Using Neural Network Technologies to Simulate the Working Processes of Ship Steam Boilers

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Abstract

On the ships of the merchant and passenger fleet, it is relevant to use powerful ship steam boilers of a wide design class. Marine boilers, as objects of automatic control systems, are subject to the influence of a significant number of internal and external disturbing factors. Such influences often lead to self-oscillatory processes of the controlled parameters of a ship's boiler with significant nonlinearities.

For the optimal tuning of automatic control systems for the working processes of ship boilers, exact knowledge of mathematical models of controlled processes is required. Due to the presence of significant nonlinear characteristics, it is proposed to use neural networks in modeling processes.

As shown by the modeling processes in the MatLab (System Identification Toolbox) program, the use of nonlinear ARX models with a built-in neural network apparatus makes it possible to display the experimental working processes of ship parameters with a high degree of adequacy. Obtaining nonlinear mathematical models with high adequacy will improve the process of adaptation of automatic control systems for ship boilers and optimize environmental parameters.

Keywords

Steam-boiler, SCADA systems, ARX model, neural network, identification, validation, neuralnet

1. Introduction

On the ships of the passenger and tanker fleet, the technological scheme of operation of two auxiliary steam boilers (ASB) and one utilization boiler (USB) for a common steam line has found wide application (Fig. 1). With such a design solution, auxiliary boilers, performing the function of generating steam of high temperature and pressure, are subject to the influence of deep external disturbances associated with the mode of operation of the steam turbine and cargo operations on ships [1-5].

Experimental transient processes of two ASBs of Mitsubishi MAC 35 t / h, installed on the oil

tanker "Minerva Roxanne" and obtained using the monitoring system "ACONIS-2000", are shown in Fig. 2 [6].

Analysis of the type of transient processes (Fig. 2) allows us to conclude that with a sharp increase in the electric and steam load, the turbine control system immediately increases steam consumption, however, the combustion mode of the ASB has not yet been built and an imbalance occurs in the production and consumption of steam, as a result of which the pressure drops. steam in the main line and in the path of the working medium of the boiler. An oscillatory mode is formed, characterized by significant nonlinearity. The ability of the ASB to change the

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steam production in accordance with the change in the external (electrical) load is called the maneuverability of the boiler [7]. This condition for the operation of the ABS requires the use of faster-acting ACS so that changes in loads do not cause deep deviations in the parameters of the working environment. The indicator of the rate of change in the load is the change in pressure in the working path of the boiler dP/dt, MPa/min.

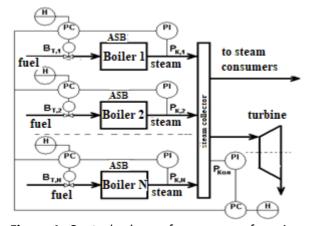


Figure 1: Control scheme for a group of marine auxiliary steam boilers MITSUBISHI MAC 35, connected by a common steam pipelines and working on the SHINKO turbine: PC - pressure regulator; H - remote control; RI - pressure gauge

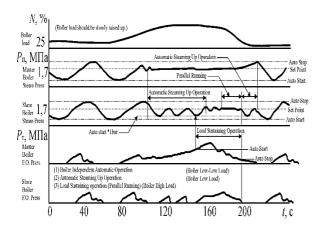


Figure 2: Transient characteristics of the WPC during parallel operation of the oil tanker "Minerva Roxanne" at the SPTU: N - load; Pn - steam pressure; RT - fuel pressure [8]

2. Development of mathematical models

Nonlinear models are used to compile a

mathematical model for the "fuel consumption - vapor pressure" channel when the WPC is operating in a maneuverable mode [9].

There are two classes of nonlinear regressions [9], with the help of which the nonlinear model of the transient regime is composed (see Fig. 3.10):

- regressions, non-linear with respect to the input and output included in the analysis (explain) variables (regressors), but linear in the estimated parameters (coefficients of the equations);

- regressions, non-linear in the estimated parameters. For example, the linear structures of ARX and ARMAX models discussed above can be extended to nonlinear structures as follows:

- using non-linear ARX regressors, that is, non-linear expressions of time-delayed input and output variables;

- replacing the weighted sum of linear regressors with a nonlinear ARX model, which has a more flexible nonlinear display function:

$$F(y(t-1), y(t-2), y(t-3), ..., u(t), u(t-1), u(t-2), ...),$$

the arguments for F are the y and u regressor models. For clarity, the nonlinear model of the ARX structure can be displayed in the block diagram in Fig. 3.

Using the System Identification Toolbox application (Fig. 3 - 4), a discrete ARX [4] model was obtained, which uses the Z-transform apparatus:

Discrete-time IDPOLY model:

A(z)y(t) = B(z)u(t) + e(t) $A(z) = 1 + z^{\Lambda-1} + 0.5 z^{\Lambda-2}; B(z) = 0.415;$

e(t) –discrete white noise, where $z^{-1} = e^{-sT}$ is the delay operator; T - sampling interval.

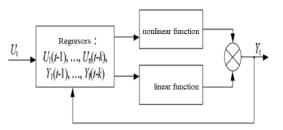


Figure 3: Block diagram of a nonlinear ARX model

The process of determining the degree of adequacy of the selected model is shown in Fig. 5. According to the analysis of the degree of adequacy of the analyzed models, calculated in the software application (see Fig. 5), it was found that the ARX model demonstrates the highest degree of convergence with the experimental data. operate on the common steam line of the turbine, using the SCADA monitoring system ACONIS-2000E, installed in the central control room of the ship, the experimental characteristics obtained (Fig. 6 - 7).

For the process under study - two auxiliary boilers installed on the tanker "Minerva Roxanne", which

Nodel Type Estimation			
Model structure: Nonlinear ARX	T	Model name: nla	nx1
		Initial model: <none></none>	
Regressors Model Properties			
	Inputs (u) Outputs (y	Regressors Pred	icted uts (ÿ)
becity delay and number of terms in :	standard redressors for outbut prede;		
	Delay	No. of Terms	Resulting Regressors
Channel Name		No. of Terms	Resulting Regressors
Channel Name Input Channels		No. of Terms	Resulting Regressors power(t-1), power(t-2)
Specify delay and number of terms in Channel Name Input Channels power Output Channels		No. of Terms 2	

Figure 4: Nonlinear ARX model describing the process of changing the vapor pressure of the ASB

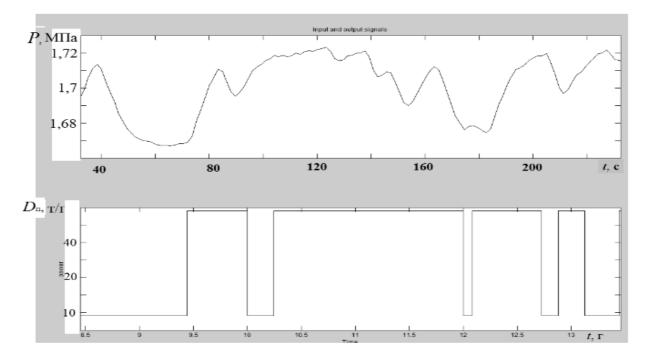


Figure 5: The investigated process in the System Identification Toolbox application obtained on the basis of the used nonlinear model

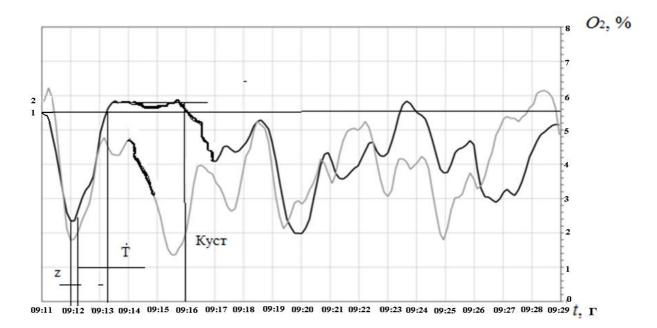


Figure 6: Transient characteristics of ACS content of O_2 in the exhaust gases of the combined (1) and auxiliary (2) ASB of the oil tanker "Minerva Roxanne": T - time constant, K_{fix} - coefficient, z - delay

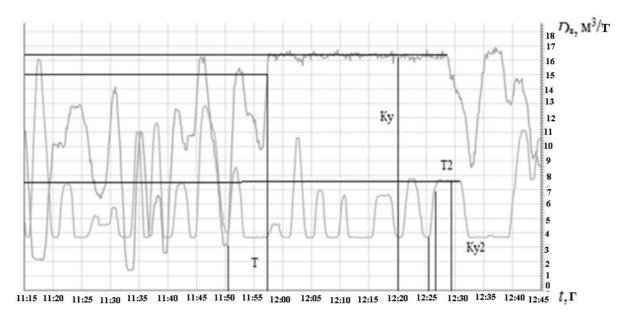


Figure 7: Screenshot from the mnemonic diagram showing the change in the feed water flow rate in the combined (1) and auxiliary (2) ASB, working together in transient modes on the tanker "Minerva Roxanne"

It should be noted that control objects demonstrate significant nonlinear characteristics, therefore, to obtain a model of the system under consideration, a nonlinear ARX model was used.

3. Review of the validation process

The process of identification and validation on an independent data set in the System Identification Toolbox (SIT) is shown in Fig. 8 -9.

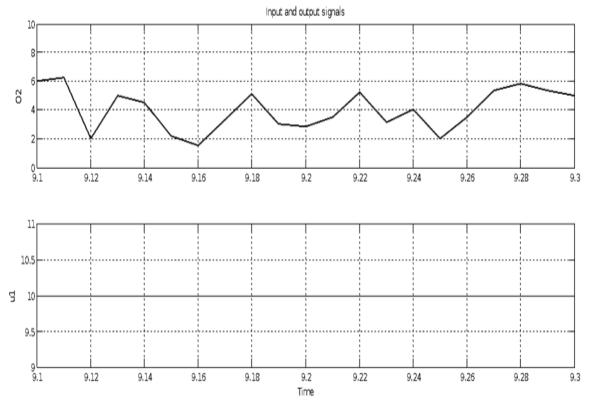


Figure 8: Experimental dependence of the oxygen content in the exhaust gases

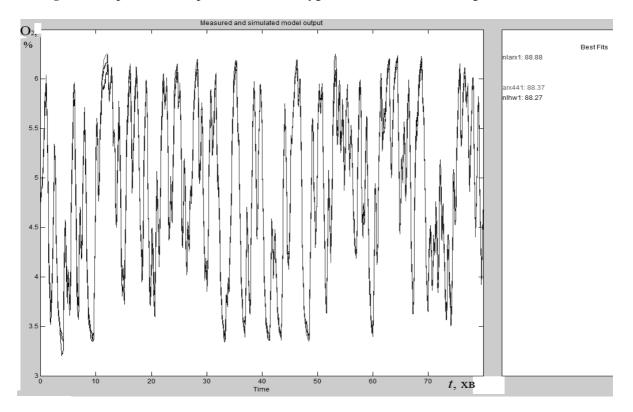


Figure 9: Determining the degree of adequacy of nonlinear models in the System Identification Toolbox during verification: nlarx1 - nonlinear ARX model with a degree of adequacy of 88.8%

In fig. 10-11 show the view of the nonlinear model and its three-dimensional surface, as

determined using the SIT application.

\Lambda Nonlinear Models	B			
Model Type Estimation				
Model structure: Nonlinear ARX	Model name: nlar2 Initial model: </th			
Regressors Model Properties				
	Inputs (u) Outputs (y) Utputs (y) Regressors Utputs (y) Utputs (y) Nonlinear Block Cutputs (y) Nonlinear Block Outputs (y)			
Nonlinearity: Wavelet Network Properties of Wavelet Network Number of units in nonlinear block: Select automatically Enter: Select interactively during estimation Advanced	✓ Workspace IDNLARX model with 1 output and 1 input Input name: u1 Output name: y1 Standard regressors corresponding to the orders na = 2, nb = 2, nk = 1 No custom regressors Nonlinear regressors: y1(t-1)			
	y1(t-2) u1(t-1) u1(t-2) Nonlinearity estimator: sigmoidnet with 10 units Loss function: 3.8758e-029 Sampling interval: 0.01 Model modified after last estimate			

Figure 10: Structure and parameters of non-linear ARX model

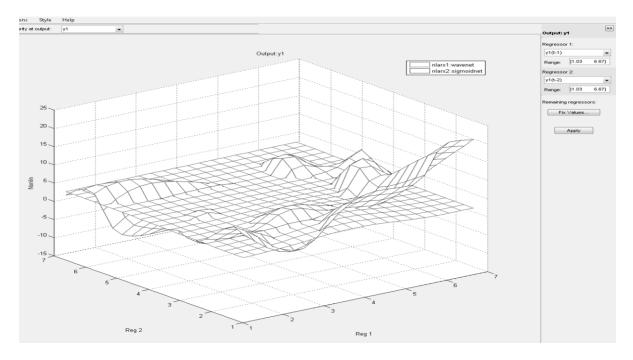


Figure 11: Three-dimensional surface of the acquired non-linear ARX model

It should be noted that the System Identification Toolbox provides several nonlinear estimates of g(x) for nonlinear ARX models. Nonlinearity is formed in the form of a wavelet, a sigmoid network (sigmoidnet), a binary tree (treepartition), a multilevel neural

network (neuralnet), and a linear estimation (linear) [10-11]. By default, a non-linear estimation in the form of a wavelet is used (see Fig. 10).

4. Conclusions

Based on the study, the results were obtained that make it possible to improve the toolkit for using the nonlinear ARX model in the form of a multilevel neural network and a linear assessment for parametric identification of the oxygen content characteristic in the exhaust gases from the thermal load of the ASB, which makes it possible to display the process under study with a degree of adequacy equal to 95%, and use the obtained model of a high degree of adequacy for analyzing the process of the appearance of oxygen corrosion in the equipment of a ship's boiler.

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