Neural networks based combinatorial identification model for increasing redundancy of sensors information in marine control systems

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Summary – The model structure for dynamic system parameters monitoring, designed to increase the redundancy of sensor information and improvement of marine control system availability, is presented. The model consists of two subsystems, the first one for on-line monitoring and the second for off-line monitoring. The off-line monitoring subsystem is based on combinatorial identification of interrelationship between any two disjunctive subsets of analysed parameters primary set. The approximative regression neural networks were used for that purpose and probabilistic neural network was applied for efficiency evaluation of each simulation model. The procedure could be performed for all possible parameter combination within the steady process modes, defined previously. Afterwards, it is possible to choose the optimal model according to the obtained efficiency rank-list of all simulation models. The main on-line subsystem function is a faultlessness control of system sensors. If failure of one or more sensors occurs, the optimal simulation model for estimation of lost sensor information is activated. Moreover, residual monitoring between measured real-time sensor data and simulated data for each steady process mode of trained off-line subsystem can be used for diagnosing faults and/or significant deviations of conventional sensor control.

I. INTRODUCTION

Precision and reliability of various control systems depend upon quality and accuracy of the sensor information. That is particularly important for the marine control systems that are specific for their redundancy being often, for objective reasons, at insufficiently high level.

Utilization of modern non-conventional solutions, realized by linking computer intelligence algorithms with knowledge databases, is recommended.

A specific multifunctional structure for sensor information analysis and processing has been proposed in this article. The concept is based on correspondence between the on-line and the off-line control and monitoring subsystems.

The primary function of the off-line subsystem is to permanently identify interrelationships of the parameters analyzed. Operating system identification problems consist in most of the cases in developing certain mathematical models that serve to determine analytical expressions of dependence function of output parameters on the input parameters of the system.

The most complicated identification problems arise when analytical expressions of such functions are to complex or even impossible to determine. Just for that very reason the combinatorial approach, using neural networks as one of the possible solutions of the problem, has been used. The proposed combinatorial model, based on generalized regression neural networks (GRNN), enables identification and simulation of certain number of working system parameters using any other class of the remaining parameters, thus representing an adequate generalization of the model, presented previously [1].

Additionally, after the simulations have been computed, an iteration procedure model for estimating the efficiency of the obtained results by means of probabilistic neural network (PNN), has been proposed. It finally allows the possibility of choosing the optimal simulation model for determine the interrelationship of the working parameters inside the corresponding operating mode of the system.

On the other side, the primary function of the on-line subsystem is to control correct sensor work, to diagnose their failures and/or faults and to take measures if problems occur.

The purpose of the presented model is a significant increase of the sensor information redundancy in cases when total interruption of the sensor work occurs but also when the information obtained significantly differs from the routine and expected ones.

II. COMBINATORIAL IDENTIFICATION AND SIMULATION MODEL

Generalized regression neural network is one of the most used networks for the function approximation [2]. Extremely short time required for its creation and further use for identification and simulation make this method particularly convenient.

GRNN consists of four layers. The input layer has R neurons, where R is the number of arguments of the multivariable function which is approximated using the GRNN network. The first hidden radial basis layer and the second hidden linear layer have Q neurons, where Q is a number of samples sets for learning. The output layer has only one neuron. The learning set consists of $Q \times R$ data that can be written in a matrix form

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1R} \\ p_{21} & p_{22} & \cdots & p_{2R} \\ \vdots & \vdots & \ddots & \vdots \\ p_{Q1} & p_{Q2} & \cdots & p_{QR} \end{bmatrix}_{Q \times R}, \qquad (1)$$

and of Q target data that can be written in a matrix form

$$\mathbf{T} = \begin{bmatrix} t_1 & t_2 & \cdots & t_Q \end{bmatrix}_{Q\times 1}^{T}. \tag{2}$$

Detailed review and description of the GRNN are given elsewhere [1], [2] and are omitted in this work.

On the other hand, the use of probabilistic neural network mainly concerns the classification problems.

The network classifies the presented sample in one of the predetermined classes, according to the criteria that the samples from the learning set are associated with these classes.

The PNN network, as well as the GRNN network, also consists of four layers, however since its architecture has been described in detail elsewhere [1], [2], these items are omitted in this study.

A. The identification and simulation model structure

In the following section we propose the combinatorial identification and simulation model of the system by means of the GRNN networks.

Let $X = \{x_1, x_2, ..., x_R\}$ be the set of R parameters of a system and let Q states of that system be known, where each state is described by an appropriate sample. The space of these states may be written in the matrix form

$$\mathbf{M}_S = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1i} & \cdots & x_{1R} \\ x_{21} & x_{22} & \cdots & x_{2i} & \cdots & x_{2R} \\ \cdots & \cdots & \ddots & \vdots & \ddots & \vdots \\ x_{Q1} & x_{Q2} & \cdots & x_{Qi} & \cdots & x_{QR} \end{bmatrix}_{Q\times R}. \tag{3}$$

Problems of the system theory often require the determination of relationship among the system parameters.

Theoretically, in the system with R parameters, l among them may be expressed by the $m \le R - l$ parameters in

$$N_l = \binom{R}{l} \cdot (2^{R-l} - 1) \tag{4}$$

ways. Considering that $l = 1,...,R-1,$ the total number of these ways is equal

$$N_{tot} = \sum_{l=1}^{R-1} \binom{R}{l} \cdot (2^{R-l} - 1). \tag{5}$$

Technical problems usually refer to determination of one parameter $(l = 1)$ dependence on a number of remaining parameters. For that purpose let x_i be arbitrarily selected parameter from the set X. It can be considered as the function of more variables whose arguments are the elements of any $r-$ member subset

$$A = \{x_1, x_2, ..., x_r\} \subseteq X \setminus \{x_i\}, \tag{6}$$

where $r = 1,2,...,R-1,$ i.e.

$$x_i = F(x_1, x_2, ..., x_{i-1}, x_{i+1}, ..., x_r). \tag{7}$$

These functions are in total $N = 2^{R-1} - 1$.

However, the most remarkable advantage of this combinatorial model is the fact that one doesn't have to keep searching dependence of only one parameter upon the number of others remaining, but merely to search dependence of any of $l < R$ parameters on any other $m < R$ parameters, under condition that $m + l \le R$.

Let X_l and X_m be the sets of l and m parameters respectively.

In the set of $\mathbb{Q}$ known samples, that are in total $Q = card(\mathbb{Q}),$ the parameters values from the X_l set have the same values for the arguments values of this sample, regardless the number of arguments $m < R$.

Let the samples of the arbitrarily selected set $\mathbb{Q}_1 \subset \mathbb{Q}$ be the learning samples and the samples of the set $\mathbb{Q}_2 \subseteq \mathbb{Q} \setminus \mathbb{Q}_1$ be the testing samples.

Now the identification of the system can be done with samples of the set $\mathbb{Q}_1$ using the GRNN networks obtaining for each sample N_{tot} approximated values of particular parameters from the set X_l, i.e. $Q_1 \cdot N_{tot}$ for all $Q_1 = card(\mathbb{Q}_1)$ samples.

As the approximation of the N_{tot} functions is performed, we shall create one GRNN network for each of them. For that purpose, to each of them the input $\mathbf{P}_1$ matrix is presented, being the corresponding submatrix of the $\mathbf{M}_S$ matrix and $Q_1 \times m$ format. Besides, to each GRNN network, we present always the same target matrix $\mathbf{T}_1$, that is the corresponding submatrix of the $\mathbf{M}_S$ and $\mathbb{Q}_1 \times l$ format.

After the N_{tot} matrices of the weight coefficients $\mathbf{IW}^{1,1} = \mathbf{P}_1$ have been formed and N_{tot} related matrices of the aim $\mathbf{LW}^{2,1} = \mathbf{T}_1,$ the system was identified N_{tot} times.

On each of N_{tot} obtained identification models we shall test the samples from the $\mathbb{Q}_2$ set and they in total are $Q_2 = card(\mathbb{Q}_2)$. Now the approximated parameter values from the X_l set will not be equal for the same sample, but they will change with regard to the number of m arguments through which the approximation has been performed. Exactly in this part the differences among the N_{tot} identification models will be created and the efficiency of each of them will depend exactly on approximation possibilities of the GRNN networks, but also on the information "quality" which the parameters, used for approximation, provide.

We shall present to each single model, i.e. to each GRNN network, the input matrix $\mathbf{P}_2$, being the corresponding submatrix of the matrix $\mathbf{M}_S$ and $Q_2 \times m$ format. The elements of this matrix are from the testing set $\mathbb{Q}_2$, and its format depends exclusively on the number of parameters through which the approximation has been performed. After the simulations carried out, we shall obtain $Q_2 \cdot N_{tot}$ approximated values of parameters from the set X_l, where for each of the N_{tot} approximations of parameters from the set X_l the corresponding approximated values are written in the form of matrix

$$\mathbf{S}_j = [X_l]_{ij}^{sim}, \quad j = 1,2,...,N_{tot}. \tag{8}$$

with format $Q_2 \times l$.

B. Efficiency evaluation of the simulation models

In the following section we shall propose the model for the efficiency evaluation of the simulation results by means of the PNN network.

From obtained simulation results $\mathbf{S}_j$, $j = 1,2,...,N_{tot}$, we can form the following matrix (9)

$$\mathbf{S}^1 = \begin{bmatrix} s_{1,1}^i & s_{1,2}^i & \cdots & s_{1,j-1}^i & s_{1,j}^i & s_{1,j+1}^i & \cdots & s_{1,N_{tot}}^i \\ s_{2,1}^i & s_{2,2}^i & \cdots & s_{2,j-1}^i & s_{2,j}^i & s_{2,j+1}^i & \cdots & s_{2,N_{tot}}^i \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{Q_2,1}^i & s_{Q_2,2}^i & \cdots & s_{Q_2,j-1}^i & s_{Q_2,j}^i & s_{Q_2,j+1}^i & \cdots & s_{Q_2,N_{tot}}^i \end{bmatrix}$$

of the format $(Q_2 \cdot l) \times N_{tot}$ and it will be presented to the PNN network as the input matrix, where $i = 1,2,...,l$.

Every vector column $\mathbf{S}_j = [\, s_{1,j}^i \quad s_{2,j}^i \quad \cdots \quad s_{Q_2,j}^i \,]_{(Q_2 \cdot l) \times 1}^T$ will be uniformly associated to the $j-$class. All the N_{tot} classes may be written as vector row

$$\mathbf{Tc}_1 = [1 \quad 2 \quad \cdots \quad j-1 \quad j \quad j+1 \quad \cdots \quad N_{tot}] \tag{10}$$

of the $1 \times N_{tot}$ format and by means of it the matrix of aims $\mathbf{T}^1$ and $N_{tot} \times N_{tot}$ format is formed. After the input matrix $\mathbf{S}^1$ and the target matrix $\mathbf{T}^1$ have been presented to the PNN network, the weight coefficient matrices $\mathbf{IW}_1^{1,1} = \mathbf{S}^1$ and the target matrix $\mathbf{LW}_1^{2,1} = \mathbf{T}^1$ are formed.

Trained PNN network can now perform the classification. The sample that will be classified is a vector column $\mathbf{S}_l$, obtained as the corresponding submatrix of the matrix $\mathbf{M}_S$ and of format $(Q_2 \cdot l) \times 1$. The elements of the vector column $\mathbf{S}_l$ represent real values of the parameters from the parameter set X_l for each sample of the matrix $\mathbf{P}_2$.

The classification is performed by iteration process within $N_{tot} - 1$ steps using $N_{tot} - 1$ PNN networks with results that we can interpret as follows.

In the first step, by means of the first PNN network, we classify the vector column $\mathbf{S}_l$ in one of the previously N_{tot} defined classes. Without loosing the general concept, let's suppose that the PNN network has classified the sample $\mathbf{S}_l$ in the $j-$th class. Thus, it is shown that the affiliation of the sample $\mathbf{S}_l$ in the $j-$th class is the most probable. In other words, the $j-$th simulation model is the best one.

In the second step we reduce the number of samples and the number of classes for one, omitting $j-$th sample and $j-$th class.

We present to the second PNN network the following input matrix

$$\mathbf{S}^2 = \begin{bmatrix} s_{1,1}^i & s_{1,2}^i & \cdots & s_{1,j-1}^i & s_{1,j+1}^i & \cdots & s_{1,N_{tot}}^i \\ s_{2,1}^i & s_{2,2}^i & \cdots & s_{2,j-1}^i & s_{2,j+1}^i & \cdots & s_{2,N_{tot}}^i \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ s_{Q_2,1}^i & s_{Q_2,2}^i & \cdots & s_{Q_2,j-1}^i & s_{Q_2,j+1}^i & \cdots & s_{Q_2,N_{tot}}^i \end{bmatrix} \tag{11}$$

of the $(Q_2 \cdot l) \times (N_{tot} - 1)$ format and the target matrix $\mathbf{T}^2$ of the $(N_{tot} - 1) \times (N_{tot} - 1)$ format, obtained from the row vector class

$$\mathbf{Tc}_2 = [1 \quad 2 \quad \cdots \quad j-1 \quad j+1 \quad \cdots \quad N_{tot}] \tag{12}$$

of dimension $1 \times (N_{tot} - 1)$. After the weight coefficient matrices $\mathbf{IW}_2^{1,1} = \mathbf{S}^2$ and the target matrix $\mathbf{LW}_2^{2,1} = \mathbf{T}^2$, have been formed, the second PNN network performs classification of the sample $\mathbf{S}_l$ in one of the remaining $N_{tot} - 1$ classes, to which most probably belongs.

By iteration repeating of this procedure for another $N_{tot} - 3$ times, the hierarchical sequence of N_{tot} simulation models is produced

$$\mathbf{S}_1^h, \mathbf{S}_2^h, \ ..., \ \mathbf{S}_{N_{tot}}^h \tag{13}$$

according to their efficiency.

Simulation model $\mathbf{S}_1^h$, eliminated in the first step, is the most efficient and it is the first in that sequence. The second simulation model $\mathbf{S}_2^h$ was obtained in the second step of the iteration procedure. The last one and the only left, is the simulation model $\mathbf{S}_{N_{tot}}^h$, obtained after the $N_{tot} - 1$ classifications were performed.

As already mentioned before, the procedure is iteratively repeated for $N_{tot} - 1$ times with the final result of generating the rank-list of all N_{tot} simulations that were performed.

In general, the question is put forward why to seek for the optimal simulation model at all, if at the first step of the above mentioned iteration procedure the best one is already selected. There are few reasons for it and here we are going to explain the two of them being the most important.

The first reason is undoubtedly the complexity of numerical operations that proceed during the identification and simulation procedures. Despite the present-day relatively low costs of the RAM memory and processor speed, by processing extremely large sets of data and a great number of parameters, there is a real risk of rupture of numerical calculations and algorithms before they are finished. High level of reliability that is demanded in marine control systems is more than sufficient reason why the extraordinary attention is needed when we deal with these issues.

The second reason is general and it is characteristic not only for the identification of the marine dynamic processes but for any other identification as well. The problem has been evaluated before [1]. It can be simply deduced from the presented simulation results that very often some parameters not only do not offer information of sufficient

quality for satisfying identification, but their "inexpert" impact may contaminate and disturb the efficiency of multivariable identification and simulation models.

Graphical presentation of simulation results is particularly convenient for optimal model determining and for illustration purpose few main results achieved in [1] are presented in the following text.

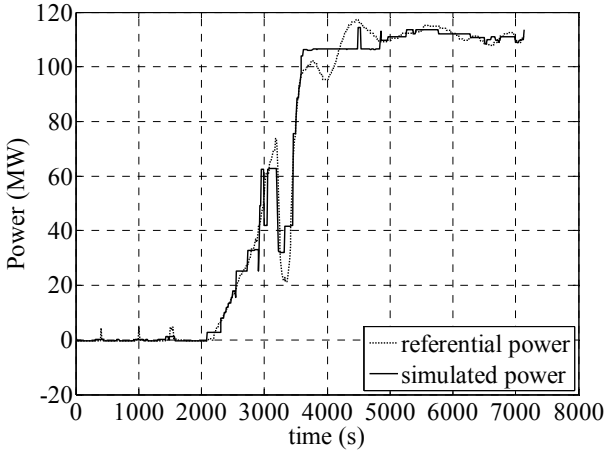
For instance, among other things, relationship between output power and remaining analysed parameters of ABB 210 MW steam turbine in all possible input parameter combinations was identified by means of GRNN model in [1].

Turbine bearing temperatures measured on four characteristic positions, axial shifts and relative vibrations were elements of input parameter set.

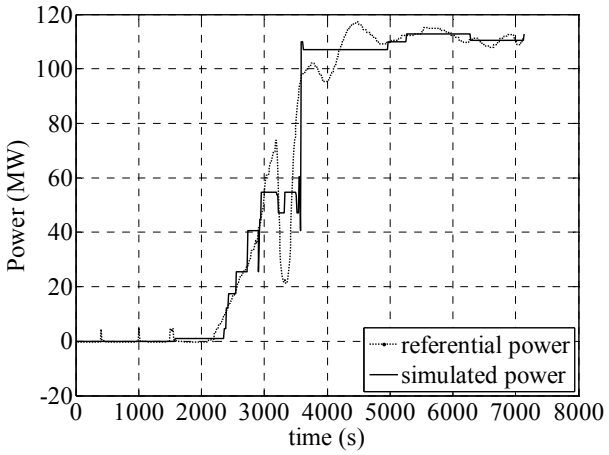
Simulations were performed on a sample of parameters that have been measured during a little less than three hours. During the measurement, the revolution of turbine was constant (3000 rpm), but the output power was considerably variable because of various consumer demands.

Graphical illustration of simulation results for the best, "optimal" and the worst simulation model is presented on figures 1*a*, 1*b* and 1*c* respectively.

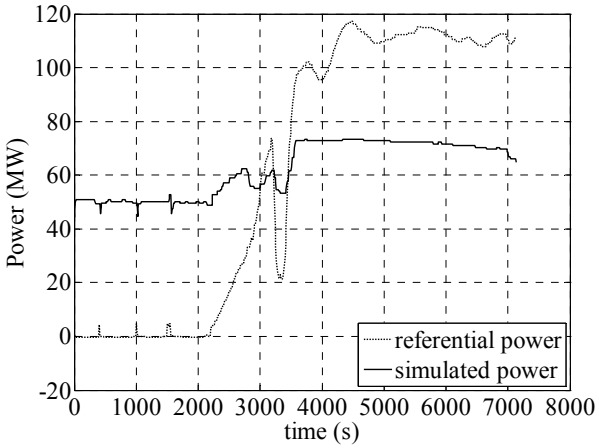
It is quite clearly even without analytical calculations what can we expect from the best (Fig. 1*a*) and what from the worst (Fig. 1*c*) simulation model.



(a)



(b)



(c)

Fig 1. Response of GRNN network for simulated steam turbine output power in relationship of all analysed parameters *(a)*, in relationship of bearing temperatures *(b)* and in relationship of turbine axial shifts *(c)*
Source: [1]

As already mentioned before, extremely weak results of some simulation models can clearly indicate parameters that not only do not offer information of sufficient quality, but their existence may contaminate input parameter set.

On the other side, not only that we can evaluate what subset of input parameter set gives the best simulation model, but we may also determine some eventually new significant interrelationship between analysed parameters.

These results and conclusions could be of a great importance even in classical approaches of mathematical modelling of certain problems. This is especially important for exceptionally complex models because of possibility of leaving out particular parameters with previously evaluated relatively minor effect on output parameter set.

III. THE MODEL STRUCTURE FOR INCREASING REDUNDANCY OF SENSOR INFORMATIONS

In the final section we propose the model structure whose primary function is to increase redundancy of sensor information in marine control systems. Block diagram of the redundancy increasing structure based on the model presented in II. is illustrated in Fig. 2.

The model comprises two basic subsystems. The function of the off-line subsystem is the continuous sensor information processing. It may operate in a real time, although it is not necessary. It is in correlation with the on-line subsystem which provides continuously sensor information in the form of time matrix.

On the other hand, the on-line subsystem has several functions. The primary function is the continuous checking of sensor accuracy and detection of possible failures or faults. Its secondary function is the data transfer into the off-line subsystem as long as the conventional sensor control points the proper functioning with absolute reliability [5], [6].

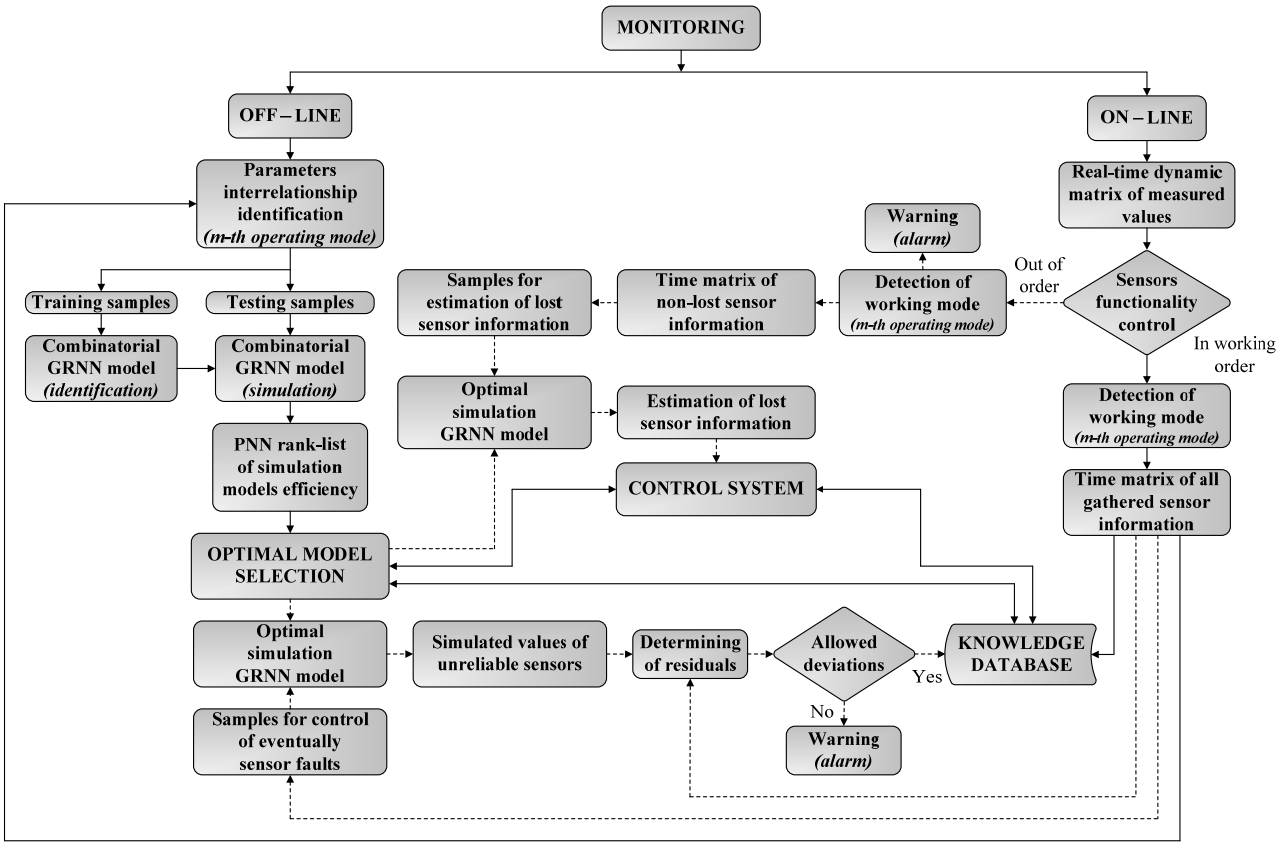


Fig. 2. Proposed model structure for increasing redundancy of sensor information in marine control systems
Source: Authors

For the various operating modes the off-line subsystem classifies the collected sensor information of all the parameters observed and categorize them into learning and testing samples. The learning samples pass through the previously described combinatorial GRNN model, thus identifying the system for the various operating modes. Depending on changes of the parameter values within the same operating mode of the system, it is possible to setup the identification to satisfying accuracy.

On the other hand, testing samples serve to show the efficiency of the identification itself, but also to evaluate and determine the best simulation model that will be used should one or more sensors stop functioning. The efficiency evaluation of the simulation models is carried out according to the previously described PNN model.

As far as the conventional sensor control points the failure [5], [6], the related operating mode is detected and by control system the alarm is sent to the operator. The time matrix of the non-lost sensor information is generated and the estimation of the lost parameters begins, using the optimal simulation GRNN model. Simpler and very efficient parameter estimations of one sensor have been shown before [1], [3], [7], using various artificial neural networks.

However, the lost information estimation of major number of failed sensors, as well as the sensors that show certain operating problems, can also be performed in a simple and efficient way, as described in section II.

Namely, even when the conventional control displays accurate sensor function, their functionality can be additionally controlled and the minimal divergence of usual values can be perceived. For that purpose, the previously trained off-line subsystem will predict the sensor information values in the routine operating mode and will compare them with the collected sensor information in the real time. To provide the maximum reliability of this diagnostic sub-system, the off-line subsystem should be trained using the data collected in the period in which 100% reliability of the sensor accuracy could be guaranteed. Determining of residuals between the simulated and measured values defines divergences which, in the case they pass over the allowed limits, indicate alert to the operator via the control system.

By this combined approach in on-line and off-line operating mode significant advantages in sensor information analysis and processing can be achieved. The main advantage of the off-line data analysis consists in possibility of using the less demanding statical neural networks, but also in the opportunity to provide processing with non real-time data. It relates primarily to the possibilities of fine tuning of the networks in order to achieve optimal simulation results and also in the possibility to prepare the model up front for the largest number of different scenarios in solving the diagnostic problems.

In the study following this one, the most important parts of the programming code of the whole model described here will be presented, as will the results of simulation examinations for the chosen parameter group of the ship engine room with a two-stroke slow speed diesel engine control system. Particular attention will be given to the criteria of choice of the optimal simulation model.

IV. CONCLUSION

The need for increasing the sensor information redundancy is especially pronounced in marine control systems. The reliability required by classification societies grows larger on a daily basis due to the level of automation demands.

The combinatorial model, based on artificial neural networks with the possibility of controlling the accuracy of a single or multiple sensors functionality is presented. In that manner, the model may present an alternative and/or expansion for conventional automatic control systems in cases when input and output parameters are in any relationship.

More over, the possibility of diagnostics of both failures and faults in sensor functionality, as well as the adequate mechanism for estimation of the lost sensor information has been shown.

The primary advantage of proposed model is particularly expressed when the analytical expression of relationship between input and output parameters couldn't be determined.

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