Abstract: The trends in expansion of electric power systems and changes in the conditions of their operation have led to complicate power system operation, increased its changeability and unpredictability that call for prompter and more adequate response of controls systems. This paper presents the hybrid model for the short-term prediction the parameters of expected operating conditions based on joint usage of artificial neural networks models and Hilbert-Huang Transform. The hybrid model was proposed to increase the accuracy of prediction the non-stationary and non-linear processes (power flow in the 500 kV intersystem transmission line).

Keywords: energy system, prediction, Hilbert-Huang transform, artificial neural network, hybrid model

1. INTRODUCTION

The presence of efficient system for wide-scale monitoring and prediction of electric power system (EPS) is one of the key conditions for reliable work of systems intended for EPS operation and emergency control [5, 6]. The problem of short-term prediction of the parameters of expected operating conditions. The forecast of the state vector’s components enable the computation of the parameters of EPS with some anticipation. The prediction active power flows of determination of margins for transfer capabilities of ties is the expected conditions. This is necessary to efficiently use the power margins in the operating conditions and automatic control through appropriate control actions.

Short-term prediction of parameters can be carried out by means of dynamic estimation of the state by Kalman’s filter [2], forgetting approach [9] or with help of conventional statistical methods of the analysis of time series and regression models (for example, Autoregressive Integrated Moving Average (ARIMA) Autoregressive Conditional Heteroscedasticity (ARCH), Generalized Autoregressive Conditional Heteroscedasticity (GARCH) and others), and novel information technologies, first of all technologies of an artificial intelligence.

Most of the works emphasize that the highest accuracy of the state parameters forecast can be obtained on the basis of artificial neural networks (ANN) models. The readers may refer to [3] for more details. In the cases when state variables are rather variable and nonstationary it is more sensible to use the neural network models. Certain interest present hybrid models [11], based on joint use ANN models and Hilbert-Huang Transform (HHT) [1].

This paper presents the hybrid model for the short-term prediction the parameters of expected operating conditions based on joint usage of ANN models and HHT.

2. DEVELOPMENT OF AN HYBRID MODEL FOR SHORT-TERM PREDICTION

2.1. Short-term prediction based on ANN

The success of applying ANN is explained by the circumstance that the neural network architecture makes it possible to obtain the models with “good” approximation properties. It is to be noted that for short-term prediction the best ANN structure are follow:

- multilayer perceptron – MLP
- radial basis function – RBF
- generalized regression neural network – GRNN

Multilayer perceptron

Neurons in this network are organized by layers and interact only with neurons of the neighboring (previous and subsequent) layers. For such ANN the output value of the k-th neuron \( y_k \) is mathematically determined as

\[
\mathbf{y}_k = f \left( \sum_{n=1}^{N} w(n) \mathbf{\psi}_n \right)
\]

where \( w(n) \) are weighting coefficient of the n-th hidden layer, \( \mathbf{\psi}_n \) are output signals of the hidden layer neurons.

Radial basis function

Such neural networks represent a special family of artificial neural networks, in which the neurons of a hidden radial layer implement radial-basis functions of the following type . The obtained architecture of radial networks has a structure similar to the multilayer structure of sigmoid networks with one hidden layer.

Generalized regression neural network

It represents a structure that contains along with a hidden radial layer both probabilistic hidden and output layers.
These networks are based on the method for approximation of probability density with the help of Gaussian kernel functions

\[ \psi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}. \]  

The GRNN networks are learned practically in a flash, which is extremely important for on-line predictions, and are robust to the presence of bad data.

The paper suggests an intelligent\(^1\) approach based on the neural network technologies to short-term prediction of the nonstationary regime parameters, implemented in the subsystem of prediction (Figure 1, blocks 1-4) within the intelligent software ANAPRO, presented in detail [8, 9].

1. Application of nonlinear optimization algorithms
   - Neuro-Genetic Input Selection, NGIS, allows one to reject some input data as less informative
   - Simulation annealing method, SA, provides the procedure of selecting efficient forecast model for each individual sample

2. Application of committee machine, CM, allows one to divide a complex forecasting problem into a set of simple forecasting problems by allocating them among neural networks-experts

Visualization of forecast results in the form of diagrams and tables

Adaptation of forecast model to the changes in the network topology or in the composition of initial data.

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\(^1\) The term “intelligent” is used in reference to the approaches, methods, systems and complexes using artificial intelligence technologies

\(^2\) Probably neural networks

Application of the SA algorithm makes it possible to analyze the properties of the initial sampling and organize a competition-based system among different neural network prediction models when during the process of nonlinear optimization the best prediction model is selected. In the neural network prediction the ANN structures themselves are the forecasting models.

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### 2.2 Hilbert-Huang Transform

Hilbert-Huang transform consists of two parts: empirical mode decomposition (EMD) and Hilbert transform. First, we consider the EMD method.

The signal \( x(t) \) (Figure 3, top) is supposed to be decomposed into basis of special functions, called intrinsic mode functions (IMF) by empirical EMD (Figure 3, bottom). An IMF is defined as a signal that satisfies the following two criteria:

1. extreme numbers and zero-crossings on the entire interval are supposed to congruent;
2. the median value of envelopes which are defined by local maxima and minima are supposed to be zeros for intrinsic mode functions at any point.

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Figure 1. Prediction subsystem of the ANAPRO software.

The use of nonlinear optimization algorithms in block 2, namely, the methods of simulated annealing (SA) and neuro-genetic input selection (NGIS) [3, 4], provides the procedure of choosing the best prediction model for each individual sampling. For example in the process of learning sampling analysis based on the NGIS algorithm individual input data can be rejected as less informative. This method represents optimization on the basis of random search techniques and combines the capabilities of genetic algorithm and PNN\(^2\)/GRNN networks to automatically determine optimal combinations of input variables (Figure 2).

The PNN/GRNN networks allow the best results to be “remembered”, which improves the previous results. Owing to the radial layers with Gaussian function in the structure of PNN-algorithm, bad data in the input sampling can be reduced to minimum.

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![Figure 2. Algorithm of neuro-genetic selection.](image)

![Figure 3. Input signal \( x(t) \) (top). EMD applied to \( x(t) \) (bottom).](image)
In contrast to standard methods of time series processing, the method of IMF construction starts from the highest frequency component, and the last extracted function is usually monotone, or has one extreme. Let the original signal \( x(t) \) be given, then algorithm of empirical mode decomposition can be presented as follows:

**Step 1.** Let \( r_{j1}(t) = x(t), j = 1 \).

**Step 2.** Search for \( j \)-th IMF using the sifting procedure:

1. Let \( i = 1 \) and \( h_{i1}(t) = r_{j1}(t) \).
2. Find local minima and local maxima for \( h_{i1}(t) \). Form an envelope \( e_{\text{min},i}(t) \) and upper envelope \( e_{\text{max},i}(t) \) by corresponding interpolation the local minima and maxima;
3. Compute the middle value \( m_{i1}(t) = (e_{\text{min},i}(t) + e_{\text{max},i}(t))/2 \) and find \( h_{i1}(t) = h_{i1}(t) - m_{i1}(t) \) such as \( e_{\text{min},i}(t) \leq h(t) \leq e_{\text{max},i}(t) \), for all \( t \). Let \( i = i + 1 \);
4. Repeat steps b) - d) until \( h(t) \) satisfies a set of predetermined stopping criteria (following from properties of IMF). Let \( c(t) = h_{i1}(t) \).

**Step 3.** Compute residue \( r(t) = r_{j1}(t) - c(t) \). Then let \( j = j + 1 \) and repeat step 2 until the number of extrema in residue \( r(t) \) is less than 2. Thus, at the end of decomposition process, the original signal can be represented as follows:

\[
x(t) = \sum_{j=1}^{j=n} c_j(t) + c_j(t) = \sum_{i=1}^{i=q} c_i(t) + \sum_{j=1}^{j=n} c_j(t) + r_j(t), \quad (3)
\]

where \( q < p < n \), \( c_i(t) \) - are the high frequency noise components, \( c_i(t) \) - are the components representing the physical properties of the series and \( c_i(t), r_j(t) \) - are trend non-sinusoidal components. It is to be noted that for the majority of analyzed realizations, the requested number of IMF are less than 10. For more detailed description of EMD algorithm readers may refer to [1],[10].

Next step in HHT is Hilbert transform (HT). Application of HT for each IMF provides us with the values of instantaneous frequency and instantaneous amplitude for each time moment \( t \). Let us describe the HT more in details. For the given real signal \( x(t) \) we write its complex representation as follows

\[
z(t) = x(t) + ix_{\mathcal{H}}(t),
\]

where \( ix_{\mathcal{H}}(t) \) is the Hilbert transform of \( x(t) \), given by

\[
x_{\mathcal{H}}(t) = \frac{1}{\pi P.V.} \int_{-\infty}^{\infty} \frac{x(\xi)}{t-\xi} d\xi.
\]

In formula (4) \( P.V. \) stands for the Cauchy principal value of the integral. We can rewrite (4) in an exponential form

\[
z(t) = A(t)e^{it},
\]

where

\[
A(t) = \sqrt{x^2(t) + x_{\mathcal{H}}^2(t)},
\]

and

Then instantaneous angular frequency, which by definition is the time derivative of the instantaneous angle (7), can be writing as follows:

\[
\omega(t) = \frac{d}{dt} \arctg \frac{x_{\mathcal{H}}(t)}{x(t)},
\]

**2.3. The hybrid model**

In this work we propose the hybrid model based on joint usage of the HHT and ANN in order to improve the accuracy of the short-term prediction of the mode’s regimes nonstationary parameters. In this case the hybrid model’s construction to be fulfilled as follows:

1) Based on EMD algorithm, which is presented in the section 2.2, initial non-stationary signal is decomposed into the several IMFs. Following the Hilbert transform the corresponding instant amplitude \( A(t) \) and instant frequency are calculated.
2) The computed values of IMFs and \( A(t) \) are used as input values for neural network model.
3) By means of algorithms of neural-genetics selection and the simulated annealing the neural network model is constructed. This ANN model is learned to predict the corresponding changes of modes’ (regime) parameter on the given interval of anticipation.

**3. EXPERIMENTAL CALCULATIONS**

The suggested hybrid model was used to make short-term forecasts of active power flows in the electric networks of the Interconnected power system of Siberia. For this purpose the studied time series was decomposed into IMFs by the Huang method (Figure 4), and the Hilbert transform was employed to obtain the amplitudes, \( A \). The latter along with IMFs were used as input values of the selected neural network model.

**3.1. Short-term prediction for a lead-time interval of 1 minute**

The array of the learning sample included 5760 (4 days) minute measurements of active power flows. To make a short-term forecast of the parameter the SA procedure was used to create an MLP-type neural network (hybrid model I). Its input layer contained nine IMFs and the values of amplitude \( A_{1:4} = \frac{1}{4} \). As a result of learning the NGIS algorithm excluded \( A_{1:4} = \frac{1}{16} \) from the input layer (Figure 5).

To assess the influence of individual IMF amplitudes on the accuracy of the forecast an MLP-type neural network model (hybrid model II) was developed. In this model “a priori” all IMF amplitudes were excluded. The analysis has shown that the forecast error in hybrid model II is higher than in hybrid model I (Table 1).
Figure 4. The real active power flow in 04.02.08 (top) Results of EMD applied (bottom)

Figure 5. An MLP-type ANN for a short-term prediction of active power flow with a lead time interval of 1 minute.

Table 1. Results of a short-term prediction of active power flows on the basis of hybrid and neural network models for a lead time interval of 1 minute

<table>
<thead>
<tr>
<th>Model</th>
<th>Average forecast error in a 2-hour interval, %</th>
<th>Correlation coefficient, r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural network model</td>
<td>12.34</td>
<td>0.83</td>
</tr>
<tr>
<td>Hybrid model I</td>
<td>5.89</td>
<td>0.92</td>
</tr>
<tr>
<td>Hybrid model II</td>
<td>7.61</td>
<td>0.91</td>
</tr>
</tbody>
</table>

In addition to the calculation of an average error the calculation of the coefficient of correlation, $r$ between actual and forecast values of the studied variable (Table 1) was made to assess the forecast quality.

The calculation results illustrated in Figure 6 and presented in Table 1 show that hybrid model I provides the best forecast accuracy.

In analogy with the previous case the array of learning sample contained 5760 (4 days) minute measurements of active power flows. To make a short-term forecast of the active power flow value the SA procedure was used to form an MLP-type neural network. Its input layer contained 7 IMFs and the values of amplitude from 1 to 6. As a result of learning the NGIS algorithm excluded all amplitudes and the first two intrinsic mode functions IMF1 and IMF2 (Figure 8) from the input layer.

The results of calculations are presented in Figure 8 and Table 2. The obtained model shows that the NGIS algorithm rejected first two high-frequency IMFs and all amplitudes. This means that in the prediction for a large lead time interval the high-frequency IMFs and amplitudes do not influence much the forecast of non-stationary state variables.
Figure 8. An MLP-type ANN for a short-term forecast of active power flow with a lead time interval of 3 minutes.

Table 2. The results of a short-term active power flow prediction on the basis of hybrid neural network models for a lead time interval of 3 minutes

<table>
<thead>
<tr>
<th>Model</th>
<th>Average forecast error in a 2-hour interval, %</th>
<th>Correlation coefficient, r</th>
</tr>
</thead>
<tbody>
<tr>
<td>Neural network model</td>
<td>16.12</td>
<td>0.57</td>
</tr>
<tr>
<td>Hybrid model</td>
<td>10.22</td>
<td>0.68</td>
</tr>
</tbody>
</table>

4. CONCLUSION

The problem of short-term prediction of expected operating conditions is studied. In order to increase the accuracy of prediction we propose the hybrid model based on joint application of ANN and HHT. The computational experiments have demonstrated the significant influence of individual IMF’s amplitudes on the prediction accuracy. In an future work we intend to provide the comprehensive studies of the instantaneous amplitudes of individual IMF’s influence on accuracy of the prediction.

5. REFERENCES

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Books:

Conference or Symposium Proceedings:

110