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COMPARISON OF TWO PI METHODS APPLIED TO FDI 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 research is centred on frequency techniques applied to identify ship's model parameters (PI) including non-structured or partially known structured models 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, Feed-forward neural networks trained with backpropagation conjugate gradient algorithm are massively used. Finally, PI results are used in FDI tasks, where nominal plant parameters are 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.

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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 modelling 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, A. S. (1976), Isermann, R. (1984), Frank, P. M. (1987a), Gertler, J. J. (1988), Patton, R. J. and Chen, J. (1991). Among the classic books on the subject are those of Himmelblau, D. M. (1978), Pau, L. F. (1981), Basseville M. (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 section a brief list on process model based fault detection methods is given:

1. Fault detection with parameter estimation Gertler, J. J. (1988) Isermann, R. (1992), Isermann, R. (1993), Mosler, O., Heller and R. Isermann (2001), Newmann, D. (1991).
   – Equation error methods
   – Output error methods
   – Frequency techniques

2. Fault detection with state-estimation.
   (a) Dedicated observers for multi-output processes.
   – State Observe, excited by one output Clark, R. N. (1978a):
   – Kalman filter, excited by all outputs] Mehra, R. K. and Peschon, J. (1971):, Willsky, A. S. (1976),.
   – Bank of state observers, excited by all outputs Willsky, A. S. (1976),
   – Bank of state observers, excited by single outputs Frank, P. M. (1987a)

– Bank of state observers, excited by all outputs except one Frank, P. M. (1987a).
(b) Fault detection filters for multi-output processes Beard, R. V. (1971).

3. Fault detection with parity equations Isermann, R. (1984), Gertler, J. J. (1991):, Patton, R. J. and Chen, J. (1994):.
   (a) Output error methods.
   (b) Polynomial error methods.

4. Fault detection using analytical redundancy Ragot J., Maquin D., Kratz, F., 2000.
   (a) Static analytical redundancy.
   (b) 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 optimisation 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. 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

Goals to be achieved

Afore-mentioned diagnosing techniques, when applied to non-linear type one and type two processes, suffer from lack of detectability. For this reason the following work will be oriented to the problem of fault detection, fault isolation, and fault estimation by a novel parameter estimation method using 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:

— Implementation of a fault tolerant data acquisition method by means of frequency based techniques to achieve a consistent database

— Implementation of two PI methods based on the association of frequency responses with functional approximation

— Comparison of both methods on a ship model steering process

Subsequent sections are devoted to the description of such technique, resulting in an interesting complement or substitute to some conventional mentioned techniques.

FREQUENCY BASED PARAMETER ESTIMATION TECHNIQUES

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 non-linear 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 methods described below, in this section, are proposed.

Process Characteristics Based on HB Tests

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. HB 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 have changed. The method requires a relay feedback or a closed loop controlled by a relay around the setpoint as shown in figure 1.

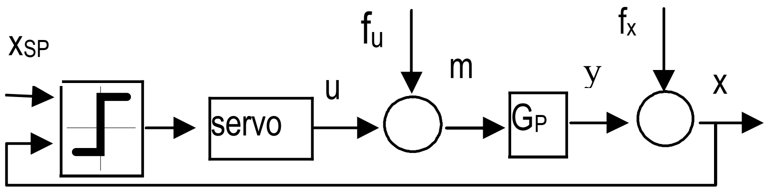

Fig. 1. Structure of the HBT

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.

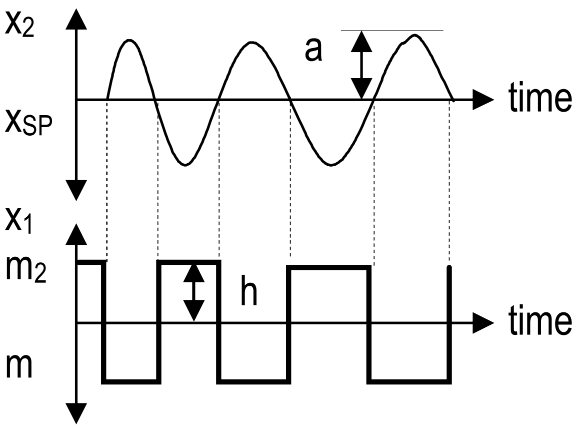

Fig. 2. Input output signals of HBT

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

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

Consequently the ultimate amplitude of the transfer function is given by

$$a = \frac{4h}{\pi K_u} \tag{4}$$

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:

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

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

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

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.

Nevertheless, when systems transfer functions are 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 (6) can be rearranged as follows:

$$(\omega_u, a) = f(P_i, V_i); \tag{7}$$

If the relay of height *h* inserted as a feedback controller is externally forced to change its eight to a new value, which means to change the manipulated variable, then a different pair of ultimate period and amplitude is achieved. Such idea is expressed as

$$\begin{aligned} & m_1 \Rightarrow h_1 \Rightarrow (\omega_{u1}, a_1) \\ & m_2 \Rightarrow h_2 \Rightarrow (\omega_{u2}, a_2) \\ & \vdots \\ & m_i \Rightarrow h_i \Rightarrow (\omega_{ui}, a_i) \end{aligned} \tag{8}$$

Consequently, the application of (5) yields

$$\begin{vmatrix} (\omega_{u1}, a_1) \\ (\omega_{u2}, a_2) \\ \vdots \\ (\omega_{ui}, a_i) \end{vmatrix} = f(P_i, V_i) \tag{9}$$

Expression (8) states any pair of ultimate period and amplitude of the group described by (9) is function of the complete set of plant parameters and related external variables (coupling variables).

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.

$$H(f) = \int_{-\infty}^{\infty} h(\tau) e^{-j2\pi f\tau} d\tau \tag{10}$$

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. Using random noise excitation best minimizes noise and non-linearity, but short impulses or rapid sweeps (chirps) may also be used. The selected excitation signal for this study is of the type given as

$$f(\omega t) = \sum_{i=1}^{n} A_i Sin(\omega_i t) \tag{11}$$

with two or three relevant frequencies and same amplitude yielding for the case of three relevant frequencies

$$f(\omega t) = A_1 Sin(\omega_1 t) + A_2 Sin(\omega_2 t) + A_3 Sin(\omega_3 t) \tag{12}$$

Excitation function can be applied simultaneously or sequentially. Obviously when simultaneously, the CLFRT is faster that sequentially but under noisy systems accuracy is poorer.

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 work.

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, 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, including FFT and cross-spectral methods.

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 figure 3.

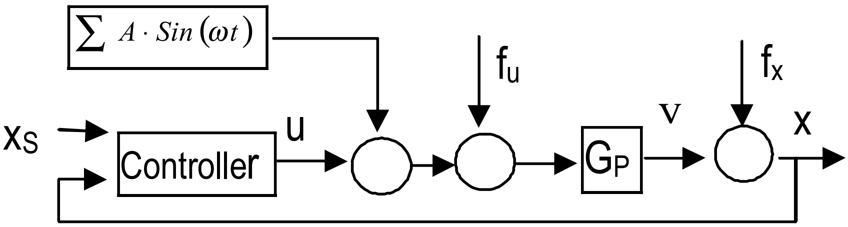

Fig. 3. Structure of the CLFRT

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

$$(|G|_{\omega}, \phi_{\omega}) = f(P_i); \quad i = 1, \cdots M \tag{13}$$

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

$$(|G|_{\omega}, \phi_{\omega}) = f(P_i) = |G|_{\omega N}, \phi_{\omega N} \tag{14}$$

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. (13) and (14) 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, (13) can be rearranged as follows:

$$(|G|_{\omega}, \phi_{\omega}) = f(P_i, V_i) \tag{15}$$

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

$$\begin{aligned} &A_1, \omega_1 \Rightarrow (|G|_{\omega 1}, \phi_{\omega 1}) \\ &A_2, \omega_2 \Rightarrow (|G|_{\omega 2}, \phi_{\omega 2}) \\ &\vdots \\ &A_n, \omega_n \Rightarrow (|G|_{\omega n}, \phi_{\omega n}) \end{aligned} \tag{16}$$

for identification purposes the amplitude of the excitation signal can be selected 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 (15) yields

$$\begin{vmatrix} (|G|_{\omega 1}, \phi_{\omega 1}) \\ |G|_{\omega 2}, \phi_{\omega 2}) \\ \vdots \\ (|G|_{\omega n}, \phi_{\omega n}) \end{vmatrix} = f(P_i, V_i) \tag{17}$$

Expression (17) states that any pair of amplitude and phase is function of the complete set of plant parameters and related external variables (coupling variables).

Advantages of the 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 set-point. 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

GENERAL PROCEDURE

To fulfil the requirements for training a feedforward backpropagation neural network, a database for every PI method is needed. For the case of HBT, a database relating ship parameters P_{ij} and the associated pairs of (a_{Uj}, P_{Uj}) must be achieved. Figure 4(a) shows the implementation of HBT to achieve the actual demanded data. For the case of CLFRT, a database relating ship parameters with the magnitude and phase responses are needed. 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(b) shows the implementation of CLFRT to achieve the actual demanded data

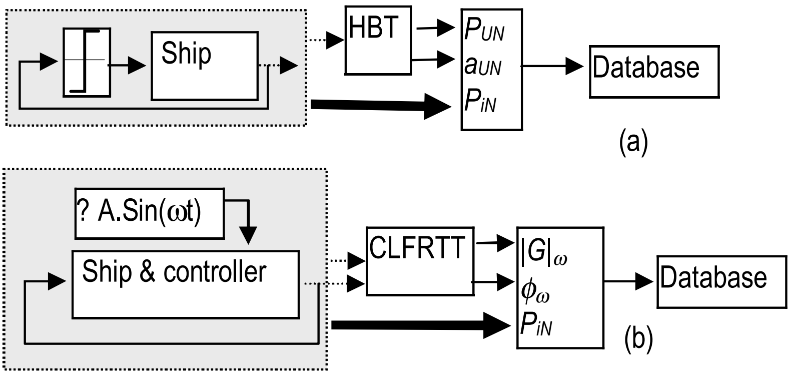

Fig .4. Tasks to achieve the necessary data to be used in NN training. (a), HBT. (b) CLFRT.

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 figure 5. Figure 5 illustrates the case of a plant with known model structure and three (but could be any other quantity) accessible (known by any means) parameters P_1, P_2 and P_3. It shows a ship in which an HBT is executed. As consequence of applied HBT, a database is filled with achieved data. With the recent data contained into the database, a training session is performed and a NN based model for the patter parameter is achieved. The same sequence can also be performed under CLFRT in the same order that for HBT.

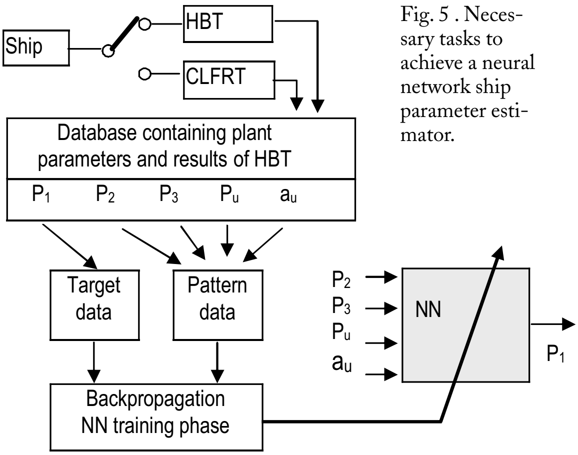

Fig. 5 . Necessary tasks to achieve a neural network ship parameter estimator.

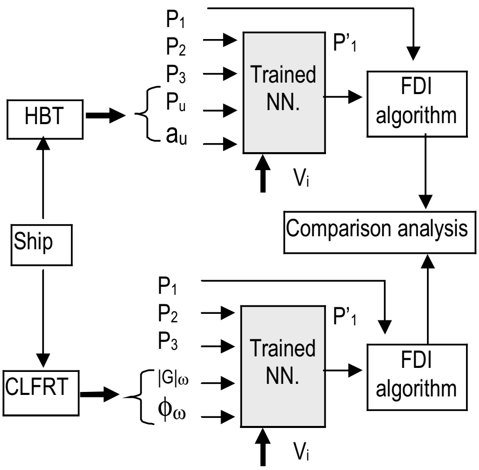

Fig. 6. Scheme of paramostic tasks and comparison of PI methods.

Figure 6 shows the scheme adopted for comparison purposes on the basis of parameter estimation, which consists in a group of trained neural networks, ready to identify one or more plant parameters, w hen real time or actual data is applied to the inputs. So that, the tasks necessary to identify at least a plant parameter, requires again the on line HBT or CLFRT tasks to obtain the actual pair of ultimate gain and period or alternatively, the 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 straightaway applied on the last phase of the FDI task.

APPLICATION TO PI USING A NOMOTO MODEL

In order to validate the PI methods by comparison of model parameters accuracy, one of the simplest models of a ship is selected Ferreiro García R., Haro Casado M.(2006),. The transfer function from rudder angle δ to heading ψ is described for our purposes under a Nomoto model as

$$G(s) = \frac{\psi(s)}{\delta(s)} = \frac{b}{s(s+a)} \tag{18}$$

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

$$a = a_0 \frac{u}{l} \quad \text{and,} \quad b \approx 0.5\left(\frac{u}{l}\right)^2 \frac{Al}{D} \tag{19}$$

with l the ships length in m, u the ship velocity in m/s, A the rudder area in m^2, and D, the ship's 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 as 20 m^2. Consequently, the simulation model necessary to validate both the parameter identification procedures is of the type

$$G(s) = \frac{0.5\left(\frac{u}{l}\right)^2 \frac{Al}{D}}{s(s + a_0 \frac{u}{l})} \tag{20}$$

where the servo model is shown in figure 7.

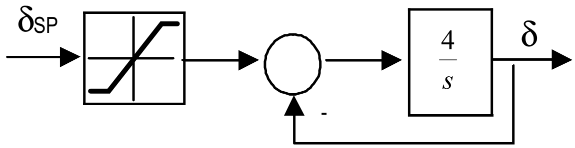

Fig. 7. Simplified rudder-servo model

The closed loop controller is an adaptive PID adjusted by gain scheduling to adapt its parameters as function of ship displacement under the criterion of minimum overshoot and response time. According such requirements, the PID parameters are shown in able I.

$D/10^3$ PID	4	6	8	10
Kp	4	3.4	2.9	2.6
Ti	120	135	160	190
Td				

Table I. PID parameters as function of displacement

Training procedure

Both PI methods are then applied by simulation on the closed loop model, and consequently, two databases shown in tables II and III were achieved. Input 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, where rudder area is 20 m^2.

u	$D/10^3$	$\lvert G\rvert_{\omega 1}$	$\phi_{\omega 1}$	$\lvert G\rvert_{\omega 2}$	$\phi_{\omega 2}$
4	4	0,0801045	-68,0906	0,0416869	-89,5841
4	6	0,0815297	-73,8223	0,0415882	-95,779
4	8	0,0820465	-78,9383	0,0407358	-103,086
4	10	0,0813522	-83,8892	0,0394238	-109,301
6	4	0,07857	-63,2443	0,0413649	-81,0538
6	6	0,0788952	-65,1473	0,041328	-84,9855
6	8	0,0793861	-67,5302	0,0413907	-87,3135
6	10	0,0797526	-70,0747	0,041473	-90,4957
8	4	0,0779755	-61,4826	0,041303	-79,5276
8	6	0,0781531	-63,0128	0,0413122	-80,7345
8	8	0,0784074	-63,4854	0,0412631	-81,2487
8	10	0,0786551	-64,0515	0,0411353	-84,4931
10	4	0,0778708	-59,4287	0,0414477	-76,4577
10	6	0,0777866	-61,1995	0,0412255	-79,3707
10	8	0,0778946	-62,6008	0,0412056	-80,3609
10	10	0,0779463	-63,2211	0,0411875	-80,8526

Table II. Database for CLFRT method

The data of such consistent databases 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')

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

After several training sessions with different data structures from the database, some of the training results are shown in table IV.

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 expected to be more effective than HBT.

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

u	$D/10^3$	Pu	a
4	4	88.2353	0.181148
4	6	93.75	0.163727
4	8	93.75	0.109534
4	10	88.2353	0.0852799
6	4	68.1818	0.338723
6	6	75	0.270966
6	8	75	0.18365
6	10	75	0.157505
8	4	62.5	0.399597
8	6	62.5	0.282363
8	8	62.5	0.233929
8	10	62.5	0.174988
10	4	55.5556	0.623681
10	6	55.5556	0.351874
10	8	55.5556	0.290567
10	10	55.5556	0.245539

Table III. Database for HBT method

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

Table IV. Training characteristics

approach are achieved in the FDI tasks. FDI task is then carried out using simple rules in a rule based task. Residuals necessary to implement the last phase of FDI task, are achieved by comparing the actual ship velocity with the estimated one. As consequence of such comparison, display 2 and display 3 of figure 8 shows respectively –0.1147 and 0.09682. Under the assumption of a fault free process, then CLFRT method is more accurate than HBT.

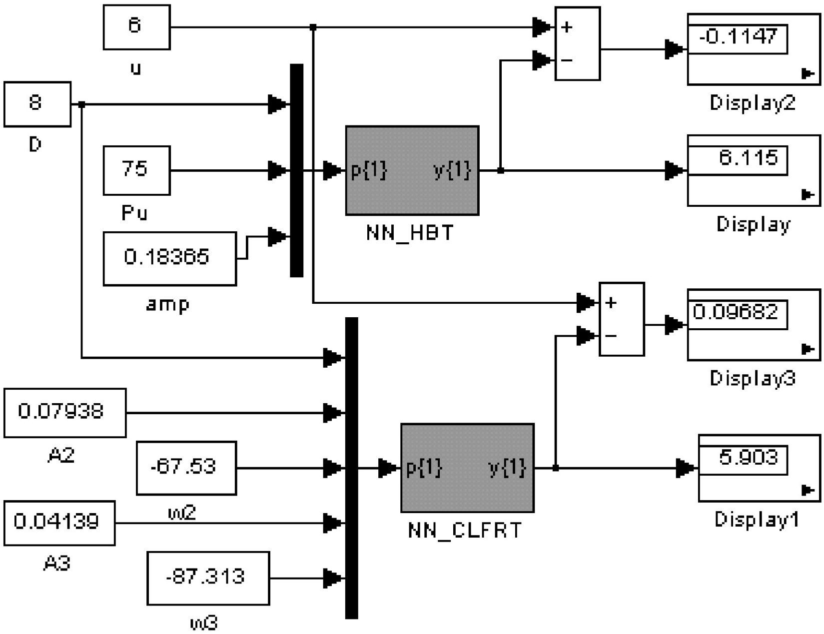

Fig. 8. Implementation of both PI methods for comparison purposes.

CONCLUSIONS

The aim of this research was to compare both PI strategies which consists in develop and implement a method to detect and isolate faults on the basis of parameter variation detection on a ship 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.

As a result of comparison of both methods, CLFRT is more accurate than HBT, and hence, FDI task is more reliable.

The most relevant disadvantages of both frequency based methods are due to:

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

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COMPARACIÓN DE DOS MÉTODOS DE IDENTIFICACIÓN DE PARÁMETROS APLICADOS A LA DETECCIÓN Y AISLAMIENTO DE FALLOS EN LA DINÁMICA DE BUQUES

Resumen

La mayor parte de los sistemas no lineales de los tipos uno y dos sufren de escasez de detectabilidad al aplicar métodos de detección y aislamiento de fallos basados en modelos. Este trabajo está centrado en técnicas frecuenciales aplicadas para identificar parámetros del modelo de un buque incluyendo modelos no estructurados o parcialmente estructurados, utilizando aproximadoRes funcionales basados en redes neuronales por propagación hacia atrás. Se presentan los resultados de la comparación entre dos estrategias de identificación basadas en técnicas frecuenciales. Tales técnicas frecuenciales consisten en:

—Mapear la respuesta frecuencial asociada con los parámetros del buque cuando al aplicar el método del balance armónico en lazo cerrado (HBT).

—Mapear la respuesta frecuencial asociada con los parámetros del buque cuando se añade una señal de excitación a la salida del controlador por realimentación (CLFRT).

Las citadas respuestas frecuenciales acumuladas en una base de datos asociadas a los parámetros del buque, proporcionan los aproximadores funcionales para la identificación de parámetros. Se utilizan masivamente redes neuronales artificiales entrenadas por propagación hacia atrás mediante el algoritmo del gradiente conjugado. Finalmente, los resultados de las tareas de identificación de fallos son utilizados en la detección y aislamiento de fallos en línea y los resultados de ambos métodos de identificación son comparados entre sí para establecer baremo de calidad.

INTRODUCCIÓN

Este trabajo comienza describiendo los antecedentes de los métodos de detección y aislamiento de fallos en base a la estimación de parámetros. A continuación se describen dos métodos frecuenciales (HBT y CLFRT) de estimación de parámetros del buque en base a la utilización de redes neuronales como aproximadotes funcionales. Seguidamente, se realiza una aplicación de la identificación de parámetros utilizando los métodos frecuenciales propuestos con el modelo de Nomoto y posteriormente se comparan los resultados de ambos métodos para establecer un baremo de calidad.

RESULTADOS

La figura 8 muestra ambos métodos de identificación de parámetros listos para identificación. Los resultados de una sesión de identificación muestran que la precisión en la determinación de los parámetros conseguida mediante el método CLFRT es mejor que la conseguida mediante HBT, de acuerdo con el criterio MSE (mean square error) de la tabla I. En consecuencia, se aplican las técnicas de detección y aislamiento de fallos o anomalías con valores aceptables de identificación de parámetros que proporcionan los correspondientes residuos dentro del espacio de paridad. La tarea de detección y aislamiento es llevada a cabo por medio de razonamiento basado en reglas. Los residuos necesarios para implementar la última fase de aislamiento de anomalías se llevan a cabo comparando la velocidad real del buque con la velocidad estimada por el modelo dependiente de los parámetros estimados. Como consecuencia de tal comparación, se han obtenido resultados de los residuos de -0.1147 para HBT y 0.09682 para CLFRT, constatando que es de mayor calidad el método de CLFRT frente a HBT, bajo la suposición de un ensayo en condiciones nominales o libre de fallos.

CONCLUSIONES

El objetivo de este trabajo consistía en comparar ambos métodos de identificación de parámetros posteriormente utilizados para la detección y aislamiento de anomalías en base a modelos, aún ante fallos de medida de los sensores de salida debidos a desvíos de la misma (drift).

Además, el método está enfocado hacia plantas de los tipos uno y dos donde exhiben inherentemente falta de detectabilidad. Tal, es el caso de los buques.

Las ventajas más relevantes de tales estrategias son:

— Los métodos de identificación de parámetros basados en técnicas frecuenciales como HBT y CHFRT no dependen de la calidad de la medida cuando ésta está afectada de desvío constante.

— Las pruebas en línea pueden ser aplicadas con el buque operando en condiciones normales y dentro del punto de consigna nominal sin perturbar sus tareas de operación.

— Estas estrategias pueden ser utilizadas con estructuras de modelos parcialmente conocidas

Como resultado de las comparaciones de calidad de ambos métodos, se tiene que CLFRT es más preciso que HBT y por consiguiente, las tareas de detección y aislamiento resultan mas eficaces con el método CLFRT

Las desventajas mas relevantes de tales técnicas de identificación se enumeran a continuación como:

— El tiempo necesario para estimar los parámetros del modelo aumenta con la precisión requerida y el número de parámetros a determinar

— El esfuerzo computacional aumenta con la precisión requerida y el número de parámetros a ser estimados