



Short-Term Forecasting Parameters of EPS for Systems of Operating and Emergency Control

V.G. KURBATSKY, D.N. SIDOROV, V.A SPIRYAEV, N.V. TOMIN
Melentiev Energy Systems Institute SB RAS
Russia
tomin@isem.sei.irk.ru

KEYWORDS

Power system, frequency, active power flow, emergency control, forecast, artificial neural networks, Hilbert-Huang Transform.

1 INTRODUCTION

Improvement of the efficiency of systems of emergency and secure control of electrical power systems (EPS) is largely dependent on the wide-scale monitoring and forecasting the parameters of the expected operation regime of the EPS, especially it depends on the frequency of the electrical network and the active power flows.

The powerful instrument to study dynamic characteristics of EPSs in real time for different system states. It is a system of operating condition monitoring that enhances control efficiency of normal and emergency conditions in the current market environment.

Qualitative forecasting of frequency is an important optimization parameter of system-wide management of the United National Power Grid of Russia. Such forecast can prevent a sharp abrupt change of control inputs at random nature of the frequency change caused by various malfunctions or failures of technical means of control systems, inaccuracy of input data, etc. Forecast of active power flows provides an estimation of supply ties expected operation condition capacities to preserve the stability of the weak coupling of internal and external sections of EPS by issuing an appropriate control actions on regulating stations and units.

In according with [2, 3] time sequence of individual stages of monitoring, forecasting and control of operating conditions is shown in Fig.1

In essence this combination of stages represents a comprehensive system providing stability, reliability and controllability of modern power systems. At the same time from the viewpoint of efficiency of this system it is essential to increase the adaptability of control and improve coordination of the control stages, means and systems.

2 ANALISYS OF DINAMIC OF CHANGE IN EPS PARAMETERS OPERATING CONDITIONS

Implementation of market principles in planning and control of operating conditions, expansion of the area of coordinating operation control of EPSs in terms of time (from design of control systems to their realization by dispatching and automatic devices) and situation (coordination of dispatching, continuous automatic and discrete emergency control) all cause fast dynamics of change in EPS operating conditions

Load power in EPS varies constantly. The deviation of system load variation from the planned one lead to frequency deviations from rated one. Analysis of dynamic of change active power flows and frequency in Irkutsk power system (fig. 2) were performed by S.S. Smirnov [4].

The diagram illustrates the power system configuration for the Krasnodar Nuclear Power Plant. It features a 500 kV busbar (1) connected to a 220 kV busbar (2). A 220 kV line (45) is shown on the left. The system includes several 220 kV busbars (13, 18, 17, 19, 21, 22, 23, 24, 25) and 110 kV busbars (30, 29, 28, 27, 26). Transformers are represented by circles with arrows, and breakers by symbols with a diagonal line. The diagram also shows a 35 kV busbar (31) and a 6.3 kV busbar (6). The system is grounded through reactors (37-42) and a reactor (36). The diagram is labeled with various numbers (1-45) and voltage levels (220 kV, 110 kV, 35 kV, 6.3 kV, 500 kV).

Figure 3 illustrates power change of one of two transmission lines (TLs) 500 kV, that is regulated by the power flow control system.

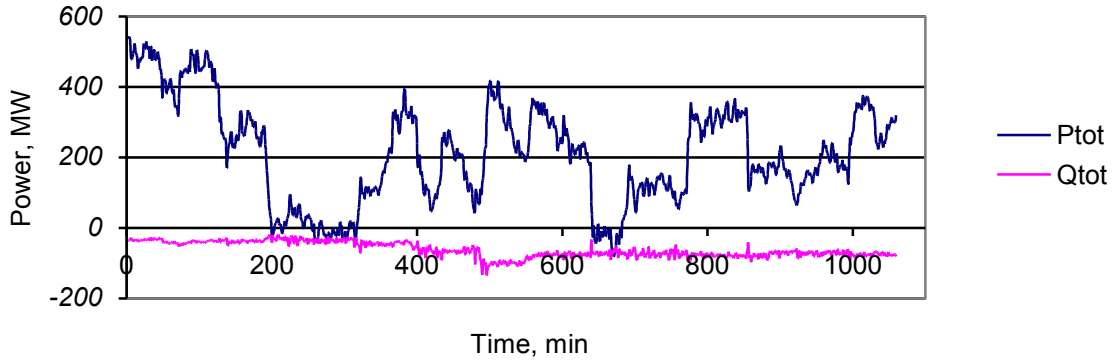


Fig. 3: Change in exchange power of one TL 500 kV

Power deviations from the average value for one transmission line (TL) are ± 200 MW at the limiting transmitted power 750 MW. It is noted, that power deviations linked not only with change of load power, but with restriction on the regulate power of units electric stations.

To estimate the dynamics of frequency variation the frequency measurements were carried out in Irkutsk EPS during 4 days. The frequency deviations are shown in Fig.4. Most of the deviations lie within the limits ± 20 mHz.

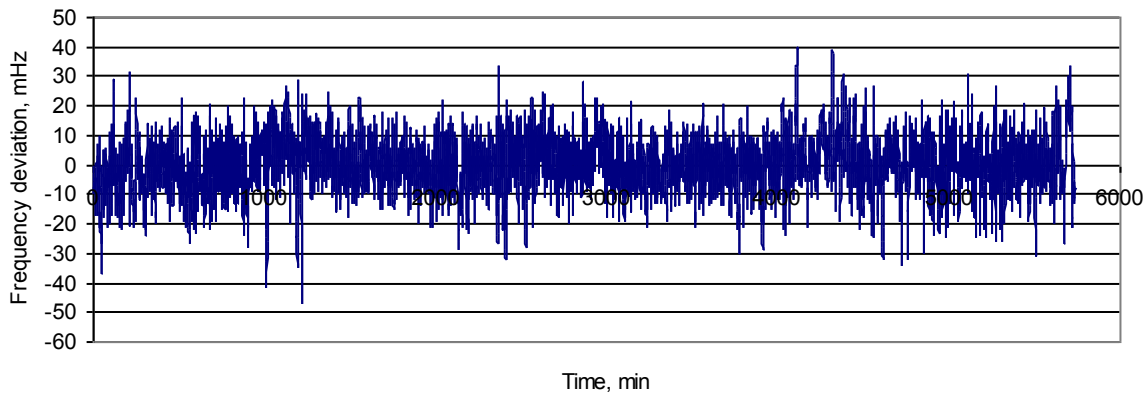


Fig. 4: Frequency deviation with «1 minute» averaging period

3 INTELLIGENT HYBRID MODEL FOR SHORT-TERM FORECASTING OF THE EXPECTED OPERATION CONDITIONS EPS

In order to forecast the parameters EPS there are widely used probabilistic models, neural network modeling techniques, genetic algorithms, etc.

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 [5], [6]. In many practical cases the application of different ANNs can provide the satisfactory forecast. But data preprocessing and analysis can significantly improve the forecast. In this paper we employ Hilbert-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);
- Hilbert transform (HT)

3.1 Empirical mode decomposition

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 nonstationary signal. The signal and its decomposition are shown in Fig. 5.

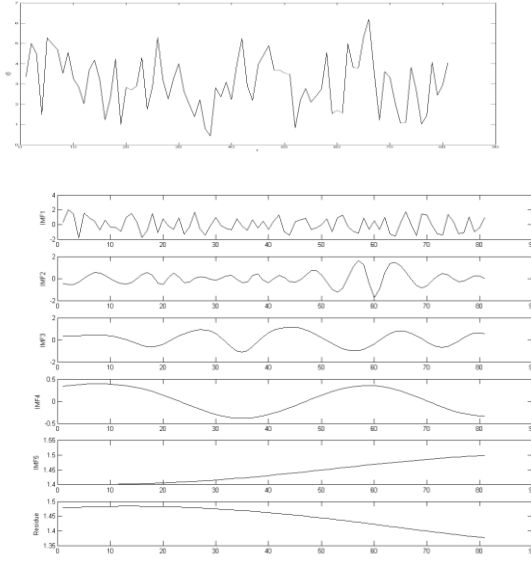


Fig. 5. Input signal $x(t)$ (top). Set of IMF's $x(t)$ (bottom).

Step 3. Compute residue $r_j(t) = r_{j-1}(t) - c_j(t)$. Then let $j = j + 1$ and repeat step 2 until the number of extrema in residue $r_j(t)$ 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 $q < p < n$, $c_i(t)$ are the high frequency noise components, $c_j(t)$ are the components representing the physical properties of the series and $c_k(t)$, $r_n(t)$ are trends, non-sinusoidal components.

3.2 Hilbert transform

Application of HT for each IMF provides us with the values of instantaneous frequency and instantaneous amplitude for each time moment t .

For the given real signal $x(t)$ we write its complex representation as follows

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

where $ix_H(t)$ 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

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

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

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

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

- Let $i = 1$ and $h_{i-1}(t) = r_{j-1}(t)$;
- 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;
- Compute the middle value $m_{i-1}(t) = (e_{min,i-1}(t) + e_{max,i-1}(t)) / 2$ and find $h_i(t) = h_{i-1}(t) - m_{i-1}(t)$ such as $e_{min,i-1}(t) \leq h_i(t) \leq e_{max,i-1}(t)$, for all t . Let $i = i + 1$;
- Repeat steps a) - c) until $h_i(t)$ satisfies a set of predetermined stopping criteria (following from properties of IMF). Let $c_j(t) = h_i(t)$.

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:

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

3.3 Intelligent hybrid model

Construction of intelligent hybrid model create on base two-stage adaptive approach. In the first stage the time series interval is decomposed into empirical mode functions to which the Hilbert transform is applied to compute the instant amplitude and frequency in every time sample. At the second stage, the modal functions and the instantaneous amplitude are used to automatically find optimal combinations of input variables for the subsequent application of standard algorithms for ANN forecasting for construction of intelligent hybrid model.

The technology of search for optimal combinations of input variables employs the nonlinear optimization algorithms (method of simulated annealing (SA) and neural-genetic input selection, NGIS which provide the procedure of selection of the best predictive model for each sample.

It is to be noted that the SA algorithm can select a neural network model for which the input parameters (modal functions and / or amplitudes) will be the most significant.

4 EXPERIMENTAL CALCULATIONS

The proposed intelligent hybrid model was employed to make short-term forecasts of active power flow on TL500 kV and the frequency of buses on the 220 kV large power node.

For this purpose the studied time series was decomposed into IMFs by the Huang method, 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”, which presented in detail in [5], [8].

4.1 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 (intelligent hybrid model). 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.

In order to evaluate the accuracy of parameters EPS different metrics were employed:

- MAPE metric;

$$MAPE = \frac{1}{n} \sum_{t=1}^n \frac{|x_t - \bar{x}_t|}{x_t} \cdot 100\%, \quad (8)$$

- Mean absolute error (MAE metric):

$$MAE = \frac{1}{n} \sum_{t=1}^n |x_t - \bar{x}_t|; \quad (9)$$

- Root mean squared error (RMSE metric):

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (x_t - \bar{x}_t)^2}, \quad (10)$$

where A_t is actual value of parameter at t , F_t forecasted value of parameter at t and n is number of measurements.

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

Table 1: Comparison of the active power flow forecasts results with anticipation 1 minute for different models

Period	Error	ANN type of MLP	HHT-ANN Hybrid Model
20:00 – 21:00	MAPE (%)	10.1	5.2
	MAE	6.2	1.8
	RMSE	33.1	3.1
21:00 – 22:00	MAPE (%)	9.1	4.3
	MAE	6.7	1.6
	RMSE	34.1	1.7

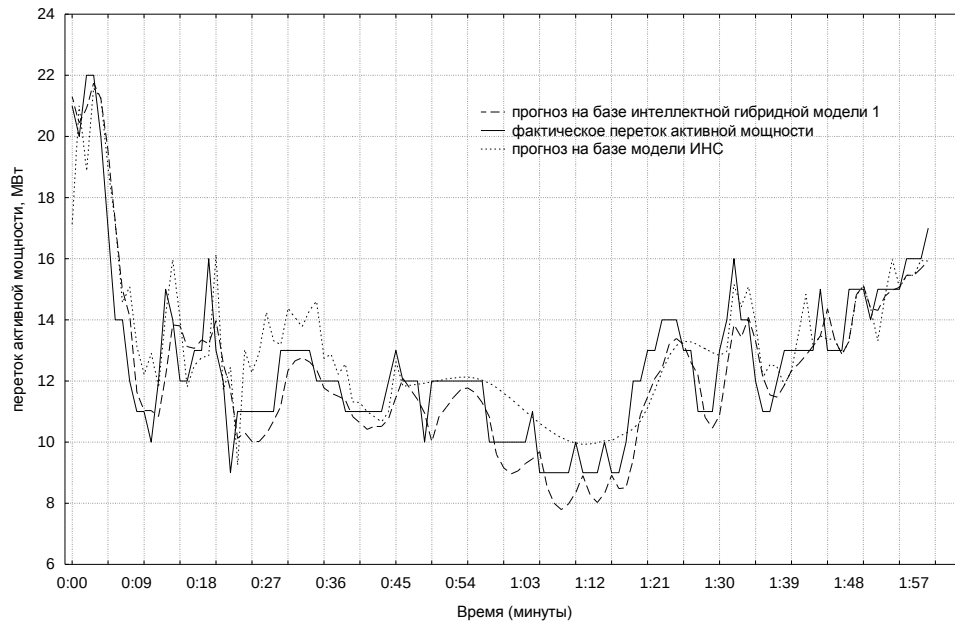


Fig. 6: Forecast of active power flow for a lead time interval of 1 minute.

4.2 Forecast of frequency for a lead time interval of 2 minute

The array of the learning sample included 360 (6 hour) minute measurements of active power flows. To make a short-term forecast of the parameter the SA procedure was used to create an general regression neural network, GRMM (intelligent hybrid model). 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 A1 and A3 from the input layer. Result of the frequency forecasting is presented in Table 2 and Fig. 7.

Table 2: Result of the frequency forecasts results with anticipation 2 minute for intelligent hybrid model

Parameter	Mean error for interval of 30 minute		
	MAPE, %	MAE	RMSE
Frequency	0,011	0,0057	0,0069

**Actual Trends in Development of Power System Protection and Automation
30 May – 3 June 2011, Saint Petersburg**

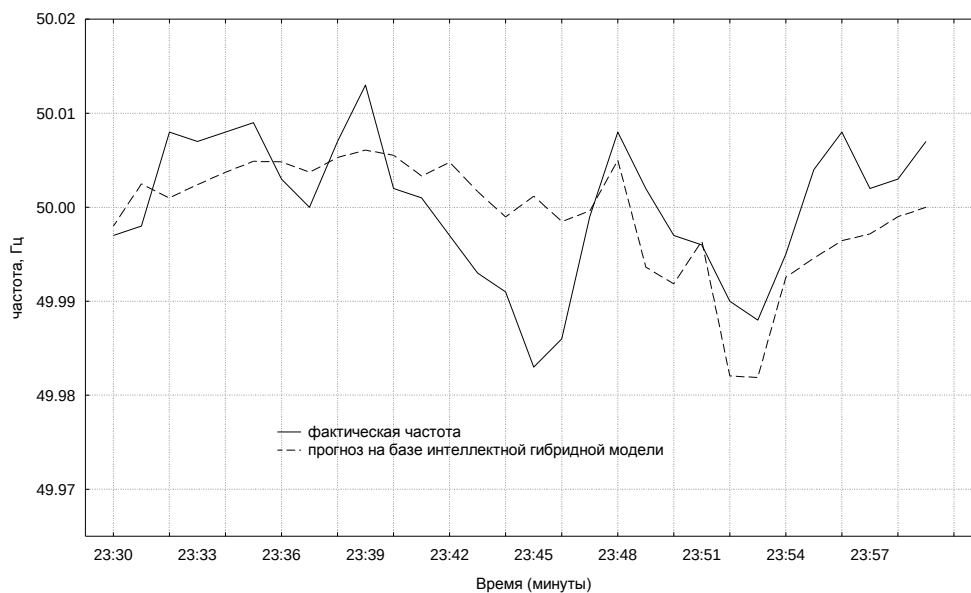


Fig. 7: Forecast of frequency for a lead time interval of 2 minute.

5 CONCLUSION

The problem of short-term forecasting of expected operating conditions of EPS. 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 improvement in forecast accuracy. In particular, in comparison with traditional neural network forecasting the improved forecast not less than 4% for different intervals of the predictions of the profile of EPS.

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.

REFERENCES

- [1] N.I. Voropai, I.N. Kolosok, V.G. Kurbatsky, P.V. Etingov, N.V. Tomin, E.S. Korkina, A.S. Paltsev. Intelligent coordinated operation and emergency control in electric power systems / Proc. Conference on Control Methodologies and Technology for Energy Efficiency (CMTEE-2010), Vilamoura, Portugal, 2010
- [2] N. I. Voropai, A. M. Glazunova, V.G. Kurbatsky, D.N. Sidorov, V. A. Spiryaev, N.V. Tomin. Operating Conditions Forecasting for Monitoring and Control of Electric Power Systems / Proc. the IEEE ISGT Europe 2010 Conference, Gothenburg, Sweden, 2010.
- [3] N. I. Voropai. Smart Grid: myths, reality, perspectives // Energeticheskay politika, №2, 2010. P. 9-13.
- [4] Smirnov S.S. Measurement results of frequency and exchange power fluctuations in Russia's power system / Proc. 4th International Conference "Liberalization and Modernization of Power Systems: Coordinated Monitoring and Control towards Smart Grids", Irkutsk, 2009. P. 121-125
- [5] Tomin N.V. Application of Neural Network Technologies for Price Forecasting in the Competitive Electricity Market, Proc. of the International Young Conference of Energetic "IYCE'2009, Budapest, 2009.
- [6] Kurbatsky V.G., Tomin N.V. Application of ANAPRO software for analysis and forecasting of state parameters and process characteristics in electric power systems, Proceedings of the 8th Baikal All-Russian Conf. "Information and mathematical technologies in science and management." Part 1. – Irkutsk: SEI SB RAS, 2008. – P.61-76.

- [7] Huang H.E., Shen Z., Long S.R., Wu M.C., Shih H.H., Zheng Q., Yen N.-C., Tung C.C. and Liu H.H. “The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis”. *Proc. R. Soc. Lond. A* (1998) 454, P. 903–995.
- [8] Kurbatsky V.G., Tomin N.V. The intelligent “ANAPRO” software in problems of monitoring in power distribution network, *Software & Systems*, 4, 2010, P. 148-152
- [9] Kurbatsky V., Sidorov D., Spiryaev V., Tomin N. Using the Hilbert-Huang transform for ANN prediction of nonstationary processes in complex power systems // 8 World Energy System Conference “WESC’2010”. Romania, Targoviste. P. 106-110.