STUDY THE QUALITY OF GLOBAL NEURAL MODEL WITH REGARD TO LOCAL MODELS OF CHEMICAL COMPLEX SYSTEM

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Abstract: *In the paper global modeling of complex systems with regard to quality of local models of simple plants is discussed. Complex systems consists of several sub-systems. As a global model multilayer feedforward neural networks are used. It is desirable to obtain an optimal global model, as well as optimal local models. A synthetic quality criterion as a sum of the global quality criterion and local quality criteria is defined. By optimization of the synthetic quality criterion can be obtained the global model with regard to the quality of local models of simple plants. The quality criterion of the global model contains coefficients which define the participation of the local quality criteria in the synthetic quality criterion. The investigation of influence of these coefficients on the quality of the global model of the complex static system is discussed. The investigation is examined by a complex system which is composed from two nonlinear simple plants. In this paper complex system means real chemical object (i.e. a part of the line production of ammonium nitrite).*

Keywords: *complex system, neural network, global modeling*

ACM Classification Keywords: *I.2.6 ARTIFICIAL INTELLIGENCE, Learning - Connectionism and neural nets*

Introduction

In the area the design of complex control systems, there are numerous difficulties associated with constructing appropriate models of complex systems and determining their parameters. One of the basic issues to be considered a model of system as a whole, i.e. to develop a global model and ensuring the quality of approximations of system components, e.g. the development of local models.

The classic task of modeling a complex system is to find optimal values of parameters of adopted mathematical model based on the established quality criteria. Mathematical methods of identification of complex objects are based on the distribution of components. The next step is to construct models of individual components (i.e. simple objects) and search for them optimal parameters. The next step is the submission of the optimal models of simple models of the complex system [Bubnicki, 1980]. Obtained in this way model is not globally optimal, because while searching of the parameters of simple models do not take into account the interaction of components of a complex system during the modeling process. In this case we are dealing with a local modeling. The opposite approach to the local modeling is a global modeling of complex systems [Dralus and Swiatek 2000(1)], [Świątek, 2004].

Application of neural networks that have the ability to approximate nonlinear functions [Hornik, 1989] allow us to build and determine a global model parameters. The assumption of a global model to reflect the structure of a complex system in the work, and reflect the interactions of the components of a complex system during determination of model parameters. This allows us to build a more accurate model than the decomposition method [Dahleh and Venkatesh, 1997], [Dralus and Swiatek, 2000(1)], [Drałus and Świątek, 2009].

Modeling of static complex objects

Complex system are difficult to model. In principle, the methods of mathematics are not capable of modeling complex objects. To make this possible a complex system should be decomposed to simple objects [Bubnicki, 1980]. Then, separate simple objects can be modeled as independent by any methods for simple objects without considering the fact that they are part of the complex system. After obtaining the optimal parameters of simple models, assembles the complex model, which corresponded to an complex system structurally. Created in this way complex model is locally optimal, but it is not globally optimal. New fields and modern tools allow us to build global models without their decomposition. One of these tools are neural networks that allow to build a global model, which corresponds to the structure of a complex system.

By learning neural networks can to obtain satisfactory parameters of the model. Complex systems can have a varied structure. In this paper, the complex system has a cascade structure, which often occurs in industrial factories.

Global model taking into account local models

A complex system, which consists of cascaded in series *R*-th simple plants is shown in Figure 1. Simple plants are designated as O1, ..., O_R. The global model structure should correspond to the structure of the complex system. Thus, a global model has a cascade structure, and consists of *R*-th simple models designated as M_r. In a global model (see Figure 1) the *r*-th output of simple model M_r is the input to the next simple model M_{r+1}, as in the complex system. On the other hand, in the global model, besides simple models, local models can be distinguished. Then, the output of the simple object O_r is the input to the next local model M_{r+1}.

Physically the simple model M_r and the local model M_r is the same model (one set of neural network weights). They only differ in the input signals and way of learning. Local models will be used to build a global model taking into account the quality of local models.

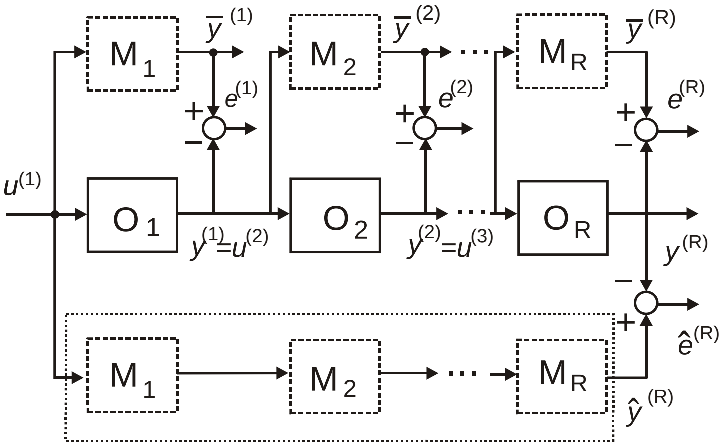

Fig. 1. Block diagram of complex system and its global model

In the global model, for each *r*-th local model is defined a local quality index as a difference between the output $\bar{\boldsymbol{y}}^{(r)}$ of the *r*-th local model and the output $\boldsymbol{y}^{(r)}$ of the *r*-th simple object:

$$Q^{(r)}(\boldsymbol{w}^{(r)}) = \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J_r}\left(\bar{y}_j^{(r),k} - y_j^{(r),k}\right)^2 \tag{1}$$

where: $\boldsymbol{w}^{(r)}$ – weights of the *r*-th model simple/local model, K – a number of patterns J_r – a number of outputs of the *r*-th object.

For simplicity, in the global model is defined only one global quality index as a difference between the output $\hat{\boldsymbol{y}}^{(R)}$ of the *R*-th simple model and the output $\boldsymbol{y}^{(R)}$ of the *R*-th simple object:

$$Q(\boldsymbol{W}) = \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{J_R}\left(\hat{y}_j^{(R),k} - y_j^{(R),k}\right)^2 \tag{2}$$

where: $\boldsymbol{W}$ – weights of a global model, K – a number of patterns, J_R – a number of outputs of R-th object.

As a reminder, the output $\hat{\boldsymbol{y}}^{(R)}$ of the R-th simple model is the output of the global model, which corresponds to the output $\boldsymbol{y}^{(R)}$ in the complex system.

On the basis quality indices $Q^{(r)}$ of local models and the global quality index Q was formulated synthetic quality criterion of the global model with regard to the quality of local models. Thus, the synthetic quality criterion may take the form of a weighted sum indices of quality:

$$Q_S(\boldsymbol{W}) = \alpha_0 Q(\boldsymbol{W}) + \sum_{r=1}^{R} \alpha_r Q^{(r)}(\boldsymbol{w}^{(r)}) \tag{3}$$

where: $\boldsymbol{W}$ – weights of a global model, α_r – weighting coefficients of local models, such that $0 \le \alpha_r \le 1$, $\sum_{r=1}^{R} \alpha_r = 1$, α_0 – weighting coefficients of a global model, such that $0 \le \alpha_0 \le 1$.

The weighting coefficients α_r determine an individual participation of the quality indices $Q^{(r)}$ of local models in the synthetic quality criterion (3), while the weighting coefficient α_0 determines the participation the global quality index Q in this synthetic quality criterion Q_s. There are others method to take into account quality local models in a global model, for example a penalty function [Dralus and Swiatek, 2002].

By minimizing the synthetic quality criterion Q_s can be calculated parameters of the global model.

Backpropagation learning algorithm for a global model with regard to local models

A multilayer neural network is a global model therefore to minimize the global quality index (3) a learning algorithm is derived based on back propagation of errors. The base learning algorithm for multilayer networks is the gradient descend. According to this algorithm an increment of weight for criterion (3) is calculating as:

$$\Delta w_{ji} = -\eta \frac{\partial Q_S(\boldsymbol{W})}{\partial w_{ji}} \tag{4}$$

Calculations of the gradient (3) of the global criterion led to a new complex backpropagation learning algorithm. However, the speed of that learning algorithm according to the gradient is small and depends on the choice of learning rate η. Other algorithms are much faster. One of them is Rprop algorithm [Riedmiller and Branun, 1992]. As in the case the complex gradient algorithm, the algorithm Rprop has been modified and adapted for the learning of complex neural networks, having the structure of the global model called the complex Rprop [Dralus and Swiatek, 2000 (2)].

Changing the weights in the complex Rprop learning algorithm in following layers:

- in the output layer:

$$\Delta w_{ji}^{(R),M} = -\eta_{ji}^{p} \operatorname{sgn}\left(\sum_{k=1}^{K} f'(z_j^{M,k}) \alpha_R \left(\bar{y}_j^{(R),k} - y_j^{(R),k} \right) \hat{u}_i^{M-1,k} \right) - \eta_{ji}^{p} \operatorname{sgn}\left(\sum_{k=1}^{K} f'(z_j^{M,k}) \alpha_0 \left(\hat{y}_j^{(R),k} - y_j^{(R),k} \right) \hat{u}_i^{M-1,k} \right) \quad (5)$$

- in the hidden layers:

$$\Delta w_{ji}^{(r),m} = -\eta_{ji}^{p} \operatorname{sgn}\left(\sum_{k=1}^{K} f'(z_j^{m,k}) \sum_{l=1}^{I_{m+1}} \delta_l^{(r),m+1,k} \, w_{lj}^{(r),m+1} \, \hat{u}_i^{m-1,k} \right) \quad (6)$$

- in the "binding" hidden layers, i.e. in output layers of the simple models of a complex model:

$$\Delta w_{ji}^{(r),m} = -\eta_{ji}^{p} \left(\sum_{k=1}^{K} f'(z_j^{m,k}) \left(\sum_{l=1}^{I_{m+1}} \delta_l^{(r+1),m+1,k} \, w_{lj}^{(r+1),m+1} + \alpha_r \left(\bar{y}_j^{(r),k} - y_j^{(r),k} \right) \right) \hat{u}_i^{m-1,k} \right) \quad (7)$$

In this algorithm, the learning speed ratio η is adaptive and in *p*-th step of learning is:

$$\eta_{ji}^{p} = \begin{cases} \min\left(a \cdot \eta_{ji}^{(p-1)}, \eta_{\max}^{p} \right) & \text{if} \quad S_{ji}^{p} \cdot S_{ji}^{(p-1)} > 0 \\ \max\left(b \cdot \eta_{ji}^{(p-1)}, \eta_{\min}^{p} \right) & \text{if} \quad S_{ji}^{p} \cdot S_{ji}^{(p-1)} < 0 \\ \eta_{ji}^{(p-1)} & \text{if} \quad S_{ji}^{p} \cdot S_{ji}^{(p-1)} = 0 \end{cases} \quad (8)$$

where: $S_{ji}^{p} = \frac{\partial Q_s(W(p))}{\partial w_{ji}}$; $\eta_{\max} = 50$; $\eta_{\min} = 10^{-6}$; *a*=1,2; *b*=0,5 [Zell, 1993].

The complex Rprop algorithm was used to learning neural networks, of which is built a global model and local models.

Simulations

For simulations was chosen a complex chemical object. This object is the production line of ammonium nitrite. It consists of several parts but, only the first two objects was selected for modeling (see Figure 2). So, the complex system for simulation consists of two simple non-linear objects connected in series.

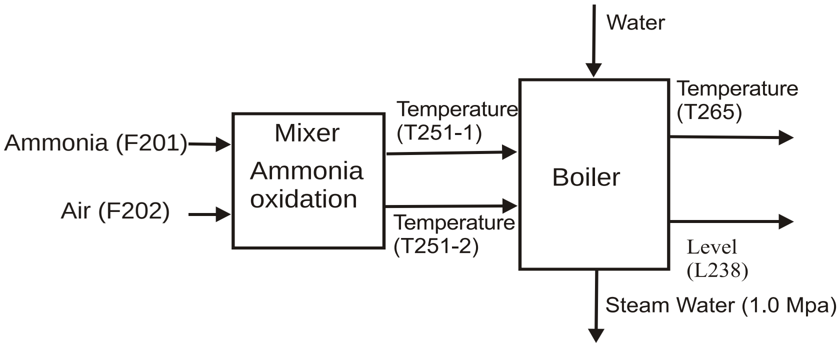

Fig. 2. The part of the installation for the production of ammonium nitrite

In Figure 3 is shown a simplified block diagram of the chemical object as a part of the production line of ammonium nitrite. In the block diagram is omitted immeasurable signals (water, steam), treated it as a constant disturbance. Input signals for the complex system are: u_1 - the flow of ammonia (F201), u_2 - the air flow (F202). The output of the first object is the input of the second object: $y_1^{(1)}$ - temperature (T251-1), $y_2^{(1)}$ - temperature (T251-2). The outputs of the second object are: $y_1^{(2)}$ - the temperature in the boiler (T265); $y_2^{(2)}$ - the solution level in the boiler (L238). These data are also the output of the complex system.

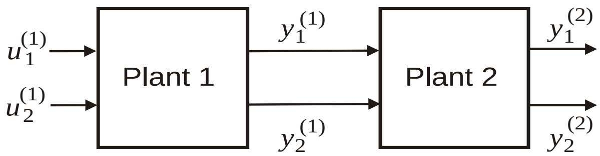

Fig. 3. Block diagram of the chemical object

Measuring learning and testing data include four days from instantaneous reports, recorded every two hours, come from the industrial production line of ammonium nitrite. The learning data was created by combining data from two days, they contain 24 items. Data from two subsequent days are the testing data. For simplified chemical object shown in Figure 3 was built a global model from a neural network, which is shown in Figure 4.

The neural model is a complex model, which corresponds to the structure of the complex system. The neural model has the following structure: 2-7T-4T-2L-7T-4T-2L. The complex model is divided into two simple models of the structure: 2-7T-4T-2L, connected in series. Simple models are simultaneously the local models and have two hidden layers with nonlinear activation functions of hyperbolic tangent (T), in the output layer the activation function is linear (L).

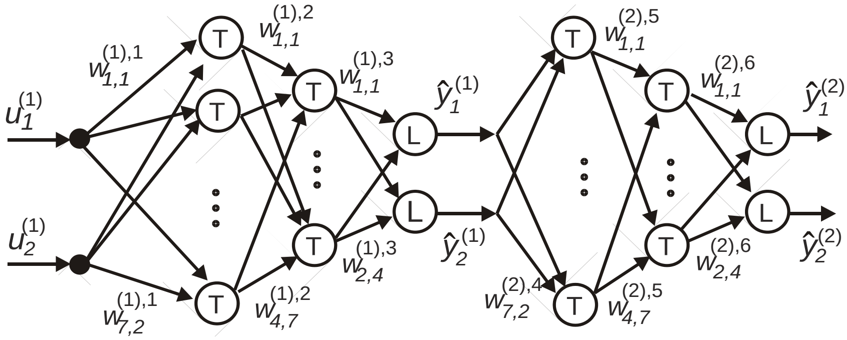

Fig. 4. The structure of the global model built from neural networks

The learning data for the neural network derived from a real object, they have a very large range, e.g. air flow hovers around 5900, and the level of the liquid solution oscillates near value of 70. Thus, all data must be scaled to the range [0..1], in which work functions of activation. Scaling was based on dividing the input and output by the maximum value appropriate for the individual data according to the formula:

$$y_j^s = \frac{y_j}{y_{\max}} \tag{9}$$

:

Where: y_j^s - is the scaled *j*-th component of the vector $\boldsymbol{y}$, y_j - the current value of the *j*-th element of the vector, $y_{\max}$ - value of the largest element in the vector $\boldsymbol{y}$.

An additional criterion for assessing the quality of modeling was adopted relative percentage error, abbreviated RPE, calculated for the *j*-th output of the *r*-th simple model with respect to the corresponding outputs a simple object:

$$\text{RPE}_j^{(r)} = \frac{\sum_{k=1}^{K} \left| \hat{y}_j^{(r)}(k) - y_j^{(r)}(k) \right|}{\sum_{k=1}^{K} \left| y_j^{(r)}(k) \right|} \cdot 100\% \tag{10}$$

Table 1. The values of quality indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =1.

α_1	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s
	For learning data				For testing data			
0,001	9.8E+6	124000	105	134000	1.8E+6	91200	112	92900
0,01	116000	350	118	1630	3430	116	114	206
0,1	2470	120	108	463	3170	122	126	490
0,2	3170	122	126	858	2070	117	108	562
0,3	2100	116	113	824	2050	118	119	757
0,4	2070	117	108	1010	2010	117	109	929
0,5	2190	117	108	1260	2210	117	109	1220
0,6	2050	118	119	1400	1960	116	113	1280
0,7	1950	116	110	1510	1950	120	119	1460
0,8	2010	117	109	1740	2000	115	112	1680
0,9	2130	116	110	2040	2030	116	114	1900
0,99	2120	117	109	2210	2010	117	116	2050
0,999	2200	117	109	2310	2020	117	116	2080

Table 2. The values of quality indices for learning and testing data after 500 epochs of learning for the coefficient α_0=0.5.

α_1	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s
	For learning data				For testing data			
0,001	1.8E+6	91200	112	92900	1.8E+6	86000	57	87700
0,01	3430	116	114	206	4880	67	62	146
0,1	3170	122	126	490	4170	71	64	513
0,2	2070	117	108	562	1970	70	75	488
0,3	2050	118	119	757	2030	70	70	693
0,4	2010	117	109	929	1940	69	77	856
0,5	2210	117	109	1220	2310	70	69	1220
0,6	1960	116	113	1280	1920	70	71	1220
0,7	1950	120	119	1460	1850	71	71	1350
0,8	2000	115	112	1680	1970	70	59	1620
0,9	2030	116	114	1900	2010	70	69	1850
0,99	2010	117	116	2050	1980	70	73	2000
0,999	2020	117	116	2080	2000	71	71	2030

Simulations were performed for three values of the coefficient α_0 (i.e. for $\alpha_0 = 1, \alpha_0 = 0.5$ and $\alpha_0 = 0.1$) which defines the scope of the influence of the global quality index Q on the synthetic quality criterion (3). The coefficients α_r determine the influence of local quality indices on the synthetic quality criterion. Changes in the weighting factors in the synthetic quality criterion were held so that each time their sum was 1 i.e. $\alpha_1 + \alpha_2 = 1$.

The values of the quality of local models $Q^{(r)}$, the global quality index Q and the synthetic quality criterion Q_s for changes in the coefficients α_1 and α_1 for coefficient $\alpha_0 = 1$ can be found in Table 1. Simulation results for coefficient $\alpha_0 = 0.5$ are presented in Table 2 and for coefficient $\alpha_0 = 0.1$ in Table 3. Time of learning of the global model by using the complex Rprop algorithm was 500 epochs.

Table 3. The values of quality indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =0.1.

α_1	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s	$Q^{(1)}$	$Q^{(2)}$	Q	Q_s
	For learning data				For testing data			
0,001	116000	350	118	477	122000	306	71	435
0,01	2470	120	108	154	2270	71	71	100
0,1	2210	117	109	337	2310	70	69	301
0,2	2030	117	116	511	1990	69	71	460
0,3	1970	118	117	685	1840	70	72	608
0,4	1950	117	116	862	1880	71	72	802
0,5	1900	115	112	1020	1780	70	69	932
0,6	2100	117	116	1320	2080	70	69	1280
0,7	2000	116	114	1450	1990	70	72	1420
0,8	1970	117	115	1600	1910	70	73	1550
0,9	1930	119	118	1760	1870	70	72	1700
0,99	1960	118	118	1950	1890	70	72	1880
0,999	1960	117	116	1970	1900	70	71	1910

While the learning process of neural network the simple models interact to each other through the flow of learning signals from the input to the output, and by the flow of errors from the output layer to the input layer of the network. Local models may affect the value of the global performance index Q . The learning process allows to determine of the global model parameters to achieve appropriate accuracy of the model. Network learning process can be terminated if the global quality index Q has achieved the desired small value. An another criterion for the termination of the learning process can be the condition that each quality index of the local model has achieved the established minimum value.

In Table 4, Table 5 and Table 6 are shown the relative percentage errors i.e. value of indices RPE for the learning data and the testing data.

Table 4. The values of RPE indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =1.

α_1	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$
	[%]	[%]	[%]	[%]	[%]	[%]
	For learning data			For testing data		
0,001	43.5	26.3	0.69	43.1	26.0	0.55
0,01	5.41	1.50	0.76	5.12	1.46	0.64
0,1	0.79	0.74	0.68	0.71	0.65	0.62
0,2	0.94	0.78	0.81	0.93	0.64	0.60
0,3	0.73	0.72	0.74	0.69	0.64	0.62
0,4	0.71	0.67	0.68	0.66	0.65	0.64
0,5	0.76	0.67	0.70	0.69	0.65	0.64
0,6	0.72	0.75	0.78	0.66	0.64	0.63
0,7	0.70	0.69	0.72	0.65	0.65	0.65
0,8	0.71	0.67	0.70	0.65	0.65	0.65
0,9	0.74	0.69	0.72	0.68	0.65	0.65
0,99	0.74	0.68	0.70	0.68	0.65	0.63
0,999	0.76	0.67	0.70	0.70	0.65	0.62

Table 5. The values of RPE indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =0.5.

α_1	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$
	[%]	[%]	[%]	[%]	[%]	[%]
	For learning data			For testing data		
0,001	25.2	25.2	0.67	25.2	24.6	0.56
0,01	0.96	0.74	0.74	1.00	0.62	0.59
0,1	0.94	0.78	0.81	0.93	0.64	0.60
0,2	0.71	0.67	0.68	0.66	0.65	0.64

Table 5 continued. The values of RPE indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =0.5.

α_1	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$
	[%]	[%]	[%]	[%]	[%]	[%]
0,3	0.72	0.76	0.78	0.66	0.64	0.63
0,4	0.71	0.67	0.70	0.65	0.65	0.65
0,5	0.76	0.87	0.70	0.70	0.65	0.62
0,6	0.70	0.72	0.75	0.65	0.64	0.64
0,7	0.70	0.77	0.78	0.64	0.64	0.64
0,8	0.72	0.72	0.72	0.65	0.64	0.57
0,9	0.72	0.73	0.75	0.66	0.64	0.63
0,99	0.71	0.74	0.76	0.66	0.64	0.65
0,999	0.72	0.74	0.76	0.66	0.64	0.64

The index RPE(1) expresses the quality of the first local model, the index RPE(2) expresses the quality of the second local model, and RPE(out) expresses the quality of the global model according to formula (10).

Table 6. The values of RPE indices for learning and testing data after 500 epochs of learning for the coefficient α_0 =0.1.

α_1	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$	$RPE^{(1)}$	$RPE^{(2)}$	$RPE^{(out)}$
	[%]	[%]	[%]	[%]	[%]	[%]
	For learning data			For testing data		
0,001	5.41	1.50	0.76	5.16	1.46	0.63
0,01	0.79	0.74	0.68	0.71	0.65	0.63
0,1	0.76	0.67	0.70	0.70	0.65	0.62
0,2	0.72	0.74	0.76	0.66	0.64	0.64
0,3	0.71	0.75	0.77	0.64	0.63	0.65
0,4	0.70	0.74	0.76	0.64	0.64	0.64
0,5	0.69	0.72	0.74	0.63	0.64	0.62
0,6	0.74	0.75	0.77	0.67	0.64	0.63
0,7	0.72	0.73	0.75	0.65	0.64	0.64
0,8	0.71	0.74	0.76	0.65	0.64	0.65
0,9	0.70	0.76	0.78	0.64	0.64	0.64
0,99	0.70	0.76	0.78	0.65	0.64	0.64
0,999	0.71	0.75	0.76	0.65	0.64	0.64

An Influence of the coefficient α_1 on the model quality

In Table 1, Table 2 and Table 3 are shown the influence of weighting coefficients α_1 (and α_2) on the quality of local models, on the global index Q and the synthetic index Q_S for the three-values of the coefficient α_0 (for $\alpha_0 = 1$, $\alpha_0 = 0.5$ and $\alpha_0 = 0.1$) for the learning data. and the testing data. The data from Table 2 for $\alpha_0 = 0.5$ are shown in the form of graphs in Figure 5, respectively for the learning data and in Figure 6 for the testing data.

For a detailed analysis of the influence of α_1 and α_2 factors, in addition the results for the coefficient $\alpha_0 = 0.5$ are presented graphically (as the most representative).

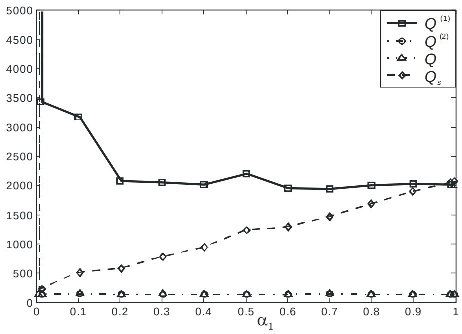

Fig. 5. Quality indices for the learning data, for coefficient $\alpha_0 = 0.5$

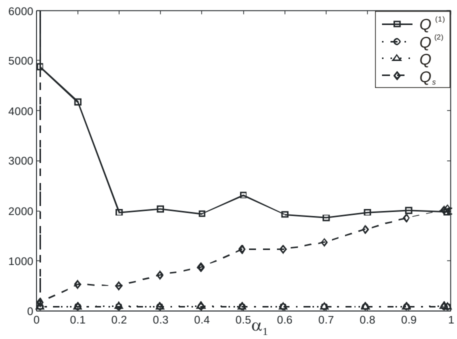

Fig. 6. Quality indices for the testing data for coefficient $\alpha_0 = 0.5$

By analyzing in detail the results e.g. for the selected value $\alpha_0 = 0.5$, can be seen that the increase in the coefficient values α_1 from 0.01 to 0.2 causes the monotonic and rapid decline in the values of quality index $Q^{(1)}$ of the first local model. Then, index $Q^{(1)}$ very slowly and a small oscillating reaches a minimum value $Q^{(1)}$=1950 for the ratio $\alpha_1 = 0.7$. For the testing data, index $Q^{(1)}$ as a function of coefficient α_1 behaves similarly. The minimum value of index $Q^{(1)}$)=1850 reaches for $\alpha_1 = 0.7$ as well as for the learning data.

For the learning data, the increase in the factor α_1 (decrease α_2) the course of quality index $Q^{(2)}$ is oscillating with small fluctuations which are almost constant except for one high value for $\alpha_1 = 0.001$. The index $Q^{(2)}$ reaches a global minimum ($Q^{(2)}$=115) for

$\alpha_1 = 0.8$. For the testing data, the course of index $Q^{(2)}$ is very similar like for the learning data. The level of index $Q^{(2)}$ is somewhat lower and reaches a global minimum ($Q^{(2)}$=67) for the $\alpha_1 = 0.01$ ($\alpha_2 = 0.99$).

The global quality index Q has variable course but at the same level as the index $Q^{(2)}$. For the learning data, the index Q starts with value of $Q = 112$ for $\alpha_1 = 0.001$, and at the end of the range i.e. for $\alpha_1 = 0.999$ reaches $Q = 116$. The index Q reaches a minimum for $\alpha_1 = 0.2$, equal to Q =108. For the testing data, index Q for a change starts with the global minimum of $Q = 57$ (for $\alpha_1 = 0.001$), then its course is variable and at the end of the range of coefficient α_1 reaches $Q = 71$ ($\alpha_1 = 0.999$). For coefficient $\alpha_1 = 0.2$ reaches the maximum value of index $Q = 75$ (for the learning data at this point was the global minimum).

Global synthetic Q_s index, which is a weighted sum of $Q^{(1)}$ and $Q^{(2)}$ by α_1 and α_2, and Q by α_0 has a variable course. For the learning data, index Q_s has a high value for $\alpha_1 = 0.001$ (due to the large value of $Q^{(1)}$, see Figure 5). Starting with the $\alpha_1 = 0.01$where index Q_s has the minimum value (Q_s=206) the index Q_s increases monotonically up to a maximum value (Q_s=2080) for $\alpha_1 = 0.999$. For the testing data, the course of index Q_s is very similar to the course as for the learning data. The minimum value equal to 146 the index Q_s reaches for $\alpha_1 = 0.01$ and the maximum value equal to 2030 reaches for $\alpha_1 = 0.999$.

An Influence of coefficient α_0 on the model quality

Analysis of an influence of α_0 coefficient on a model quality is based on the results contained in all Tables.

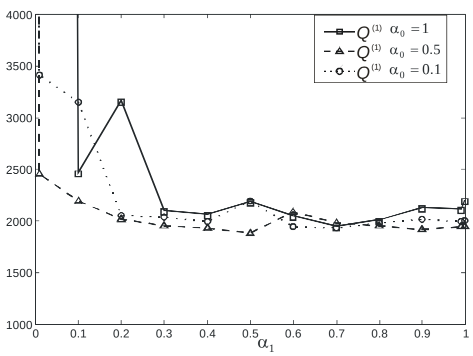

Fig. 7. Quality index $Q^{(1)}$ of first local model for the learning data

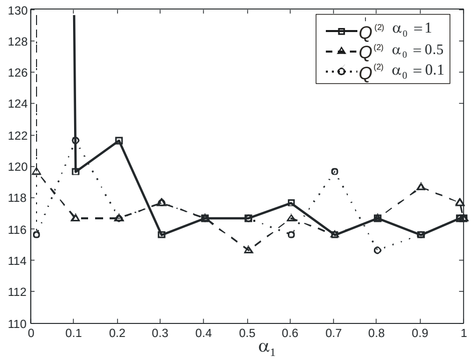

Fig. 8. Quality index $Q^{(2)}$ of second local model for the learning data

Increase of the factor α_0 that is increase participation of the global index Q in the synthetic criterion Q_s, increases the quality index $Q^{(1)}$ of the first local model except results for $\alpha_1 = 0.6$ and $\alpha_1 = 0.7$ for the learning data and testing data. So if factor α_0 increases then values of quality index $Q^{(1)}$ also increases (it is worsening, see Fig. 7).

Courses of indices $Q^{(2)}$ of second local model are oscillating and are interwoven, so it is difficult to determine the influence of the coefficient α_0 across the range α_1 variability. For example, for the selected coefficient $\alpha_1 = 0.5$ the index $Q^{(2)}$ achieves the best results for $\alpha_0 = 0.1$ which is the global minimum of index $Q^{(2)}$ for the learning data, but for the testing data the global minimum is for another value of coefficient α_1 (see Figure 8).

The global quality index Q has also variable courses. Oscillations are greatest for small values of α_1 from 0.001 to 0.3. For values of α_1 above 0.3 waveforms of index Q to stabilize and for $\alpha_1 = 0.5$ reaches a local minimum (see Figure 9). Analyzing graphs and not refer to individual deviation from the averaged values can be seen that the larger the value of factor α_0 the lower value of the index Q, for the learning data. For factor $\alpha_0 = 1$ the quality index Q has the global minimum when factor α_1 is equal 0.001 (see Figure 9)).

For the testing data, the influence of coefficient α_0 is different in different range value of α_1. For the smallest values of coefficient α_1 from $\alpha_1 = 0.001$ to $\alpha_1 = 0.3$ the lowest values the index Q takes for $\alpha_0 = 1$. For The range of values of α_1 (i.e. $\alpha_1 = 0.4$ to $\alpha_1 = 0.6$) the index Q takes the smallest value for $\alpha_0 = 0.1$.

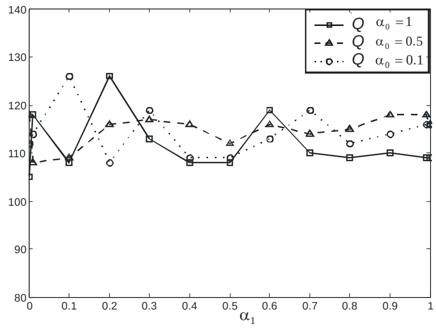

Fig. 9. Quality index Q of global model for the learning data

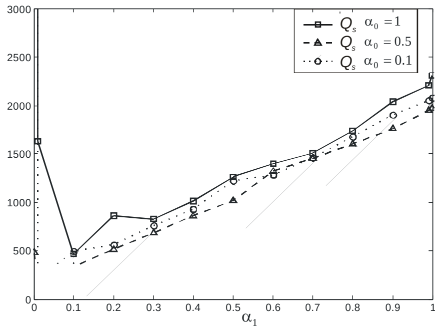

Fig.10. Synthetic quality criterion Q_s for the learning data

However, from $\alpha_1 = 0.7$ to $\alpha_1 = 0.9$ the index Q takes the lowest values for $\alpha_0 = 0.5$. At the end of coefficient $\alpha_1 = 0.99$ and $\alpha_1 = 0.999$ the index Q is the smallest for $\alpha_0 = 1$. The larger the value of coefficient α_0 that is a larger share of the global index Q in the synthetic quality criterion (3), the quality of the global model is better. For learning data, the influence of coefficient α_0 on the quality index Q can be seen more clearly and more explicitly (Figure 9). For the testing data, that influence is not as clear-cut and slightly different than for the learning data.

Synthetic index Q_s has a different course than the others. It starts from large values of $\alpha_1 = 0.001$, for coefficient $\alpha_1 = 0.01$ the index Q_s reaches the global minimum, and then increases almost monotonically with increasing α_1 until it reach the maximum for $\alpha_1 = 0.999$, depending on α_0 (see Figure 10). Changeability of the index Q_s is similar for both the learning and the testing data. The graphs clearly shows the influence of the factor α_0 on the quality index Q_s. The smaller values of coefficient α_0, the smaller the value of index Q_s for both the learning data and the testing data. This can be explained by the fact that the quality criterion Q_s is proportional to the component $\alpha_0 Q$. Thus, the higher α_0, the larger index Q_s. But we must remember Q_s

is a synthetic criterion, and depends on the values its components i.e. the indices $Q^{(1)}$, $Q^{(2)}$ and Q .

For the learning and the testing data the indicator of RPE$^{(1)}$ its course is almost monotone decreasing. The lowest values of the indicators RPE$^{(1)}$ takes for $\alpha_0 = 0.1$ and the largest takes for $\alpha_0 = 1$ except for ($\alpha_1 = 0.6$ and $\alpha_1 = 0.7$ (see Figure 11). For $\alpha_0 = 0.1$ the indicator RPE$^{(1)}$ reaches a global minimum for $\alpha_1 = 0.5$. At the point at which the coefficient α_1 takes the value 0.5 ($\alpha_1 = 0.5$) the indicator RPE$^{(1)}$ has the global minimum for all values of coefficient α_0 for the learning data and the testing data.

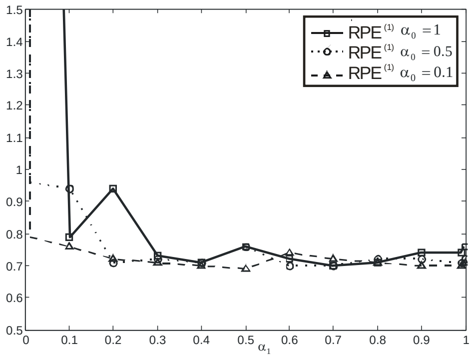

Figure 11. Quality index RPE$^{(1)}$ of the first local model for the learning data

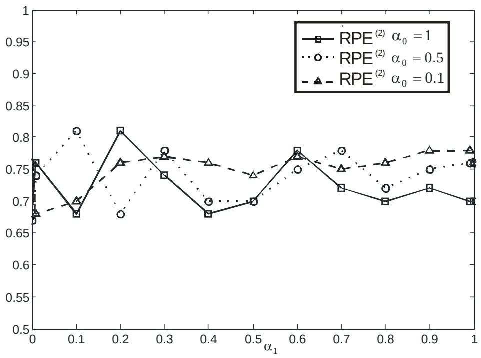

Figure 12. Quality index RPE$^{(2)}$ of the second local model for the learning data

The course of index RPE$^{(2)}$ is oscillating (see Figure 12). For the learning data, the best results i.e. lowest values of indicator RPE$^{(2)}$ was obtained for $\alpha_0 = 1$ and highest values of indicator RPE$^{(2)}$ was obtained for $\alpha_0 = 0.1$. However, for three different values of α_1 are exceptions (Figure 12). For the testing data, index RPE$^{(2)}$ oscillations are smaller (Table 5). However, for boundary values of coefficient $\alpha_1 = 0.001$ and $\alpha_1 = 0.999$ the best results of indicator RPE$^{(2)}$ are for coefficient $\alpha_0 = 1$. Generally, the best results of indicator RPE$^{(2)}$ was achieved for coefficient $\alpha_0 = 1$, with the exception of only two values of coefficient $\alpha_1 = 0.2$ and $\alpha_1 = 0.6$.

In Figure 13 are shown the output signals of first simple plant and simple model, and in Figure 14 are shown the output signals of second simple plant and simple model for the learning data for coefficients: $\alpha_0 = 0.5$, $\alpha_1 = 0.5$ and $\alpha_2 = 0.5$.

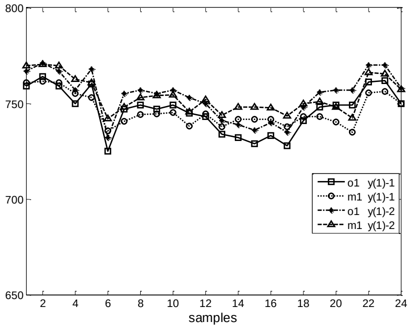

Fig. 13. The output signals of the first simple plant and simple model for the learning data

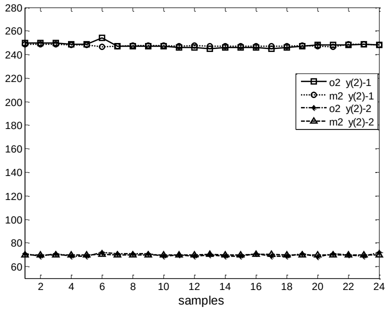

Fig. 14. The output signals of the second simple plant and simple model for the learning data

The simulations and the results show that the task of modeling complex systems is not a simple problem. The more that we had to do a simple case of a complex system consisting of two simple objects. The results obtained show relationships in the complex model, what is the quality of a global model and local models as a function of α coefficients. The complex Rprop learning algorithm, which was used to simulations also has an impact on the results, which are in some cases inconclusive. Other algorithms such as the complex Bacpropagation in conjunction with the more unequivocal complex system, which consists of two non-linear mathematical functions give a more clear results [Drałous, 2010]. However the complex Rprop algorithm in comparison with the complex Backpropagation is much faster and more reliable. Although not entirely clear results in some points, however, we can infer much about the quality of the global model taking into account the quality of local models. This knowledge can be used in other cases of modeling as well as in practice to design an optimal control of complex objects.

Conclusion

In this paper was presented the global model with respect to quality of local models of the chemical object. The global model and local models are built of multilayer neural networks. The influence of weighted coefficients α_1 and α_2 in the synthetic quality criterion (3) on the quality of the global model and the quality of local models was studied. The complex Rprop neural networks learning algorithm was used. By changing of coefficient α_0 was also studied the influence of the global quality criterion Q on the quality of the global model and the quality of local models. The results for the learning data and the testing data was presented.

The obtained results show that by proper selection of coefficients α_1 , α_2 , and α_0 can to influence on the quality of local models and the quality of the global model. On this basis, you can specify for which values of the coefficients α_1 and α_2 , and α_0 can seek the model globally optimal.

The presented method and simulations are useful for investigation of computer control system for complex systems.

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