	-169.578	1.2063	-216.937	0.54935	-246.144
8	1.5	2.24055	-158.235	1.15893	-209.083	0.544081	-241.943
8	2	1.98747	-149.661	1.10825	-202.368	0.537241	-237.839
8	2.5	1.78496	-142.778	1.05757	-196.489	0.529349	-233.889
8	3	1.61891	-137.027	1.00984	-191.35	0.520752	-230.147
12	1	2.06794	-188.796	0.837469	-228.929	0.360271	-250.356
12	1.5	1.91327	-179.58	0.831012	-224.72	0.360459	-248.385
12	2	1.79584	-172.928	0.821058	-220.806	0.360388	-246.325
12	2.5	1.68784	-167.169	0.809019	-217.086	0.359211	-244.129
12	3	1.59328	-162.306	0.795808	-213.571	0.357161	-241.682
16	1	1.64839	-197.36	0.634568	-234.822	0.262523	-252.148
16	1.5	1.599	-192.165	0.63431	-232.208	0.263625	-250.943
16	2	1.54376	-187.441	0.632822	-229.754	0.264482	-249.729
16	2.5	1.48812	-183.036	0.63041	-227.379	0.267983	-246.672
16	3	1.41268	-179.102	0.627119	-225.063	0.268751	-245.759

Table 3c: Database data

J/10	B	Mag1	Fase1	Mag2	Fase2	Mag3	Fase3
4	1	2.30435	-155.432	1.34389	-202.762	0.729246	-236.15
4	1.5	1.75764	-143.802	1.19672	-190.562	0.694227	-226.756
4	2	1.46539	-134.268	1.0749	-181.304	0.658557	-218.842
4	2.5	1.24321	-126.515	0.974055	-173.921	0.623996	-211.988
4	3	1.05873	-119.575	0.890096	-167.81	0.590342	-205.912
8	1	1.74741	-196.424	0.800775	-233.478	0.37953	-252.361
8	1.5	1.59163	-186.692	0.785816	-227.684	0.377651	-248.597
8	2	1.46714	-178.939	0.768332	-222.412	0.374142	-245.538
8	2.5	1.36609	-172.588	0.749183	-217.57	0.370842	-242.526
8	3	1.27612	-167.111	0.729291	-213.103	0.366509	-239.698
12	1	1.27229	-210.531	0.546219	-242.903	0.252041	-255.862
12	1.5	1.20753	-204.765	0.544517	-240.108	0.253264	-255.043
12	2	1.16342	-199.088	0.541939	-237.312	0.252438	-253.977
12	2.5	1.13264	-194.392	0.538631	-234.645	0.250191	-252.564
12	3	1.10846	-190.626	0.534576	-232.029	0.24936	-250.258
16	1	0.989041	-217.14	0.40513	-244.317	0.211469	-258.976
16	1.5	0.939164	-212.4	0.404896	-242.563	0.185839	-258.426
16	2	0.926884	-209.136	0.404357	-241.125	0.186544	-257.876
16	2.5	0.917435	-205.998	0.403286	-239.783	0.186443	-256.939
16	3	0.909402	-203.069	0.402598	-238.682	0.186211	-255.534

Table 4: Performance of the VSD

P_i	cps	Epochs	MSE	Gradient
J	0.6-1-1.4	390/500	0.35617/0	21.295/1e-6
B	0.6-1-1.4	100/500	0.02040/0	2.6004/1e-6
J	0.8-1.2-1.6	233/500	1.02925/0	7.6725/1e-6
B	0.8-1.2-1.6	152/500	0.05465/0	2.2189/1e-6
J	1-1.4-1.8	226/500	1.66875/0	3.3820/1e-6
B	1-1.4-1.8	120/500	0.05524/0	2.8037/1e-6

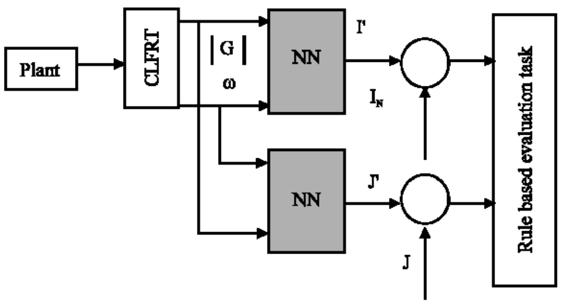


Fig. 10: Test to check the performance of inertia and friction load

corresponding to target J_L in the index MSE values, it is observed some differences, which indicate the degree of accuracy that can be expected.

If the number of parameters to be estimated is reduced (from two to one for instance), the accuracy of estimated parameters increases drastically. Nevertheless, our objective is to estimate as much as possible parameters with minimum data in the database, which imply estimating many parameters by penalizing its accuracy into a range of acceptable values.

In Table 4 it is observed that MSE from training results is variable for every CLFRT. Such value is an indication of the accuracy that can be expected.

Faults diagnostic task: The first task to be carried out is the on line parameter estimation on the basis of trained neural networks. The task of fault diagnosis consists of the determination of the type of fault with as many details as possible, such as the fault size, location and time of detection. Rule based inference methods are applied. Starting from some priory knowledge regarding the safety or normal plant parameters, J and I, every deviation from expected nominal values are considered as faults located at physical parts responsible for such deviations.

Figure 10 shows the case where the Inertia and friction loads are to be checked. In this task it is assumed that the rest of plant parameters remain constant.

Fault isolation is carried out by means of a rule based procedure. If residuals arising from estimated inertia and friction loads increases over a predetermined value, obviously, it is an indication of a fault associated with parameters involved in such residual. So that, isolation of faults on the basis of residuals is a deterministic task.

RESULTS AND DISCUSSION

There are shown three databases in appendix I, achieved as results of applying the CLFRT under three frequency ranges. In Fig. 11-13 there are shown the three parameter estimators corresponding to the three frequency ranges. Such parameter estimators are shown for comparison purposes although in practice only one of them is to be applied. Both parameter estimators supply the estimated values as function of input data. The results of comparing the estimated values with the nominal ones, yields the residuals, which are used to detect the associated faults. Consequently, if a fault is detected, then the faulty parameters give us an indication of the fault location. In Fig. 11-13 the results of parameter estimation, as well as the corresponding residuals. It is observed that no relevant differences appear between both residuals, which means that the servo-system is operating free of faults related with the inertia and friction.

Previous to the described application, several experiments were carried out to validate the proposed methodology. Some of them were performed under simulation for systems of type 1 and 2. It must be noted that for plants described by type zero models, with large damping coefficients no advantages of the method are detected because conventional methods are quite effective.

The aim of this research was to develop and implement a method to detect and isolate faults on the basis of parameter variation detection in processes even when under faulty measuring systems (output sensor drift). Furthermore, the method is focused towards plants of type 1 and 2 where conventional FDI methods don't solve effectivelly such problems.

Pointing towards contributions, the following were achieved:

- The estimation of plant parameters by means of the application of a series of CLFRT.
- The application of the CLFRT even under faulty measuring system (drfit).
- The possibility of increasing parameter estimates accuracy by increasing the number of series of CLFRT, which means increasing the database size.

The most relevant advantages of this strategy are:

- FDI method doesn't depend on the quality of measuring system in cases of sensor drift.
- The on-line test can be applied with the plant operating under nominal setpoints, without disturbing or interrupting operation or production.

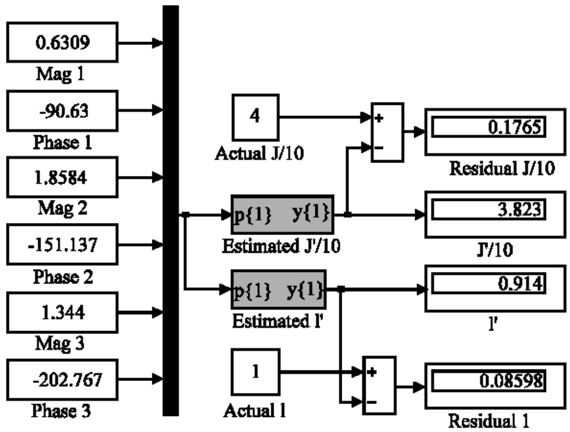


Fig. 11: Identification results for database of Table 3a

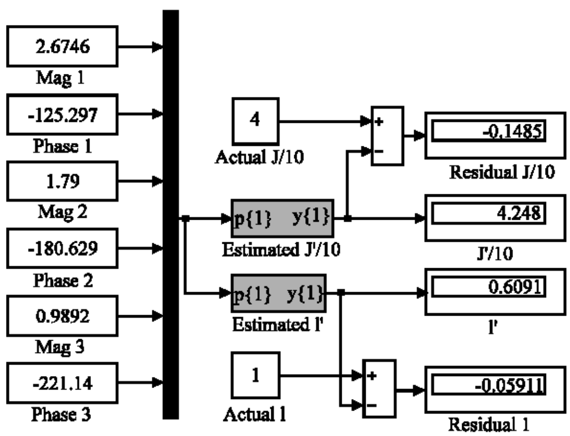


Fig. 12: Identification results for database of Table 3b

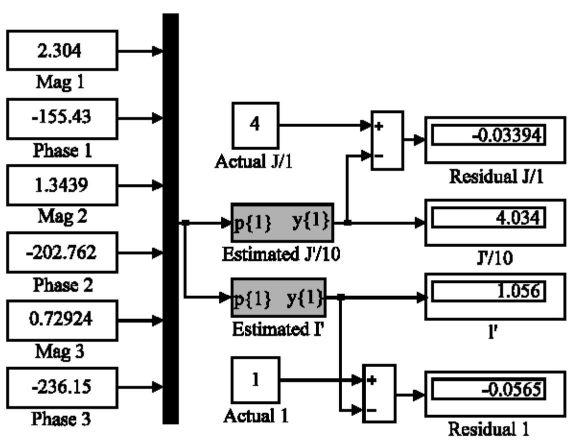


Fig. 13: Identification results for database of Table 3c

- The strategy is useful under partially known model structures.

The most relevant disadvantages are:

- The time necessary to estimate the parameters increase, as does both the accuracy and number of parameters to be estimated.
- The computational effort increases with the required accuracy and number of parameters.

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