Application of Hybrid Neural Network Models for Short-Term forecasting Parameters of Electric Power System of Asian Region

V. G. Kurbatsky, N.V. Tomin

Abstract - **The modern electric power system (EPS) of the Asian region is characterized by non-uniformity of accommodation of sources and consumers of power resources, and significant dissociation of electric network area. Sophisticated operation conditions for Asian EPS's need a powerful instrument to study dynamic characteristics of EPSs in real time for different system states. It is possible only by a extensive involvement of new tools for the analysis and calculations of operating conditions, and first of all technologies of artificial intellegence.**

The paper suggests approaches for short-term forecasting of parameters of expected operating conditions with use the hybrid model based on joint application of artificial neural network (ANN). The calculations are based on the intelligent software "ANAPRO".

Index Terms – forecast, hybrid model, artificial neural networks, Hilbert-Huang transform

I. INTRODUCTION

Region North-Eastern Asia (NEA) includes Eastern Siberia and Far East of Russia, northern China, Mongolia, Korea Democratic People's Republic, the Republic of Korea and Japan [1]. Countries in the region differ greatly in political structure, economic development, energy security and climate conditions. To boost the economy of this region provided along with current construction of new interstate electric ties variable and inserts 220-500 kV DC for reliable operation of EPS from different countries in NEA. One of the key conditions for reliable work of EPS is the presence of efficient system prediction of operation parameters – load flows, power flow, voltage level, etc.

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II. PROTOTYPE OF SHORT-TERM FORECASTING MODEL OF THE PARAMETERS EPS

The blocks of monitoring and forecasting of the EPS normal, pre-emergency and post-emergency operating conditions include the following [2, 3]:

- System state estimation;
- Forecasting the parameters of expected operating conditions;
- Detection of weak points in the system in the expected operating conditions;
- Determination of margins for transfer capabilities of ties in the expected conditions;
- Visualization of the expected conditions;
- Determination of indices and criteria for transition from normal to pre-emergency condition and, vice versa, from post-emergency to normal conditions

Prototype of short-term forecasting will be developed on the basis Model-driven Development Conception (MDD) of macros of user applications. The core of the software is a system implemented on the basis of integrated software system (Fig.1).

III. THE HILBERT-HUANG TRANSFORM AND ANNS FOR SHORT-TERM FORECASTING OF NONSTATIONARY PROCESS

The conventional approaches for the short-term forecasting of nonstationary processes in complex power systems using the methodology of artificial neural networks are presented in [4], [5]. In many practical cases the application of different ANNs [6] can provide the satisfactory forecast. But data preprocessing and analysis can significantly improve the forecast. In this paper we employ Hilbert-

Fig. 1. Operation of prototype of short-term forecasting model of the parameters EPS in terms of macro conception

Huang Transform (HHT) [7] as one of the most promising tool in the area. Here we concentrate on HHT more in details since this transform is in the core of the proposed approach to short-term forecasting of nonstationary processes.

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

According to EMD, the signal $x(t)$ is supposed to be decomposed into basis of special functions, called intrinsic mode functions (IMF) by special empirical algorithm. An IMF is defined as a signal that satisfies the following two criteria:

- extreme numbers and zero-crossings on the entire interval are supposed to congruent;
- 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.

Let us demonstrate the decomposition on certain nonstrationary signal. The signal and its decomposition are shown in Fig. 2.

Algorithm of such decomposition can be presented in the following steps:

Step 1. Let $r_0(t) = x(t)$, $j = 1$.

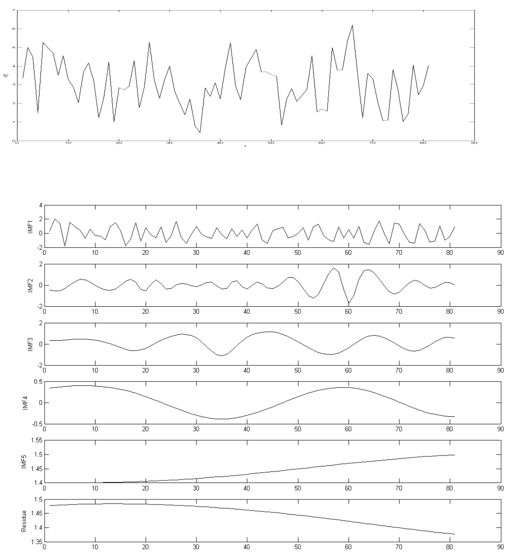

Fig. 2. Input signal *x*(*t*) (top).Set of IMF's *x*(*t*) (bottom).

Step 2. Search for j-th IMF using the sifting procedure:

a) Let $i = 1$ and $h_{i-1}(t) = r_{j-1}(t)$;

b) Find local minima and local maxima for $h_{i-1}(t)$. Form an lower $e_{min,i-1}(t)$ and upper envelope $e_{max,i-1}(t)$ by corresponding interpolation the local minima and maxima;

c) Compute the middle value mi−1(t) = (emin,i−1(t) + emax,i−1(t)) /2 and find hi(t) = hi−1(t) − mi−1(t) such as emin,i−1(t) ≤ hi(t) ≤ emax,i−1(t), for all t. Let i = i + 1;

d) Repeat steps a) - c) until hi(t) satisfies a set of predetermined stopping criteria (following from properties of IMF). Let cj(t)= hi(t).

Step 3. Compute residue rj(t) = rj−1(t) − cj(t). Than let j = j +1 and repeat step 2 until the number of extrema in residue rj(t) is less than 2. Thus, at the end of decomposition process, the original signal can be presented as follows:

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) =$$

$$= \sum_{i=1}^{q} c_i(t) + \sum_{j=q+1}^{p} c_j(t) + \sum_{k=p+1}^{n} c_k(t) + r_n(t), \quad (1)$$

where q < p < n, ci(t) are the high frequency noise components, cj(t) are the components representing the physical properties of the series and ck(t), rn(t) are trends, 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 [7] and [8]. In this paper we continue our studies [9], where only EMD was used jointly with ANN for time series forecasting. In this paper the Hybrid model was enriched full HHT transform usage.

So, the next step of 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

$$z(t) = x(t) + ixH(t), \quad (2)$$

where ixH(t) is the Hilbert transform of x(t), given by

$$x_H(t) = \frac{1}{\pi} PV \int_{-\infty}^{+\infty} \frac{x(s)}{t-s} ds. \quad (3)$$

In formula (3) PV stands for the Cauchy principal value of the integral. We can rewrite (2) in an exponential form

$$z(t) = A(t) e^{i\psi(t)}, \quad (4)$$

where

$$A(t) = \sqrt{x^2(t) + x_H^2(t),} \quad (5)$$

and

$$\psi(t) = arctg \frac{x_H(t)}{x(t)} \quad (6)$$

Then instantaneous angular frequency, which is the time derivative of the instantaneous angle (6), can be writing as follows:

$$\omega(t) = \dot{\psi}(t) = \frac{d}{dt} arctg \frac{x_H(t)}{x(t)}. \quad (7)$$

Let us demonstrate our Hybrid model construction, based on HHT и ANN technologies. 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) and instant frequency are calculated.

2) The computed values of IMFs and As 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.

IV. EXPERIMENTAL CALCULATIONS

The proposed Hybrid model was employed to make short-term forecasts of active power flows in the electric networks of the Interconnected EPS of Asia. For this purpose the studied time series was decomposed into IMFs by the Huang method (Fig. 3), 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. The calculations are based on the intelligent software “ANAPRO”.

- *Forecast of active power flow 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 $A_i, i = \overline{1,6}$. As a result of learning the NGIS algorithm excluded $A_i, i = \overline{1,4}$ from the input layer (Fig. 4).

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 I).

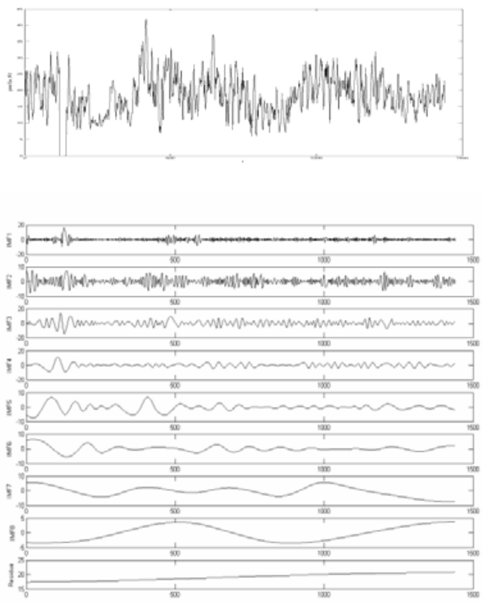

Fig. 3. The real active power flow in 04.02.08 (top) Results of EMD applied (bottom)

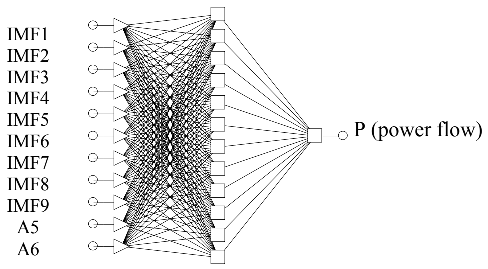

Fig.4. An MLP-type ANN for a short-term prediction of active power flow with a lead time interval of 1 minute.

TABLE I

RESULTS OF A SHORT-TERM PREDICTION OF ACTIVE POWER FLOWS ON THE BASIS OF HYBRID AND NEURAL NETWORKS MODELS FOR A LEAD TIME INTERVAL OF ONE MINUTE

Model	Average forecast error in a 2-hour interval, %	Correlation coefficient, r
Neural network model	12.34	0.83
Hybrid model I	5.89	0.92
Hybrid model II	7.61	0.91

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 I) was made to assess the forecast quality.

The calculation results illustrated in Fig. 5 and presented in Table I show that hybrid model I provides the best forecast accuracy.

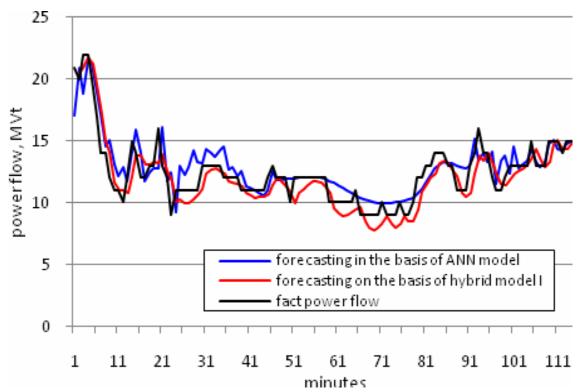

Fig. 5. Forecast of active power flow for a lead time interval of 1 minute.

Additionally, the work included the study of the extent to which the first 6 most variable IMF amplitudes, influence the forecasted value. For this purpose the ANN was taught. Its input parameters were the amplitudes from 1 to 6 and the output value represented a forecasted active power flow. The calculations have shown that amplitudes A2, A5 and A6 are significant in most cases when power flow is forecasted.

- *Forecast of active power flow for a lead time interval of 3 minute*

On 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 (Fig. 6) from the input layer. 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.

The results of calculations are presented in Fig. 6 and Table II.

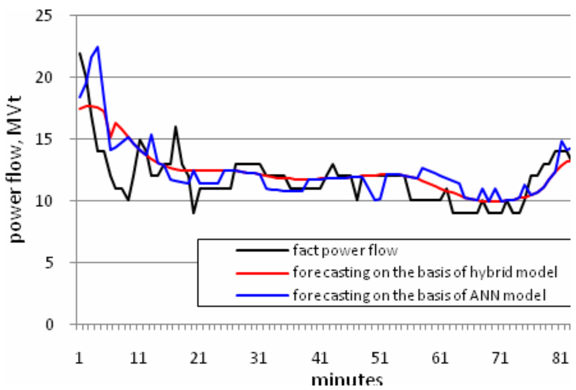

Fig. 6. An MLP-type ANN for a short-term forecast of active power flow with a lead time interval of 3 minutes.

TABLE II

THE RESULTS OF A SHORT-TERM ACTIVE POWER FLOWS PREDICTION ON THE BASIS OF HYBRID AND NEURAL NETWORKS MODELS FOR A LEAD TIME INTERVAL OF THREE MINUTES

Model	Average forecast error in a 2-hour interval, %	Correlation coefficient, r
Neural network model	16.12	0.57
Hybrid model	10.22	0.68

V. CONCLUSIONS

The problem of short-term forecasting of expected operating conditions of NEA region 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 forecasting.

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VII. BIOGRAPHIES

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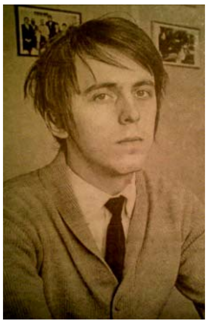

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