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TRENDS ON MODELLING TECHNIQUES APPLIED ON SHIP'S PROPULSION SYSTEM MONITORING

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ABSTRACT

The aim of the work deals with some aspects regarding modelling techniques using analytical redundancy usually applied in fault detection, fault isolation, decision making and system recovery when monitoring severe or critic control systems such as ship propulsion systems, in order to achieve fault tolerant control systems. To get such modelling objectives, back-propagation neural networks are used as universal functional approximation devices or soft sensors whose outputs are compared with real-time data to achieve residuals.

Keywords: Neural networks, Back propagation, Residual generation, Functional redundancy.

INTRODUCTION TO THE STRUCTURE OF THE SHIP PROPULSION SYSTEM

Low performance of ship propulsion system associated to automation system can cause a relevant reduction in the ship's ability to propel and manoeuvre itself, which requires effective means to prevent faults, avoiding to develop into a failure. Several algorithms and methods from different research areas can be used to analyse the system and subsequently detect, isolate, and decide about the faults to recover the system. The ship propulsion system described was presented as an international benchmark by (M. Blanke, et al. 2003), (D. Herrmann, 2000) and was used as a platform for development of new ideas and comparison of methods.

The topics treated in this paper are based in the increasing demand of modeling strategies focused on structural analysis. It is shown how residual generators

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are directly deduced from analysis of structure and how functional redundancy can be obtained. The dynamics of the propulsion system is non-linear. Furthermore, some essential faults are non-additive. The implication is that some residual generators become nonlinear. This work illustrates how such real-life phenomena can be handled in the general framework at modeling level. Detailed modeling and data recorded from maneuvering trials with the ferry give a realistic scenario for test of diagnostic methods and techniques to obtain fault tolerance.

Ship propulsion system

An outline of the propulsion system chosen for the benchmark is shown in figure 1 (of table 1 for a list of symbols) (R. Izadi-Zamanabadi and M. Blanke, 1998,1999).

The main components are described by the following blocks:

— *Diesel dynamics* gives engine torque to drive the propeller shaft.
— *Shaft dynamics* provides shaft speed given diesel and propeller torques.
— *Propeller characteristics* provide propeller thrust and load torque from shaft speed n, propeller pitch ϑ and water speed V_a (speed of advance).
— *Ship speed dynamics* determines ship speed from propeller thrust and external forces.
— *Propeller pitch and shaft speed controllers* (governor) control the propeller pitch and shaft speed.

The coordinated control level calculates set-points for shaft speed and propeller pitch controllers.

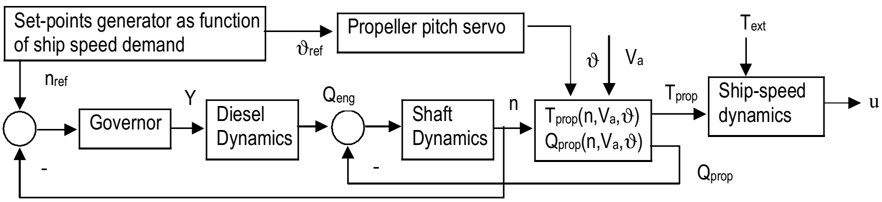

Fig. 1. Block diagram of the generic ship propulsion system

Symbol	Unit	Explanation
I_t	Kgm^2	Total inertia I
K_y	Nm	Torque coefficient
n	rads^{-1}	Shaft speed
$R(u)$	N	Hull resistance
T_{prop}	N	Propeller thrust
T_{ext}	N	External force
$1 - t$	-	Thrust deduction factor

Symbol	Unit	Explanation
u	ms^{-1}	Ship speed
V_a	ms^{-1}	Water velocity
$1 - w$	-	Wake fraction
Q_{eng}	Nm	Diesel torque
Q_f	Nm	Shaft friction torque
Q_{prop}	Nm	Propeller torque
Y_d	0...1	Fuel index
ϑ	-1...1	Propeller pitch

Table 1. List of symbols used in the ship propulsion system

MODELS OF THE PROPULSION SYSTEM: CONVENTIONAL APPROACH

The overall function of the propulsion system is to maintain the ship's ability to propel itself and to manoeuvre. Propulsion requires thrust ahead whereas manoeuvres require ahead and astern thrust ability. With a positive shaft speed n, this is obtained by an appropriate change of the propeller pitch ϑ, which is the angle that the propeller blades are twisted.

The component hierarchy is treated as belonging to two levels. Lower level components are the diesel engine with shaft speed controller, the propeller with the pitch controller, and the ship's speed dynamics. The upper level comprises coordinated control for the lower level components and overall command to the propulsion system. Reconfiguration will take place at the upper level, but lower-level controllers should be fault-tolerant, if possible, to maintain their primary services.

Upper-level components.

Upper level components are the following:

— *Command handle:* A command handle's position constitutes the main man-machine interface (MMI).

— *Combinator:* Use-modes with different interpretations of handle position are available:

-Manoeuvring: Handle position determines n and ϑ;

-Economy: Handle position determines n_{com} and ϑ_{com};

-Set speed: Maintain a set ship speed using measured ship speed U.

— *Efficiency optimiser:* The efficiency optimiser determines the set of n and ϑ that achieves the desired ship speed $U_{ref} = f_{sc},(h)$ as determined by the handle position, without ship speed feedback.

— *Ship speed control*: Ship speed control aims at maintaining a set ship speed within a narrow margin. This component uses measured ship speed as one of its input variables.

— *Diesel overload control*: Overload is avoided by reducing the propeller pitch if diesel torque is close to maximum at a given shaft speed.

Lower-level components.

The lower level consists of the shaft speed and the propeller-pitch controllers and the physical components of the propulsion system. In a component-based analysis, the physical components related to the pitch control function are lumped together to a new entity called propeller pitch control.

Propeller pitch control.

The pitch control is an aggregated component that comprises a large hydraulic actuator turning the propeller blades, the feedback from a pitch sensor, a controller and the drive electronics. In its original implementation, this component has only one version of the usemode um_1, which denotes the automatic mode. In order to obtain fault tolerant properties, other versions are added. The math model for physical parts of the component is composed of the following equations:

$$\vartheta_m = \vartheta + v_\vartheta + \Delta\vartheta \tag{1}$$

$$\vartheta = max(\vartheta_{min}, min(\vartheta, \vartheta_{max})) \tag{2}$$

$$\dot{\vartheta} = max(\dot{\vartheta}_{min}, min(u_\vartheta, \dot{\vartheta}_{max})) + \Delta\dot{\vartheta}_{inc} \tag{3}$$

The control signal is generated according

$$u_\vartheta = k_t(\vartheta_{ref} - \vartheta_m)$$

Here, ϑ_m is the measured propeller pitch, d/dt[ϑ_{min}, ϑ_{max}] the rate interval set by the hydraulic pump capacity and geometry, and [ϑ_{min}, ϑ_{max}] is the physical interval for propeller-blade travel. n_ϑ is the measurement noise. Two faults are included in the model: leakage $\Delta\vartheta'_{inc}$, and pitch sensor fault $\Delta\vartheta$.

Shaft speed control.

The input to the shaft speed controller, which is called the governor, is given by the shaft speed reference n_{ref} and the measured shaft speed n_m. The output is the throttle of the diesel engine, which is proportional to the fuel index Y. The governor is a PI controller. Anti-windup is part of the integrating action, and K is the anti-windup gain. The controller is given by

$$n_m = n + v_n + \Delta n \tag{4}$$

$$\dot{Y}_i = \frac{k_r}{\tau_i}((m_{ref} - n_m) - K(Y_{PIb} - Y_{PI})) \tag{5}$$

$$Y_{PIb} = Y_i + k_r \cdot (n_{ref} - n_m) \tag{6}$$

$$Y_{PI} = \min(\max(Y_{PIb}, Y_{Ib}), Y_{ub}) \tag{7}$$

Y_{lb} and Y_{ub} are the lower and upper bounds for the integrator part of the governor, and Δn the measurement fault. The governor comprises fuel index limits to keep the diesel engine within its allowed envelope of operation.

A similar formal description can be made for each physical component, but this is omitted for brevity.

Diesel engine.

The diesel engine generates a torque Q_{eng}, which is controlled by its fuel index Y, to drive the shaft (M. Blank and J. S. Andersen, 1984). The diesel engine dynamics can be divided into two parts. The first part describes the relation between the generated torque and the fuel index. It is given by the transfer function

$$\frac{Q_{eng}(s)}{Y(s)} = \frac{K_y}{\tau_c s + 1} \tag{8}$$

where K_y is the gain constant and τ_c, is the time constant corresponding to torque build-up from cylinder firings (M. Blanke, 1981).

The second part expresses the torque balance of the shaft:

$$I_m \dot{n} = Q_{eng} - Q_{prop} - Q_f \tag{9}$$

Q_{eng} is the torque developed by the diesel engine, Q_{prop} is the torque developed from the propeller, and Q_f is the friction torque.

Propeller thrust and torque.

A controllable pitch propeller (CP) has blades that can be turned by means of a hydraulic mechanism. The propeller pitch ϑ can be changed from 100 % (full ahead) to -100 % (full astern) with asymmetric or different thrust efficiency.

The propeller thrust and torque are determined by the following bilinear relations:

$$T_{prop} = T_{|n|n}(\vartheta)|n|n + T_{|n|V_a}(\vartheta)|n|V_a \quad (10)$$

$$Q_{prop} = Q_{|n|n}(\vartheta)|n|n + Q_{|n|V_a}(\vartheta)|n|V_a \quad (11)$$

V_a is the velocity of the water passing through the propeller disc (speed of advance)

$$V_a = (1-w)U \quad (12)$$

where w is a hull-dependent parameter or wake fraction. The coefficients $T_{|n|n}, T_{|n|V_a}, Q_{|n|n}$ and $Q_{|n|V_a}$ are complex functions of the pitch ϑ. T_{prop} and Q_{prop} are calculated by interpolating between tables of data measured in model propeller tests. K_T and K_Q, denote thrust and torque coefficients in (13) and (14), which depends on advance number J defined in table 2, and propeller pitch.

$$T_{prop} = K_T \rho D^4 |n|n \quad (13)$$

$$Q_{prop} = K_Q \rho D^5 |n|n \quad (14)$$

where D is the propeller diameter and r the mass density of water.

Velocities		*Power*	
Ship's speed	u	Effective towing power	$P_E = R_{(U)} \cdot u$
Arriving water velocity to propeller (speed of advance)	u_A	Thrust power delivered by propeller to water	$P_T = \frac{P_E}{\eta_H}$
Effective wake velocity	$u_w = u - u_A$	Power delivered to propeller	$P_D = \frac{P_T}{\eta_B}$
Wake fraction coefficient	$W = \frac{u - u_A}{u}$	Power of main engine (brake power)	$P_B = \frac{P_D}{\eta_S}$
Advance number	$J = \frac{u_A}{n \cdot D}$		
Resistance		*Efficiencies*	
Towing resistance	$R_{(U)}$	Hull efficiency	$\eta_H = \frac{1-t}{1-W}$
Thrust force developed by the propeller	T_{prop}	Prop. effic.(open waters) " " (behind hull)	η_0 $\eta_B = \eta_H \cdot \eta_R$
Thrust deduction factor	$F = T_{prop} - R_{(U)}$	Propulsion efficiency	$\eta_D = \eta_H \cdot \eta_B$
Thrust deduction coefficient	$t = \frac{T_{prop} - R_{(U)}}{T_{prop}}$	Shaft efficiency	η_S
		Total efficiency	$\eta_T = \frac{P_E}{P_B} = \eta_H \cdot \eta_B \cdot \eta_S$

Table 2. Conventional parameters involved on ship dynamics

Ship speed dynamics.

The following non-linear differential equation approximates the ship speed dynamics:

$$(m - X_{\dot{U}})\dot{u} = R(u) + (1 - t_T)T_{prop} + T_{ext} \qquad (15)$$

$$u_m = u + v_U$$

The term R(u) describes the resistance of the ship in the water. It is a negative quantity. $X_{U'}$ represents the added mass in surge, which is negative. The thrust deduction ($1\text{-}t_T$) represents the net thrust lost due to the propeller-generated flow at the ship's stern. T_{ext} is the external force brought about by the wind and the waves. v_U is the measurement noise.

Some scenarios for fault diagnosis

The faults considered relevant in this system are summarized in table 3.

Fault	Symbol	Type
sensor faults	$\Delta\vartheta$	additive - abrupt
hydraulic leak	$\Delta\vartheta'_{inc}$	additive - incipient
sensor faults	Δn	additive - abrupt
diesel fault	ΔK_y	multiplicative - abrupt

Table 3. Faults considered

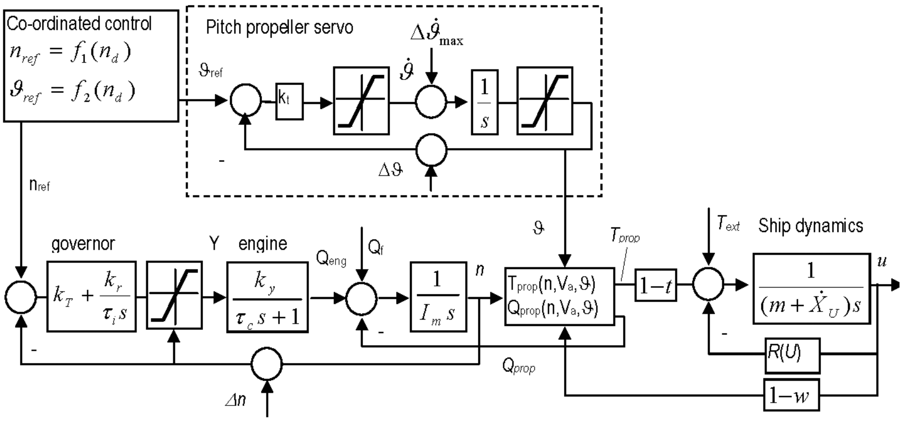

Fig. 2 Propulsion system with saturation phenomena shown for shaft speed and pitch controller.

A formal analysis of fault propagation shows that they have different degrees of severity. Some are very serious and need rapid fault detection and accommodation to avoid serious accidents if the component failure occurs during a critical manoeuvre. The time to detect and reconfigure is hence essential. Some of the faults are based on actual events that have caused serious damage due to the lack of fault-tolerant features in existing propulsion control systems. Figure 2 locates the generic blocks with possible faults of the benchmark in the system block diagram.

MODELS OF THE PROPULSION SYSTEM: PROPOSED APPROACH

Introduction

Described conventional approach exhibits some linear transfer functions combined with non-linear function models in which non linear and time-variant coefficients coexists. An alternative approach to the conventional modeling method described in last section (M. Blanke et al., 2003), can be achieved by modeling the propulsion system by means functional approximation devices in those cases where non-linear and time variant coefficients are present. Necessary data to achieve the proper functions has been acquired from maneuvering trials (R. Izadi-Zamanabadi and M. Blanke, 1999).

Neural Network based functional approximation

Neural Networks (NN) are essentially nonlinear function approximators that utilize process inputs to predict process output. The technical promise of neural-network technology comes from the fact that universal approximators are created using a multi-layer network with a single hidden layer that can approximate any continuous function to any desired degree of accuracy. Soft sensors that utilize NNs must be adapted to the special requirements of the process industry. In particular, it is necessary to compensate for the delay in the process output for changes in upstream conditions. Thus, a NN typically has one output (the predicted variable) and any number of upstream measurements as inputs with compensation of process delay. Figure 3 shows a three-layer feedforward NN.

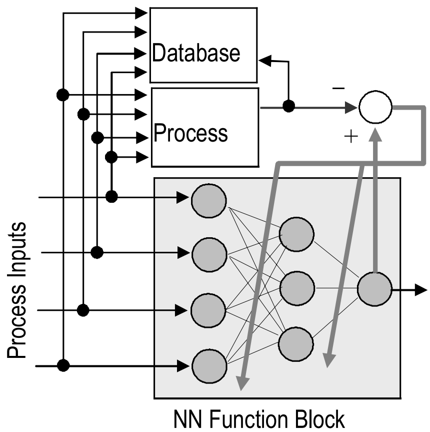

Fig. 3. Structure of a NN Function Block for on-line training.

An object oriented tool provides easy-to-use means for developing and training the NN model. This tool gives us a practical way to create virtual sensors for measurements previously available only through the use of lab analysis or online analysers. Such tools are configured in a way easy to understand and use, allowing process engineers to produce extremely accurate results even without prior deep knowledge of NN theory. In figure 3 it is shown the structure of a NN Function Block connected to operate in an on-line training phase.

Alternative approach to monitoring system

A ship's resistance is particularly influenced by its speed, displacement, hull form and hull conditions. The total resistance R_T consists of many source-resistance R which may be classified into three main groups: frictional resistance, residual resistance and air resistance.

Hull resistance R due to hydrodynamic forces in surge motion is a nonlinear function of the ship velocity and wet surface which is associated to ship mass at constant trim. So that, using experimental data from towing tank tests, following function describes the total hull resistance as

$$R_{(u,m)} = f(u,m), \ \frac{du}{dt} = 0 \tag{16}$$

By means of sea trials the effective brake power of main engine P_B and effective towing power P_E may be associated to the hull resistance and external forces. Considering the influence of external forces the effective towing power is,

$$P_E = P_B \cdot \eta_T = (R_{(u,m)} + T_{ext}) \cdot u \tag{17}$$

With data achieved from steady state sea trials, a database with a set of brake powers, ship velocities, ship displacements, and hull resistances in absence of external forces, can be associated by means of functional approximation procedures under nominal hull conditions. So that, if such conditions change, the differences must be achieved by comparing nominal with actual conditions (parity relations). To do that, a virtual sensor consisting in a back propagation feedforward neural network (BPNN) properly trained and structured as a set of inputs and an output, can approximate the hull resistance into the range of possible displacements and velocities of the ship. Figure 4 shows the virtual sensors for brake power and hull resistance achieved by applying functional approximation by means of BPNNs.

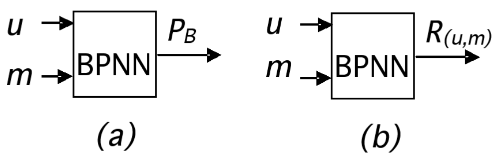

Fig. 4. Functional approximation. (a), brake power. (b), hull resistance.

Functional approximation by means of (16) is an alternative to conventional observers applied in solving FDI tasks in (M. Blanke, et al. 2003), (J. P. Gauthier, 1992)

The total efficiency under sea going conditions is then achieved by using (17) as shown in figure 5. If the difference between actual total efficiency and nominal efficiency estimated by functional approximation is greater than a proposed threshold *Thr2*, then a prejudicial force related with hull resistance is present. Such unwanted force or added resistance may be due to a problem on the propeller or to the increase of resistance of ship's hull. In the same way, the nominal associated brake power ca be compared with actual *Thr1*, to alert of a problem related with propulsion efficiency.

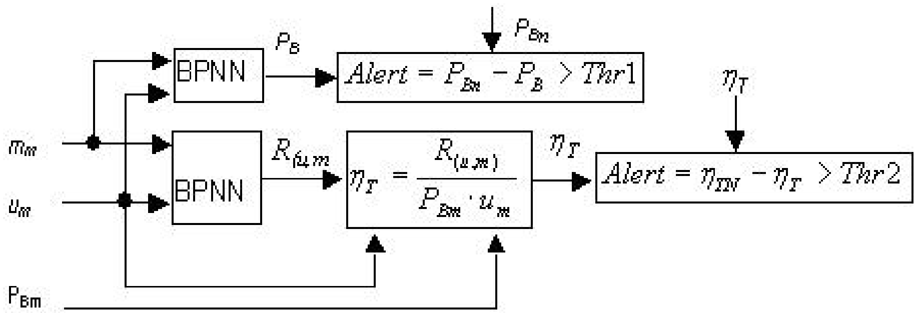

Fig. 5. Diagnosing the hull resistance and propulsion efficiency

As is well-known, the effective brake power P_B of a Diesel engine is proportional to the mean effective pressure (mep) P_e and engine speed n, that is

$$P_B = C \cdot P_e \cdot n \tag{18}$$

Functional redundancy can be applied by using (18) against P_B achieved by functional approximation as described in figure 4(b). If abnormal differences exists, then it is highly probably the presence of a fault in the P_B measuring device or in the device responsible for P_B generation, that means the propulsion engine. In order to avoid ambiguity with regard to measuring device, then triple redundancy is proposed. Then function to be applied could be achieved as follows: The operating curves for an engine indicate that the load torque Q is a nonlinear function of both the fuel flow rate F and the output shaft speed n. Consequently, the steady state dynamic behavior of the engine may be approximated by a BPNN structured as two inputs (F, n)and an output Q. Given the actual load torque, then, brake power is obviously achieved as described by (19). Figure 6 shows the BPNN necessary to approximate the function given by (19).

$$Q = f(F, n)$$
$$P_B = Q \cdot n \tag{19}$$

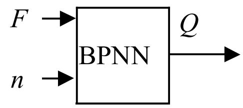

Fig.6. Load torque achieved by functional approximation with BPNN as function of fuel flow rate and engine speed.

Discussion of results

A conventional modeling technique proposed as an international Benchmark in propulsion system monitoring is compared with the proposed modeling technique based in functional approximation by means of massive application of virtual sensors based in conjugate-gradient back propagation neural networks.

Results shown in mentioned benchmark were compared with results achieved by applying proposed models described by (16), (17), (18) and (19).

The hull resistance as function of ship speed and ship cargo conditions at constant trim is shown in figure 7.

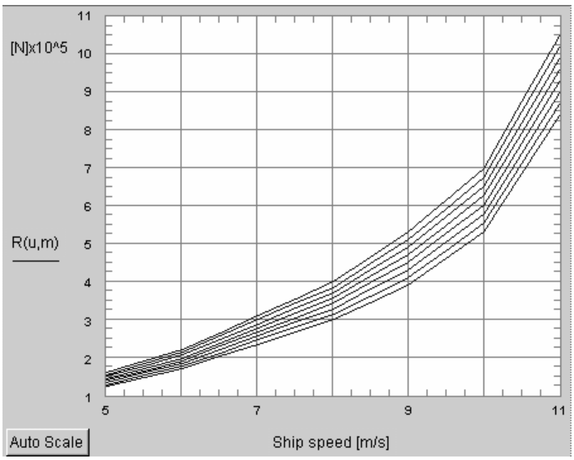

Fig. 7. Ship hull resistance as function of ship speed and ship loading conditions for different velocities.

The lower line belongs to a 16500 tons displacement and the upper line to the 23500 ton displacement. Intermediate lines belongs to 1000 tons difference between each other. Mentioned line functions are very different from those of conventional hull resistance coefficients mainly when ship speed is greater than 7-8 m/s..

Figure 8 shows the ship estimated speed due to propulsion system activity in which a step input in speed demand was applied. Two lines (dashed and continuous) are shown in each graph. Dashed lines belongs to proposed model while continuous line represents the conventional model used in benchmark. Left hand graph shows the ship speed as function of time and right hand graph shows the hull resistance as function of time.

As proposed modeling technique is experimental instead of empiric, it reflects virtually the real scenario. Slightly differences are observed after some reasonable time. Such differences are interpreted as modeling error which are prejudicial when processed as parity relations in searching for residuals.

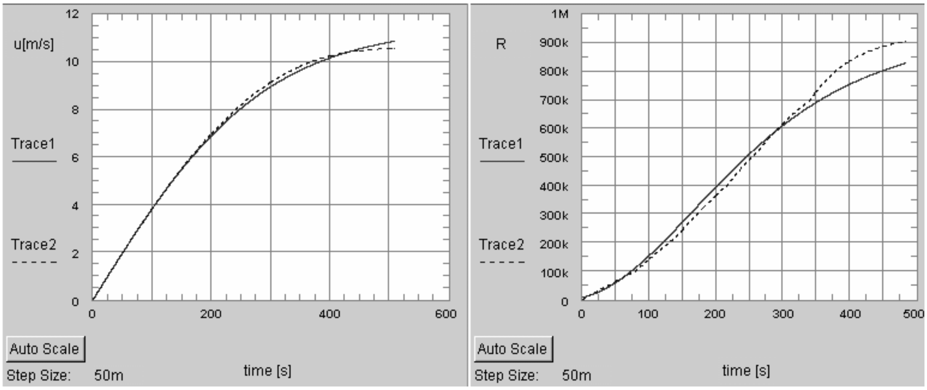

Fig. 8. Comparison of model results. Dashed line, functional approximation model. Continuous line, conventional model used in benchmark. Ship full loaded conditions (23500 Tons)

Nevertheless, in figure 9 there are shown the same curves for ship unloaded (ballast). The differences are much more relevant. It means that modeling errors are greater when ship is unloaded. It is due to ship nominal conditions which belongs to the conditions of full loaded ship. From the point of view of residuals generation,. mentioned differences are very important because they introduce an important degree of error in the residuals and an important lost of precision when malfunction detection is to be carried out.

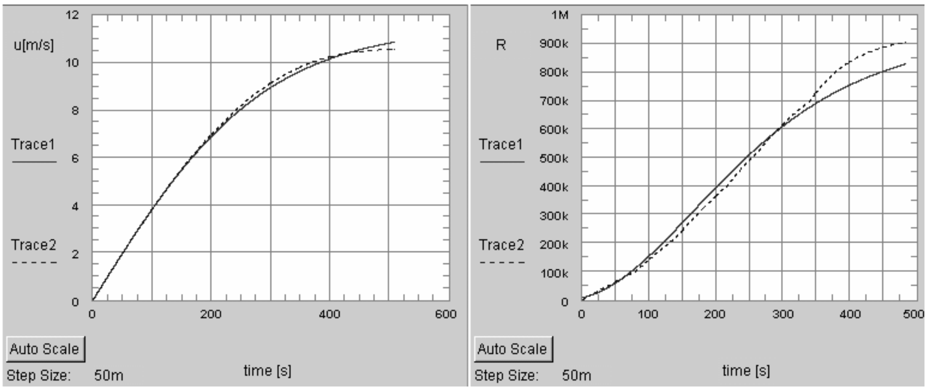

Fig. 9. Comparison of model results. Dashed line, functional approximation model. Continuous line, conventional model used in benchmark. Ship ballast loaded (16500 Tons)

The main drawbacks of using conventional modeling techniques with regard to proposed, are:

— The exaggerated deviations of ship parameters from nominal cargo conditions (ballast or full loaded conditions) are responsible for very different dynamic behaviors.
— The determination of coefficients used in (13) and (14) which depends on the advance number J, is a tedious task.
— The advance number depends on the speed of advance V_a and ship speed u, which depends on wake fraction. Wake fraction is affected of uncertainty because of variations in nominal conditions (speed and mass variation).
— The variation of ship mass at least in a 50% of total mass, and consequently the added mass and hull resistance contribute also to large modeling errors.

SOME CONCLUSIONS

By comparing simulation results achieved from the benchmark with those achieved by applying proposed functional approximation based models, different responses has been found, which used by means of parity relation, provides precisely and useful residuals when focused on fault detection tasks.

The fact of using functional approximation to describe nonlinear functions, reduce drastically the possibility of modeling errors, which makes the nonlinear residual generators sufficiently precise and flexible in a wide range of dynamic situations.

It has been shown that mentioned drawbacks disappear by applying neural network based modeling as virtual sensors and observers. As results of proposed enhancements due to different modeling techniques, ship speed, hull resistance and total mass (ship mass plus added mass) are easily predicted, providing relevant data in monitoring the propulsion system.

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