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COMBINATORIAL NEURAL NETWORKS BASED MODEL FOR IDENTIFICATION OF MARINE STEAM TURBINE CLUSTERED PARAMETERS

ABSTRACT

This paper presents a combinatorial model for the identification and simulation of a certain number of parameters of marine steam turbine plant for LNG tankers based on the classification and approximation neural networks. The model consists of two basic parts. In the first part, parameters are classified in adequate clusters by means of self-organizing neural network, while the combinatorial identification of clusters interrelationship is carried out in the second part by means of static feed-forward neural networks. In the following part, the successfulness of the achieved results is analyzed by generating an adequate rank-list of all identification-simulation models. This approach gives a clear insight into certain cluster interdependences which can significantly contribute in following applications which are based on the estimation and prediction of the lost sensor information not depending on the cause of their loss. Although all of the above is distinctly expressed in marine propulsion control systems, it should be pointed out that in this way significantly increased reliability and redundancy of the sensor information directly reflect on considerable increase in technical security of the whole ship as a floating object.

KEY WORDS

marine steam turbines, marine control systems, neural networks, identification, clusterization

1. INTRODUCTION

Problems closely related to redundancy, reliability and safety of marine control systems are particularly emphasised considering the operating environment they are set in. The ship has always presented a specific environment in which many factors that affect steady and reliable functioning within certain marine subsystems are intertwined. Navigational systems, as far as safety and manoeuvring abilities of the ship are concerned, are important to the same extent as her propulsion systems. Although this primarily refers to the main engine, complexity of all marine engine room subsystems and their mutual interaction make this control system an exceptionally complex one because it is conditioned by high efficiency degree, reaction time, reliability and safety along with low tolerance threshold.

Current and future levels of automatic control optimize marine propulsion systems more and more, so that we witness daily a general trend of decrease in the number of crew members. While the ship owner substantially cuts back on costs considering crew members, on the other hand the shortage of qualified and trained crew must be recompensed by systems which are significantly increased in redundancy, adaptability, reliability and safety.

Because of these reasons, one of possible solutions for increasing redundancy of sensor information in marine propulsion system, which is based on application of computer intelligence, is proposed in this paper. Primarily, in this manner, the quality support in form of knowledge base that can be used for solving a whole range of problems from identification and estimation to predicting sensor information is achieved.

A whole range of papers in the last couple of years has been dedicated to the identification of control system parameters by using computer intelligence. In this area, mostly those papers which offer solutions for an estimation of lost sensor information [1], [2], [3], [4], [5] stand out as well as those papers which expand these approaches using function analysis of single sensors and their malfunction detection [2], [5], [6], [7], [8]. Authors in [5], [9], and [10] also provide an insight into the interaction between monitoring and application of the aforementioned approaches. Large majority of papers dealing with this area is based on approximate possibilities of computer intelligence algorithms with the goal to recompense the lost sensor by using a specific number of observed parameters. Certain generalizations of such models are provided by authors in [4] and [11], and one of these generalizations will also be suggested in this paper.

In order to make the identification of a certain subsystem as reliable and correct as possible, it is essential to process the samples of analyzed parameters, to clear all the background noise, and even, if necessary, to organize them into certain classes according to some characteristic features. Dealing with the application of artificial neural networks for those purposes, self organizing neural networks should be singled out as one of the most commonly used methods [1], [12], [13], and [14].

One of possible approaches in improving identification results of marine control systems is suggested in this paper. The suggested model consists of two parts where the second part relies directly on the first part, and it is basically composed of function parameter clusterization and their identification. Specifically, by using self organizing neural network, the chosen parameters can be promptly and simply classified into certain clusters according to their common features [12], so it is to be expected that the identification of the dependence between these obtained clusters should yield more satisfactory results. At the same time, in order not to dwell on classical fusion of sensor information, i.e. on the principle by which one sensor is replaced by a certain number of sensors functioning together interactively, a combinatory approach has been introduced which allows us to assess the successfulness to identification of any cluster group from any other cluster group remaining. This finally enables a choice of the most efficient identification-simulation model, which mostly depends, namely, on the problem which needs to be resolved.

The second part of this paper presents theoretical characteristics and description of the model, while the third part presents its validation. For that purpose the chosen function parameters of marine steam engine have been used. For the clusterization of system parameters Kohonen's self organizing neural network was used, while back propagation neural networks were used for the combinatory identification of the clusters. The assessment of successfulness of individual identification-simulation models was carried out by using classic statistics methods, mean squared error and linear regression. As a computer backup while training, validating and testing neural networks, a PC of standard characteristics (Dual Core 2.6 GHz, 3.25 GB RAM) was used, along with MATLAB R2008b software package installed on 32-bit operating system MS Windows XP.

2. COMBINATORIAL MODEL OF CLUSTER PARAMETER IDENTIFICATION BASED ON NEURAL NETWORKS

Let us denote with $X = \{x_1, x_2, \ldots, x_R\}$ set of R parameters of some system and if Q states of that system are known, where every state is described by an adequate sample, then the space of those states can be written in matrix form

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

Problems of system theory often demand determining the interdependence of some system's parameters. So theoretically, in the system with R parameters, I of them can be expressed through $m \le R - I$ parameters in

$$N_I = \binom{R}{I} \cdot (2^{R-I} - 1) \tag{2}$$

ways.

The technical problems are most commonly reduced to determining one parameter's dependence ($I = 1$) on a certain number of the remaining ones [17], [18]. For this purpose, let us denote x_i as an arbitrary chosen parameter from the set X. It can be understood as a more variable function whose arguments are elements of any r-member subset.

$$A = \{x_1, x_2, \ldots, x_r\} \subseteq X \backslash \{x_i\}, \tag{3}$$

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

$$x_i = F(x_1, x_2, \ldots, x_{i-1}, x_{i+1}, \ldots, x_r). \tag{4}$$

But in the following model, we shall suggest that the parameters of the observed system first be clustered into responding clusters. This way we shall avoid the problem area which is formed when the identification of the system is carried out by randomly chosen parameters without predetermined connection between them, and on the other hand that will significantly improve the results of identification.

For the purpose of clustering, a self-organizing Kohonen's neural network (SOM) will be used, a network which is at the same time one of the most commonly used methods when it comes to clustering data by neural networks usage [15], [16].

The architecture of SOM network that follows the idea of the model presented in this paper is shown in *Figure 1*.

Input layer is presented with a matrix of all parameter values whose format is $Q \times R$, where Q represents a number of stages noticed, and R a number of neurons in the input layer. The number of neurons S^1 in the competitive layer defines the dimension and the topology of the SOM network.

The characteristic of the competitive layer is manifested in the fact that it can be used to classify a set

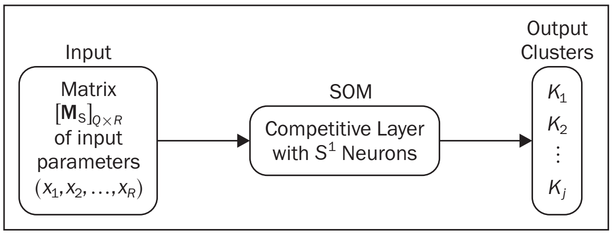

Figure 1 - SOM network architecture

Source: authors according to [15]

of incoming data, independent on a number of parameters, into a determined number of classes depending on the number of neurons in a layer. Neurons will be positioned in 2D topology which enables a visual presentation of distribution, but also a 2D topology approximation of a set of incoming data.

The training of the SOM network will be done by using SOM batch algorithm which characteristically reinforces the adaptation of the network after all of the samples have been presented to the network. The process of training is enforced iteratively until the network is stabilized. After the completion of training, the neighbouring neurons have similar values. Since SOM is a function which preserves metric characteristics of a set of samples, network clustering is also a sample set clustering. Thus, in the input layer, we have again R of clustered classes in a shape of disjunctive subsets which in union make an entire set of input parameters.

The sets of clustered samples by which the identification of the system will be done, will be presented in the following text by output clusters. For this purpose, a combinatorial approach with the basic idea to determine a whole range of interdependencies of any cluster or a group of clusters on any remaining set of data clusters will be used.

The identification of the clustered parameters of the system will be made by approximate two-layer feed forward neural network. In the hidden layer which consists of S neurons, a sigmoid function is used as an activation one, while the linear function is an activation function of the output layer which consists of Q neurons. The architecture of the two-layer feed forward network that follows the model of this work is schematically shown in *Figure 2*.

For the training of these networks the Levenberg-Marquardt back propagation algorithm will be used, which has in many researches and analyses shown to be the algorithm that trains the network in the shortest possible time and brings it to a set goal from training, through validation and all the way to testing [15].

For purposes of rating successfulness of individual identification model classic statistics methods will be used, such as mean squared error (*MSE*) and linear regression (*LR*). MSE presents an average value of the sum of squared differences between referent and their corresponding calculated values. The smaller the *MSE*, the better is the realization of the approximation. On the other hand, the *LR* regression measures the correlation between referent and calculated values. *LR* values closer to one suggest an exceptionally strong correlation, whereas values closer to zero suggest merely a coincidental connection of the values analyzed.

When it comes to combinatorial approach, the idea is as follows: achieved clusters will be combinatorially sorted out by classes. This means that the cluster combinations of the first class will represent approximations of any particular cluster on other remaining clusters, combinations of the second class will represent approximations of any ordered pair of clusters on other remaining clusters, etc. Finally, the combinations of $(j-1)$-th class will represent approximations of any ordered $(j-1)$-tuple on the remaining cluster. Symbolically, it can be written down as follows:

– 1st class cluster combinations – j combinations can be written as

$$K_1 = f_{1,1}^{NN}(K_2, \ldots, K_j) \tag{5}$$

$$K_2 = f_{1,2}^{NN}(K_1, K_3, \ldots, K_j) \tag{6}$$

$$\vdots$$

$$K_j = f_{1,j}^{NN}(K_1, K_2, \ldots, K_{j-1}) \tag{7}$$

where $f_{1,j}^{NN}$ is an approximate function, i.e. j-th neural network of the first class

– 2nd class cluster combinations – $\binom{j}{2}$ combinations can be written as

$$(K_1, K_2) = f_{2,1}^{NN}(K_3, \ldots, K_j) \tag{8}$$

$$(K_1, K_3) = f_{2,2}^{NN}(K_2, K_4, \ldots, K_j) \tag{9}$$

$$\vdots$$

$$(K_{j-1}, K_j) = f_{2,\binom{j}{2}}^{NN}(K_1, K_2, \ldots, K_{j-2}). \tag{10}$$

If we continue to do this for a total of $(j-1)$ times, the combinations of the $(j-1)$-th class, of which there is a total of j, can be written as

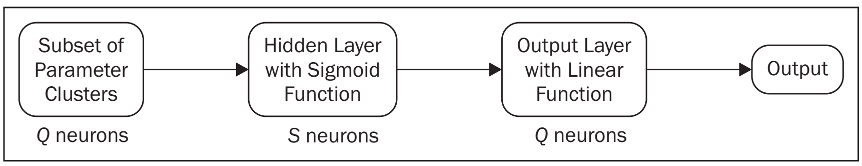

Figure 2 - The architecture of the two-layered feed-forward neural network

Source: authors according to [15]

$$(K_1, K_2, \ldots, K_{j-1}) = f^{NN}_{j-1,1}(K_j) \tag{11}$$

$$(K_1, K_2, \ldots, K_j) = f^{NN}_{j-1,2}(K_{j-1}) \tag{12}$$

$$\vdots$$

$$(K_2, K_3, \ldots, K_j) = f^{NN}_{j-1,\binom{j}{j-1}}(K_1). \tag{13}$$

All cluster combinations from the first to $(j-1)$-th class come to a total of

$$\binom{j}{1} + \binom{j}{2} + \ldots + \binom{j}{j-1} = 2^j - 2. \tag{14}$$

Since by increasing the number of clusters the number of all cluster combinations grows even more notably, we shall introduce notation for the purpose of monitoring more easily the individual combinations of a single class. So the combinations of the first class shall be marked with 1.1, 1.2, ..., 1.j, combinations of the second class with 2.1, 2.2, ..., 2.$\binom{j}{2}$, etc.

At the same time, each combination of each class undergoes an identification process based on neural networks, so it is practical to introduce a concept of identifying each single class. That way we could schematically show each of $2^j - 2$ identifications. For example, we could schematically show the first $(f^{NN}_{1,1})$ identification of the first class the way it is done in *Figure 3*.

$(K_2, \ldots, K_j)$ clusters are input into a two-layer feed-forward network, and the values of K_1 cluster are simulated. K_1 cluster referent values and calculated values O_1 are the basis for analysis of identification successfulness by using the aforementioned *MSE* and *LP* methods. After grading individual phases from training to testing, all the data that characterize this identification are written into archives for the purpose of further analysis. This relates to characteristic network values and successfulness results.

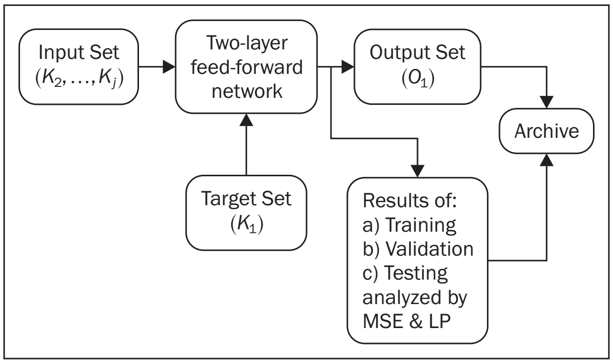

Figure 3 - Block-diagram for identification model 1.1

After the model of the first combination of the first class is completed, we move over to the second combination of the first class. The procedure is identical to the one described before with the difference that the network is now presented with second combination clusters of the first class $(K_1, K_3, \ldots, K_j)$ and K_2. Here also the obtained data are archived for the purpose of further examining and grading.

When all the identification processes of all classes and combinations are processed in the way we described before, we are left with an archive of significant information useful in more ways at our disposal. In marine control systems it can easily be transformed into a knowledge base and in this way it can be repeatedly helpful in increasing the safety, reliability and redundancy of the system itself. This can include a wide spectrum of applications, from estimation of the lost sensor information, detection of faults and malfunctions to supporting fuzzy system of process regulation or as an alternative and complement to the existing sensor systems [19], [20].

With statistic and/or optimization methods the optimal method can be easily determined between $2^j - 2$ identification models, considering the problem which needs to be resolved at a certain point.

3. MODEL VALIDATION AND ANALYSIS OF OBTAINED RESULTS

In the continuance of this paper we shall make a validation of the proposed model with the corresponding analysis of the obtained results. For this purpose we will use a disposable set of data from a Kawasaki Heavy Industries marine steam turbine with a power of 28 MW at 83 min^{-1} on the propeller axis. Among disposable data there were four temperatures measured on turbine bearings, two on the front and two on the back side of the high-pressure part of the turbine, two axial shifts measured on the front side of high-pressure turbine and two relative vibrations measured on the back side of the high-pressure turbine.

The readings have been chosen for two characteristic time intervals. The first interval I_1 represents a period during which LNG tanker gradually increases the number of revolutions and increases the nominal power from 30% to 80% of maximum load, which is equivalent to the increase of turbine power from 8.5MW to 22.5MW. It definitely needs to be mentioned that during this interval the weather was calm without significant external disturbances such as wind, waves or sea currents.

Unlike the first interval, the second interval I_2 was chosen during bad weather with significant external disturbances. Along with a strong wind and high waves, the ship plunged on a few occasions, i.e. the ship's propeller partially emerged above sea surface which, cumulatively observed, reflected on the operation of the turbine itself, and therefore reflected also on the parameters analyzed. The characteristics of the chosen measured parameters are concisely presented in *Table 1*.

Table 1 - Characteristics of measured values of the chosen parameters

Measured value	Variable	Measurement unit	Interval I_1		Interval I_2	
			Min.	Max.	Min.	Max.
Temperature 1 of the bearing metal 1, front A	T1FA	°C	63.06	97.335	98.94	101.56
Temperature 1 of the bearing metal 1, front B	T1FB	°C	64.155	98.07	99.675	102.28
Temperature 2 of the bearing metal 1, back A	T2BA	°C	42.915	67.08	54.195	56.61
Temperature 2 of the bearing metal 1, back B	T2BB	°C	42.69	67.665	54.78	57.195
Axial shift A	ASA	mm	-0.047	0.12	-0.019	0.258
Axial shift B	ASB	mm	-0.055	0.112	-0.04	0.224
Relative vibrations shaft - turbine bearing A	RVA	μm	60.33	105.15	60.63	65.01
Relative vibrations shaft - turbine bearing B	RVB	μm	67.38	113.37	67.38	70.74

3.1 Operating Parameters Clustering

Let us denote

$$X = \{\text{T1FA, T1FB, T2BA, T2BB, ASA, ASB, RVA, RVB}\}$$

as a set of $R = 8$ parameters of the steam turbine plant presented in *Table 1*.

Since in the first time interval I_1, $Q_1 = 5{,}500$ readings were chosen, that means that the input matrix will have a format of $Q_1 \times R = 5{,}500 \times 8$.

For parameter clustering we use Neural Network Clustering Tool program module, as a part of Neural Network Toolbox of MATLAB R2008b software package.

The input layer consists of 8 neurons, competitive layer of 10 neurons and the output layer of 100 neurons.

After the training phase which is based on Batch Unsupervised Weight/Bias learning method [15], the network is fully adapted. The visualization of the adapted weight coefficients which link every input vector with every neuron is the best indicator for possible correlations between input vectors, i.e. parameters of the input matrix. One such visualization for the first analyzed interval is shown in *Figure 4*.

Even by just superficially analyzing weight surfaces of the input vectors it is clear that there exists a strong correlation between certain parameters which we can divide into four clusters by two parameters, as follows:

$$K_1 = (\text{T1FA, T1FB}) \tag{15}$$

$$K_2 = (\text{T2BA, T2BB}) \tag{16}$$

$$K_3 = (\text{ASA, ASB}) \tag{17}$$

$$K_4 = (\text{RVA, RVB}). \tag{18}$$

There is an almost identical situation with parameters of the second time interval I_2. Although the ship and the power turbine and therefore the analyzed parameters were significantly influenced by external factors, an almost identical clustering of the parameters was obtained anyway. The only noticeable difference in relation to the first interval is a slightly less expressed correlation between parameters RVA (Input 7) and RVB (Input 8). But since we are dealing with relative vibrations, and at the same time bearing in mind the circumstances under which the second interval was chosen, the differences are not surprising. These differences are neglected in this paper because they represent the reason for implementing adaptive cluster identification which is not a part of this paper but the one that will follow.

3.2 Identification of Parameter Clusters

After a successfully accomplished clusterization of parameters into four characteristic clusters, we shall define, for $j = 4$, combinations of 1st, 2nd and 3rd class, and their corresponding identification models. Thus we differ:

– Cluster combinations of 1st class – 4 combinations

$$K_1 = f_{1,1}^{NN}(K_2, K_3, K_4) \quad \text{(identification model 1.1)} \tag{19}$$

$$K_2 = f_{1,2}^{NN}(K_1, K_3, K_4) \quad \text{(identification model 1.2)} \tag{20}$$

$$K_3 = f_{1,3}^{NN}(K_1, K_2, K_4) \quad \text{(identification model 1.3)} \tag{21}$$

$$K_4 = f_{1,4}^{NN}(K_1, K_2, K_3) \quad \text{(identification model 1.4)} \tag{22}$$

– Cluster combinations of 2nd class – 6 combinations

$$(K_1, K_2) = f_{2,1}^{NN}(K_3, K_4) \quad \text{(identification model 2.1)} \tag{23}$$

$$(K_1, K_3) = f_{2,2}^{NN}(K_2, K_4) \quad \text{(identification model 2.2)} \tag{24}$$

$$(K_1, K_4) = f_{2,3}^{NN}(K_2, K_3) \quad \text{(identification model 2.3)} \tag{25}$$

$$(K_2, K_3) = f_{2,4}^{NN}(K_1, K_4) \quad \text{(identification model 2.4)} \tag{26}$$

$$(K_2, K_4) = f_{2,5}^{NN}(K_1, K_3) \quad \text{(identification model 2.5)} \tag{27}$$

$$(K_3, K_4) = f_{2,6}^{NN}(K_1, K_2) \quad \text{(identification model 2.6)} \tag{28}$$

– Cluster combinations of 3rd class – 4 combinations

$$(K_1, K_2, K_3) = f_{3,1}^{NN}(K_4) \quad \text{(identification model 3.1)} \tag{29}$$

$$(K_1, K_2, K_4) = f_{3,2}^{NN}(K_3) \quad \text{(identification model 3.2)} \tag{30}$$

$$(K_1, K_3, K_4) = f_{3,3}^{NN}(K_2) \quad \text{(identification model 3.3)} \tag{31}$$

$$(K_2, K_3, K_4) = f_{3,4}^{NN}(K_1) \quad \text{(identification model 3.4)} \tag{32}$$

For each cluster combination of particular classes, the corresponding parameter identification has been made by means of a two-layer feed-forward neural network in a way that was already described in 2. It only

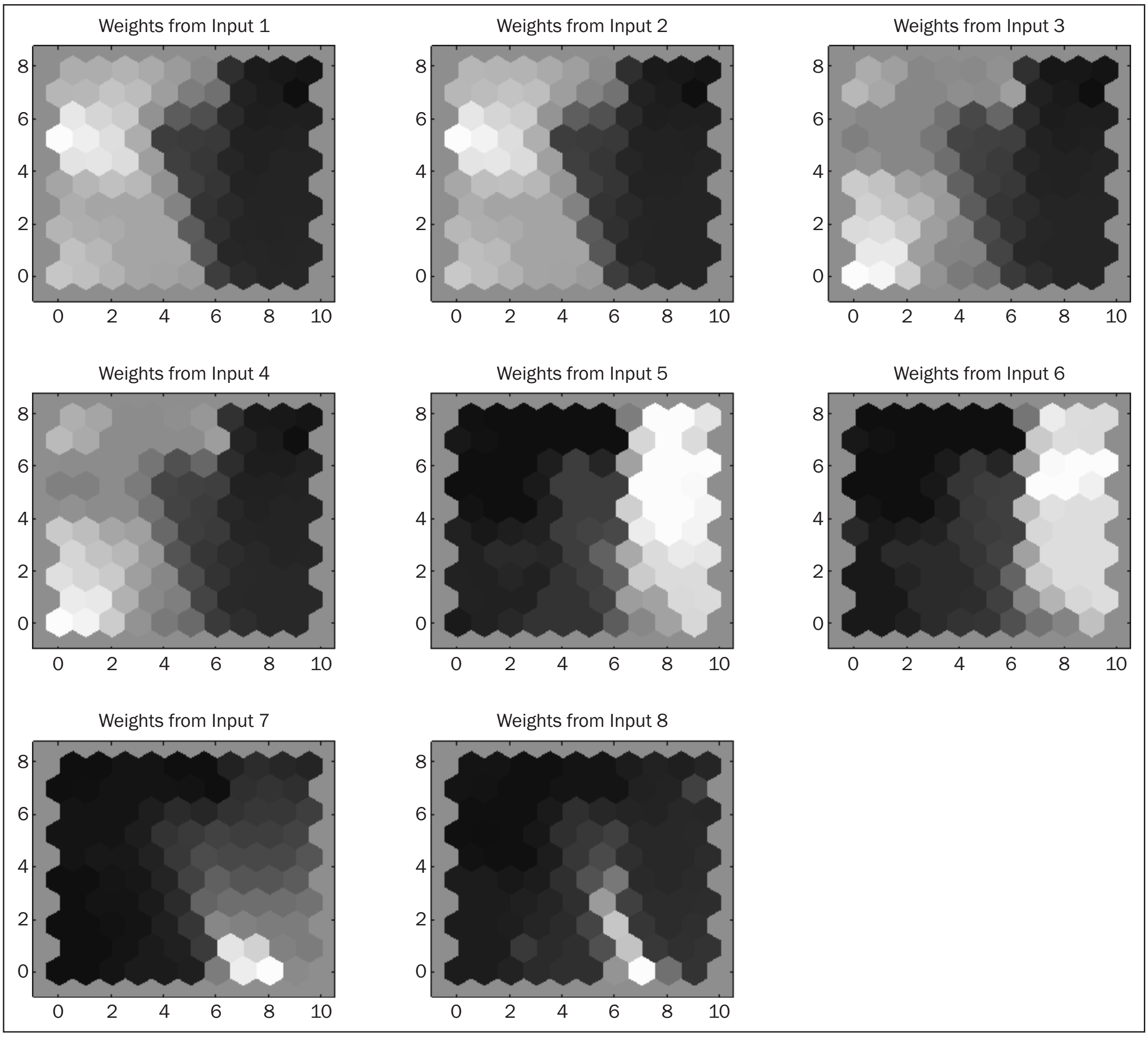

Figure 4 - Surfaces of trained weight coefficients of the SOM network for 8 input parameters from the first time interval

needs to be added that all identifications were made with 30 neurons in the hidden layer.

In our specific case, since $j = 4$, we distinguish $2^4 - 2 = 14$ different combinations because of which we had to identify the system 14 times. As a grade of successfulness of each individual model taken into consideration was a mean squared error (MSE) of training and testing, linear regression of training, validating and testing, time frame needed for all three phases, and the number of epochs, i.e. iterations needed for the network to reach the goal.

The network has by random choice distributed presented samples into samples for training (70% of samples), validation samples (15%) and testing samples (15%). In this way the possibility of deliberate data manipulation was avoided.

As an illustrative example, *Figure 5* shows a graphic presentation of results obtained during training, validation and testing phases for the identification model 1.3.

Some models have proven as better ones, some as worse, but this was exactly the intention of this approach. All of the obtained grades of individual model successfulness for the first interval are shown in *Table 2*. It definitely needs to be mentioned that the time time [s] relates primarily to time needed for training, i.e. training of neural networks of individual identification models, and that the time needed for simulating new samples is incomparably faster.

3.3 Analysis of the Obtained Results

If we focus only on linear regression results, we can without doubt conclude that the clustering was a fully justified undertaking, because the correlation between referent and calculated values is extremely strong which in any case favours this approach.

To get in general a maximally clear and high-quality view of the results obtained, an idea of creating appro-

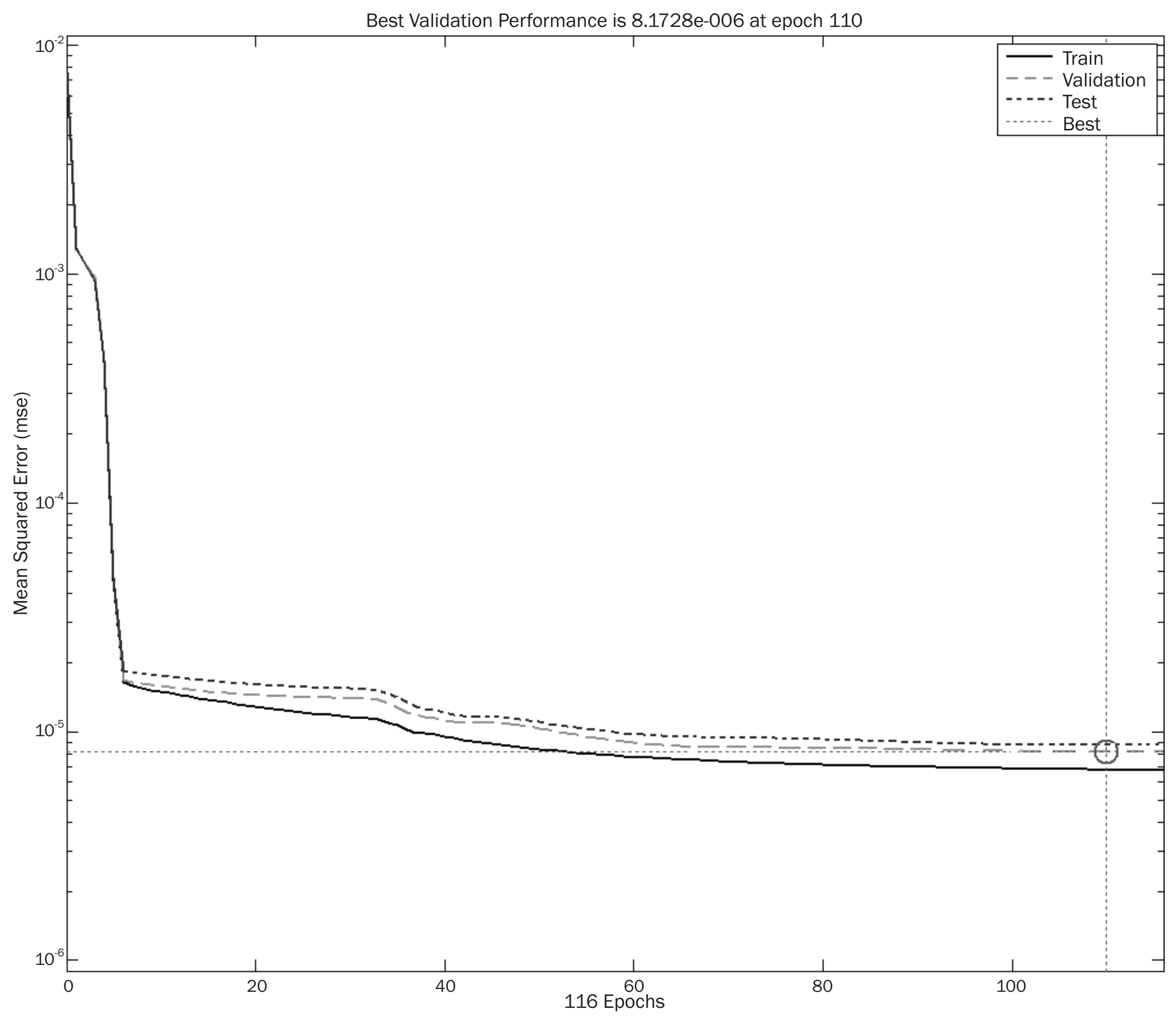

Figure 5 - Results obtained for the identification model 1.3 during training, validation and testing phases

Table 2 - Characteristic values for grading successfulness of the individual identification model in the first time interval

Identification model	MSE – train	MSE – test	LR – all	Time [s]	Epochs/Iterations
1.1	0.36861	0.37643	0.99851	51	187
1.2	0.06167	0.06467	0.99944	89	324
1.3	0.0000068	0.0000087	0.99924	112	116
1.4	0.49567	0.61267	0.99745	49	164
2.1	0.67825	0.74444	0.99864	38	70
2.2	0.14672	0.15904	0.99995	318	303
2.3	0.70886	0.75314	0.99687	87	164
2.4	0.04875	0.06771	0.99997	64	126
2.5	0.52193	0.50575	0.99866	53	103
2.6	0.75815	0.33674	0.99976	206	401
3.1	1.09505	1.18560	0.99867	48	55
3.2	3.80743	3.69791	0.97814	133	120
3.3	1.91803	2.04981	0.99261	107	114
3.4	1.58997	1.79704	0.98418	91	136

Table 3 - Ranking list of successfulness of identification models by time intervals

Rank	Interval I_1	Interval I_2	Intervals I_1 and I_2
1.	1.3	2.4	2.4
2.	2.4	2.1	1.3
3.	1.2	2.2	2.2
4.	2.2	1.3	1.2
5.	2.6	3.1	2.1
6.	1.1	1.2	1.1
7.	2.5	1.1	3.1
8.	1.4	2.3	2.5
9.	2.1	3.2	2.3
10.	3.1	3.3	2.6
11.	2.3	2.5	1.4
12.	3.4	3.4	3.2
13.	3.3	1.4	3.3
14.	3.2	2.6	3.4

priate rank-lists of identification models imposes itself as a suitable solution considering their successfulness shown through the mean squared error of training and testing, as well as linear regression. If we cumulatively observed the successfulness of individual models by individual rank-lists, we would easily get one uniform rank list considering all three criteria. *Table 3* in fact shows a rank-list of successfulness considering all three grading criteria at the same time.

From *Table 3* it can be clearly noticed that the usual practice of simulation of just one parameter by using a certain number of the remaining ones is not the optimal choice at all. What's more, simulation models of the 2nd class combinations have shown somewhat better than 1st class models. Thus, in our case we could choose model 2.4 as the optimal identification-simulation model, i.e. mapping of a set of 4 input vectors into a set of 4 output vectors. Even model 3.1 is by all characteristics above some 1st and 2nd class models, which clearly indicates that the possibility of simulating a larger number of outputs with a lesser number of input parameters, i.e. clusters, should not be thrown out.

4. CONCLUSION

Clustering of the marine propulsion system parameters can significantly contribute to the quality of identifying parameter clusters, while a combinatorial approach enables a choice of the optimal identification-simulation model for determining dependence of one group of clusters on other group of clusters.

Change of conditions, i.e. internal or external factors which are characteristic for a ship and marine environment will cause changes in SOM weight coefficients, so a different clustering of parameters is possible. Therefore, the identification-simulation models will also alter, which represents an adaptive optimization, so that the control system, even in different scenarios characteristic for marine propulsion, can always have at its disposal the optimal model for possible estimation of the lost sensor information.

It also needs to be added that the presented model is relatively universal, and with slight modifications, it is surely easily applicable in other marine systems and their subsystems. That way it can significantly contribute to the quality, reliability and safety of marine control systems in general.

Further research should be oriented to the analysis of operating modes of marine steam turbines and affliction of those modes to model adaptation. For that purpose, the application of dynamic adaptive optimization is recommended. The proposed model could be generalized for all operating modes with that approach. With adequate adaptive optimization techniques the time for neural networks training could also be much shorter which should eventually result in acceleration of model adaptation process to changed operating conditions.

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SAŽETAK

KOMBINATORNI MODEL ZA IDENTIFIKACIJU KLASTERIZIRANIH PARAMETARA BRODSKE PARNE TURBINE TEMELJEN NA UMJETNIM NEURONSKIM MREŽAMA

U radu je iznesen kombinatorni model za identifikaciju i simulaciju određenog broja parametara brodskog parnoturbinskog postrojenja LNG tankera temeljen na klasifikacijskim i aproksimacijskim neuronskim mrežama. Model se sastoji iz dva osnovna dijela. U prvom se dijelu parametri klasificiraju u odgovarajuće klastere pomoću samoorganizirajuće neuronske mreže, dok se u drugom vrši kombinatorna identifikacija međusobne ovisnosti klastera pomoću statičkih unaprijednih neuronskih mreža. U nastavku se analizira uspješnost dobivenih rezultata uz generiranje odgovarajuće rang liste identifikacijsko-simulacijskih modela. Na ovaj se način dobiva jasan pregled ovisnosti među pojedinim klasterima što može značajno doprinijeti u daljnjim primjenama koje su temeljene na estimaciji i predikciji izgubljenih senzorskih informacija neovisno o uzroku gubitka istih. Iako je sve navedeno posebno izraženo u brodskim sustavima upravljanja propulzijom, treba istaknuti da se na ovaj način značajno povećanje pouzdanosti i redundantnosti senzorskih informacija direktno odražava i

na značajno povećanje tehničke sigurnosti cijelog broda kao plovnog objekta.

KLJUČNE RIJEČI

brodske parne turbine, brodski sustavi upravljanja, neuronske mreže, identifikacija, klasterizacija

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