COMPARISON OF TWO FREQUENCY BASED PI METHODS ON SHIPS DYNAMICS

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Abstract: Most of non-linear type one and type two control systems suffers from lack of detectability when model based techniques are applied on fault detection and isolation (FDI) tasks. This work is focused on frequency techniques applied to identify ship's model parameters (PI) including non structured or partially known structured model using backpropagation neural networks as functional approximators. The results of the comparison of two strategies based in frequency techniques are presented. Such frequency techniques are:
-Mapping the frequency response associated to system parameters when a closed loop controlled ship is excited by the well known harmonic balance test (HBT).
-Mapping the frequency response associated to system parameters when closed loop controlled ship is excited by a group of sinusoidal inputs added to the manipulated variable (CLFRT).
With achieved frequency response mappings, system parameters are associated by means of functional approximation techniques. In this case, Feedforward neural networks trained with backpropagation conjugate gradient algorithm are massively used. Finally, PI results will be used in FDI tasks, where nominal plant parameters will be matched against on-line estimated parameters on a parity space approach.

Keywords: Backpropagation, Conjugate gradient, Parameter identification, Fault detection, Frequency response, Harmonic balance, Neural Networks.

1. FREQUENCY BASED PARAMETER ESTIMATION TECHNIQUES

1.1 Introduction.

This research work is focused on the problem of fault detection, fault isolation 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.

Conventional 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, the method described below, in this section, is proposed.

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, R. (1984, 1992, 1993), Mosler et all. (2001). 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.

Among the most important work in the field of parameter identification carried out on frequency techniques is Eugene A. Morelli (2002), Lucas et. all. (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 J. Schwarz et. all., (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 [18] Douwe K. de Vries et. all (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.

1.2 Process Characteristics Based on HBT

The output of a nonlinear system under the effect of a disturbance or a step input may go into a steady-state oscillation about an equilibrium point and still be considered stable. Such an oscillation is called a limit cycle and is a periodic though not sinusoidal oscillation whose amplitude and frequency are dependent only upon the magnitude of the input and the characteristics of the system for non linear systems and are dependent only upon the characteristics of the system for linear systems.

The ultimate amplitude and frequency are particular characteristics of all transfer functions. HBT is a procedure formerly used in process controllers auto-tuning which is an attractive technique for determining the real time ultimate frequency and gain of a process. 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 values of ultimate frequency and ultimate amplitude is observed, this means that some parameters of transfer function has changed. The method requires a relay feedback or a closed loop controlled by a relay around the setpoint as shown in figure 1.

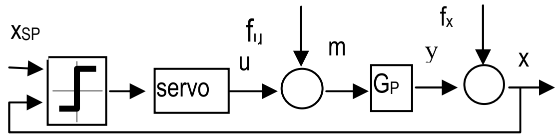

Fig. 1. Structure of the Harmonic Balance Test

With regard to figure 2, a relay of height h is inserted as a feedback controller. The manipulated variable m is increased by h above the steady-state value. When the controlled variable x crosses the setpoint, the relay reduces m to a value h below the steady-state value. The system will respond to this "bang-bang" control by producing a limit cycle, provided the system phase angle drops below -180°, which is true for all real processes.

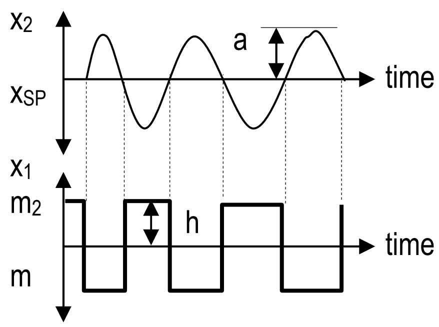

Fig. 2. Input output signals of Harmonic Balance test

The period of the limit cycle is the ultimate period (P_u) for the transfer function relating the controlled variable x and the manipulated variable m. So the ultimate frequency is given as

$$\omega_u = \frac{2\pi}{P_u} \tag{1}$$

A series Fourier expansion of the relay output shows that the amplitude of first harmonic component is $\frac{4h}{\pi}$, and the error signal has the amplitude

$$a = \frac{4h}{\pi}\left|G(i\omega_u)\right| \tag{2}$$

The condition for sustained oscillation (limit cycle) is that

$$\arg G(i\omega_u) = -\pi \text{ and } K_u = \frac{1}{\left|G(i\omega_u)\right|} \tag{3}$$

Consequently the ultimate amplitude of the transfer function is given by

$$a = \frac{4h}{\pi K_u} \quad (4)$$

where h = height of the relay, a = amplitude of the primary harmonic of the output x.
It follows that if any change in system parameters takes place, then the ultimate frequency, ultimate amplitude, or both, will change also. Such concept can be defined as a function of ultimate frequency and ultimate amplitude of primary harmonic of the output. This property is expressed as:

$$(\omega_u, a) = f(P_i); \quad i = 1, \cdots M \quad (5)$$

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

$$(\omega_u, a) = f(P_{iN}) = \omega_{uN}, a_{uN} \quad (6)$$

where ω_{uN} and a_{uN} are the nominal ultimate frequency and amplitude respectively corresponding to the nominal parameters set P_{iN}.

It should be noted that Eq. (5) and (6) give us approximate values for ω_u and a_u because the relay feedback introduces an additional nonlinearity into the system. However, for most systems, the approximation is close enough for engineering purposes.

1.3 Process Characteristics Based on CLFRT .

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.

$$H(f) = \int_{-\infty}^{\infty} h(\tau) e^{-j2\pi f \tau} d\tau \quad (7)$$

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.The selected excitation signal for this study is of the type given as,

$$f(\omega t) = \sum_{i=1}^{n} A_i Sin(\omega_i t) \quad (8)$$

with three relevant frequencies and same amplitude yielding

$$f(\omega t) = A_1 Sin(\omega_1 t) + A_2 Sin(\omega_2 t) + A_3 Sin(\omega_3 t) \quad (9)$$

Excitation function can be applied simultaneously or sequentially. Obviously when simultaneously, the CLFRT is faster than sequentially in detriment of accuracy. For proper measurement, it is also important to take into account the nature of the type of signals that we are dealing with. To account for all of the above, it can be used digital signal processing techniques, including FFT and cross spectral methods.

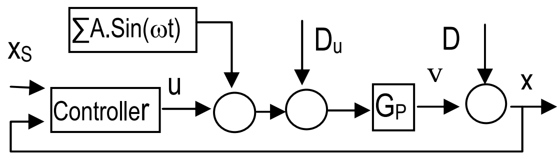

Fig. 3. Structure of the CLFRT

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. Figure 3 shows the structure of CLFRT.

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 figure 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 $(|G|_\omega, \phi_\omega) = f(P_i); \quad i = 1, \cdots M$, 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

$$(|G|_\omega, \phi_\omega) = f(P_i) = |G|_{\omega N}, \phi_{\omega N} \quad (10)$$

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

1.4. Advantages of both methods

These methods has several distinct advantages over conventional parameter estimation methods:
a). It doesn't depend on the output measuring errors (drift of system output sensors)

b). 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 or the relay eight for HBT.
c) They are closed loop tests, so the process will not drift away from the setpoint. This is precisely why the methods works well on highly nonlinear processes. The process is never pushed very far away from the steady-state conditions

1.5. Achieving a consistent database

To fulfil the requirements for training a feedforward backpropagation neural network, a database ship parameters P_{ij} and the associated pairs of (a_{Uj}, P_{Uj}) must be achieved.

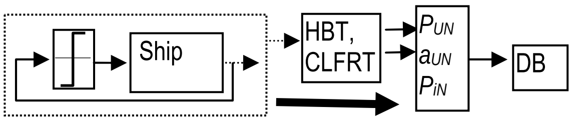

Fig.4. HBT to achieve the necessary data to be used in NN training.

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 4 shows the implementation of HBT or CLFRT to achieve the actual demanded data.

The simplest way 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 figure 5.

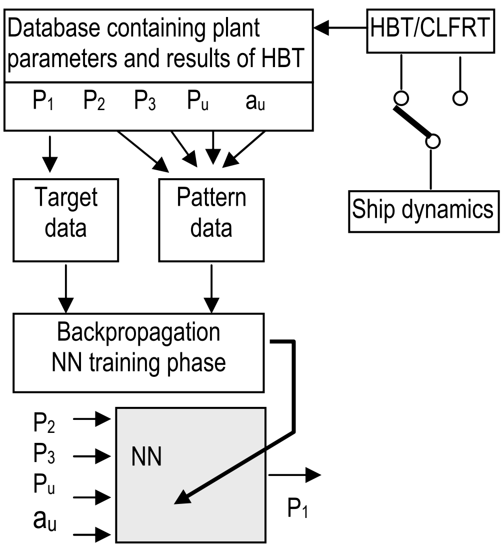

Fig. 5 . Necessary tasks to achieve a neural network ship parameter estimator.

Figure 5 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.

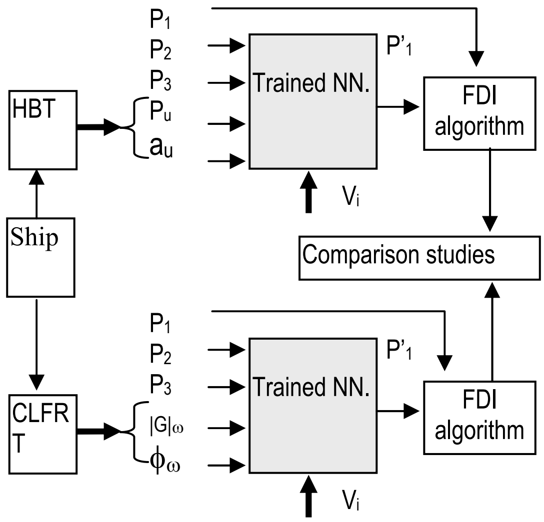

Fig. 6. Scheme of parameter estimation, diagnostic tasks and comparison of methods.

Figure 6 shows a parameter estimator, which consists in group of trained neural networks as shown in figure 4, ready to identify one or more plant parameters, 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 HBT or CLFRT to obtain the actual pair of ultimate gain and period or alternatively frequency response data. By introducing such actual values including the rest of known parameters to the neural network inputs, it yields at the output, the actual value of the plant unknown parameter. The accuracy in the value of the estimated parameter is crucial because it will be applied directly on successive applications such as diagnostic tasks.

2. APPLICATION OF THE PI METHOD TO A NOMOTO MODEL

In order to validate the PI methods by comparison of model parameters accuracy, the most simple model of a ship is selected. The transfer function from rudder angle δ to heading ψ is described under a Nomoto model as

$$G(s) = \frac{\psi(s)}{\delta(s)} = \frac{b}{s(s+a)} \qquad (11)$$

where according with Äström and Wittenmark (1989), model parameters can be approached as

$$a = a_0 \frac{u}{l} \text{ and } b \approx 0.5\left(\frac{u}{l}\right)^2 \frac{Al}{D}, \qquad (12)$$

with l the ships length in m, u the ship velocity in m/s, A the rudder area in m^2 ,and D, the ships displacement in m^3. According described Nomoto model, the parameters a and b depends on the ship velocity u and ship displacement D. The rudder servo operates with a speed of 4 degrees/s limited to ± 30 degrees. The ruder area is assumed to be 20 m^2. Consequently, the simulation model necessary to validate both parameter identification procedures is of the type

$$G(s) = \frac{0.5\left(\frac{u}{l}\right)^2 \frac{Al}{D}}{s(s + a_0 \frac{u}{l})} \qquad (13)$$

The simplified servo model is shown in figure 7.

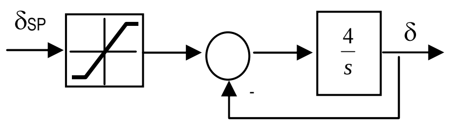

Fig. 7. Simplified rudder-servo model

Frequency responses are achieved on the basis of proposed model used in simulation. Acquired data to achieve the necessary database uses ship velocities from 4 to 10 m/s while ship displacement varies from 4000 to 10000 tons on the container ship.

2.1. Training procedure

Following the scheme depicted with figure 5, the data of a consistent database achieved on the basis of Nomoto model is 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') (14)

which consists of a feedforward Backpropagation NN with two hidden layers and ten neurons per layer, trained by means of ,'traincgf' algorithm, a conjugate gradient algorithm.

The number of hidden layers and neurons per layer is selected so that the training results are satisfactory, that means no performance is gained bay augmentation of hidden layers or neurons per layer. After several training sessions with different data structures from the database, some of the training results are shown in table I. In order to validate the trained neural networks, some indexes are presented in the above table.

Table I. NNs Training results

Training algorithm	Epochs	MSE	Gradient	Test
Traincgf-srchcha	100/100	0.0989	5.426e-6	CLFRT
Traincgf-srchcha	100/100	0.1209	2.979e-6	HBT

Mean Square Error (MSE) is an acceptable performance index to evaluate the estimates accuracy of training results as shown in table I. By comparing the values of rows corresponding to the index MSE, some differences are observed, which indicates the degree of accuracy that could be expected when on-line parameter estimation method is applied. For CLFRT, MSE = 0.0989 and for HBT MSE = 0.12088. Consequently, CLFRT procedure is more effective than HBT.

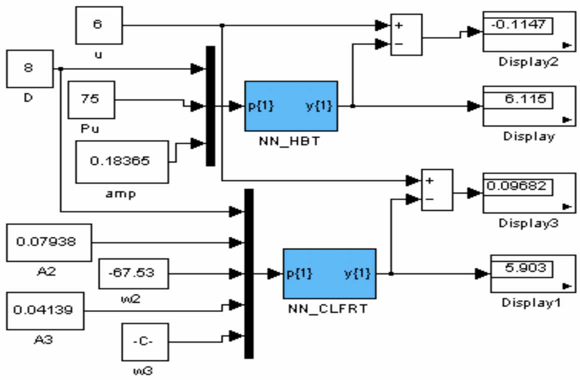

Fig. 8. Implementation of both PI methods for comparisson purposes.

3. SOME RESULTS

Figure 8 shows both PI methods ready to be used on parameter identification. The results of a PI session shows that the accuracy of parameters achieved by using CLFRT is better than using the HBT, according with the MSE value of table I. Consequently, with acceptable parameter identification values, the residuals of the parity space approach are achieved. FDI task will be then carried out using for instance an residual analysis into a parity space approach, followed by a decision-making rule based task.

4. CONCLUSIONS

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 type 2 where conventional PI methods are not quite effective.

The most relevant advantages of these strategies are:

- PI method when applying HBT and CLFRT doesn't depend on the quality of measuring system in cases of sensor drift.
- The on-line test can be applied with the ship operating under nominal setpoints, without disturbing or interrupting the ship course for instance.
- The strategy is useful under partially known model structures.

The most relevant disadvantages encountered are:

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

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