Intelligent identification of telecommunication channels in the distributed systems for digital control of power facilities

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Abstract: This paper presents the results and problems of telecommunication power amplifier modeling. The research tool is the mathematical apparatus of artificial neural networks. Simulation of the device was made according to the black box principle, operating solely with input and output data of the power amplifier under study. The criterion for the quality of model estimation was the signal-to-noise ratio adopted in radio engineering. Brief results of the previous research are shown. The problems associated with the simulation of a power amplifier operation basing on neural networks were investigated. An example is given of nonlinear distortions appearing in the device under consideration. The description is given of the joint work of a neural networks group based on analog signal clustering which works according to the principle of Grossberg's adaptive resonance theory. The application results of this type of systems are shown. Discussing the problems concerning the use of this approach to simulation of the investigated processes.

1. Introduction

The domains for research work in the sphere of intelligent identification of power facilities management are quite extensive. In particular, one of the popular control methods is the use of artificial neural networks. They are widespread in medicine, economics, technology, etc., and by large and well-known corporations and companies such as Google, Microsoft, Yandex and many others. The relevance of using this mathematical apparatus will be required for quite a long time because the range of neural networks application is very diverse. Hence, the mathematical model of this type was chosen in this work as a research tool.

The problem set forth in this was formulated as follows: a power amplifier is connected to the telecommunication channel output and two data arrays are available, one of which was fed to the input to the object under study, and the other was read at its output. These two datasets format was presented in an integrated manner. It is necessary to build a neural network that, when a reference sequence of complex numbers is fed to its input, will result in the set of corresponding data at the amplifier’s output which differs from the reference data by the mean square deviation value –40 dB. Whereas it is customary in radio engineering, to calculate the ratio between target and received data in decibels but not their absolute difference, the formula below is applied to calculate the simulation errors.

\[ EVM = 10 \cdot \log_{10} \left( \frac{\sum_{i=1}^{N} |e_i|^2}{\sum_{i=1}^{N} |x_i|^2} \right) \]

where \( x \) is the reference sequence output, \( e \) is the difference between the received data and \( x \), \( N \) is the considered sample size, a number of signals.
This study is a continuation of [1], it contains the analysis of various approaches to a power amplifier simulation using the black box method and the neural networks resources. In the previous publication, the use of an ordinary two-layer network was described, its training was carried out using the well-known method of reverse error propagation. Nesterov’s method was also used as a modification of this algorithm and showed a sufficient gain in the model convergence rate.

2. Simulation problems
Certain limitations are imposed on the power amplifiers development process related to the device size and power consumption. In this regard, the nonlinear distortions level increases due to the deviations of the transfer characteristic from linear.

The actual power amplifier has an output power limit determined by the type of switching circuit, the type of amplifier element, bias voltage and supply voltage. Therefore, starting from a certain value of the input power level the dependence ceases to be linear and the system gain decreases with increasing input power. Figure 1 is a diagram of the output/input power dependence in the case of a linear power amplifier (solid line) and nonlinear one (dashed line) [2].

![Figure 1. Output power versus input power.](image)

Examining the input and output signals, one can see that the noisiest component is at the level of low amplitude values. Dividing the sample into its constituents does not give a significant advantage, since the neural network cannot by its nature repeat the noised values of the supplied images. Obviously, alternative methods should be used to process this data, which is the subject of this study.

3. Using the adaptive resonance theory
One can cluster the training set and select a particular neural network for each class for training. Grossberg adaptive resonance theory was chosen as a tool for this, its essence is dividing an analog signal into parts which satisfy the coefficient of "similarity". In figure 2 the examples are shown of one class of input signal and the corresponding output one.

Whereas the training in such a neural network is effected without a teacher, then in case of a high "similarity" coefficient in the result of identical classes clustering, they can be in plenty. Therefore, one can limit their set to 10. Each data batch with such limitation will be trained by a separate model of the sgdm type, since it demonstrated the best generalizing ability of such data in comparison, e.g., with RMSProp or adam [3]. Training will continue until each neural network reaches the learning limit of -30 dB relative EVM error. The architecture of such a network will be small: only 24 values of the input layer, 48 of the hidden one and 12 of the output. And accordingly, the data set will be quite large, since training models will be about 10. But, as can be seen in figure 3, this structure works very poorly.
Figure 2. Example of one class of clustered input.

Figure 3. An example of the operation of neural networks trained for each class separately.

If we analyze the network operation solely by classes, the results will be unsatisfactory. Data in the table shown in figure 4 in the fourth column displays the relative errors for each model that is trained exclusively for its class, respectively.

![Table Image]

Figure 4. Relative errors of each model.

As a result, having analyzed the functioning of each neural network, it had turned out that each model of the class was retrained. This is due to the fact that models are trained exclusively to their patterns and, in connection with this, the generalizing ability deteriorated much more than it was intended.

If we consider functioning of the network obeying the adaptive resonance theory, then significant problems arise, e.g., if to memorizing hundreds and thousands of realizations of the same dynamic process is required, then with small values of the similarity parameter in the recognition mode, the memory of the neural network shall never get a sufficient amount of necessary information to make reasonable solutions. And at large values of this parameter similar data differing only in a small number of secondary details, are stored in memory as prototypes of different image classes [4]. Thus, this class of neural networks is quite sensitive to noise, and it leads to an increased number of errors in the simulated process.

4. Analysis of training by signal spectrum
Alternatively, one can use Fast Fourier Transform as an additional data preprocessing and then try network training by signal spectrum.
In figures 5, 6 an example of a signal spectrum is shown for 48 values of the real and imaginary parts, respectively.

**Figure 5.** An example of a signal spectrum of the real part.  
**Figure 6.** An example of the spectrum of the imaginary part.

Such data will be fed to the network inputs. Accordingly, the entire sample is normalized before training, and the inverse Fourier transform of readings at the network outputs will be performed to check the quality of the model. It was found out that with the previous architecture the model demonstrates a rather unsatisfactory result. Relative error reached the value of approximately -2 dB for test data. In figure 7 both the target data and received data of the test sample are shown.

**Figure 7.** An example of target and received data from the model.

Analyzing the training sample, it was found that the signal spectrum at the input and output of the network is modified noticeably, as shown in figure 8.

**Figure 8.** An example of input and output data bursts in the model.  
**Figure 9.** An example of input and output data bursts in the model.
It happens due to the different dimensions of the Fourier transform vector. In this regard, the neural network inputs and outputs will be the same. An example after such a transformation is shown in figure 9.

And accordingly, after training, the model demonstrated relative error in the -14.3 dB test dataset. An example of target and acquired data is shown in figure 10.

![Figure 10. An example of target and received data from the model.](image)

To train the model by the signal spectrum the model architecture, e.g., the number of neurons in the layers was expanded. The input and output layers will then consist of 200 neurons, whereas the neurons number in the hidden layer is 800. We will also increase twice the number of epochs, i.e. to 1200. The table shows the summary indicators of the model with such an architecture.

| Algorithm  | Theining algorithm       | Data mixing | Relative error, dB |
|------------|--------------------------|-------------|--------------------|
| sgdm       | Never                    | -21.3379    |
|            | Each epoch               | -20.8667    |
|            | Before training          | -20.9133    |
|            | Never                    | -19.2077    |
| adam       | Before training          | -19.9591    |
|            | Each epoch               | -16.7946    |
|            | Never                    | -13.097     |
| rmsprop    | Every epoch              | 1.02794     |
|            | Before training          | -13.0204    |

Figures 11, 12 show examples of a target and obtained data in the test sample using the sgdm and rmsprop algorithms, respectively.

![Figure 11. An example of target and received data from a model trained with the sgdm algorithm.](image)
Figure 12. An example of target and received data from a model trained with the rmsprop algorithm.

The table shows that these algorithms demonstrate comparable results while the rmsprop algorithm in some examples showed a relative error order of magnitude worse than training on a quasi-periodic signal dataset.

5. Conclusion
Therefore, we can conclude that operating with input and output data only is not enough to achieve high accuracy of the power amplifier model since in the signal under investigation the noisiest is the output in comparison with the input.

For example, in order to analyze the operation of a neural network, an output signal from a power amplifier (without noise) was fed to its input and the input signal was trained. The results of this model reached an accuracy of about -37 dB for the test dataset despite the significant nonlinearity of the amplifier.

It was found out that neural networks approximate the input signal very well, recognize the dynamics of data changes, but they are unable to learn the noisy signal component which limits its capabilities when such a process is simulated. In the future, the research of the considered algorithms of neural network simulation may be continued using the output signal filtering procedures.

References
[1] Podvalny S and Likhotin M 2018 Investigating the capabilities of artificial neural networks for the simulation of a telecommunication amplifier operation J. Information technologies for modeling and control pp 417-423
[2] Shutov V 2015 Microwave power amplifiers linearization by digital predistortion (physical-math. sciences degree) p 146
[3] URL: Rapidly converging modern learning algorithms for neural networks do not guarantee the achievement of the best generalizing ability [Electronic resource]: Access mode: World Wide Web. http://neuropro.ru/memo346.shtml
[4] Zakovorotny A 2016 New architectures and learning algorithms for neural networks of adaptive resonance theory J. Scientific Result. Series "Information Technology" pp 4-11